# ROBOTS AND AI

## A NEW ECONOMIC ERA

Edited by
Lili Yan Ing and Gene M. Grossman

ROUTLEDGE

# Robots and AI

Robots and artificial intelligence (AI) are powerful forces that will likely have large impacts on the size, direction, and composition of international trade flows. This book discusses how industrial robots, automation, and AI affect international growth, trade, productivity, employment, wages, and welfare. The book explains new approaches on how robots and artificial intelligence affect the world economy by presenting detailed theoretical framework and country-specific as well as firm-product level-specific exercises.

This book will be a useful reference for those researching on robots, automation, AI and their economic impacts on trade, industry, and employment.

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# Robots and AI
A New Economic Era

## Edited by Lili Yan Ing
## and Gene M. Grossman

**While most – if not all – jobs can be replaced by robots and AI, love cannot be.**

To Lee Jae Hun
LYI

To Jean Baldwin Grossman
GMG

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# 1 Introduction

*Lili Yan Ing and Gene M. Grossman*

This book was written and edited by humans.

But soon many books, goods, and services will be produced, operated, and supported by industrial robots that rely on artificial intelligence.

Over the past three centuries, we have witnessed various technological advances that have revolutionized production methods, business organization, and the way people work and live. Paradigm-changing innovations included the steam engine, the electric motor, the digital computer, and a range of products and services falling under the rubric of Information and Communications Technology (ICT).

More recently, we have seen remarkable advances in the availability and uses of industrial robots and artificial intelligence (AI). George Devol is credited with inventing the first industrial robot in the late 1950s. The National Inventors Hall of Fame dubbed him the "grandfather of robotics" for his patent on the first digitally-operated, programmable, robotic arm that came to be known as Unimate. In 1961, Unimate was installed on the assembly line at General Motors' Inland Fisher Plant in Ewing, New Jersey. The machine transported die castings from the assembly line and welded them to the body of the car. In so doing, it substituted for human labor in performing a task that was tedious and dangerous. Soon afterward, Devol and his business associate, Joseph Engelberger, formed the world's first robot manufacturing company, which they named Unimation.

By 1967, industrial robots were being traded internationally. Unimate was exported to the Swedish firm Svenska Metallverken for use in the die-casting process for the company's downstream client, Volvo. Soon, Unimate was being manufactured by the Kawasaki Robot Company in Japan under a technical licensing agreement and marketed throughout Europe. It continued to be used mainly for "pick-and-place" tasks involving heavy and dangerous materials (Wallen, 2008; Gasparetto and Scalera, 2019). Meanwhile, a German firm, Keller and Knappich Augsburg (KUKA), had installed the first automatic welding systems for refrigerators and washing machines as well as the first multi-spot-welding line used by Volkswagen (Futura-Automation, 2019).

Before long, companies in Japan were installing robots for use in its fast-growing manufacturing sector. Kawasaki Robots sold its Kawasaki-Unimate

2000 to the nascent automobile sector. Japanese firms imported the Versatran from US producer AMF for automated handling of car parts. By 1972, Unimate's welding robots were also being used by Nissan Motors (Flamm, 1986). Kawasaki (Kawasaki Robotics, 2021) claimed that its robots could save the work of twenty employees, while being cleaner and safer than human labor.

In the years that followed, other emerging economies followed Japan's lead. Hyundai Motor, the largest automotive producer in South Korea, began to import industrial robots for use in its production processes (Sung, 2004). By 1985, Taiwan had developed assembly robots for applications in electronics and light assembly, while Singapore had installed about 0.6 industrial robot per thousand manufacturing workers (Flamm, 1986). As the technology developed further, faster and more sophisticated robots began to be used for a range of other manufacturing processes.

The annual number of installations of industrial robots worldwide more than doubled from 2012 to 2019, reaching a total of 373,240 by the end of that period. The operational global stock of robots increased from 1 million in 2009 to about 2.7 million in 2019. China, and to a lesser extent Japan, became the fastest new adopters of industrial robots. Together they contributed almost two-thirds of the global growth of industrial robots from 2012 to 2019 (Stanford University, 2021). The automotive and electronic industries remain the two heaviest users of industrial robots, absorbing between them about 59% of the new sales of total industrial robots in 2019 (IFR, 2020). The rapid growth in investment surely reflects the precipitous decline in prices; the average cost of an industrial robot fell by more than 60% between 2005 and 2017, from USD 68,659 to USD 27,074. Further price declines to under USD 11,000 are expected by 2025 (Ark Invest, 2021). A combination of other factors, such as the increase in robot functionality and flexibility, the improved ease of use and interface, and growing awareness of the potential applications of robotic technology are also contributing to the worldwide growth in robot usage (Furman and Seamans, 2019).

Research on artificial intelligence began at Dartmouth College in 1956. Textbooks define AI as a non-human system that perceives its environment and takes actions to maximize the probability of achieving its goals. More colloquially, the term AI is used to describe computations that mimic human cognitive functions, such as "learning" or "problem solving." By the middle of the 1960s, the Department of Defense was investing heavily in research on AI, and laboratories had been established all over the world. AI has improved massively in the last decade, primarily due to the invention of machine learning techniques (particularly deep neural networks) that enable the computers to have superior predictive power at substantially reduced costs (Agrawal et al., 2019; Taddy, 2019). Many AI-driven machines are now as good or better than humans in several instinctual and unconscious mental tasks, as they can mimic human thinking in tasks involving perception, mobility, and pattern recognition (Baldwin, 2019). Thanks to the advances in AI, more responsive and adaptable robots that can better interact with humans, have improved sensory capabilities, and that can better interact

with their environment to perform non-routine, uncertain, and more complex tasks are becoming widely available at ever-lower costs. Indeed, the application of AI to industrial robots is considered the most economically important among its various potential uses (Cockburn et al., 2019).

Global corporate investment in AI increased by almost sixfold, mounting from USD 12.7 billion in 2015 to as high as USD 67.9 billion in 2020. The United States and China dominate AI investment with a 76% combined contribution over the period from 2015 to 2020. But increases in demand for AI-related technologies are being observed around the globe. Brazil, India, Canada, Singapore, and South Africa recorded the highest growth in AI-related hiring from 2016 to 2020 (Stanford University, 2021).

## Economic benefits and costs of industrial robots and AI

Technological advances drive economic growth. Industrial robots, especially those that apply artificial intelligence, offer perhaps the greatest scope for technological improvement and productivity gains in the modern industrial era. Robots can increase the speed and precision of industrial processes while making them safer and more reliable. They can leverage the time of workers, while freeing humans to engage in more conceptual and interpersonal tasks. AI can be used to enhance the quality and variety of products available to consumers, provide new forms of entertainment, and offer solutions to pressing medical and environment problems. Clearly, the potential for robots and AI to improve the quality of life is enormous.

At the same time, new technologies almost always carry unintended consequences. Industrial robots, armed with AI, are bound to take over a range of tasks in production and thereby displace workers in the labor market. Workers who perform tasks that can be performed more efficiently by robots may see a fall in wages and a need to change jobs. Job displacement often brings loss of self-esteem and significant economic and social adjustment costs. Moreover, industrial robots threaten to widen income inequality after a period of diverging fortunes for different skill groups, while AI raises concerns about personal privacy and possibly much worse.

The enormous potential for productivity gain from robots and AI coupled with their far-reaching and quite unequal effects on workers with different skills have made them a fertile topic for economic research. Economists have been keen to understand how technologies that directly substitute for humans in the performance of certain tasks might have very different effects on income distribution and worker welfare than earlier technological improvements, many of which were mostly complementary to labor.

## Robots and AI: productivity and trade

Early research on the benefits of industrial robots and AI has emphasized two potential sources of gain. First, these technological advances reduce production

and operational costs. Robots can perform many tasks faster than humans and with greater precision and accuracy. AI can be used to predict problems along the production line and to leverage computation as an input to production. Agrawal et al. (2019), Atkinson and Ezell (2019), and Varian (2019), for example, have studied the potential productivity gains from the use of AI and robots and the associated declines in total production costs. Second, and perhaps less obvious, industrial robots and AI can help markets to function more efficiently. AI can be used to learn about human preferences, to allocate goods and services from where they are most readily available to where they are needed, thereby enhancing efficiency in logistics and delivery. These potential benefits of AI have been touted in recent work by Parkes and Wellman (2015), Atkinson (2019), Milgrom and Tadelis (2019), Davenport et al. (2019), and McKinsey and Company (2019).

Previous studies have found large productivity gains and substantial price-reducing effects of the application industrial robots and AI at both the firm and aggregate levels. Notable examples of papers with such findings include Acemoglu and Restrepo (2018), Autor and Salomons (2018), Graetz and Michaels, (2018), Agrawal et al. (2019), Koch et al. (2019), and Acemoglu et al. (2020). Some authors also find that industrial robots and AI promote international trade. For example, Brynjolfsson et al. (2019) report that an AI-based application that provides automated translation service on a digital-trading platform increased exports by 17.5%. Goldfarb and Trefler (2019) explain how industrial robots and AI can facilitate not only goods trade, but also trade in services.

## Robots and AI: employment and wages

Recent research also focuses on the worrisome consequences of automation and AI for employment and wages, especially for those less-skilled workers performing routine tasks that can be performed by machines. Drawing on the existing literature, Baldwin (2019) reports that between one and six of every ten jobs is at risk of being replaced by robots in the coming two decades. Estimates vary with estimation methods, but findings range from 36% for Finland (Pajarinen and Rouvinen, 2014), 47% for Germany (Brzeski and Burk, 2015), and 47% for the United States (Frey and Osborne, 2017), to as high as 60% globally (Bughin et al., 2017).

Automation and AI are likely to have heterogeneous effects in the labor market. High-skilled workers, those employed in technology-intensive sectors, and those performing non-routine tasks may benefit as industrial robots leverage their productivity. Workers with less education, especially those performing manual tasks on the production line, are most at risk; see, for example, Autor et al. (2015), Graetz and Michaels (2018), Humlum (2019), Furman and Seamans (2019), Stemmler (2019), Cheng et al. (2019), Acemoglu and Restrepo (2020), and Barth et al. (2020). Greater digitalization in smart factories and advanced robotics might reduce the importance of labor costs in determining competitive advantage, laying greater emphasis instead on skills, complementary services, and other

aspects of firm ecosystems (Hallward-Driermeier et al., 2017). Yet, recent studies also argue that the productivity gains at the firm level that result from the adoption of automation and AI could potentially expand demand (Autor and Salomons, 2018; Bessen, 2018), which in turn may enhance labor as these firms expand or create new tasks and occupations in service firms and elsewhere (Autor and Salomons, 2018; Acemoglu and Restrepo, 2019; Dauth et al., 2021; Koch et al., 2019; Autor et al., 2020).

Baldwin (2019) stresses the need for labor-market research that focuses on occupations in addition to jobs. Displacement of jobs by machines generates adjustment costs, as workers need to move within firms to perform different tasks, or search for new jobs in different firms or expanding industries. But most occupations conduct non-routine as well as routine tasks, so the medium-term outlook may not be so bleak, as workers shift their attention to tasks that machines cannot perform. Recent studies increasingly adopt a task-based approach to estimating the labor-market impacts of industrial robots and AI, and these typically predict less dire outcomes than those that focus on displacements. For example, Arntz et al. (2016) using a task-based approach, estimate that only about 9% of occupations in OECD countries are highly vulnerable to automation.

Whereas research findings are mixed about the net effects of continued advances in the use of industrial robots and AI on certain segments of the labor market, there is little disagreement about the distributional implications. Automation has undoubtedly contributed to the fall in the labor share in national income; see the review by Grossman and Oberfield (2022, forthcoming). Among workers, the more-skilled workers whose human capital is most complementary to the new technologies are bound to gain relative to the less-skilled workers for whom industrial robots are substitutes; see Autor et al. (2015), Arntz et al. (2016), Graetz and Michaels (2018), Bessen et al. (2019), Stemmler (2019), Cheng et al. (2019), Gregory et al. (2019), and Acemoglu and Restrepo (2020). The new occupations and tasks that AI will create will also likely benefit the more skilled and better educated members of the labor force (Tirole, 2017; Acemoglu and Restrepo, 2018; Stemmler, 2019; Barth et al., 2020; Dauth et al., 2021). These likely implications of the new technologies for income distribution come on the heels of more than two decades of wage divergence and threaten to further the social tensions that the greater dispersion has already ignited.

## This book

Despite the vibrant and burgeoning literature, much remains to be known about the economic effects of continued automation and the further development of AI. How will these innovations affect countries at different levels of development and different regions within countries? What are the occupations of the future? How can policy best prepare societies for these anticipated technological changes? How will the technological developments affect world cooperation and trade, for example by influencing the organization of global value chains?

This book contributes to this ongoing project of research and learning. The contributors to this volume take stock of the existing literature and draw lessons from it, while extending it and taking it in new directions. The chapters of this book are diverse in their topical and geographic coverage and in their methodological approaches, be they theoretical or empirical, structural, or reduced form. Yet they share a common faith that rigorous economic research can help us to prepare for an uncertain and, for some, an intimidating future.

The book is organized in two parts. The first six chapters (Chapters 2–7) mostly examine labor-market impacts of automation and AI. They analyze how workers will be affected by the adoption of these new technologies in a variety of occupations and in different countries and regions. The focus here is on employment, wages, and worker welfare. The final three chapters (Chapters 8–10) focus more on productivity and trade, trying to measure the likely gains along these dimensions from technological advances in robotics and AI in developed and developing countries.

Chapter 2 by Aghion, Antonin, Bunel, and Jaravel surveys the recent literature on the effects of automation on labor demand. They describe two contrasting views of the impacts of automation. In the more pessimistic view, robots primarily substitute for labor at the task level. Then the direct effect of automation is to reduce labor demand in firms that adopt robots, which exerts downward pressure on the equilibrium wage. This direct effect may be counteracted in general equilibrium by a wage drop that induces non-automating firms to employ more labor while incentivizing the creation of new activities for labor to perform or the accumulation of capital that boosts labor demand in view of the complementarity between capital and labor at the aggregate level. In either case, employment falls at automating firms and workers relocate to firms that do not automate or to new tasks that cannot be performed by robots. The alternative, more optimistic view stresses that firms that install robots become more productive, thus expanding their market share at the expense of firms that do not automate. Also, the productivity gains in automating firms may translate into lower prices that stimulate consumer demand and expand the overall size of the market. In this scenario, automation increases employment in the firms that adopt robots and might even push the equilibrium wages higher.

Aghion et al. note that, while the evidence that is based on variation across industries and local labor markets is mixed, the newer studies that make use of firm-level data support a more optimistic view of automation. Most of the studies using firm-level data do not find evidence of a falling equilibrium wage, nor even of a declining labor share in firms that automate. Concerning AI, they cite Babina et al. (2020), who find that firms that invest in AI experience faster sales and employment growth than their non-investing counterparts.

Finally, Aghion et al. report on their own previous work using firm-level data from France. In their data, estimates using data on aggregate employment zones find little or no support for the negative view at the aggregate level. When they drill down to the firm or plant level, the productivity-enhancing effects of automation seems clear. Firms that automate gain market share and produce at larger

scale. They also find no evidence that automation increases the wage of more-skilled workers relative to that of less-skilled workers in firms that choose to automate. Moreover, they report an overall positive effect of automation on employment even at the industry level. Aghion et al. conclude that automation is not the enemy of labor. By modernizing the production process, automation makes firms more competitive, which enables them to win new markets and hire more workers in a globalized world.

In Chapter 3, Bonfiglioli, Crinò, Gancia, and Papadakis develop a simple but illuminating model that highlights the interaction between automation and off-shoring. In the model, industrial robots might take over tasks formerly performed by domestic workers, but, in the presence of offshoring, they might instead displace foreign workers. This distinction proves to be critical for the wage and welfare effects of automation. In autarky, robots must, of course, displace domestic workers. Then, substituting robots for domestic labor in performing some tasks generates a productivity effect and a capital-deepening effect that tend to raise domestic wages, but a displacement effect that has the opposite impact on wages. In the presence of offshoring, if robots displace domestic workers, there is an additional terms-of-trade effect that adversely impacts the welfare of domestic workers. Domestic workers may suffer from automation in situations where they would have gained in autarky. In contrast, if robots displace foreign workers and thereby bring part of the production process back home, automation is always beneficial for domestic workers.

Motivated by these theoretical findings, the authors study the effects of imports of industrial robots between 1990 and 2015 on US local labor markets. Using a "shift-share" analysis, they estimate that imported robots displaced local workers but nonetheless boosted domestic wages due to positive productivity effects (in line with the Aghion et al. findings reported in Chapter 2). Next, they investigate the relationship between local labor market impacts and offshoring. They show that occupations at risk of replacement by robots have similar task content to those that have been deemed offshorable. They also find the negative employment effects of automation to be weaker in occupations that are offshorable than in occupations that are less readily moved abroad. Finally, they show – in keeping with their theoretical results – that commuting zones that are more exposed to off-shoring experience smaller job displacement from robot imports than commuting zones that are less exposed.

Chapter 4 by Faia, Laffitte, Mayer, and Ottaviano points to another, possibly adverse effect of automation on employment and wages and stress a difference between automation and offshoring. Citing Bainbridge (1983), who described a "paradox of automation," they model the idea that automation often requires the efficient completion of complementary tasks that can only be performed by workers with specialized human capital. Therefore, automation may induce increased specialization by workers, who need not only *more* skills, but *particular* skills. Faia et al. refer to the possibility that new technologies demand workers with specialized knowledge in "core competencies" as "core-biased technological change."

If the paradox of automation is operative, firms should become more selective in their hiring practices as they invest in industrial robots. With greater search and selectivity, the duration of unemployment spells should lengthen while mismatch between worker skills and firm tasks should be reduced. The authors verify these predictions using data on European occupations and industries for the period from 1995 to 2010, finding that automation generates greater skill concentration, longer unemployment spells for displaced workers, and less educational mismatch between firms and workers. Interestingly, selectivity instead fell in industries with high offshorability. They rationalize these findings in a model in which automation strengthens the forces of assortative matching between workers' skills and firms' tasks, whereas offshoring does just the opposite.

In Chapter 5, Furusawa, Kusaka, and Sugita also study the effects of improvements in industrial robots while considering advancements in AI as a separate technological development. They assume that industrial robots perform manual tasks that low-skilled workers would otherwise perform whereas AI substitutes for high-skilled labor in performing more conceptual tasks. Using a quantitative general-equilibrium model of task-based production in seventeen industries and fifty countries that features input-output relationships and global value chains, they simulate counterfactual histories in which trade costs and robot technologies remain at their 1993 levels. They find that advances in robot technology indeed contributed to lower wages for unskilled workers in some countries, but the labor-market effects were modest compared to those of falling trade costs. Meanwhile, robots generated productivity improvements that benefited workers in some other countries. When they simulate the effects of a tenfold further increase in the productivity of robots and AI, they find that the former has much greater labor-market impacts compared to the latter, largely because the estimated elasticity of substitution between AI and high-skilled labor is much smaller than the elasticity of substitution between robots and low-skilled labor. Only for Germany and Japan do they find significant impacts of advances in AI technology, these being the two countries where AI tasks shares are relatively large. Finally, they predict that advances in robot technology will increase wage inequality in most countries, whereas advances in AI technology will have the opposite effect on wage inequality.

Baldwin and Dingel pose a rather different question in Chapter 6. Leveraging recent work on telecommuting induced by the COVID-19 pandemic, they ask how many of the newly remote jobs are likely to move overseas and how important such "telemigration" will be in the development process. Assessing the prospects for telemigration requires estimates not only of how many jobs are potentially offshorable, but also of how many of the workers that reside abroad have the relevant skills to perform these tasks and how substitutable these foreign workers are for their domestic counterparts. To address these questions, they estimate a gravity model of telemigration in which the tally of jobs in the importing country that can be performed remotely plays the role of the "importer mass"; the population of suitably skilled workers in the exporting

country plays the role of the "exporter mass"; and the Ghemawat (2007) measure of the cultural, administrative, geographic, and economic ("CAGE") distance between countries captures bilateral trade frictions.

Using their estimates of the gravity equation, they simulate the effects of further reductions in barriers to trade in services. The baseline simulations take the elasticities with respect to trade costs to be constant, and then further liberalization is likely to have only very modest effects, because the initial service flows are rather small. In a speculative final section, the authors relax the assumption that trade elasticities are constant and consider instead the possibility that the relative productivity of the emerging country as a function of the task index rises sharply at first but flattens out as more tasks are performed there. In other words, they assume that the manifest comparative advantage of the South in tasks that it already performs has a different shape than its latent comparative advantage in tasks that are currently nontraded. In this scenario, small changes in the trade costs for services can have quantitatively large impacts on extent of telemigration, as the equilibrium moves from the status quo into a range of much higher trade elasticities.

In Chapter 7, Hanson studies the forces that guide the location of AI-related activities across the United States. Hanson first identifies AI-related jobs using keywords that appear in Bureau of Census occupational titles. Then, using an approach proposed by Lin (2011), he estimates the regional growth in jobs related to AI by weighting employment growth in AI-related occupations by the share of job titles in these occupations that were added since 1990. He finds that, overall, the pattern of regional specialization in AI-related activities mirrors that for ICT. However, foreign-born and native-born workers within the sector tend to cluster in different locations. Whereas specialization of the foreign-born in AI-related jobs is strongest in high-tech hubs with a preponderance of private-sector employment, native-born specialization in AI-related jobs is strongest in centers for military and space-related research.

Hanson then proceeds to investigate the factors that drive regional employment growth in AI-related jobs. He associates changes in patterns of regional specialization in private AI activities with changes in the regional supplies of college-educated immigrants. The author estimates the relationship between the employment share of AI-occupations in a commuting zone and the projected local increase in college-educated immigrants, where the projection is based on the national growth of college-educated immigrants from each country of origin and the initial distribution of immigrants by nationality across commuting zones. He finds that growth in the supply of foreign-born workers can account for much of the regional growth in employment in AI-related occupations since 2000. An inflow of educated immigrants has virtually no effect on employment growth for native workers, suggesting that any substitution that may occur is offset by complementarities. Overall, the results in the chapter highlight the importance of immigration policy to continued technological progress in AI activities.

Chapter 8 by Artuc, Bastos, Copestake, and Rijkers examines how the installation of industrial robots in advanced countries affects trade with developing

countries. As suggested by Bonfiglioli et al. in Chapter 3, robots might substitute for low-skilled workers in tasks offshored to low-wage countries. Moreover, low-income countries may lack the skills and infrastructure needed to participate intensively in emerging global value chains if automation reduces the importance of low labor costs as a source of international competitiveness. Motivated by these concerns, the authors of this chapter investigate what effect automation may have had on the trade participation and patterns of developing countries. Is there evidence that growing use of industrial robots in the advanced countries reduces export opportunities for developing countries?

The authors first constructed and calibrated a multi-sector, multi-country model of two-stage production and trade in which robots can take over some (potentially different) range of tasks in each sector. They simulate a decline in the price of robots, holding fixed the ranges of tasks that robots can perform. Not surprisingly, this induces industries in the North to install more robots. But they find, as well, that exports from South to North expand in the same sectors that experience the greatest robotization. This possibly counterintuitive finding reflects that robots improve productivity in the North, and so the scale of production expands, which in turn expands their demand for intermediate goods produced in the South. The authors extend their model to include China as a separate country, noting that its robot stock has expanded more than in other developing countries. They study the impacts of China's governmental support for investments in robots and find that these may increase or decrease wages in China depending on the size of the subsidies. As China induces installation of more robots, its trade pattern comes to resemble that in the North, which reduces its trade with those countries and expands its trade with countries in the South.

Artuc et al. recognize that their calibrated model is intended to capture long-run effects and that automation might generate short-run adjustment costs. After pointing to evidence of short-run adverse employment effects in the local labor markets of some middle-income countries, especially for the least mobile workers who previously performed tasks now executed by robots, they proceed to study firm-level drivers of adoption of robots in developing countries and firm-level consequences of robot adoption. They find that the initially larger and more globally connected firms in the South are more likely to adopt robots and, when they do so, they increase their market shares at the expense of firms that do not automate. Thus, the spread of industrial robots can impose adjustment costs not only on less-mobile and less-skilled workers, but also on smaller and less globally active firms.

In Chapter 9, Ing and Zhang study automation in a developing country at a very detailed level. They focus on firms in Indonesia, using product-level data on production and trade for 2008 to 2012. Inasmuch as Indonesia imports most of the industrial robots that it uses, and the firm-level data report imports of this category of capital goods, Ing and Zhang have an excellent measure of investment in robots at the firm level.

Ing and Zhang examine both the characteristics of firms that import industrial robots in Indonesia and the subsequent performance of such firms. Firms that

import robots are more productive than others, pay lower shares of their revenues to labor, but pay higher wages. Over the five-year period, the firms that automated achieved greater growth in outputs, greater growth in employment, and larger export shares. The also produced goods of higher quality. In Indonesia, automation is associated with an increased demand for production workers, analogous to the findings of Aghion et al. for France. Ing and Zhang rationalize their empirical findings with a model of heterogeneous firms that choose their investment in robots and their product quality to maximize profits. In their model, the more productive firms automate more tasks, produce higher quality, and thereby generate more revenues and hire more workers.

In Chapter 10, Sun and Trefler study trade in AI-enabled services. In particular, they examine trade in mobile applications, using a novel data set on international downloads of smartphone apps from 2014–2020. They merge these data with data on AI patents held by the app's parent company, from which they develop a measure of "AI deployment" by year, exporting country, and application category.

The analysis entails regression of various outcomes on AI deployment. Recognizing that deployment is endogenous, they construct an instrument that is meant to capture exogenous shocks to the cost of deployment. With analogy to factor endowment theories of trade, they note that countries with deep expertise in AI are likely to have cheap and ready access to the inputs used in deploying AI, which in turn confers a comparative advantage to them in producing apps that use this input intensively. Accordingly, they form their instrument by interacting a measure of a country's expertise in AI with a measure of an app category's AI intensity.

When the authors estimate a gravity equation for app downloads, they find that greater AI deployment causes a sixfold increase in downloads at the level of the importer-exporter dyad, app category, and year. An increase in AI deployment also causes a doubling of the number of different bilaterally traded apps. Deployment induces high levels of creative destruction, that is, entry into and exit from download of app varieties in the importing countries. Finally, AI deployment generates gains from trade; consumer welfare in 2020 from app downloads is estimated to be 2.5% higher than it would have been under a counterfactual with no AI deployment.

Collectively, the research reported in this book paints a relatively optimistic picture of a future with more industrial robots and improved artificial intelligence. The studies provide further evidence that use of industrial robots and AI raises productivity and lower costs. Although these technologies do seem to substitute for relatively low-skilled labor in certain tasks, the induced productivity gains and attendant output expansion offset the direct negative effects on these low-wage workers. Automation and AI can encourage greater international division of labor in global value chains and promote trade in AI-enabled services. Like all new technologies, there will be adjustment costs that must be managed by policymakers. But it seems from the research in this book and elsewhere that, overall, the forthcoming technological developments in the robotics and AI

sectors ought to be welcomed, not discouraged. Along with the development of robots and AI, it is our responsibility to ensure that they are human-centric and designed to improve human welfare.

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# 2 The Effects of Automation on Labor Demand

## A Survey of the Recent Literature

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## 1. Introduction

Should we fear or welcome automation? On the one hand, fear may prevail if we believe that human workers will be replaced by machines which perform their tasks, thereby increasing unemployment and reducing the labor share. On the other hand, we may welcome automation since it spurs growth and prosperity, as illustrated by the big technological revolutions – steam engine in the early 1800s, electricity in the 1920s – none of which generated the mass unemployment anticipated by some.

The fear that machines will destroy human jobs began long ago. Already in 1589, when William Lee invented a machine to knit stockings, the working class was so fearful of the consequences that he was rejected everywhere and even threatened. Then came the first industrial revolution, the "steam engine revolution", and in its wake the so-called Luddite movement. Despite a 1769 law protecting machines from being destroyed, destruction intensified as the weaving loom became widespread, culminating with the Luddite rebellion in 1811–1812.

The second industrial revolution, the "electricity revolution", occurred first in the US in the late 19th century. Thirty years later, economists began to express concern about the unemployment that this revolution would generate. In 1930, Keynes wrote, "We are being afflicted with a new disease of which some readers may not yet have heard the name, but of which they will hear a great deal in the years to come – namely, technological unemployment."[1] Once again, the prediction of a large-scale increase in unemployment did not materialize.

More recently, the information technologies (IT) and artificial intelligence (AI) revolutions have raised similar fears: by creating further opportunities to automate tasks and jobs, IT and AI may increase unemployment and reduce wages. Consequently, the idea that one should tax robots has become influential in recent years.

In this paper, we discuss the effects of automation on employment, appealing to both the existing literature on AI and automation and our recent empirical work using French data (Aghion et al., 2019, 2020). We first spell out the two contrasting views on the subject. A first view sees automation as primarily destroying jobs, even if this may ultimately result in new job creations taking advantage of the lower equilibrium wage induced by the job destruction. The prediction is that automation should reduce employment, wages, and the aggregate labor share. According to

this first view, automation may reduce both the aggregate number of jobs and wages, thus reducing the well-being of workers. An alternative viewpoint emphasizes the market size effect of automation: namely, automating firms become more productive, which enables them to lower their quality-adjusted prices and thereby increase the demand for their products; the resulting increase in market size translates into higher employment by these firms. We provide empirical support for the second view, drawing from our empirical work on French firm-level data and a growing literature covering multiple countries.

The chapter is organized as follows. Section 2 presents the debate. Section 3 describes the emerging empirical consensus towards the more optimistic view of automation, with positive direct effects on employment at the firm level. Drawing on our recent empirical work, Section 4 describes the main methodological approaches and the main findings from the literature using data on French plants, firms, and labor markets in recent years. Section 5 concludes.

## 2. The debate: what are the direct and indirect effects of automation on employment?

In this section we briefly present the two contrasting views of automation and employment.

### a. The "negative" view: negative partial equilibrium effects and positive general equilibrium effects of automation on aggregate labor demand

The "negative" view[2] implies that automation reduces demand for labor and pushes wages downward. The "partial equilibrium" (PE) effect is a fall in labor demand through the substitutability between labor and machines at the task level. This effect may then be counteracted in general equilibrium (GE) according to several channels, which are summarized in Table 2.1 and described hereafter.

In Acemoglu and Restrepo (2016) it is counteracted by the fact that automation depresses the equilibrium wage, which in turn encourages the creation of activities that initially employ labor (before being themselves subsequently automated); this in turn increases the demand for labor and therefore limits the wage decline. In Aghion, Jones and Jones (2017), the PE effect on labor demand is counteracted by a "Baumol Cost Disease" GE effect whereby labor becomes increasingly scarce relative to capital over time, which pushes wages upward (due to the complementarity between labor and capital at the aggregate level).

More formally, Acemoglu and Restrepo (2016) assume that final output is produced by combining the services of a unit measure of tasks $X \in [N - 1, N]$, according to:

$$\Upsilon = \left( \int_{N-1}^{N} X_i^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}}$$

Table 2.1 Summary of Theoretical Predictions on the Impact of Automation on Labor Demand

| Authors | PE Effect of Automation | GE Effect of Automation | Predicted Impact on Employment in Automating Firms | Predicted Impact on Wages in Automating Firms |
|---|---|---|---|---|
| **Acemoglu & Restrepo (2020)** | Fall in labor demand through the substitutability between labor and machines at the task level. | Increase in labor demand through a fall in wages and the endogenous creation of new tasks for which labor has a comparative advantage. | Decrease | Decrease |
| **Aghion, Jones & Jones (2017)** | Fall in labor demand through the substitutability between labor and machines at the task level. | Increase in labor demand through the complementarity between capital and labor at the aggregate level. | Decrease | Ambiguous |
| **Aghion, Antonin, Bunel & Jaravel (2020)** | Increase in labor demand through the increase in productivity and in consumer demand. | Business stealing effects reducing labor demand at non-automating firms. | Increase | Ambiguous |

where: (i) tasks $X_i$ with $i > I$ are non-automated, produced with labor alone; (ii) tasks $X_i$ with $i < I$ can be automated, that is, capital and labor are perfect substitutes within tasks, with $\sigma - 1$ denoting the constant elasticity of substitution between tasks; (iii) $N$ indexes the productivity of tasks;[2] (iv)

$$X_i = \alpha(i)K_i + \gamma(i)L_i$$

where: (a) $\alpha(i)$ is an index function with $\alpha(i) = 0$ if $i > I$ and $\alpha(i) = 1$ if $i < I$; (b) $\gamma(i) = e^{A_i}$. $\gamma(i)$ is the productivity of labor in task $i$. Acemoglu and Restrepo assume that $\gamma(i)$ is strictly – exponentially – increasing, so that labor has a comparative advantage in the production of tasks with a high index.

In the full-fledged Acemoglu-Restrepo model with endogenous technological change, the dynamics of $I$ and $N$ (i.e., the automation of existing tasks and the discovery of new lines) result from endogenous directed technical change. Under reasonable parameter values guaranteeing that innovation is directed towards

using the cheaper factor, there exists a unique and (locally) stable Balanced Growth Path (BGP) equilibrium.

Stability of this BGP follows from the fact that an exogenous shock to $I$ or $N$ will trigger forces that bring the economy back to its previous BGP with the same labor share. The basic intuition for this result is the following: if a shock leads to over-automation, then the decline in labor costs will encourage innovation aimed at creating new – more complex – tasks that exploit cheap labor, that is, it will lead to an increase in $N$. In other words, the negative effect of automation on labor demand in partial equilibrium is mitigated by a general equilibrium effect, whereby the depressing effect of automation on wages encourages entry of new activities that initially take advantage of labor becoming cheaper.

Aghion, Jones, and Jones (2017) point to another counteracting force, namely the "Baumol Cost Disease" effect, which prevents automation from depressing wages too much. There it is the complementarity between existing automated tasks and existing labor-intensive tasks, together with the fact that labor becomes increasingly scarce relative to capital over time, that allows for the possibility that the labor share remains constant over time.

More formally, final output is produced according to:

$$Y_t = A_t \left( \int_0^1 X_{it}^\rho di \right)^{\frac{1}{\rho}}$$

where $\rho < 0$ (i.e., tasks are complementary), $A$ is knowledge and grows at constant rate $g$ and, as in Zeira (1998):

$$X_{it} = \begin{cases} L_{it} \text{ if not automated} \\ K_{it} \text{ if automated} \end{cases}$$

Under the assumption that a fraction $\beta_t$ of tasks is automated by date $t$, we can re-express the previous aggregate production function as:

$$Y_t = A_t (\beta_t^{1-\rho} K_t^\rho + (1 - \beta_t)^{1-\rho} L^\rho)^{1/\rho}$$

where $K_t$ denotes the aggregate capital stock and $L_t \equiv L$ denotes the aggregate labor supply.

In equilibrium, the ratio of capital share to labor share at time $t$ is equal to:

$$\frac{\alpha_{K_t}}{\alpha_L} = \left( \frac{\beta_t}{1 - \beta_t} \right)^{1-\rho} \left( \frac{K_t}{L_t} \right)^\rho$$

Hence an increase in the fraction of automated goods $\beta_t$ has two offsetting effects on $\frac{\alpha_{K_t}}{\alpha_L}$: (i) first, a positive effect which is captured by the term $\left( \frac{\beta_t}{1-\beta_t} \right)^{1-\rho}$, which we label the partial equilibrium effect of automating tasks (holding the ratio $\frac{K_t}{L_t}$ constant); (ii) second, a negative effect captured by the term $\left( \frac{K_t}{L_t} \right)^\rho$, as we recall that $\rho < 0$, which we label the GE effect of automation. This latter

effect relates to the well-known Baumol Cost Disease: namely, as $\frac{K_t}{L_t}$ increases due to automation, labor becomes scarcer than capital which, together with the fact that labor-intensive tasks are complementary to automated tasks (indeed we assumed $\rho < 0$), implies that labor will command a sustained share of total income.

While the previous two models emphasize different counteracting forces that limit the wage decline induced by automation, both have in common that the partial equilibrium effect of automation is to destroy employment. In particular, this effect would be observed within firms that automate.

### b. The "positive" view: positive partial equilibrium effects and negative general equilibrium effects of automation on labor demand

Recent work suggests a more "positive" view of automation: the direct effect of automation may be to increase employment at the firm level, not to reduce it.[3] The reason is that firms and plants that automate become more productive. This allows them to offer a better quality-adjusted price than their competitors, and therefore to "steal business" away from their competitors, and more generally to expand the size of their markets (domestic and foreign). This in turn increases their demand for labor.[4]

Note that this channel does not exclude the possibility that total labor demand, at the national, industry, regional or commuting zone level may not respond so positively to automation and may even react negatively to it. There may be an overall negative effect if automating firms induce a sufficiently large decline in employment for non-automating firms and cause their exit. But a main difference with the "old view", is that, here, the direct dominant effect of automation is the positive productivity effect, which may then be counteracted by a "creative destruction" or "eviction" effect in general equilibrium. Furthermore, the negative GE effect is partly borne by international competitors, which has implications for the desirability of taxing robots.

### c. Implications for the taxation of robots

A growing theoretical literature has examined the reasons that may justify the taxation of robots, notably limiting the potential rise in income inequality that automation might create. Costinot and Werning (2018) examine whether taxation or protectionist trade policies might help to better distribute the economic benefits of AI technologies.[5] Their results indicate that taxing the innovators or developers of the technology is undesirable because it would impede innovation; yet, if robots lead to an increase in inequality, a modest tax on the use of technology (as opposed to innovation *per se*) may be the optimal prescription because of distributional concerns.

Optimal policy depends on the elasticity of employment and inequality to robotization, which highlights the importance of distinguishing empirically

between the two aforementioned views. As discussed in Aghion et al. (2020), the second view implies that unilateral taxation of robots by a given country could be counterproductive for industrial employment in that country, because of business stealing effects across countries. According to that view, the positive effect of automation will benefit countries that keep automating, while the negative GE effect will be shared across countries, given that competition operates in world markets. Therefore, as explained by Aghion et al. (2020), unilateral taxes on robots or other automation technologies may be detrimental to domestic employment: "without international coordination, in a globalized world attempts to curb domestic automation in an effort to protect domestic employment may be self-defeating because of foreign competition."

In the next section, we confront the two views with recent evidence from the literature, covering many countries and time periods. Research designs using variation across industries or labor markets deliver mixed evidence with regards to the impact of automation on labor demand. Recent firm-level evidence delivers clear causal evidence supporting the "new view", with an increase in labor demand at automating firms.

## 3. A survey of the empirical evidence from the recent literature

Early analyses hypothesized an increase in technological unemployment (Keynes, 1930; Leontief, 1952; Lucas & Prescott, 1974), however they lacked empirical support. A next generation of studies were able to confront theoretical models with data. Their analyses have been primarily conducted at the national or industry level and have mostly conveyed the idea of automation having a negative impact on aggregate employment and aggregate wages: automation is primarily reducing labor demand. Yet these analyses fall short of describing the process that goes on within firms. It is only over the past few years, thanks to the increasing availability of new firm-level datasets, that analyses of the effects of automation on employment could be performed at a more disaggregated level.

In this section, we provide an overview of the recent empirical literature on automation and employment. As our literature survey illustrates, the profession has evolved from the more "negative" view of automation as primarily destroying jobs, towards the more "positive" view of automation as enhancing productivity, market size, and therefore labor demand and employment.

### a. *Mixed evidence from research designs using variation across industries and labor markets*

How should automation be measured? Until recently, the number of reliable sources on which empirical analyses of automation could be built was limited.[6] But since the 2010s, the International Federation of Robotics (IFR) has provided data on the deployment of robots by country and industry, and machine learning algorithms have made it possible to measure automation using text analysis of patents. Therefore, recent papers notably investigate these new measures

of automation, that is, the number of robots (Autor & Dorn, 2013; Acemoglu & Restrepo, 2020; Cheng et al., 2019; Dauth et al., 2021; Graetz & Michaels, 2018), or automation-related patents (Mann and Püttmann, 2017; Webb, 2020).

As regards the first measure based on IFR data, Graetz & Michaels (2018) use the robot aggregate count from IFR data on a panel of seventeen developed countries and find no effect of automation on aggregate employment, despite a reduction of the low-skilled workers' employment share. Meanwhile, they show that robot densification is associated with increases in both total factor productivity and wages, and with decreasing output prices. Using the same measure on a panel of fourteen European countries, Klenert et al. (2020) find that robot use is correlated with an increase in total employment.

However, the empirical findings in Acemoglu and Restrepo (2020) suggest that the job destruction effect of robotization dominates. More precisely, the authors analyze the effect of the increase in industrial robot usage between 1990 and 2007 on US labor markets. Using variation in robot adoption between commuting zones they estimate the labor market effects of robots by regressing the local change in employment and wages on the local exposure to robots.[7] The authors find that one more robot per thousand workers reduces the employment to population ratio by about 0.2 percentage point and wage growth by 0.42%, while productivity increases and labor share decreases. According to their estimates, each robot installed in the US replaces six workers. The Acemoglu-Restrepo methodology has been applied to several other countries. Chiacchio et al. (2018) find a displacement effect between three and four workers per robot in six European countries, but do not point to robust and significant results for wage evolution. Aghion et al. (2019) find a displacement effect of ten workers per robot using French administrative data. However, using German data, Dauth et al. (2021) report a null effect of exposure to robots on aggregate employment. For low- and mid-skilled workers, they report lower wages.

Attractive as it may be, this methodology based on aggregate robot count has some shortcomings. First, a robot is a specific type of automation that is precisely designed to replace human work, whereas broader measures of automation may encompass machines that only partially substitute for human work. Another concern stems from the fact that IFR data are available only at the country level. Computing a local measure of exposure to robots – a Bartik measure – requires making the strong hypothesis that the number of robots installed by a given industry, divided by the importance of the industry in the commuting zone, is the same across commuting zones. Yet, robotization by a given industry may be more intense in commuting zone A than in commuting zone B even if the shares of that industry are the same in both regions. Furthermore, the IFR data is only available for 13 industries within manufacturing, making it difficult to add a large set of industry-level controls without overfitting and thus raising the possibility that variation in automation rates across industries may be correlated with industry-level unobservables affecting labor demand (e.g., initial skill

composition may vary across industries with differing rates of automation). A final potential concern is that variations in the robots exposure index across commuting zones are mostly related to the spatial distribution of automotive activities over the US territory in 1990, since industrial robots are predominant in the automotive industry – automotive robots account for more than one-third of total robots.

Another privileged measure of automation, based on text analysis of patents, also yields mixed results. For instance, Webb (2020) uses a measure of automation that relies on the overlap between patent texts and workers' tasks.[8] This measure is applied to two historical case studies, software and industrial robots. Webb highlights the displacement effect: jobs that were highly exposed to previous automation technologies saw declines in employment and wages over the relevant periods. However, the results of Mann and Püttmann (2017), who also measure automation using patent texts, paint a different picture.[9] Linking automation patents to industries and local labor markets, they find a positive effect of automation on employment.

Whether it be the robot count or the patent measure, the aggregate measures of automation/robotization at the country or industry level provide inconclusive evidence. Cross-country or industry-level research designs make it difficult to isolate a clear causal link between automation and employment. Firm-level research, that has grown recently, sheds new light on this issue.

### b. Firm-level research designs provide causal evidence supporting the "new view"

A number of recent studies using firm-level data supports the prediction a direct positive effect of automation on employment in automating firms: in France (Acemoglu et al., 2020, Aghion et al., 2020), in the Netherlands (Bessen et al., 2019), in the United Kingdom (Chandler and Webb, 2019), in Canada (Dixon et al., 2019), in Denmark (Humlum, 2019), and in Spain (Koch et al., 2021). Table 2.2 reports the order of magnitude of employment (and wage) elasticities to automation at the firm-level from these recent papers.

This positive effect may reflect either a net creation of jobs by automating firms or lower separation rates by these firms. Several of these studies provide quasi-experimental evidence to establish that automation *causes* an increase in employment at the firm level. In the next section, we describe the methodology in detail, focusing on our own empirical work on automation and employment at the plant and firm levels.

Thus, the "negative" story faces difficulties when confronted by firm-level data. At odds with the predictions of the "pessimistic" story, most of the previously-mentioned studies do not find evidence of a falling equilibrium wage nor of a declining labor share (e.g., Bessen et al., 2019; Dixon et al., 2019; Humlum, 2019; Koch et al., 2021; Aghion et al., 2020).

Babina et al. (2020) bring out a similar result with firm-level investment in AI technology. Firms that invest more in AI experience faster growth in sales and

*Table 2.2* Recent Estimates of Effects of Automation on Firm-level Employment and Wages

| Authors | Country and Time Period | Measure of Automation | Method | Impact on Firm-Level Employment | Impact on Firm-Level Wages |
|---|---|---|---|---|---|
| **Acemoglu, Lelarge, and Restrepo (2020)** | France 2010–2015 | Robot adoption by firms (versus non robot adoption) | OLS | Increase in hours worked for robot adopters between + 5.4 % (employment weighted estimates) and 10.9 % (unweighted estimates) | +0.9 % (unweighted estimates), non significant (employment weighted estimates) |
| **Aghion, Antonin, Bunel, & Jaravel (2020)** | France 1994–2015 | Automation: machines stock | Event study, IV | Elasticity between 0.2 (OLS) and 0.4 (IV) | N/A |
| **Bessen, Goos, Salomons, & van den Berge (2019)** | Netherlands, 2000–2016 | Automation "spikes" using automation expenditures (all automation technologies) | Event study | Automating firms have 1.8 to 2% higher employment compared to non automating firms | Not significant |
| **Dixon, Hong, and Wu (2019)** | Canada, 1996–2017 | Robot capital stock (imports of robotics hardware and robot purchases) | Event study | Elasticity of firm employment to robot capital stock in the [0.7–2]% interval | N/A |
| **Koch, Manuylov, and Smolka, (2021)** | Spain, 1990–2016 | Robot adoption | Event study | 4-year elasticity to robot adoption: 10% | Not significant |

Source: cited papers.

employment both at the firm- and industry-levels. AI allows the expansion of the most productive firms *ex ante*: they grow larger, gain sales, employment and market share. The authors report a null effect on productivity in the short run, perhaps because of the novelty of AI technologies, which are not fully mastered by workers.

Overall, these studies support the view that automation inside a firm fosters greater labor productivity. It drives quality-adjusted prices down for consumers[10] and increases product demand and market share of the firm, which can result in net job growth. Provided that demand is elastic enough to prices, then growth in demand will offset job losses.[11] The increase in the market share will only last until markets become saturated (Bessen, 2019). As Autor (2015) states it, "journalists and even expert commentators tend to overstate the extent of machine substitution for human labor and ignore the strong complementarities between automation and labor that increase productivity, raise earnings, and augment demand for labor."

Firm-level results are not directly informative about the impact of automation on labor demand at the aggregate level. For example, the productivity effect may contribute to the crowding-out of non-automating firms by automating firms. Since the productivity effect inside the automating firms generates an increase in product demand, the market share of these firms goes up at the expense of its non-automating competitors. Empirically, firms whose competitors adopt robots experience significant declines in value added and employment (Acemoglu, 2020; Aghion et al., 2020; Koch et al., 2021). For example, Koch et al. (2021) find that robot-adopting firms create new jobs and expand the scale of their operations, while non-adopters incur negative output and lose employment because of tougher competition with high technology firms.[12]

Thus, drawing on different measures of automation, different countries, and various time periods, recent micro studies consistently point to the importance of the productivity effect, with positive employment effects within automating firms and potential displacement effects across firms.

### c. Which workers benefit or lose from automation?

Separate from the debate about the impact of automation on overall labor demand, there is a debate about the types of jobs that are created or destroyed and the distributional effects of automation. The economics literature has long considered technological change to be labor augmenting and favorable to skilled workers. In the wake of the IT and computer revolution in the 1990s, research has investigated the skill bias of technological progress. This hypothesis indeed supported the idea of complementarity between technology and skilled workers (see Acemoglu & Autor, 2011, for an overview). Technological change would result in the polarization of the job market, i.e., the slower increase in mid-wage occupations compared to both high-wage and low-wage occupations.

In the 2000s, following the critique of Card & DiNardo (2002), and the seminal paper of Autor et al. (2003), the labor-replacing view of automation

for routine tasks has become prevalent. According to this idea, automation replaces routine jobs, and creates more demand for non-routine jobs that cannot be performed by machines. Several studies have documented the decline in manufacturing and routine jobs (Autor et al., 2003; Jaimovich & Siu, 2012; Autor & Dorn, 2013; Charnoz & Orand, 2017; Blanas et al., 2019).

Coming back to firm-level studies, some of them highlight a reallocation of workers between occupations (Bessen, 2019; Bonfiglioli et al. 2020; Humlum, 2019; Acemoglu et al., 2020). Humlum (2019) notably reports a shift from low-skilled to high-skilled workers in Denmark: labor demand shifts from production workers toward tech workers, such as skilled technicians, engineers, or researchers. In the same vein, Bonfiglioli et al. (2020) show that robot imports by French firms increase productivity along with the employment share of high-skill professions. Similarly, Bessen (2019) shows that computer automation causes growth in well-paid jobs and decreases in low-paid jobs. Using Canadian data, Dixon et al. (2019) document a polarization effect: investments in robotics are associated with shrinking employment for mid-skilled workers, but with increasing employment for low-skilled and high-skilled workers, notably managerial activities. This shift from low-skilled to high-skilled workers may also contribute to boosting measured productivity (Humlum, 2019; Acemoglu et al., 2020).

Yet, some studies do not find any reallocation effect between different types of workers and occupational categories (Aghion et al., 2020). This could be explained by a reallocation effect within jobs, since automation technologies generally do not replace entire jobs but only a certain number of tasks (Acemoglu and Autor 2011). Some human skills may become more valuable than ever in the presence of machines (Brynjolfsson & McAfee, 2011). Automation may thus lead to a restructuring of the task content of different jobs "within worker" (Aghion et al., 2020), enhancing labor productivity and employment, but without any change in the skill structure of firm's labor force.

This is precisely the issue that Arntz et al. (2017) raise when they question Frey and Osborne's (2017) analysis on the future of AI. Frey and Osborne (2017) tried to forecast the probability of computerization of 702 jobs and concluded that 47% of employment in the US was at risk of automation in the next ten or twenty years, while only 33% of jobs had a low risk of automation. But their analysis disregards the task content of jobs. Arntz et al. (2017) show that, when factoring in the heterogeneity of tasks within occupations, only 9% of all workers in the US face a high risk of automation.

## 4. Recent empirical evidence from France

We illustrate the main points from the preceding literature review using French data, drawing from our recent work (Aghion et al., 2019, 2020). We first show that labor market level analysis using IFR data provides mixed support in favor of the negative view. Second, we show that firm level and plant level analyses using alternative measures of automation provide quasi-experimental evidence

supporting the second view. We present the methodology and main results from our existing work, as well as novel complementary specifications.

## a. Labor market level analysis using IFR data

Aghion et al. (2019) reproduce the method developed by Acemoglu and Restrepo (2017, hereafter AR) using French data over the 1994–2014 period, analyzing the impact of increased robotization on employment at the aggregate employment zone level.[13]

To measure exposure to robots at the labor market – defined as commuting zone – level, AR built a local exposure index, which combines two elements: (i) the number of robots per worker in each of industry on the one hand and (ii) the pre-existing share of employment in industry $i$ for a given commuting zone $c$. Thus, this local exposure index exploits the initial heterogeneity in industry employment structures across commuting zones to distribute cross-industry variation in the stocks of robots in the various industries, observed nationwide during the sample period. More formally, the increases in robot exposure at the commuting zone level is defined as:

$$US\ robot\ exposure\ 1993-2007_c = \sum_{i \in I} l_{ci}^{1990} \left( \frac{R_{i,2007}^{US}}{L_{i,1990}^{US}} - \frac{R_{i,1993}^{US}}{L_{i,1990}^{US}} \right)$$

where the sum is over all the 19 industries $i$ in the IFR data; $l_{ci}^{1990}$ stands for the 1990 share of employment in industry $i$ for a given commuting zone $c$; $R_i$ and $L_i$ stand for the stock of robots and the number of people employed in a particular industry $i$.

Keeping with AR, Aghion et al. (2019) measure the increase in robot exposure in a French employment zone[14] between 1994 and 2014 as:

$$Robot\ exposure\ 1994-2014_c = \sum_{i \in I} \frac{L_{ic,1994}}{L_{c,1994}} \left( \frac{R_{i,2014}}{L_{i,1994}} - \frac{R_{i,1994}}{L_{i,1994}} \right)$$

where $L_{ic,1994}$ refers to employment in the employment zone $c$ in industry $i$ in 1994, $L_{c,1994}$ refers to employment in employment zone $c$ in 1994, and $L_{i,1994}$ refers to employment in industry $i$ in 1994. $R_{i,1994}$ and $R_{i,2014}$ respectively stand for the total number of robots in industry $i$ in 1994 and 2014. This index reflects the exposure to robots per worker between 1994 and 2014. The outcome variable of interest is the evolution of the employment-to-population ratio between 1990 and 2014.

In the baseline OLS specification, we study the impact of exposure to robots on the evolution of employment-to-population ratio. Then we add controls such as an exposure index for information and communication technologies (ICT) *TICExp*$_r$, built in a similar way as the exposure to robots index and an international trade exposure index *TradeExp* to China and Eastern Europe. In some

regressions, we also add a vector $X_c$ of control for the employment zone $c$: demographic characteristics, manufacturing shares, broad industry shares, broad region dummies, and specific industry shares within manufacturing. The identification assumption is that, conditional on this set of controls, industries that are exposed to an increase in the rate of automation are not simultaneously affected by unobserved shocks to labor demand or labor supply.[15] We can write:

$$\Delta \frac{L_{c,1994}}{Pop_{c,1994}} = \alpha + \beta_1 RobotsExp_c + \beta_2 TradeExp_c + \beta_3 TICExp_c + \gamma X_c + \epsilon_c$$

To measure the impact of exposure to robots on local labor markets, the strategy adopted is similar to the one initiated by Autor et al. (2013): the observed change in robot exposure in U.S. industries is instrumented with changes in robot exposure in the same industries in other developed economies. This approach helps address U.S.-specific threats to identification affecting the OLS approach: one may imagine a shock, which we do not capture in our controls, but which may impact both the installation of robots and local labor markets dynamics. Following AR, the stocks of robots in industries from other developed countries (Germany, Denmark, Spain, Italy, Finland, Norway, Sweden, and the United Kingdom) are used to build other indexes of exposure to robots. These new indexes are then used to instrument the exposure index built on the French stock of robots.

In this shift-share IV research design, identification arises from the heterogeneity in robotization shocks across industries, which is projected to the regional level. Identification stems from the robotization shocks $\frac{R_{i,2007}^{US}}{L_{i,1990}^{US}} - \frac{R_{i,1993}^{US}}{L_{i,1990}^{US}}$ and $\frac{R_{i,2014}}{L_{i,1994}} - \frac{R_{i,1994}}{L_{i,1994}}$. Indeed, as described in Borusyak et al. (2021), the employment shares $l_{ci}^{1990}$ are not tailored to exposure to robotization: they are "generic", in that they could conceivably measure an observation's exposure to multiple shocks, both observed and unobserved. Accordingly, it is important to control for industry-level characteristics that may contaminate the industry-level identifying variation, such as whether an industry belongs to manufacturing. Absent such controls, we would conflate the potential effects of robotization with broad sectoral trends.[16]

Table 2.3 displays the results of the OLS estimation. This table shows a negative correlation between exposure to robots and change in employment-to-population ratio. However, we observe that the level of significance decreases as more controls are added. Significance is lost in column (5) once a control for the local manufacturing industry share is included and the point estimate falls substantially, indicating that broad sector trends play an important role. The correlation is marginally significant in column (6) and non-significant in columns 7 through (10), where we add several types of controls simultaneous or exclude the commuting zones with the highest exposure to robots.

In the instrumental variable regression shown in Table 2.4, the coefficients of robot exposure are significant when we consider broad controls from columns

*Table 2.3* Effect of Robot Exposure on Employment-to-Population Ratio, 1990–2014, OLS Estimates

| | *Dependent Variable: Change in Employment-to-Population Ratio 1990–2014 (in %-age Points)* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* | *(7)* | *(8)* | *(9)* | *(10)* |
| *Robots Exposure$_{1994–2014}$* | −1.090*** | −0.749*** | −0.594** | −0.515** | −0.169 | −0.549* | −0.398 | −0.430 | −1.074 | −1.035 |
| | (0.253) | (0.263) | (0.239) | (0.243) | (0.239) | (0.294) | (0.244) | (0.324) | (0.768) | (0.783) |
| *TIC Exposure$_{1994–2014}$* | | −3.099* | −2.397 | −2.495* | | −0.304 | −0.165 | −0.154 | 1.519 | 1.493 |
| | | (1.586) | (1.594) | (1.455) | | (1.620) | (1.576) | (1.588) | (1.641) | (1.648) |
| *Trade Exposure$_{1994–2014}$* | | −0.743*** | −0.690*** | −0.825*** | | 0.0857 | −0.123 | −0.124 | 0.200 | 0.201 |
| | | (0.247) | (0.215) | (0.239) | | (0.243) | (0.278) | (0.280) | (0.335) | (0.337) |
| Demographics | | | Yes | | | | Yes | Yes | Yes | Yes |
| Region dummies | | | | Yes | | | Yes | Yes | Yes | Yes |
| Manufacturing industry share | | | | | Yes | Yes | Yes | Yes | Yes | Yes |
| Other broad industry shares | | | | | | Yes | Yes | Yes | | |
| Specific manufacturing industry shares | | | | | | | | | Yes | Yes |
| Remove highly exposed areas | | | | | | | | Yes | | Yes |
| Observations | 297 | 297 | 297 | 297 | 297 | 297 | 297 | 295 | 297 | 295 |
| R-squared | 0.058 | 0.090 | 0.198 | 0.205 | 0.174 | 0.249 | 0.407 | 0.406 | 0.409 | 0.408 |

Source: Data from Aghion et al. (2019).

Notes: Demographics control variables are population share by level of education and population share between 25 and 64 years old. Other broad industry shares cover the share of workers in agriculture, construction, retail, and the share of women in manufacturing in 1994. Specific manufacturing industry shares cover the share of workers in automotive, rubber, food, and the share of women in manufacturing in 1994. Broad region dummies refer to the 13 metropolitan regions of France. Highly exposed areas are Poissy and Belfort-Montbéliard-Héricourt. Robust standard errors in parentheses. Levels of significance: *** $p <$ \$0.01, ** $p <$ \$0.05, * $p <$ \$0.1. Sources: IFR, COMTRADE, EUKLEMS, DADS, Census data.

Table 2.4 Effect of Robot Exposure on Employment-to-Population Ratio, 1990–2014, IV Estimates

| | Dependent Variable: Change in Employment-to-Population Ratio 1990–2014 (in %-age Points) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Robots Exposure$_{1994–2014}$ | −1.317*** (0.325) | −1.010*** (0.322) | −0.974*** (0.271) | −0.737** (0.296) | −0.389 (0.248) | −0.790*** (0.300) | −0.686*** (0.241) | −0.986*** (0.351) | −1.305 (0.799) | −1.221 (0.812) |
| TIC Exposure$_{1994–2014}$ | | −2.569 (1.618) | −1.699 (1.578) | −2.094 (1.444) | | −0.176 (1.590) | −0.0323 (1.518) | 0.101 (1.538) | 1.590 (1.601) | 1.547 (1.609) |
| Trade Exposure$_{1994–2014}$ | | −0.670*** (0.242) | −0.589*** (0.211) | −0.773*** (0.230) | | 0.110 (0.240) | −0.0922 (0.276) | −0.0882 (0.279) | 0.198 (0.322) | 0.199 (0.323) |
| Demographics | | | Yes | | | | Yes | Yes | Yes | Yes |
| Region dummies | | | | Yes | | | Yes | Yes | Yes | Yes |
| Manufacturing industry share | | | | | Yes | Yes | Yes | Yes | Yes | Yes |
| Other broad industry shares | | | | | | Yes | Yes | Yes | | |
| Specific manufacturing industry shares | | | | | | | | | Yes | Yes |
| Remove highly exposed areas | | | | | | | | Yes | | Yes |
| Observations | 297 | 297 | 297 | 297 | 297 | 297 | 297 | 295 | 297 | 295 |
| First-stage F-statistic | 57.2 | 42.6 | 45.8 | 46.0 | 32.6 | 28.7 | 35.1 | 18.9 | 16.5 | 16.3 |
| R-squared | 0.055 | 0.087 | 0.193 | 0.203 | 0.172 | 0.248 | 0.405 | 0.400 | 0.409 | 0.408 |

Source: Data from Aghion et al. (2019).

Notes: Demographics control variables are population share by level of education and population share between 25 and 64 years old. Other broad industry shares cover the share of workers in agriculture, construction, retail, and the share of women in manufacturing in 1994. Specific manufacturing industry shares cover the share of workers in automotive, rubber, food, and the share of women in manufacturing in 1994. Broad region dummies refer to the 13 metropolitan regions of France. Highly exposed areas are Poissy and Belfort-Montbéliard-Héricourt. Robust standard errors in parentheses. Levels of significance: *** p$ < $0.01, ** p$ < $0.05, * p$ < $0.1. Sources: IFR, COMTRADE, EUKLEMS, DADS, Census data.

(1) to (4). Column (1) begins with a regression without any control and finds a negative effect: one more robot per 1000 workers leads to a drop in the employment-to-population ratio of 1.317 percentage point. Column (2) adds controls for ICT and imports exposures and the magnitude remains the same. Then, columns (3) and (4) successively test the impact of demographic characteristics and broad region dummies, leaving the results almost unaffected. In column (5), adding a control for the manufacturing share alone is sufficient to lose significance and substantially reduce the point estimate. The result highlights again the importance of controlling for broad industry trends, as emphasized by Borusyak et al. (2021).

Combining different sets of controls, the specifications in columns (6) through (8) deliver negative and statistically significant IV estimates. In columns (9) and (10), we replace broad industry shares controls by controls for specific industry shares within manufacturing at the commuting zone level. Specifically, we control for the three 2-digit industries that have the highest number of robots at the end of the period and that account for 74% of the total number of robots in 2014: automotive, rubber, and food industries. These are key industries relative to the construction of the index. The coefficients remain large and negative; they become non-significant as these controls lead to larger standard errors.

Thus, the OLS and IV evidence from IFR data at the industry level suggest that there is a negative impact of robots on labor demand, although the results are sensitive to the choice of controls due to the small number of industries that are used as the source of identifying variation. Furthermore, the finding of a negative or non-significant effect of robotization on employment at the aggregate employment zone level could be consistent with either the "new view" or "old view" on automation and employment. Indeed, this result could reflect either the fact that robotizing firms destroy jobs and that this direct effect is not fully offset by the counteracting general equilibrium effect working through wage reduction and the resulting entry of new activities; or the fact that the positive market size effect of automation at the firm level is more than offset by the job destruction in the non-automating firms that are partly or fully driven out of the market by the automating firms. To alleviate the limitations of the research design and find out more about which of these two stories applies, we need to move to a more disaggregated analysis of the effect of automation on employment.

## b. Firm-level and plant-level analyses

In Aghion, Antonin, Bunel, and Jaravel (2020), henceforth AABJ, we use three complementary measures as proxies for automation at the firm level and plant level. At the firm level, we use the balance sheet value of *industrial equipment and machines* in euros, which is available for all French firms between 1995 and 2017. This type of capital is defined as "the equipment and machines used for the extraction, processing, shaping and packaging of materials and

supplies or for carrying out a service" (industrial machines) and "instruments or tools that are added to an existing machine in order to specialize it in a specific task" (industrial equipment). Within the manufacturing sector, this type of capital accounts for 59% of total capital. Our second measure of automation follows the Encyclopaedia Britannica (2015), which defines automation technology as a "class of electromechanical equipment that is relatively autonomous once it is set in motion on the basis of predetermined instructions or procedures".[17] For the manufacturing sector, the French statistical office (Insee) records electricity consumption for motors directly used in the production chain (motive power) since 1983. It distinguishes motive power from other potential uses of electricity such as thermic/thermodynamic or electrolysis. Thus, we are able to proxy automation by motive power, which excludes heating, cooling, or servers uses. Our third measure, also available at the firm level, uses the annual imports of industrial machines by all French firms between 1995 and 2017. Following the spirit of the previous definition of *industrial equipment and machines*, we track all the HS6-products that belong to this definition. It includes 489 different types of machines that relate to the manufacturing industry and automation. In particular, it excludes computers and IT capital, printers, elevators, etc.

In AABJ, we perform two types of event studies: (i) "extensive margin" event studies at the firm level, exploiting the timing of the large investment in industrial equipment and machines for each firm as an automation event, and (ii) distributed lead-lag analysis at the firm and plant level that allows for delayed responses to changes in automation and takes into account continuous changes in the stock of machines.

Our main finding from the event studies is that the impact of automation on employment is positive, and in fact increases over time: namely, a 1% increase in automation in a plant today increases employment by 0.2% immediately and by 0.4% after ten years. Results are similar at the firm level. In other words, conditional on surviving, automation leads to a net increase in employment by automating firms and plants. The event studies also show that automation also translates into an increase in a firm's total sales in the years following automation. The effect remains stable from year of investment in automation to eight years after.

A potential concern is the endogeneity of firm choices of automation. For instance, automation could be the result of a corporate growth strategy following a demand shock. However, the event studies show no sign of pre-trend: conditional on the controls included in the specification, plants that automate more at time *t* were on a comparable employment path in prior years and start diverging afterwards. This restricts the potential set of confounders that could explain the increase in employment – confounding shocks need to occur simultaneously to the increase in automation. To further alleviate the endogeneity concern, we examine the stability of the estimates when including more stringent time-varying controls, notably 5-digit-industry by year fixed effects and firm-year fixed effects. The specification with firm-year fixed effects only exploits variation

in automation across plants within the same firm, controlling for all time-varying demand and supply shocks at the firm level. We find that the estimates remain stable, which further restricts the set of confounders (which must operate across plants within the same firm in the same year).

All these findings speak to a "productivity" effect of automation, in line with the "positive view" spelled out in the previous section: namely, firms that automate more become more productive. This enables them to obtain larger market shares because their products offer consumers better value for money than their competitors. The resulting gain in market share prompts those firms that automate to produce at a larger scale, and therefore to hire more employees.

In AABJ, we also consider the effect of automation on wages inequality within firms. More specifically, we study its effect on the evolution of the ratio between low-skilled workers' mean hourly wage and high-skilled workers' mean hourly wage. Figure 2.1 reports the results: we observe no differences in terms of evolution between these two types of workers.

Note however that the event study research design does not fully address potential correlated demand and supply shocks that could occur exactly at the same time as the increase in automation. Thus, in order to estimate the causal effects of automation on employment, sales, wages, and the labor share across firms, we use a shift-share design.

In fact, the ideal design would randomly assign purchasing prices for machines across firms. In AABJ, our idea is to approximate this hypothetical experiment using a shift-share instrument, which leverages two components: (i) the time variation in the implicit cost of imported machines over time across international
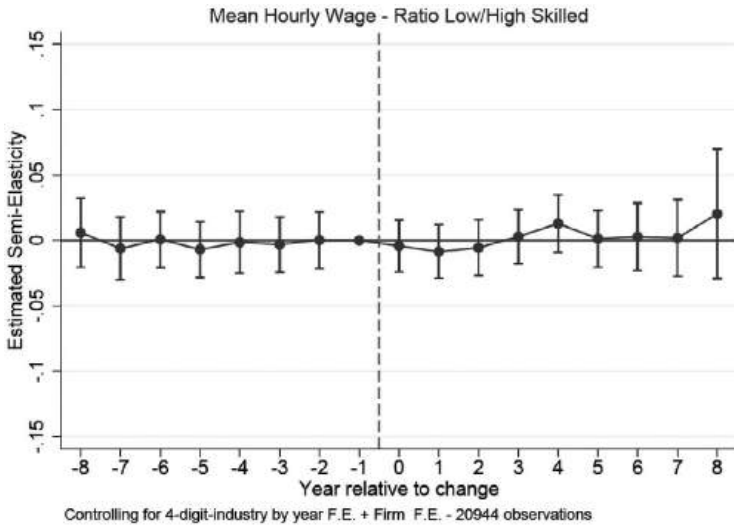


*Figure 2.1* Firm-Level Event Study of Automation on Hourly Wage Ratio between Low- and High-Skilled Workers.

Source: reproduced using AABJ data.

trading partners (the "shift" component); and (ii) the heterogeneity in pre-existing supplier relationships across French firms (the "exposure shares" component). The ideal "shock" variable would be the expected quality-adjusted price of imported machines by French manufacturing firms. However, we cannot directly observe these prices; that is why, instead, we infer changes in quality-adjusted price from changes in export flows of these foreign machines.

The intuition behind the shift-share instrument is that firms will be differentially exposed to these changes in quality-adjusted price of machines from different trading partners due to their sticky pre-existing relationships. For instance, if two French firms A and B import respectively 80% and 20% of their machines from Italy, and machines produced in Italy suddenly have a better quality-adjusted price, firm A will have more incentives to automate than firm B due to its strong established relationship with Italian suppliers of machines.

The estimates of the impact of automation on employment using the shift-share instrument are in line with the previous findings from the event studies. The elasticity of firm employment to automation that we find ranges between 0.397 and 0.444 on a five-year horizon (Table 3A of AABJ), significant at the 5% or 1% level depending on the set of controls, and the first stage F-statistic remains close to 10 in all specifications.

Next, we conduct the same exercise with sales and the labor share at firm level. We find that sales increase in response to increased automation, with elasticities ranging from 0.395 to 0.512 (Table 3B of AABJ) across specifications. Using the same specifications, we cannot reject the hypothesis that there is no impact of automation on the labor share, which in turn suggests that the productivity effect may offset the task substitution channel in a way that leaves the labor share unchanged at the firm level.

One can also look separately at specific industries. Particularly interesting is the automobile industry, which accounts for the vast majority of industrial robots. We still find a positive effect of automation on employment at the firm level, considering as treated the top 25% of firms in terms of biggest investment in industrial machines (Figure 2.2). Thus, even in an industry for which industrial robots are a non-negligible share of machines, the relation between automation and employment remains positive.

What happens when we move from firm or plant level to industry level? Using a shift-share design, AABJ find a positive effect of automation on employment also at the industry level, with point estimates ranging from 0.558 to 0.620 across specifications. This again speaks to the importance of the productivity effect: manufacturing industries are integrated into international trade. Therefore French firms that automate expand their export market at the expense of foreign firms. This in turn explains why the productivity effect is the dominant effect even at the industry level, as it is mostly foreign firms in foreign markets that suffer from the resulting business stealing. In a closed economy, domestic non-automating firms would suffer from the business-stealing by the automating firms; the increase in employment in automating domestic firms would be more likely to be counteracted by job destruction in non-automating domestic firms.
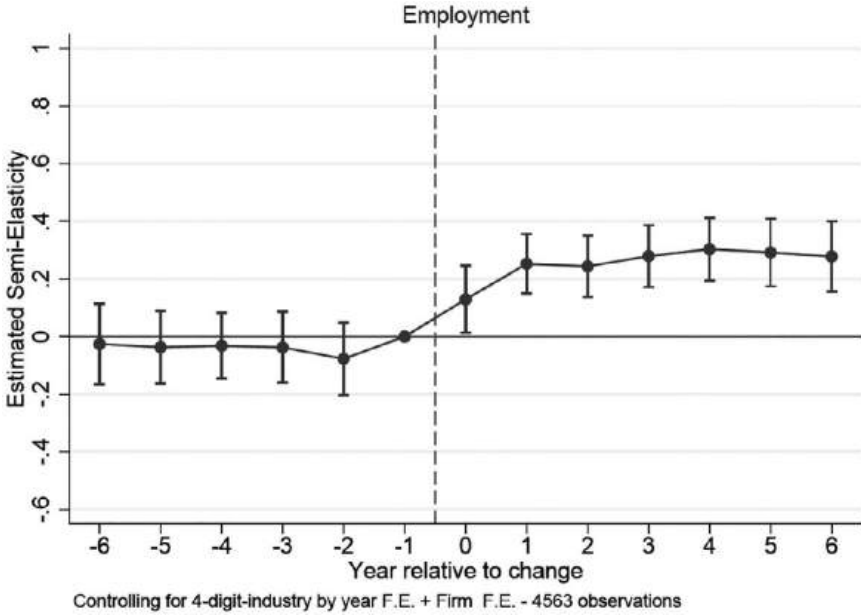
*Figure 2.2* Firm-Level Event Study of Automation on Employment in the Automotive
          Industry

Source: Data from AABJ data.
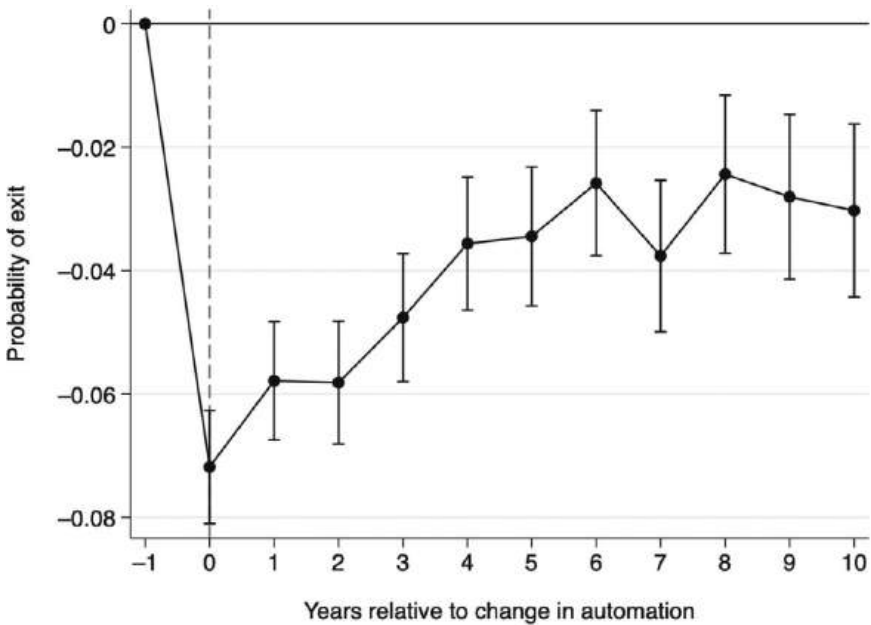


*Figure 2.3* Effect of a Substantial Investment in Industrial Equipment on Probability
          of Firm Exit.

Source: Data from AABJ (2020).

Figure 2.3, which is a novel result using data from AABJ, illustrates this business-stealing – or eviction – effect: firms that invest significantly in new industrial equipment substantially lower their likelihood of going out of business over the following ten years compared to firms that do not make such an investment.

## 5. Conclusion

In this chapter, we relied on both the existing literature and our own empirical work to discuss the effects of automation on employment. We pointed to two contrasting views on the subject. A first view sees automation as primarily destroying jobs, even if this may ultimately result in new job creations taking advantage of the lower equilibrium wage induced by the job destruction. A second view emphasizes the productivity effect of automation as the main direct effect: namely, automating firms become more productive, which enables them to lower their quality-adjusted prices and therefore to increase the demand for their products; the resulting increase in market size translates into higher employment by these firms. We provided direct empirical evidence supporting the second view in the case of France, and we showed that the empirical literature on automation and employment was also leaning in that direction in a broad set of countries.

Overall, automation is thus not in itself an enemy of employment. By modernizing the production process, automation makes firms more competitive, which enables them to win new markets and therefore to hire more employees in a globalized world.

We can think of several avenues for further empirical research on automation and the labor market. One would be to explore how automation interacts with outsourcing and international trade. Another avenue would be to distinguish between different types of sectors and industries. A third avenue would be to introduce the distinction between routine and non-routine jobs. A fourth avenue would be to refine the empirical analyses of the impact of automation on the distribution of wages at the firm level, industry level, and by skill groups. These and other extensions of the analyses surveyed in this chapter are promising directions for future research.

## Notes

1 Keynes, "Economic Possibilities for Our Grandchildren."
2 In this model, a new (more complex) task replaces or upgrades the lowest-index task. The fact that the limits of integration run between $N – 1$ and $N$ imposes that the measure of tasks used in production always remains at 1. Thus, an increase in $N$ represents the upgrading of the quality (productivity) of the unit measure of tasks.
3 See Acemoglu et al. (2020), and Aghion et al. (2020).
4 We can draw a parallel between the productivity-enhancing effect of technological progress and the productivity-enhancing effect of offshoring highlighted by Grossman and Rossi-Hansberg (2008). In the offshoring process, when some

tasks can more readily be performed abroad, firms that use this type of labor intensively augment their profitability and expand at the expense of their competitors that rely on other types of labor. This is turn leads to an increase in their labor demand.

5  Based on a general static framework with a continuum of worker types, Costinot and Werning derive optimal tax formulas that depend on a small set of sufficient statistics that require relatively few structural assumptions.

6  Earlier studies used the measure of computers or IT as a proxy (Krueger, 1993; Autor et al., 1998; Bresnahan et al., 2002; Beaudry, Doms and Lewis, 2010; Michaels, Natraj and Van Reenen, 2014).

7  The local exposure to robots is an indirect measure of robot penetration at the local level – a Bartik measure – which is based on the rise in the number of robots per worker in each national industry on the one hand and on the local distribution of labor between different industries on the other hand.

8  Webb's measure relies on the following pattern: the text of patents contains information about what technologies do, and the text of job descriptions contains information about the tasks workers do in their jobs. These two text sequences are compared in order to quantify how much patenting in a particular technology has been directed at the tasks of a given occupation. A score is attributed to each task, and the task-level scores are aggregated at the occupation level in order to construct an automation exposure score for each occupation.

9  Mann and Püttmann classify patents as automation patents if their texts describe a device that carries out a process independently of human intervention. They match patents to the industries where they are likely to be used according to the patents' technology class and derive a measure of newly available automation technology at a detailed industry and commuting-zone level.

10  Aghion et al. (2020) provide direct empirical evidence on the response of consumer prices. Bonfiglioli et al. (2020) suggest that productivity gains from automation may not be entirely passed on to consumers in the form of lower prices.

11  For a discussion on the type of workers who benefit or lose from automation, see Section 3.c.

12  Koch et al. (2021) first focus on the adoption decisions of firms. They show positive selection, that is, firms that adopt robots in their production process are larger and more productive than non-adopters before adopting robots. They also show that, conditional on productivity, more skill-intensive firms are less likely to adopt robots, and that exporters are more likely to adopt robots than non-exporters.

13  AR analyze the effect of the increase in industrial robot usage between 1990 and 2007 on US local labor markets. They find that one more robot per thousand workers reduces the employment to population ratio by about 0.37 percentage points and wage growth by 0.73 percent.

14  According to the official definition provided by Insee, an employment zone is a geographical area within which most of the labor force lives and works. It provides a breakdown of the territory adapted to local studies on employment.

15  The source of identifying variation is at the industry level and outcomes are measured at the level of local labor markets, as discussed in the recent Bartik identification literature (e.g., Adão et al., 2019 and Borusyak et al., 2021).

16  Note that this research design only speaks to the effects of automation on employment across local labor markets, using industry shocks as the source of variation. It cannot speak to the overall (country-level) macroeconomic effect of automation, which requires a model to account for reallocation of employment across industries and labor markets (e.g., Ngai and Pissarides 2007) or a source of variation at the country level.

17  Definition from Encyclopaedia Britannica (2015), "Automation".

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# 3 Robots, Offshoring, and Welfare

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## 1 Introduction

The nature and the organization of production is undergoing a radical transformation. Advances in robotics technologies have led to the widespread use of automation in tasks previously performed by workers. At the same time, improvements in communication technologies have led companies to offshore stages of production to low-wage countries. These two phenomena are having a profound effect on advanced economies. Although they are believed to bring about higher productivity and lower costs, they are also often blamed for the decline in manufacturing employment and stagnation of real wages (see, for instance, Baldwin, 2019). More recently, a new hypothesis is gaining attention: that automation, which is much more prevalent in advanced economies, can increase competitiveness and bring back jobs that had been previously relocated to low-wage countries. Examples of this process of "reshoring" have started to populate the business literature. Yet, its scope, causes and consequences are still largely unknown.

In this chapter we study the interaction between automation and offshoring, from the perspective of advanced countries. From a theoretical viewpoint, we show that offshoring can change the welfare effects of automation. In particular, if robots replace foreign-sourced tasks, automation is always beneficial for domestic workers. However, if robots replace domestically-produced tasks, automation can be welfare-reducing for workers in the adopting country, even if it would have been welfare-improving in autarky. These results underscore the importance of identifying which workers are competing with robots more directly. We therefore turn to US data across industries, occupations and local labor markets to validate the predictions of the model and assess which scenario is empirically more plausible.[1]

To illustrate our theoretical result, we start from a simple task-based model of production that incorporates the standard effects of automation. In autarky, substituting labor with cheaper robots has a productivity effect, a capital deepening effect and a displacement effect. While the first two effects raise welfare, the latter one tends to lower real wages. But the negative effect is always dominated if the supply of robot capital is sufficiently elastic.[2] In the presence of offshoring,

however, there is a new *terms-of-trade effect* that redistributes income across countries: automation lowers the relative wage of the workers that are displaced by robots the most. If automation substitutes foreign labor, domestic workers do not suffer any displacement, while they benefit from a higher productivity, capital deepening and cheaper foreign inputs. In this case, automation triggers reshoring and raises domestic welfare. However, if domestic workers are substituted by robots, they are harmed both by the displacement effect and by the increase in the cost of foreign inputs. In this case, automation can lower domestic welfare even if the higher productivity and capital deepening would compensate the displacement effect in autarky.

The model also illustrates that whether automation replaces domestic or foreign workers may depend not only on exogenous characteristics of the tasks they perform, but also on economic incentives, which depend on the wage gap between countries. This opens the possibility that, since offshoring increases foreign wages, the direction of automation may switch endogenously from domestically-produced to foreign-sourced tasks. Finally, from a normative perspective, the model implies that, since automation targeted at offshored tasks redistributes income from the foreign to the domestic country, policy makers may have an incentive to distort the use of robots strategically.

In the second part of the chapter, we move to the empirical analysis. Recent anecdotal evidence suggests that advanced countries across the world have started to shift away from foreign inputs. For instance, Walmart (2016), the biggest retailer in the world, launched the "Jobs in U.S. Manufacturing Portal" website as part of a broader "Investing in American Jobs" initiative which aims to bring manufacturing jobs back to the US. The COVID-19 pandemic has accelerated this trend by fostering automation and inducing governments to aim at increasing self-sufficiency in strategic sectors. However, systematic evidence about reshoring, defined as a reduction in the growth of offshoring which can even turn negative, is scant.

Motivated by our model, we study the effect of industrial automation between 1990 and 2015 on US local labor markets and how it relates to offshoring. To measure automation and offshoring, we use high-quality trade data on US imports of industrial robots and intermediate inputs, respectively, and assign them to industries using detailed Import Matrices. We then project these measures across 722 US commuting zones based on the industry composition of employment. We further instrument the change in US imports of industrial robots with similar changes observed in eleven European countries. With this data, we find that robot imports lower manufacturing employment. Since manufacturing is the sector where automation is concentrated, this evidence suggests that, on average, robots displace US workers. However, we also find positive effects on wages, though not always significant, consistent with the hypothesis that robots improve labor productivity.

Next, we ask how these effects depend on offshoring. To this end, we first show that occupations at risk of automation, denoted for short as "replaceable", and those classified as "offshorable", tend to have a relatively similar task

content.[3] This suggests that automation and offshoring might indeed be substitutes, in that they may affect similar occupations. Consistent with this evidence, we find that robot imports tend to lower offshoring, both at the industry and at the commuting zone level. Building on these results, we further unpack the negative employment effect of robot imports across different occupations. This exercise reveals that the employment losses are especially concentrated in occupations performing non-offshorable and replaceable tasks. Finally, we look for heterogeneous effects across commuting zones specialized in industries with a different prevalence of offshoring. This exercise reveals that commuting zones that are more exposed to offshoring experience a relatively smaller negative effect on manufacturing employment as a consequence of automation. Overall, this evidence suggests that robot imports are associated with a reduction in offshoring, which is however not enough to fully compensate for the negative displacement effect on manufacturing employment.

This chapter makes several contributions to the literature. First, from a theoretical perspective, it shows that the welfare effects of automation may be very different in the presence of offshoring. To do so, it combines models of automation (such as Zeira, 1998, Acemoglu and Restrepo, 2019, Hemous and Olsen, 2020) with models of offshoring (such as Grossman and Rossi-Hansberg, 2008, Rodriguez-Clare, 2010, Acemoglu, Gancia and Zilibotti, 2015). The literature has shown that both phenomena can have ambiguous welfare effects due to the tension between a productivity effect, which tends to benefit everybody, and a displacement effect, which tends to have adverse effects on workers that compete with robots or imports. However, this chapter highlights two important differences between automation and offshoring: first, they may affect different workers; and, second, unlike foreign labor, robots can be reproduced. The combination of these two features generates the terms-of-trade effect that can change the welfare effect of automation. Artuc, Bastos and Rijkers (2018), Krenz, Prettner and Strulik (2018) and Furusawa and Sugita (2021) also develop models of automation and trade in intermediate inputs, but assume that robots replace domestic labor only.

Second, the chapter contributes to the empirical literature on the identification of automation. Earlier papers use data from the International Federation of Robotics, which are however available for nineteen aggregate sectors only. Recognizing the high concentration of this very specialized sector, in which Japan and Germany alone account for 50 percent of global revenues, some recent papers have turned to robot imports as a measure of automation. These include Acemoglu and Restrepo (2020) and Blanas, Gancia and Lee (2019), which use cross-country data; Acemoglu, Lelarge and Restrepo (2020) and Bonfiglioli et al. (2020), which use firm-level data for France; and Humlum (2019), which uses firm-level data for Denmark. In this chapter we show how to combine data on robot imports together with Import Matrices to obtain an indicator of industrial automation that varies across time and 66 industries. Following the literature on the measurement of offshoring started by Feenstra and Hanson (1999), we also construct time-varying offshoring indicators at the industry

level using the information on imported intermediate inputs contained in the Import Matrices.

Third, in terms of empirical results, this chapter confirms the negative effect of industrial robots on manufacturing employment often found in the literature (see, for instance, Acemoglu and Restrepo, 2020, and Blanas, Gancia and Lee, 2019), but it also shows this effect to be weaker in occupations and commuting zones that are more exposed to offshoring and hence where reshoring is more likely. We obtain these findings following the shift-share approach across US local labor markets first applied to study the effect of Chinese import competition by Autor, Dorn and Hanson (2013) and automation by Acemoglu and Restrepo (2020). To unpack the effects across occupations, we use the classifications of replaceable tasks in Graetz and Michaels (2018) and of offshorable tasks in Autor and Dorn (2013).

Our results are also related to two recent papers. Using firm-level data from France, Aghion et al. (2020) find that machines have a positive effect on employment in sectors facing international competition. This is consistent with our view that automation may displace imports. On the other hand, Faia et al. (2021) show that automation can lower employment by making firms more selective and argue that offshoring may amplify this effect. Using data for a panel of 13 European countries, they document a positive correlation between measures of replaceability and offshorability and a fall over time in employment for occupations that are both replaceable and offshorable. Despite the use of different proxies, we confirm these patterns in our data. However, we also find that the employment losses in US commuting zones more exposed to robotization are concentrated in non-offshorable jobs. This evidence is consistent with the hypothesis that, while both automation and offshoring may displace workers, the effect of an increase in the former can be partially offset by a decline in the latter.

Finally, the chapter is related to the nascent literature on reshoring. The empirical evidence on this recent phenomenon is still inconclusive. For instance, Krenz, Prettner and Strulik (2018) and Carbonero, Ernst and Weber (2018) find evidence of robot-induced reshoring in a panel of countries and industries. Similarly, Faber (2020), Artuc, Christiaensen and Winkler (2019), Stemmler (2019), and Kugler et al. (2020) find evidence of reshoring in Mexico, Brazil and Colombia. On the other hand, Hallward-Driemeier and Nayyar (2019) and De Backer et al. (2016) argue that reshoring affects only a tiny minority of countries and industries, while Stapleton and Webb (2020) show that robots had a positive impact on imports and multinational activities of Spanish firms. Differently from us, these papers are mostly concerned with the impact of reshoring on developing countries, and none of them focuses on the US.

The remainder of the chapter is organized as follows. In Section 2, we build a simple model to illustrate the welfare effects of automation in the presence of offshoring. In Section 3, we construct the main variables used in the empirical analysis and describe the main patterns in the data. In Section 4, we present the results of the econometric analysis. Exploiting variation across occupations, industries and space, we study the relationship between automation and offshoring, and

how the effect of automation on labor market outcomes depends on offshoring. Section 5 concludes.

## 2 A Simple Model of Industrial Robots and Offshoring

In this section, we build a simple two-country general-equilibrium model to illustrate the welfare effects of automation and offshoring.[4] The main lesson is that the effects of automation on real wages can be very different depending on whether robots displace tasks that are performed domestically or abroad. The theory will also suggest a simple way to identify this displacement effect in the data. Since the goal is to derive qualitative results that will guide the empirical analysis, the model is deliberately kept as simple as possible.

### 2.1 The Basic Set-Up

The world economy comprises two countries, North and South, populated by $L_n$ and $L_s$ units of workers, respectively. There is a single final good, which is the numeraire and is freely traded. Production requires a set of tasks, which can be performed by workers or robots. Robots differ from workers in that they are in perfectly elastic supply and can only perform a subset of the existing tasks. Specifically, there is a constant unit cost of producing robots, and we sometimes refer to the endogenous supply of this factor as "robot capital". Workers in the two countries differ in their technological capabilities in that labor in South can only be employed in a subset of the tasks that North can perform. The production of tasks can be separated geographically at no costs. In this model, automation is the replacement of any worker with robots and offshoring is the replacement of a worker in North with one in South. We start with a one-sector model, but later consider a generalization in which workers displaced in one secotor may find employment in another. In both cases, however, we allow offshoring and automation to have general equilibrium effects.

Production of the final good $\Upsilon$ requires a measure one of tasks, which are aggregated according to a Cobb-Douglas function:

$$\ln \Upsilon = \int_0^1 \ln x_i \ di, \tag{1}$$

where $x_i$ is the output of task $i$. We denote with $p_i$ the cost of this task. Then, the demand for each task satisfies:

$$p_i x_i = \Upsilon. \tag{2}$$

With a symmetric Cobb-Douglas production function, each task gets the same share of expenditure.

Tasks can be performed by workers in North, with productivity $a_n$ and wage $w_n$, workers in South, with productivity $a_s$ and wage $w_s$, or robots, with a unit

cost $r$ (in terms of the numeraire $\Upsilon$) and productivity $a_r$. We assume $r < a_r$ which, as we will see, guarantees that some robots are always used in equilibrium. Workers in North can potentially perform any task $i \in [0, 1]$. Workers in South, instead, can only perform a measure $\lambda < 1$ of tasks, and we refer to these tasks as "offshorable". Finally, robots can only perform a measure $\kappa < 1$ of tasks, and we refer to these tasks as "replaceable". Some tasks can be both offshorable and replaceable. Accordingly, we define $\xi$ as the probability that a replaceable task is also offshorable.

We denote with $m_n$, $m_s$ and $m_r$ the measure of tasks performed in equilibrium by workers in North, South and by robots, respectively, and assume for simplicity that workers in different locations and robots cannot be combined to produce the same task. This implies that $m_s + m_n + m_r = 1$. Then, the cost of task $i$ is:

$$p_i = \begin{cases} p_n = \frac{w_n}{a_n}, & \text{if performed in North} \\ p_s = \frac{w_s}{a_s}, & \text{if performed in South} \\ p_r = \frac{r}{a_r}, & \text{if performed by robots.} \end{cases} \tag{3}$$

Imposing symmetry across tasks and labor-market clearing allows us to compute the quantity of each task produced by workers:

$$x_i = \begin{cases} x_n = \frac{a_n L_n}{m_n} & \text{if performed in North} \\ x_s = \frac{a_s L_s}{m_s} & \text{if performed in South.} \end{cases} \tag{4}$$

If task $i$ is instead performed by robots, we can combine $p_r = r/a_r$ with $p_r x_r = \Upsilon$ to solve for its quantity:

$$x_r = \frac{\Upsilon a_r}{r}. \tag{5}$$

Substituting the quantities (4)-(5) into (1), we can solve for aggregate production as:

$$\Upsilon = \left(\frac{a_s L_s}{m_s}\right)^{\frac{m_s}{1-m_r}} \left(\frac{a_n L_n}{m_n}\right)^{\frac{m_n}{1-m_r}} \left(\frac{a_r}{r}\right)^{\frac{m_r}{1-m_r}}. \tag{6}$$

Next, substituting prices (3) and quantities (4) into the demand function (2), we obtain wages:

$$w_n = \frac{m_n}{L_n} \Upsilon, \tag{7}$$

with an analogous expression for $w_s$. Intuitively, the wage is increasing in the demand for labor, which is proportional to the measure of tasks performed and total production, and decreasing in the supply of labor.

Finally, we need to solve for $m_s$, $m_n$, and $m_r$. To this end, note that if $p_s < p_n$, then offshorable tasks are cheaper in South and hence will never be produced in North. This will be the case if wages per efficiency unit of labor in South are lower than in North, i.e., $w_s a_n < w_n a_s$. In turn, this requires the technological capabilities of South, as measured by $\lambda$, to be sufficiently low. A sufficient condition is

$$\frac{\lambda}{1 - \lambda - \kappa(1 - \xi)} < \frac{a_s}{a_n} \frac{L_s}{L_n}$$

and we assume it to be always satisfied. Next, we focus on equilibria in which robots are utilized. For this to be the case, automated tasks must be cheaper than those performed by workers in North, $p_r < p_n$, which requires the cost of robots, $r$, to be sufficiently low. As we will show later, this is guaranteed by the assumption $r < a_r$. Under these conditions, workers in North perform the set of tasks that are neither replaceable nor offshorable:

$$m_n = (1 - \lambda) - \kappa(1 - \xi).$$

Robots will also be used in offshorable tasks if $p_r < p_s$, which is equivalent to $r a_s < w_s a_r$. In this case, workers in South perform the set of tasks that are offshorable but not replaceable:

$$m_s = \lambda - \kappa \xi.$$

If instead $p_r > p_s$, then workers in South are cheaper than robots, which implies that they perform all offshorable tasks, $m_s = \lambda$. Finally, there is also an intermediate case in which $p_r = p_s$ and robots are used in a subset of the task that they can perform in South.

## 2.2 Robots, Offshoring, and Real Wages

We are now in the position to study the effect of robots on real wages which, in this model, coincide with welfare and also capture the demand for labor. We focus mostly on North, although it is straightforward to derive the results for South. Substituting (7) and (6) yields:

$$w_n = a_n \left( \frac{a_s}{a_n} \frac{w_n}{w_s} \right)^{\frac{m_s}{1 - m_r}} \left( \frac{a_r}{r} \right)^{\frac{m_r}{1 - m_r}} \tag{8}$$

with

$$\frac{w_n}{w_s} = \frac{L_s}{m_s} \frac{m_n}{L_n}. \tag{9}$$

Equation (8) says that workers in North benefit from their own productivity, $a_n$, but also from cheap labor in South, $\frac{a_s}{a_n} \frac{w_n}{w_s} > 1$, and cheap robots, $\frac{a_r}{r} > 1$. It also confirms that, under the assumptions $p_s < p_n$ and $r < a_r$, robots are cheaper

than workers in North, i.e., $ra_n < w_n a_r$. Equation (9), instead, shows that the North-South wage gap, which we also refer to as the terms of trade, depends on the division of tasks between the two countries. These equations depend on the endogenous variables $m_n$, $m_s$ and $m_r$, but are general in that they also apply to other models of offshoring and automation.[5] To better understand the effects of robots and offshoring, and how they interact, we start by considering them in isolation.

### 2.2.1 Offshoring Only

Suppose first that there is no automation, i.e., $\kappa = 0$. Then:

$$w_n = a_n \left( \frac{a_s}{a_n} \frac{w_n}{w_s} \right)^\lambda = a_n \left( \frac{1-\lambda}{\lambda} \frac{a_s L_s}{a_n L_n} \right)^\lambda.$$

Offshoring, i.e., an increase in $\lambda$, has two effects. First, as long as $a_s w_n > a_n w_s$, production costs are lower in South, and hence relocating tasks there lowers prices, which benefits all workers. Second, offshoring shifts the demand for labor in favor of workers in South, thereby lowering $w_n/w_s$. This fall in the terms of trade for workers in North tends to hurt them. Overall, the efficiency effect dominates for low values of $\lambda$, when the wage gap is large, but it vanishes for high values of $\lambda$, as the wage gap disappears for sufficiently high levels of offshoring. As a result, $w_n$ is an inverted-U function of $\lambda$.

### 2.2.2 Automation Only

Consider now the case with no offshoring, i.e., $\lambda = 0$ and $\xi = 0$. Then:

$$w_n = \frac{m_n}{L_n} \Upsilon = a_n \left( \frac{a_r}{r} \right)^{\frac{\kappa}{1-\kappa}}. \tag{10}$$

Equation (10) shows that the real wage is always increasing in automation, $\kappa$. There are three effects at work here. First, as long as $a_r > r$, robots raise productivity. Second, as the measure of tasks performed by workers in North falls, there is also a displacement effect. However, the latter is offset by robot-capital deepening: the supply of robots increases so as to keep their price, $r$, constant. As a result, differently from offshoring, workers do not suffer any deterioration of their terms of trade from robots.[6]

### 2.2.3 Automation and Offshoring

We now study the effect of automation in the presence of offshoring. There are two cases to consider, depending on the relative wage in South. If the wage in South is sufficiently low, then offshoring is cheaper than using robots. We call this the "large wage gap" case. But if the wage in South is high enough, then offshorable tasks become at risk of automation. We call this the "small wage gap" case.

**Large wage gap**: $p_n > p_r > p_s$. In this case, robots replace North workers only. Without loss of generality, we can then set $\xi = 0$. Imposing $m_n = 1-\lambda-\kappa$, $m_s = \lambda$ and $m_r = \kappa$ into (8) and (9) yields:

$$w_n = a_n \left[ \left( \frac{a_s}{a_n} \frac{w_n}{w_s} \right)^\lambda \left( \frac{a_r}{r} \right)^\kappa \right]^{\frac{1}{1-\kappa}}$$

with

$$\frac{w_n}{w_s} = \frac{1-\lambda-\kappa}{\lambda} \frac{L_s}{L_n}.$$

Compared to the case without offshoring, there are two differences. First, the productivity effect of robots is stronger, because they replace workers in North that are now more expensive: $\frac{a_s}{a_n} \frac{w_n}{w_s} > 1$. As a result of this, robots can raise real wages in North even if they would not be used in autarky ($a_r < r$). On the other hand, however, automation lowers the relative demand for North workers and hence increases the relative wage of workers in South, which are not competing with robots. Hence, workers in North now suffer from a negative terms-of-trade effect. Because of the latter, robots can now lower the real wage in North, even if they would have increased it in autarky ($a_r > r$). More precisely, $w_n$ falls with $\kappa$ if

$$\ln \left[ \left( \frac{a_s}{a_n} \frac{w_n}{w_s} \right)^\lambda \frac{a_r}{r} \right] < \frac{\lambda(1-\kappa)}{1-\lambda-\kappa}.$$

This condition is more likely to be satisfied when $r$ and $w_s$ are high because in this case the productivity gains are small and the negative terms-of-trade effect may dominate.

**Small wage gap**: $p_n > p_s \geq p_r$. In this case, robots substitute workers in both countries. Consider first the case $p_s > p_r$, which implies $m_n = (1 - \lambda) - \kappa(1 - \xi)$, $m_s = \lambda-\kappa\xi$ and $m_r = \kappa$. Imposing these conditions into (8) and (9) yields:

$$w_n = a_n \left( \frac{a_s}{a_n} \frac{w_n}{w_s} \right)^{\frac{\lambda-\kappa\xi}{1-\kappa}} \left( \frac{a_r}{r} \right)^{\frac{\kappa}{1-\kappa}}$$

with

$$\frac{w_n}{w_s} = \frac{1-\lambda-\kappa(1-\xi)}{\lambda-\kappa\xi} \frac{L_s}{L_n}.$$

The novelty is that the effect of robots on the terms of trade depends on $\xi$. If $\xi > \lambda$, robots displace workers in South more than proportionally and hence improve the terms of trade of North. In this case, $w_n$ necessarily increases with $\kappa$. If $\xi < \lambda$, robots lower the terms of trade of North. In this case, the effects are qualitatively

similar to the large wage gap case discussed previously, and they become identical if $\xi \to 0$. Finally, we can also consider the case of a tie, $p_s = p_r$, in which robots and workers in South become perfect substitutes, and robots are used in an endogenous measure of tasks smaller than $\kappa\xi$. This intermediate equilibrium prevails when $p_s > p_r$ for $m_s = \lambda$, but $p_s < p_r$ for $m_s = \lambda - \kappa\xi$. In this range, the endogenous margin of robot utilization in South keeps all wages constant at $w_s = a_s r / a_r$ and $w_n = a_n a_r / r$.

We now briefly discuss some of the main implications of these results. The first lesson is that robots replacing North workers may hurt them by increasing the relative wage in South. Hence, in a world of global value chains, it is important to understand who is competing with robots. In turn, this may depend both on the technological characteristics of the tasks they perform and on the level of offshoring. The reason is that offshoring increases the relative wage in South, which makes automation of offshored tasks more profitable. More in general, the model suggests that both a decline in the cost of robots and technological catch-up in South can trigger a switch in automation from domestically sourced tasks only to offshored tasks too. These results also have important policy implications. In particular, since automation is likely to have terms-of-trade effects, which redistribute income between countries, policy makers may have an incentive to distort the use of robots strategically.

## 2.3 Extension: Two-Sector Model

Both automation and offshoring are more prevalent in the manufacturing sector. We now show how the displacement effect can be identified from the allocation of labor between sectors that are differentially exposed to automation. To this end, assume now that final output is produced combining manufacturing goods, $X$, and services, $Z$, as follows:

$$\Upsilon = X^{\alpha} Z^{1-\alpha}.$$

Labor is mobile between $X$ and $Z$. As before, manufacturing workers in North earn a share of sector revenue, $\alpha\Upsilon$, equal to the fraction of tasks they perform, $m_n^x$:

$$w_n L_n^x = m_n^x \alpha \Upsilon,$$

where $L_n^x$ is employment in manufacturing in North. The service sector is symmetric, hence $w_n L_n^z = m_n^z (1 - \alpha) \Upsilon$. Combining these expressions yields the allocation of labor in North:

$$\frac{L_n^x}{L_n^z} = \frac{\alpha}{1 - \alpha} \frac{m_n^x}{m_n^z}. \tag{11}$$

Equation (11) shows that this allocation depends exclusively on the tasks performed by domestic workers in the two sectors. The intuition is that the productivity effect affects both sectors equally and hence the allocation of labor only depends on the displacement effect. For our purposes, equation (11) also

implies that the effect of automation on the tasks performed by workers in North can be read from changes in employment across sectors. In the remainder of the chapter, we build on this result to identify the displacement effect of industrial robots and test how it varies with offshoring. Given that industrial robots are used almost exclusively in manufacturing, their adoption should have no direct effect on $m_n^z$. Hence, if we find that an exogenous shock to automation shifts workers away from manufacturing, it must be that $m_n^x$ is falling. Moreover, we will compare how the displacement effect differs across local labor markets and occupations depending on their exposure to offshoring. If we find a weaker or no displacement effect in areas or occupations where offshoring is more prevalent, it will be evidence consistent with the automation of foreign-sourced tasks.

## 3 Data and Stylized Facts

This section explains how we construct the main variables used in the empirical analysis and illustrates the main patterns in the data.

### 3.1 Data and Variables

Our empirical analysis relates automation, offshoring and labor market outcomes (employment and wages) across US local labor markets. Following Autor and Dorn (2013), Autor, Dorn and Hanson (2013) and Acemoglu and Restrepo (2019), among others, we identify local labor markets using the concept of commuting zone (CZ) introduced by Tolbert and Sizer (1996). CZs are defined as clusters of counties characterized by strong commuting ties within them and weak commuting ties among them. Our sample includes 722 CZs covering the entire mainland United States.

**Labor Market Outcomes.** For each CZ, we measure employment and wages, both on aggregate and for different sectors (manufacturing and non manufacturing) or skill groups of workers (college and non-college educated), using micro-level data from two sources: the decennial Censuses, for the years 1990 and 2000; and the American Community Survey (ACS), for the years 2005, 2010 and 2015. Both data sources are extracted from IPUMS (Ruggles et al., 2020).[7]

Following Autor and Dorn (2013), we restrict the estimation sample to working-age individuals (aged 16 to 64) who are not unpaid family workers, do not reside in institutional group quarters and have reported being employed over the previous year. We construct CZ-level employment using sample weights. To construct wages, we further exclude individuals who are self-employed or farm workers, lack information on working hours, weeks or wages, and report working less than 40 weeks per year and 35 hours per week. We compute average wages as annual wages and salary income divided by total hours worked. Wages are expressed at constant 2005 prices using the Personal Consumption Expenditure Index. We also construct CZ-level population

figures using data from the Censuses and the ACS. In the regressions, we use ten-year equivalent changes of employment-to-population ratios and log average wages, computed as 10 times the annualized change in each variable over a given period (1990-2000, 2000-2005, 2005-2010 and 2010-2015).

**Robot Exposure.** To construct our proxy for automation at the CZ level, we use high-quality data on US imports of industrial robots and project these imports across local labor markets using information on the industrial structure of employment in each CZ. We start by extracting the value of robot imports from detailed product-level import data collected by the US Customs and available for the 1989–2018 period (Schott, 2008); robot imports are classified into specific 10-digit product codes of the Harmonized Tariff Schedule (HTS) classification.[8] We apportion the overall value of US robot imports to 66 industries (defined according to the classification of the Bureau of Economic Analysis, henceforth BEA industries) using information on the cross-industry distribution of machinery (including robot) imports in each year extracted from the US Import Matrices.[9] Finally, we apportion the industry-level robot imports to individual CZs based on the industrial structure of employment in each CZ. In particular, our final measure of CZ-level robot exposure is constructed as follows:

$$\Delta Robots_{ct} = \sum_{j} \lambda_{cjt} \cdot \Delta \ln Rob\_M_{jt}, \tag{12}$$

where $c$ denotes CZs; $\Delta \ln Rob\_M_{jt}$ is the ten-year equivalent log change in US robot imports in industry $j$ over period $t$; and $\lambda_{cjt}$ is the share of industry $j$ in total employment of CZ $c$ at the beginning of period $t$.[10]

The choice of using imports to measure automation in the US is motivated by the high concentration of the robot-producing sector. The vast majority of robot production worldwide takes place in a handful of non-US countries (especially Japan and Germany), while the US is not yet a major robot producer. Most of the production of robots occurring in the US is made by local affiliates of foreign multinationals and is aimed at serving manufacturing firms operating in neighboring countries, mostly Canada and Mexico (see, e.g., Casanova, 2019). On the contrary, the US is the second largest importer of robots worldwide, and also the second country in the world in terms of net robot imports (see, e.g., Furusawa and Sugita, 2021). Consistent with this, robot imports into the US are highly correlated with the overall stock of robots installed in the country, as recorded by the International Federation of Robotics (IFR): a regression of the log change in robot imports, $\Delta \ln Rob\_M_{jt}$, on the log change in the IFR stock of robots across industries and time periods yields a coefficient of 0.998 (s.e. 0.058). While the IFR data have important limitations—most notably, they only contain counts of robots (not values) and, by encompassing domestically-sourced robots, they could reflect technological shocks affecting the domestic labor market—such a high correlation suggests that robot imports are likely to capture the bulk of the variation in the use of robots in the US.[11] In Section

4.1, we will further show that, if we use net robot imports (i.e., imports minus exports) to construct robot exposure, our main evidence is unchanged, in line with the limited size of domestic production and exports of robots in the US.

As previously mentioned, to apportion nationwide robot imports to individual industries, we use the cross-industry distribution of machinery imports obtained from the US Import Matrices. This choice is made for consistency with the use of import data but turns out to be inconsequential for the results. First, the distribution of machinery imports across industries is very similar to the distribution of total (domestic plus foreign) machinery purchases, as obtained from the US Input-Output Tables: a regression of industry shares in total machinery purchases on the corresponding shares in machinery imports yields a coefficient of 1.069 (s.e. 0.021). Consistent with this, our results are unchanged if we reconstruct $\Delta Robots_{ct}$ using industry shares in total machinery purchases to apportion robot imports to individual industries (see Section 4.1). More generally, the cross-industry distribution of machinery imports is also highly correlated with the overall stock of installed robots in the US: a regression of the log IFR robot stock on the log industry shares in machinery imports across the nineteen aggregate sectors covered by the IFR data over 1993–2016 yields a coefficient of 0.541 (s.e. 0.123). This suggests that the cross-industry distribution of machinery imports closely reflects the actual usage of robots across US industries.

Variation in $\Delta Robots_{ct}$ across CZs could be driven by CZ-specific factors that also influence labor market outcomes. For instance, positive demand shocks may induce firms to automate and simultaneously raise employment and wages. Similarly, firms may adopt robots to increase productivity after some negative labor market shock. This implies that the OLS estimates of the effects of automation on labor market outcomes could be biased, either upward or downward. To account for the potential endogeneity of $\Delta Robots_{ct}$, we build on Autor, Dorn and Hanson (2013) and construct an instrument that is meant to isolate the variation in $\Delta Robots_{ct}$ induced by supply shocks in robot exporting countries, rather than by shocks occurring in individual CZs. To construct the instrument, we source (from UN Comtrade) data on robot exports from non-US countries to eleven European economies over 1989–2018.[12] To apportion the country-level robot imports to individual industries, we use the share of each industry in total machinery imports into a given country, as extracted from country-specific Import Matrices available in the World Input-Output Database (Timmer et al., 2015). Finally, we construct the instrument as follows:

$$\Delta Robots\_Oth_{ct} = \sum_j \lambda_{cjt} \cdot \Delta \ln Rob\_M\_Oth_{jt}, \tag{13}$$

where $\Delta \ln Rob\_M\_Oth_{jt}$ is the ten-year equivalent log change in robot exports from non-US countries to the eleven European countries in industry $j$ over period $t$.

Identification requires that supply shocks boosting robot exports from non-US countries are uncorrelated with US-specific technology shocks affecting labor market outcomes in individual CZs. Similarly, demand shocks in the

eleven European importing countries must be uncorrelated with demand shocks in US local labor markets. To assuage identification concerns, we will use a highly demanding specification (presented in Section 4.1) that controls for a host of fixed effects, both at the state and at the year level. These fixed effects absorb any US-specific shock that is common to all CZs, as well as differential trends across US states. The specification also controls for several proxies for other types of shocks to trade, technology and demand conditions at the CZ level. Overall, the wealth of controls and fixed effects included in the specification should largely reassure that the IV results are not obviously driven by US-specific shocks potentially correlated with the instrument.

**Offshoring Intensity.** Following Feenstra and Hanson (1999), we measure offshoring as the share of imported intermediate inputs in total input purchases. A higher value of this ratio corresponds to a greater usage of foreign inputs in production, reflecting a more intensive relocation of production stages to foreign countries. We construct offshoring intensities for the BEA industries using US Input-Output Tables and Import Matrices over 1997–2018. We use two complementary indicators of offshoring. The first, called *broad* offshoring, considers imports of all types of inputs. The second, called *narrow* offshoring, considers only imports of inputs that are closely related to the production process of an industry and could thus be performed in house by firms.

The two indicators are constructed as follows:

$$B\_Offsh_{jt} = \frac{\sum_h I\_M_{jht}}{\sum_h \left(I\_M_{jht} + I\_D_{jht}\right)} \quad \text{and} \quad N\_Offsh_{jt} = \frac{I\_M_{jjt}}{\sum_h \left(I\_M_{jht} + I\_D_{jht}\right)},$$

where $I\_M_{jht}$ and $I\_D_{jht}$ denote imports and domestic purchases, respectively, of intermediates made by industry $j$ from industry $h$ in period $t$; and $I\_M_{jjt}$ indicates imports of intermediates made by industry $j$ from within itself at time $t$. Then, we construct the intensity of offshoring in each CZ similarly to eq. (12), using the industry-specific offshoring indicators, $B\_Offsh_{jt}$ and $N\_Offsh_{jt}$, in place of the log change in robot imports. Namely,

$$B\_Offsh_{ct} = \sum_j \lambda_{cjt} \cdot B\_Offsh_{jt} \quad \text{and} \quad N\_Offsh_{ct} = \sum_j \lambda_{cjt} \cdot N\_Offsh_{jt}. \quad (14)$$

Since we are not interested in identifying the effects of offshoring, we do not build an instrument for it.[13]

**Occupational Characteristics.** Finally, we use information on occupational characteristics to unpack the overall employment effects of automation across different groups of workers. Following Graetz and Michaels (2018), we classify each occupation according to whether workers perform tasks that can or cannot be replaced by robots. Graetz and Michaels (2018) define an occupation as "replaceable" if its title corresponds to at least one of the robot application

categories (e.g., welding, painting and assembling) identified by the IFR. We source replaceability data by occupation from Graetz and Michaels (2018).

We also classify occupations depending on how easy it is to relocate their tasks to foreign countries. Our main index of occupational offshorability is sourced from Autor and Dorn (2013). The authors use the simple average of two variables constructed by Firpo, Fortin and Lemieux (2011), who employ data from the O*Net database to measure the degree to which workers require face-to-face interaction and physical presence on the job. The index is reversed, so higher levels indicate higher offshorability. We standardize the index to have mean 0 and standard deviation 1 across occupations, and define as offshorable all occupations whose index is above the median. The two occupational characteristics are available for 331 US Census occupations. We match these characteristics to the US Censuses and the ACS using information on each worker's occupation of employment provided in the two data sources.[14]

## 3.2 Stylized Facts

We now present a number of facts about labor market outcomes, robot imports and offshoring in the US over the period of analysis. Figure 3.1 shows the evolution of employment from 1990 to 2015, based on the whole sample of
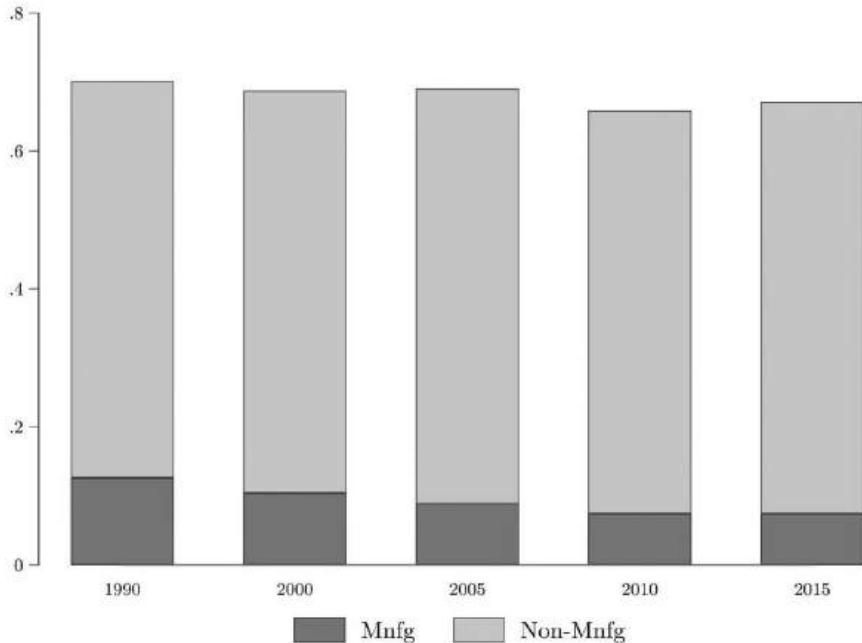


*Figure 3.1* Employment-to-Population Ratio by Sector
Source: US Censuses (1990, 2000) and American Community Survey (2005–2015).

individuals contained in the Censuses and the ACS. As a percentage of total population, overall employment has gone down from 70% in 1990 to 67% in 2015. This aggregate trend masks heterogeneity between manufacturing and non-manufacturing sectors. The employment-to-population ratio has steadily fallen in manufacturing, moving from 13% in 1990 to 7% in 2015. At the same time, employment has significantly risen relative to population in non-manufacturing sectors, passing from 57% in 1990 to 60% in 2015. The existence of a shrinking industrial sector and an expanding service sector are common trends to most industrialized countries and reflect the structural change occurring in these economies over recent decades. As we show later on, automation has contributed to these trends by inducing a reallocation of labor outside of manufacturing.

Figure 3.2 unpacks the overall trend in employment across occupations with different characteristics. The figure shows average employment-to-population ratios across CZs in a given year, separately for offshorable and replaceable occupations. The difference between the overall employment-to-population ratio and the ratio corresponding to either group is equal to the employment-to-population ratio in the complement group of (non-offshorable or non-replaceable) occupations. Employment has increased in offshorable occupations, especially after the year 2000. At the same time, after reaching a plateau in 2000, the employment share of replaceable jobs has significantly declined in subsequent years, with a rapid acceleration in 2010. These trends reveal a marked change in the occupational structure of US employment over recent decades: employment has shifted from non-offshorable to offshorable jobs and from occupations that can be replaced by robots to those that cannot.

These adjustments in the US labor market have been concurrent with significant changes in the importance of automation and offshoring. Figure 3.3 shows the evolution of US robot imports over the period of analysis. To highlight the main trends in this variable, the graph reports overall imports in each five-year interval starting in 1989. The graph also displays the evolution of the two offshoring indicators, averaged across industries in each five-year period. Two main facts emerge from Figure 3.3. First, robot imports have remained at very low levels over the 1990s and the first half of the 2000s but have rapidly risen thereafter with a marked acceleration after 2010. This confirms that automation and adoption of industrial robots have significantly gained momentum in the US over recent years.[15] Second, the growth in offshoring has decelerated in the second half of the 2000s and become negative after 2010. While the reduced incidence of offshoring could have resulted from various factors, including the shrinkage of the manufacturing sector, it could also reflect the tendency by firms to bring back foreign activites to the US. From now on, we will accordingly refer to a reduction in the offshoring indicators as "reshoring", for brevity. In this sense, the concomitant increase in robot imports and reduction in offshoring is consistent with anecdotal evidence, according to which automation is leading firms to reshore an increasing number of production stages.
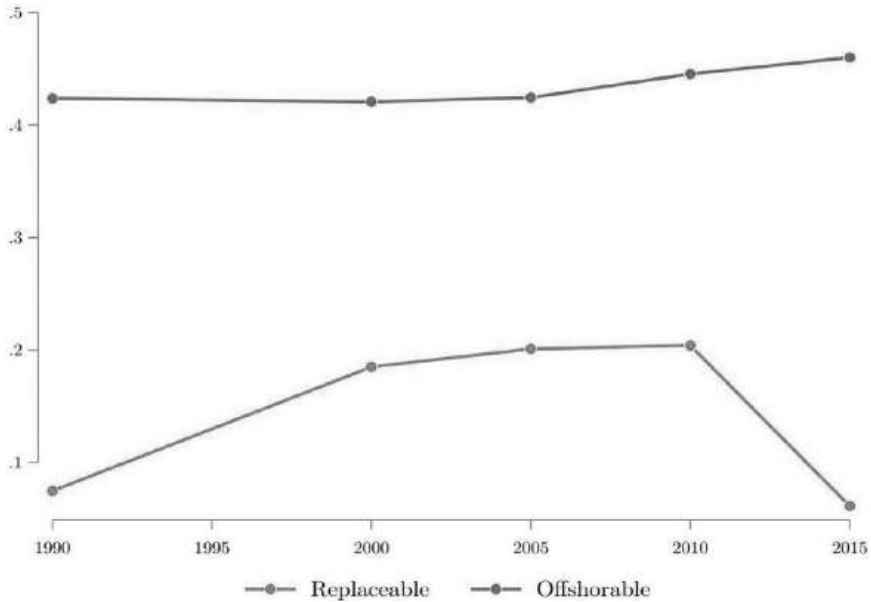
*Figure 3.2* Employment-to-Population Ratio by Occupation Group

Source: US Censuses (1990, 2000) and American Community Survey (2005-2015).

Notes: Replaceable occupations are those whose title corresponds to at least one of the robot application categories identified by the International Federation of Robotics (Graetz and Michaels, 2018). Offshorability is measured by an index capturing the degree to which workers require face-to-face interaction and physical presence on the job (Autor and Dorn, 2013). The index is rescaled so that higher values indicate higher offshorability. Offshorable occupations are those for which the index is above the sample median. All figures are arithmetic averages across CZs.

The aggregate trends in robot imports and offshoring hide heterogeneity across sectors, as shown in Figure 3.4. The latter reports the average values of robot imports per worker (panel a) and of the two offshoring indicators (panel b) over the sample period, separately for manufacturing and non-manufacturing sectors. Robot imports are almost entirely concentrated in manufacturing and still almost inexistent in services. In particular, average robot imports per worker amount to roughly 575,000$ in manufacturing and 63,000$ in non-manufacturing industries. Similarly, despite the growth of service offshoring in recent years (see, e.g., Crinò, 2010), offshoring is still higher in manufacturing than in other sectors. According to both indicators, offshoring in manufacturing exceeds offshoring in non-manufacturing industries by about three times over the period of analysis.

Since different economic activities are not equally distributed in space, the heterogeneous incidence of automation and offshoring across industries is likely to give rise to differences in the extent to which each CZ is exposed to these
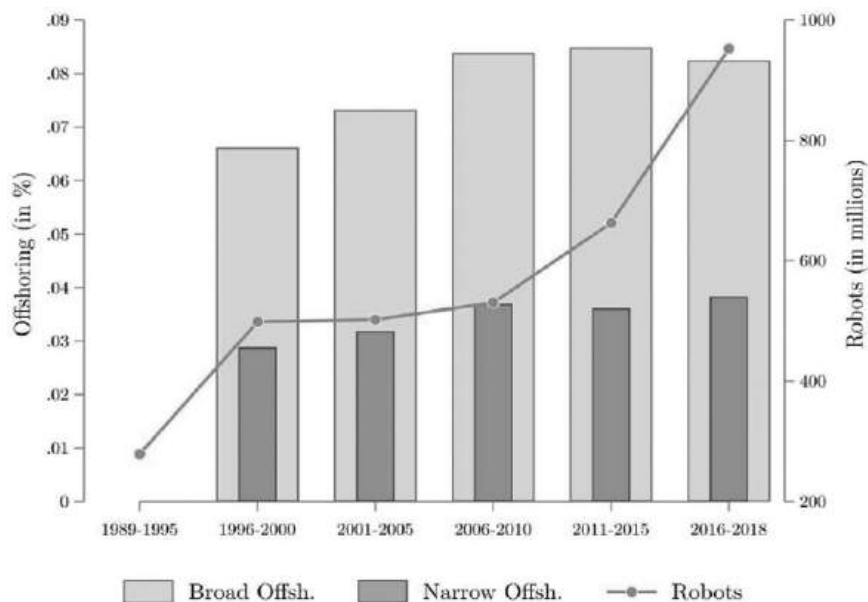
*Figure 3.3* Robot Imports and Offshoring over Time

Source: US Customs data (Schott, 2008), Import Matrices and Input-Output Tables.

Notes: *Robots* are the overall value of US robot imports in each time period. *Broad Offsh.* and *Narrow Offsh.* are averages of the two offshoring indicators across industries and years in each time period.

phenomena. To document the geographical distribution of automation and offshoring in the US, Figure 3.5 reports two maps showing the mean of $\Delta Robots_{ct}$ (map a) and the average change in offshoring (maps b) in each CZ over the sample period.[16] Two facts are worth highlighting. First, both variables vary substantially in space. Interestingly, variation is high not only across but also within states. This reflects the heterogeneous industrial structure of CZs and will be crucial for our econometric analysis. Second, the correlation between automation and offshoring is negative also across CZs. While automation has especially risen in the Great Lakes region and in coastal states, offshoring intensity has especially increased in South-Central United States. We will systematically document this negative correlation in Section 4.2. For the time being, the descriptive evidence in Figure 3.5 further corroborates the view that automation could have induced a reshoring of activities in the US.

Finally, Table 3.1 reports summary statistics on the main variables used in the regressions. All statistics are computed across CZs and time periods. The employment-to-population ratio has increased on average by 2.6 percentage points (p. p.) per decade, as the combination of a 4.6 p.p. average decadal increase in non-manufacturing industries and a 2 p.p. average decadal reduction in the

a) Robot Imports per Worker



b) Offshoring Intensity
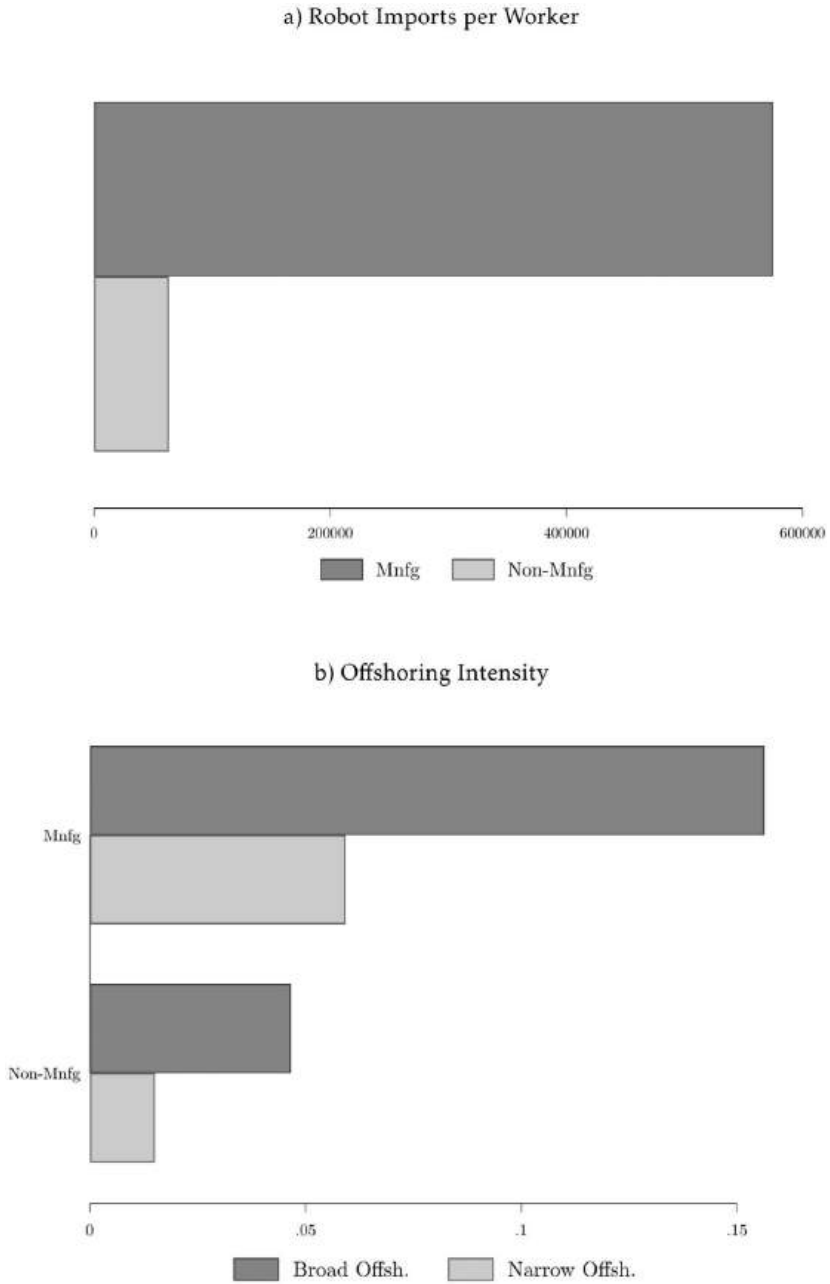


*Figure 3.4* Robot Imports and Offshoring by Sector

Source: US Customs data (Schott, 2008), Import matrices and Input-Output Tables.

Notes: All figures are averages across year and industries within a sector.

a) Robot Exposure

b) Offshoring Intensity
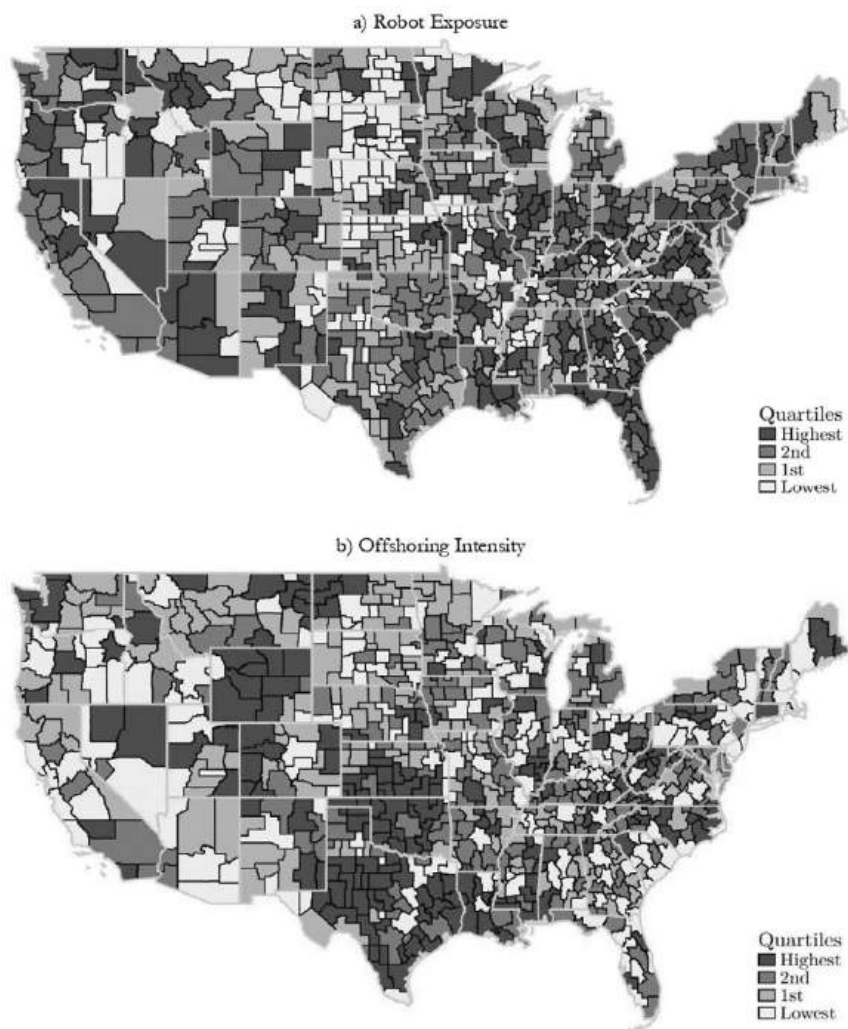


*Figure 3.5* Robot Exposure and Offshoring across Commuting Zones

Notes: The first map shows the mean of Δ *Robots* in each CZ over the sample period. The second map shows the average change in the broad offshoring indicator by CZ over time.

manufacturing sector. Average wages have risen by 0.1 log points per decade in both sectors. Table 3.1 also confirms the significant increase in automation documented before, with $\Delta Robots_{ct}$ being equal to 0.41 log points per decade on average. The high standard deviation of $\Delta Robots_{ct}$ points to significant variation in robot exposure both in space and over time, consistent with the evidence emerging from Figure 3.5. Finally, offshoring intensity is equal to 4.8 p.p. on

average according to the broad indicator and to 1 p.p. according to the narrow indicator. Also in this case, there is significant variation across CZs and time periods as suggested by the high standard deviations reported in the table.

## 4 Empirical Analysis

In this section, we present the results of the econometric analysis. We start by discussing the average effects of robot exposure on labor market outcomes across CZs. We then provide novel evidence on the relationship between automation and offshoring, exploiting variation across occupations, industries and space. Building on this evidence, we finally revisit the average employment effects of robot exposure and unpack them across occupations and CZs with different exposure to offshoring.

### 4.1 Average Effects

To study how robot exposure affects labor market outcomes across CZs, we build on Autor, Dorn and Hanson (2013) and Acemoglu and Restrepo (2019), and estimate specifications of the following form:

$$\Delta\Upsilon_{ct} = \alpha_s + \alpha_t + \beta \cdot \Delta Robots_{ct} + \mathbf{X}_{ct}^{'} \cdot \gamma + \varepsilon_{ct}, \tag{15}$$

where $\Delta\Upsilon_{ct}$ is the change in outcome $\Upsilon$ in CZ $c$ over period $t$; $\alpha_s$ and $\alpha_t$ are fixed effects for US states and time periods, respectively; $\Delta Robots_{ct}$ is our measure of

*Table 3.1* Summary Statistics

|  | Mean | Std. Dev. | Obs. |
|---|---|---|---|
| Δ Total Emp./Pop. | 0.026 | 0.043 | 2888 |
| Δ Mnfg Emp./Pop. | −0.020 | 0.041 | 2888 |
| Δ Non Mnfg Emp./Pop. | 0.046 | 0.053 | 2888 |
| Δ ln Avg Wages | 0.100 | 0.115 | 2888 |
| Δ ln Mnfg Wages | 0.105 | 0.255 | 2888 |
| Δ ln Non Mnfg Wages | 0.103 | 0.125 | 2888 |
| Δ Robots | 0.411 | 0.699 | 2888 |
| B_Offsh | 0.048 | 0.033 | 2888 |
| N_Offsh | 0.007 | 0.017 | 2888 |

Notes: Statistics for variables in changes are computed across 722 CZs and four time periods: 1990–2000, 2000–2005, 2005–2010 and 2010–2015. Statistics for variables in levels (*B_Offsh* and *N_Offsh*) are computed across 722 CZs and four years: 2000, 2005, 2010 and 2015. Changes in employment-to-population ratios and in log average wages over a given time period are expressed in decadal terms. *Robots* is the weighted average of ten-year equivalent log changes in US robot imports across industries, with weights given by the industrial structure of employment in each CZ at the beginning of each time period. *B_Offsh* and *N_Offsh* are weighted averages of the broad and narrow offshoring indicators across industries, with weights given by the industrial structure of employment in each CZ and year.

CZ-level exposure to imported robots; $\mathbf{X}_{ct}$ is a vector of controls for other observable characteristics of the CZ (details follow); and $\varepsilon_{ct}$ is an error term.

We estimate eq. (15) by stacking ten-year equivalent first differences for four time periods: 1990–2000, 2000–2005, 2005–2010 and 2010–2015. The state fixed effects control for heterogeneous trends in labor market outcomes across states, while the year fixed effects absorb shocks hitting outcomes uniformly in all CZs. The control variables $\mathbf{X}_{ct}$ include start-of-period proxies for the following CZ-level characteristics: size (log employment), demographic composition of the labor force (employment shares of female, foreign born and college-educated workers), and composition of economic activities (employment share of workers in routine-intensive occupations and offshoring intensity). These variables account for heterogeneous trends across CZs characterized by different initial conditions. $\mathbf{X}_{ct}$ also includes proxies for other shocks potentially occurring in CZ $c$ over period $t$, namely, export shocks and shocks to import competition from China and other countries. These variables control for changes in trade, technology and demand conditions concurrent with the import of robots.[17] We weight the observations by the initial-period share of each CZ in total population and correct the standard errors for clustering at the state level to account for residual correlation across CZs within the same state. We first estimate eq. (15) using OLS. Then, to account for possible endogeneity of $\Delta Robots_{ct}$, we turn to 2SLS regressions, instrumenting $\Delta Robots_{ct}$ with $\Delta Robots\_Oth_{ct}$. Because eq. (15) restricts coefficients to be the same across CZs, the parameter $\beta$ measures the average effect of robot exposure on a given outcome across US local labor markets.

Table 3.2 contains results for employment. OLS estimates are reported in panel a and 2SLS estimates in panel b. To study how the effect of robot exposure is influenced by the covariates, we first present results from a parsimonious specification including only state and year fixed effects (columns 1–3) and then add control variables (columns 4–6). We estimate eq. (15) for three different outcomes. The first, used in columns (1) and (4), is the change in total employment over population. The other two outcomes, used in columns (2) and (5) and in columns (3) and (6), respectively, are the changes in manufacturing and non-manufacturing employment over population. Because total employment is the sum of manufacturing and non-manufacturing employment, the properties of linear estimators like OLS and 2SLS imply that the estimates of $\beta$ reported in columns (2) and (3) add up to the estimate reported in column (1); similarly, the estimates of $\beta$ shown in columns (5) and (6) add up to the estimate shown in column (4). This provides us with an immediate way of decomposing the employment effects of robot exposure across manufacturing and other sectors.

The OLS estimates show a negative and statistically significant correlation between robot exposure and manufacturing employment. The correlation with non-manufacturing employment is instead positive and becomes statistically significant when adding control variables. The two effects partly offset each other, so the correlation of robot exposure with overall employment is weak and not always statistically significant. In Appendix Table B1, we dig deeper into the

*Table 3.2* Robot Exposure and Employment

|  | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
|  | Δ Total Emp./Pop. | Δ Mnfg Emp./Pop. | Δ Non Mnfg Emp./Pop. | Δ Total Emp./Pop. | Δ Mnfg Emp./Pop. | Δ Non Mnfg Emp./Pop. |
| **a) OLS** | | | | | | |
| ΔRobots | −0.012** | −0.016*** | 0.004 | −0.006 | −0.016*** | 0.010* |
|  | [0.005] | [0.004] | [0.005] | [0.004] | [0.004] | [0.006] |
| Obs. | 2879 | 2879 | 2879 | 2157 | 2157 | 2157 |
| R2 | 0.43 | 0.29 | 0.36 | 0.53 | 0.36 | 0.36 |
| **b) 2SLS** | | | | | | |
| *2nd Stage* | | | | | | |
| ΔRobots | 0.016 | −0.056*** | 0.072*** | 0.006 | −0.049*** | 0.055*** |
|  | [0.016] | [0.014] | [0.018] | [0.010] | [0.010] | [0.014] |
| Obs. | 2157 | 2157 | 2157 | 2157 | 2157 | 2157 |
| R2 | 0.23 | 0.20 | 0.01 | 0.52 | 0.30 | 0.29 |
| **1st Stage (Dep. Var.: ΔRobots)** | | | | | | |
| ΔRobots_Oth | 2.708*** | 2.708*** | 2.708*** | 4.085*** | 4.085*** | 4.085*** |
|  | [0.450] | [0.450] | [0.450] | [0.411] | [0.411] | [0.411] |
| Kleibergen-Paap *F-stat.* | 36.2 | 36.2 | 36.2 | 99.0 | 99.0 | 99.0 |
| State FE | yes | yes | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes | yes | yes |
| Control variables | no | no | no | yes | yes | yes |

Notes: The sample consists of 722 CZs and four time periods: 1990–2000, 2000–2005, 2005–2010 and 2010–2015. The dependent variables, indicated in the columns' headings except for the first-stage regressions, are ten-year equivalent changes in overall employment-to-population ratio (columns 1 and 4), manufacturing employment-to-population ratio (columns 2 and 5), and non-manufacturing employment-to-population ratio (columns 3 and 6). *ΔRobots* is the weighted average of ten-year equivalent log changes in US robot imports across industries, with weights given by the industrial structure of employment in each CZ at the beginning of each time period. The instrument *ΔRobots_Oth* is constructed analogously to *ΔRobots* using industry-level data on robot exports from non-US countries to eleven European countries. *Control variables* are start-of-period log employment, offshoring intensity (broad indicator), the employment shares of female workers, foreign-born workers, college graduates and routine-intensive occupations, and the ten-year equivalent changes in exports, imports from China and imports from other countries over total employment. The first period with available data on offshoring is 2000–2005. Regressions are weighted by the initial share of each CZ in total US population. Standard errors, reported in square brackets, are corrected for clustering within states. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

timing of these relationships. Using the parsimonious specification, we find that the correlations are stronger when estimated on later periods (2005–2010 and 2010–2015) than on earlier periods (1990–2000 and 2000–2005). This is consistent with the acceleration of robot imports occurring in the second part of the sample, as documented in Figure 3.3. Moreover, we perform a falsification test by regressing current employment changes on the first lead of $\Delta Robots_{ct}$. The coefficients are always close to zero, which further suggests that the relationship between robot exposure and employment is not driven by secular trends in outcomes that antedate an increase in automation.

Appendix Table B1 also contains an extensive set of robustness checks on the baseline specification. We show, in particular, that the main results are not driven by outliers, as they remain unchanged when excluding CZs in the top percentile of the distribution by $\Delta Robots_{ct}$ in each period. We also control for exposure to other types of capital and find that the correlations are not contaminated by other forms of investment.[18] Moreover, we find similar results when considering alternative ways of constructing robot exposure, namely, by using (i) changes in the stock of robot imports, (ii) changes in net robot imports, and (iii) the cross-industry distribution of total machinery purchases to apportion nationwide robot imports to individual industries.[19]

Finally, in Appendix Figure B1, we use alternative ways of correcting the standard errors for clustering. In particular, we account for residual correlation within CZs over time (clustering by CZ); across CZs in the same state and year (clustering by state-year); within CZs over time and across CZs in the same state and year (two-way clustering by CZ and state-year); across CZs in the same geographical neighborhood (spatial clustering); and across CZs with similar industrial structure (clustering by industry similarity).[20] The confidence intervals around $\beta$ are similar to, and frequently narrower than, the baseline confidence intervals, suggesting that correcting the standard errors for clustering within states provides a conservative inference.

We now turn to the 2SLS estimates. The bottom part of panel b shows that the first-stage coefficient on $\Delta Robots\_Oth_{ct}$ is positive, large and very precisely estimated, which underscores the strong predictive power of the instrument at explaining differences in robot exposure across CZs.[21] The second-stage coefficients, reported at the top of panel b, are larger than their OLS counterparts in absolute value, suggesting OLS estimates to be biased towards zero. Qualitatively, however, the 2SLS estimates confirm the evidence emerged from the OLS regressions. In particular, robot exposure reduces employment in manufacturing. This is consistent with robot adoption currently being larger in manufacturing than in other sectors. At the same time, robot exposure raises employment outside of manufacturing. This is consistent with the model in Section 2.3 where displaced workers in manufacturing find employment in the service sector. Overall, the two effects almost exactly cancel out, so robot exposure has no significant impact on overall employment.

To have a sense of the magnitude of these effects, we multiply the average value of $\Delta Robots_{ct}$ reported in Table 3.1 by the 2SLS coefficients shown in

columns (5) and (6) of Table 3.1. This yields –0.02 for manufacturing employment and 0.022 for non-manufacturing employment. Accordingly, in a CZ with average robot exposure, manufacturing employment would fall by 2 p.p. per decade relative to population, roughly the average change documented in Table 3.1. At the same time, non-manufacturing employment relative to population would increase by 2.2 p.p. per decade, approximately half the size of the average change reported in Table 3.1. These figures suggest that automation has significantly contributed to the reallocation of employment from manufacturing to non-manufacturing sectors occurring in the US over the sample period.

Finally, in Table 3.3, we complement the employment results by studying the implications of robot exposure for wages. The estimates show that automation increases average wages. The effect is driven by non-manufacturing sectors. Together with our previous evidence on employment, this further suggests that robot exposure increases labor demand outside of manufacturing. When separately considering college-educated and non college-educated workers, we find positive wage effects for both groups, although the point estimate is larger and precisely estimated for high-skill individuals. In manufacturing, the effect of automation on average wages is negative, albeit imprecisely estimated, consistent with automation reducing labor demand in this sector. When separately considering workers with and without a college degree, we find a small positive estimate of $\beta$ for the former group and a larger negative estimate for the latter. While none of these coefficients is precisely estimated, these results suggest that robots tend to reduce labor demand in manufacturing especially for low-skill individuals.

Overall, these results are broadly consistent with Acemoglu and Restrepo (2019), who study the effect of automation across US CZs over the 1990–2007 period using data on the stock of robots in nineteen industries from the IFR. Similarly to us, they find evidence of negative employment effects, which are more pronounced in manufacturing. However, they also find stronger negative effects on wages.

## 4.2  Robots and Offshoring

Having documented the average effects of robot exposure on labor market outcomes, we turn to the main part of the analysis. Our interest lies in understanding how automation interacts with offshoring and what consequences such an interaction could have for the US labor market. In this section, we analyze the relationship between robot exposure and offshoring using different sources of variation in the data. In the next section, we turn to investigating the implications for US employment.

As a starting point, we study the nature of tasks that can be performed by robots. Specifically, we ask whether robots are suited for tasks with a high degree of offshorability or for relatively hard-to-offshore activities. To this purpose, we take advantage of the occupation-level measures of offshorability and replaceability introduced in Section 3. We regress the offshorability index of Autor and Dorn (2013) on the replaceability dummy of Graetz and Michaels

*Table 3.3* Robot Exposure and Wages

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | *Δ ln Avg Wages* | *Δ ln Mnfg Wages* | *Δ ln Mnfg Wages (College)* | *Δ ln Mnfg Wages (Non-College)* | *Δ ln Non Mnfg Wages* | *Δ ln Non Mnfg Wages (College)* | *Δ ln Non Mnfg Wages (Non-College)* |
| | | | | **a) OLS** | | | |
| *ΔRobots* | 0.031** | 0.003 | 0.017 | 0.004 | 0.039*** | 0.044*** | 0.032 |
| | [0.012] | [0.023] | [0.030] | [0.027] | [0.013] | [0.014] | [0.022] |
| Obs. | 2157 | 2157 | 2151 | 2154 | 2157 | 2157 | 2157 |
| R2 | 0.52 | 0.20 | 0.18 | 0.08 | 0.49 | 0.51 | 0.24 |
| | | | | **b) 2SLS, 2nd Stage** | | | |
| *ΔRobots* | 0.064* | −0.075 | 0.013 | −0.102 | 0.097*** | 0.114*** | 0.055 |
| | [0.033] | [0.097] | [0.099] | [0.105] | [0.030] | [0.032] | [0.034] |
| Obs. | 2157 | 2157 | 2151 | 2154 | 2157 | 2157 | 2157 |
| R2 | 0.51 | 0.19 | 0.18 | 0.06 | 0.48 | 0.50 | 0.23 |

Notes: All regressions are estimated on a panel of 722 CZs. The dependent variables, indicated in the columns' headings, are ten-year equivalent log changes in average wages (column 1), manufacturing wages (column 2), manufacturing wages of college graduates (column 3), manufacturing wages of non-college graduates (column 4), non-manufacturing wages (column 5), non-manufacturing wages of college graduates (column 6) and non-manufacturing wages of non-college graduates (column 7). *ΔRobots* is the weighted average of ten-year equivalent log changes in US robot imports across industries, with weights given by the industrial structure of employment in each CZ at the beginning of each time period The instrument is *ΔRobots_Oth*, constructed analogously to *ΔRobots* using industry-level data on robot exports from non-US countries to eleven European countries All regressions include state fixed effects, year fixed effects and the same control variables as in Table 3.2, and are weighted by the initial share of each CZ in total US population. Standard errors reported in square brackets are correted for clustering within states ***,** and * denote significance at the 1%, 5% 10% level, respectively.

Table 3.4 Robots Exposure and Offshoring Across Occupations, Industries and Commuting Zones

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Offshorability (AD, 2013) | Offshoring (Broad) | Offshoring (Narrow) | Offshoring (Broad) | Offshoring (Narrow) | Offshoring (Broad) | Offshoring (Narrow) |
| Replaceability | 0.277** [0.130] | | | | | | |
| Δ ln Rob_M | | –0.076*** [0.006] | –0.080*** [0.005] | | | | |
| ΔRobots | | | | –0.019*** [0.004] | –0.024*** [0.003] | –0.014*** [0.005] | –0.017*** [0.004] |
| Obs. | 331 | 535 | 408 | 2157 | 2157 | 2157 | 2157 |
| R2 | 0.01 | 1.00 | 1.00 | 0.69 | 0.71 | 0.68 | 0.68 |
| Sample | Occupations | Industries Panel | | CZs Panel | | | |
| Estimator | OLS | OLS | OLS | OLS | OLS | 2SLS | 2SLS |

Notes: The regression in column (1) is estimated on a cross-section of occupations. The dependent variable is an indicator of offshorability, which measures the degree to which workers in a given occupation require face-to-face interaction and physical presence on the job (Autor and Dorn, 2013). *Replaceability* is a dummy equal to 1 for occupations whose title corresponds to at least one of the robot application categories identified by the International Federation of Robotics, and equal to 0 otherwise (Graetz and Michaels, 2018). The regressions in columns (2) and (3) are estimated on a panel of 66 industries. The dependent variables are changes in the broad and narrow offshoring indicators, respectively, over five-year periods. Δ *ln Rob_M* is the log change in US robot imports in each industry. The regressions include fixed effects for industries and sector-year pairs, and are weigthted by start-of-period industry employment. The repressions in columns (4)-(7) are estimated on a panel of CZs. The dependent variables are weighted averages of ten-year equivalent changes in the industry-level offshoring indicators, with weights given by the industrial structure of employment in each CZ at the beginning of each time period. ΔRobots is the weighted average of ten-year equivalent log changes in US robot imports across industries, with weights given by the industrial structure of employment in each CZ at the beginning of each time period. In columns (6) and (7), the instrument is ΔRobots_Oth, constructed analougously to ΔRobots using industry-level data on robot exports from non-US countries to eleven European countries. The regressions include state fixed effects, year fixed effects and the same control variables as in Table 3.2, and are weighted by the initial share of each CZ in total US population. Standard errors, reported in square brackets, are robust to heteroskedasticity in column (1), corrected for clustering within industries in columns (2) and (3), and corrected for clustering within states in columns (4)–(7). ***, ** and * denote significance at the 1, 5 and 10% level, respectively.

(2018) across 331 US Census occupations. The results are reported in column (1) of Table 3.4. The coefficient on the replaceability dummy is positive and statistically significant, implying that replaceable occupations are more offshorable than non-replaceable occupations, on average. Given that the offshorability index is standardized with mean 0 and standard deviation 1, the coefficient implies a sizable difference of 28% of a standard deviation between the average offshorability of replaceable and non-replaceable occupations.

In untabulated regressions, we have assessed the robustness of this result using two alternative offshorability indices, developed by Blinder (2009) and Blinder and Krueger (2013), respectively. The Blinder (2009) indicator assigns each occupation an offshorability degree based on the author's subjective assessment of how amenable tasks are to electronic delivery. The Blinder and Krueger (2013) indicator quantifies the offshorability of an occupation based on information from household surveys and professional coders' assessment of the ease with which tasks can be relocated abroad. Also in these cases, we found positive and precisely estimated coefficients on the replaceability dummy, suggesting that the positive correlation between replaceability and offshorability does not depend on how we measure the latter characteristic.

These results imply that automation and offshoring affect similar occupations. Accordingly, automation may act as a substitute for offshoring, allowing firms to use robots in tasks that were previously performed abroad. We now provide more direct evidence of this substitutability by studying the relationship between robot imports and the two offshoring indicators across industries. To this purpose, we regress changes in the offshoring indicators on changes in log robot imports over five-year periods across industries. We control for industry fixed effects to absorb industry-specific trends and for sector × year fixed effects to soak up common shocks across sectors; the regressions are weighted by industry employment at the beginning of each period. The results are reported in columns (2) and (3) of Table 3.4. Regardless of the offshoring indicator, the coefficient on robot imports is always negative and very precisely estimated: industries experiencing a more rapid growth in robot imports also exhibit a relatively larger reduction in offshoring. This finding is consistent with robots substituting tasks that used to be performed abroad and suggests that the rise of automation over the sample period has been associated with a reshoring of activities to the US.

In the remaining columns of Table 3.4, we complement the previous results with evidence across CZs. To this purpose, we estimate eq. (15) using changes in the two offshoring indicators as the dependent variables.[22] We run these regressions using both OLS (columns 4 and 5) and 2SLS (columns 6 and 7), to mitigate concerns with reverse causality and omitted variables; in the latter case, we use $\Delta Robots\_Oth_{ct}$ as an instrument for $\Delta Robots_{ct}$. The coefficient on $\Delta Robots_{ct}$ is always negative and highly statistically significant. Consistent with the descriptive evidence emerging from Figure 3.5, firms have more intensively resorted to reshoring in CZs characterized by stronger robot exposure.

### 4.3 Robot Exposure, Offshoring and Employment

That robots and offshoring are substitutes for one another has potentially important implications for the employment effects of automation. If robots induce reshoring, their effects are likely to be heterogeneous both across occupations and across CZs. First, automation may induce a relatively larger reduction in domestic employment in occupations that are harder to offshore. The reason is that, in offshorable occupations, automation should partly affect foreign employment and foster reshoring to the US. Second, automation may lead to a relatively smaller reduction in domestic employment in CZs characterized by a higher offshoring intensity, as the scope for reshoring is relatively larger in these CZs. We now revisit the average effects of robot exposure on employment in the light of these considerations. In particular, we allow the effects to vary across jobs and in space, and study whether this heterogeneity is consistent with the substitutability between robots and offshoring documented before.

Our first exercise consists of unpacking the effects of robot exposure across occupations with different characteristics. To this purpose, we decompose the overall change in the employment-to-population ratio across mutually exclusive groups of occupations, and then re-estimate eq. (15) using changes in group-specific employment over population as the dependent variables. The results are reported in Table 3.5. To begin with, in panel a, we divide occupations into two groups and use OLS regressions to describe the central tendencies in the data. Columns (1) and (2) show, as expected, that robot exposure is associated with a significant fall in employment in replaceable occupations but no change in non-replaceable occupations. More interestingly, columns (3) and (4) show that robot exposure is uncorrelated with employment in offshorable jobs, but strongly negatively correlated with employment in non-offshorable tasks.

In panel b, we examine this heterogeneity in greater detail by dividing occupations into four mutually exclusive groups, which are obtained by combining replaceability and offshorability. For instance, offshorable-replaceable occupations are those for which the replaceability dummy is equal to 1 and the offshorability indicator is above the sample median; the other groups are defined accordingly. The results show that the employment changes in non-replaceable occupations are uncorrelated with robot exposure regardless of offshorability. On the contrary, for replaceable occupations, employment changes are uncorrelated with robot exposure if these occupations are also offshorable but strongly negatively correlated if they are non offshorable. The 2SLS regressions reported at the bottom of the table confirm the qualitative pattern of results. Hence, automation has heterogeneous effects across occupations depending on offshorability: while offshorable occupations are largely sheltered from automation, non-offshorable occupations whose tasks can be replaced by robots bear the burden of the negative effects of automation.

Next, we turn to the second exercise and study whether the employment effects of robot exposure vary across CZs depending on offshoring intensity.

*Table 3.5* Robot Exposure and Employment Across Occupation Groups

| | (1) Replaceable (GM, 2018) | (2) Non-Replaceable (GM, 2018) | (3) Offshorable (AD, 2013) | (4) Non-Offshorable (AD, 2013) |
|---|---|---|---|---|
| | | **a) OLS** | | |
| ΔRobots | −0.010* | 0.003 | 0.006 | −0.013*** |
| | [0.005] | [0.005] | [0.005] | [0.005] |
| Obs. | 2157 | 2157 | 2157 | 2157 |
| R2 | 0.19 | 0.17 | 0.30 | 0.46 |
| | Offshorable & Replaceable | Offshorable & Non-Replaceable | Non-Offshorable & Replaceable | Non-Offshorable & Non-Replaceable |
| | | **b) OLS** | | |
| ΔRobots | 0.001 | 0.005 | −0.011** | −0.002 |
| | [0.003] | [0.005] | [0.005] | [0.004] |
| Obs. | 2157 | 2157 | 2157 | 2157 |
| R2 | 0.09 | 0.28 | 0.23 | 0.21 |
| | | **c) 2SLS, 2nd Stage** | | |
| ΔRobots | 0.018 | −0.001 | −0.033** | 0.019 |
| | [0.012] | [0.021] | [0.014] | [0.015] |
| Obs. | 2157 | 2157 | 2157 | 2157 |
| R2 | 0.06 | 0.28 | 0.21 | 0.19 |

Notes: All regressions are estimated on a panel of 722 CZs. The dependent variables are ten-year equivalent changes in employment (relative to population) in mutually exclusive groups of occupations, as defined in the columns' headings. Offshorable occupations are those for which the offshorability index developed by Autor and Dorn (2013) is above the sample median. Replaceable occupations are those whose title corresponds to at least one of the robot application categories identified by the International Federation of Robotics (Graetz and Michaels, 2018). Non-offshorable and non-replaceable occupations are defined accordingly. ΔRobots is the weighted average of ten-year equivalent log changes in US robot imports across industries, with weights given by the industrial structure of employment in each CZ at the beginning of each time period. The instrument is ΔRobots_Oth, constructed analogously to ΔRobots using industry-level data on robot exports from non-US countries to eleven European countries. All regressions include state fixed effects, year fixed effects and the same control variables as in Table 3.2, and are weighted by the initial share of each CZ in total US population. Standard errors, reported in square brackets, are correted for clustering within states. ***, ** and * denote significance at the 1, 5 and 10% level, respectively.

*Table 3.6* Robot Exposure, Offshoring and Employment, Broad Offshoring Indicator

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Δ Total Emp./ Pop. | Δ Mnfg Emp. /Pop. | Δ Non Mnfg Emp./ Pop. | Δ Total Emp./ Pop. | Δ Mnfg Emp./ Pop. | Δ Non Mnfg Emp./ Pop. |
| | **a) Baseline** | | | **b) No Machinery in Offshoring Indicator** | | |
| ΔRobots | −0.002 | −0.037*** | 0.035*** | −0.003 | −0.041*** | 0.037*** |
| | [0.011] | [0.012] | [0.012] | [0.012] | [0.012] | [0.012] |
| ΔRobots × B_Offsh | −0.057 | 0.330** | −0.387** | −0.032 | 0.377** | −0.409** |
| | [0.133] | [0.157] | [0.168] | [0.141] | [0.145] | [0.158] |
| B_Offsh | 0.067 | −0 279*** | 0.346*** | 0.062 | −0 245*** | 0.307*** |
| | [0.067] | [0.057] | [0.072] | [0.064] | [0.049] | [0.068] |
| Obs. | 2157 | 2157 | 2157 | 2157 | 2157 | 2157 |
| R2 | 0.53 | 0.36 | 0.36 | 0.53 | 0.37 | 0.36 |
| | **c) Additional Interactions of Robot Exposure** | | | **d) Exposure to Other Types of Capital** | | |
| ΔRobots | −0.259 | −0.035 | −0.224 | 0.000 | _0.047*** | 0.047*** |
| | [0.160] | [0.130] | [0.150] | [0.009] | [0.012] | [0.015] |
| ΔRobots × B_Offsh | −0.061 | 0 427*** | _0.488*** | −0.176 | 0.553*** | −0.730*** |
| | [0.125] | [0.114] | [0.173] | [0.145] | [0.179] | [0.227] |
| B_Offsh | 0.019 | −0 321*** | 0 339*** | −0.143 | −0.400* | 0.257 |
| | [0.061] | [0.062] | [0.081] | [0.222] | [0.218] | [0.262] |
| Obs. | 2157 | 2157 | 2157 | 2157 | 2157 | 2157 |
| R2 | 0.53 | 0.38 | 0.36 | 0.54 | 0.37 | 0.38 |

Notes: All regressions are estimated on a panel of 722 *CZs*. The dependent variables, indicated in the columns' headings, are ten-year equivalent changes in overall employment-to-population ratio (columns 1 and 4), manufacturing employment-to-population ratio (columns 2 and 5), and non-manufacturing employment-to-population ratio (columns 3 and 6). Δ*Robots* is the weighted average of ten-year equivalent log changes in US robot imports across industries, with weights given by the industrial structure of employment in each CZ at the beginning of each time period. *B_Offsh* is the weighted average of the start-of-period broad offshoring indicator across industries, with weights given by the initial industrial structure of employment in each CZ. In panel b, the offshoring indicator excludes imports of machinery made by each industry. All regressions are estimated with OLS; include state fixed effects, year fixed effects and the same control variables as in Table 3.2, and are weighted by the initial share of each CZ in total US population. The regressions in panel c also include interactions of Δ*Robots* with log employment and the employment shares of female workers, foreign-born workers, college graduates and routine-intensive occupations at the beginning of each period. The regressions in panel d also include four variables measuring the exposure of each CZ to software, ICT, machinery and other types of capital. These variables, which enter both linearly and interacted with *B_Offsh*, are constructed analogoulsy to Δ*Robots* using ten-year equivalent log changes in expenditure on each type of capital across industries in place of log changes in US robot imports. Standard errors, reported in square brackets, are correted for clustering within states. ***, ** and * denote significance at the 1, 5 and 10% level, respectively.

*Table 3.7* Robot Exposure, Offshoring and Employment, Narrow Offshoring Indicator

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Δ Total Emp./ Pop.* | *Δ Mnfg Emp. /Pop.* | *Δ Non Mnfg Emp./ Pop.* | *Δ Total Emp./ Pop.* | *Δ Mnfg Emp./ Pop.* | *Δ Non Mnfg Emp./ Pop.* |
| | **a) Baseline** | | | **b) No Machinery in Offshoring Indicator** | | |
| ΔRobots | −0.002 | −0.023*** | 0.021*** | −0.002 | −0.024*** | 0.022*** |
| | [0.006] | [0.007] | [0.008] | [0.007] | [0.006] | [0.008] |
| ΔRobots × N_Offsh | −0.162 | 0.322* | −0.484** | −0.139 | 0.349** | −0.488** |
| | [0.129] | [0.167] | [0.203] | [0.134] | [0.153] | [0.192] |
| N_Offsh | 0.099 | −0 319*** | 0.418*** | 0.088 | −0.335*** | 0 423*** |
| | [0.079] | [0.070] | [0.090] | [0.081] | [0.064] | [0.087] |
| Obs. | 2157 | 2157 | 2157 | 2157 | 2157 | 2157 |
| R2 | 0.53 | 0.36 | 0.36 | 0.53 | 0.36 | 0.36 |
| | **c) Additional Interactions of Robot Exposure** | | | **d) Exposure to Other Types of Capital** | | |
| ΔRobots | −0.266* | −0.038 | −0.228 | −0.007 | −0.022*** | 0.015* |
| | [0.158] | [0.122] | [0.150] | [0.005] | [0.007] | [0.008] |
| ΔRobots × N_Offsh | −0.169 | 0.389** | −0.558** | −0.303** | 0.802*** | −1.106*** |
| | [0.143] | [0.146] | [0.210] | [0.134] | [0.154] | [0.192] |
| N_Offsh | 0.040 | −0.387*** | 0.428*** | −0.267 | −0.535* | 0.268 |
| | [0.081] | [0.085] | [0.106] | [0.404] | [0.272] | [0.343] |
| Obs. | 2157 | 2157 | 2157 | 2157 | 2157 | 2157 |
| R2 | 0.54 | 0.38 | 0.36 | 0.55 | 0.37 | 0.39 |

Notes: All regressions are estimated on a panel of 722 CZs. The dependent variables, indicated in the columns' headings, are ten-year equivalent changes in overall employment-to-population ratio (columns 1 and 4), manufacturing employment-to-population ratio (columns 2 and 5), and non-manufacturing employment-to-population ratio (columns 3 and 6). *Δ Robots* is the weighted average of ten-year equivalent log changes in US robot imports across industries, with weights given by the industrial structure of employment in each CZ at the beginning of each time period. *N_Offsh* is the weighted average of the start-of-period narrow offshoring indicator across industries, with weights given by the initial industrial structure of employment in each CZ. In panel b, the offshoring indicator excludes imports of machinery made by each industry. All regressions are estimated with OLS; include state fixed effects, year fixed effects and the same control variables as in Table 3.2, and are weighted by the initial share of each CZ in total US population. The regressions in panel c also include interactions of *ΔRobots* with log employment and the employment shares of female workers, foreign-born workers, college graduates and routine intensive occupations at the beginning of each period. The regressions in panel d also include four variables measuring the exposure of each CZ to software, ICT, machinery and other types of capital. These variables, which enter both linearly and interacted with *N_Offsh*, are constructed analogoulsy to *ΔRobots* using ten-year equivalent log changes in expenditure on each type of capital across industries in place of log changes in US robot imports. Standard errors, reported in square brackets, are corrected for clustering within states. ***, ** and * denote significance at the 1, 5 and 10% level, respectively.

To do so, we augment eq. (15) with an interaction between $\Delta Robots_{ct}$ and the start-of-period level of either offshoring indicator, $B\_Offsh_{ct}$ or $N\_Offsh_{ct}$.[23] We report results for the overall employment-to-population ratio and for its manufacturing and non-manufacturing components. Given the well-known difficulty in instrumenting interaction terms, we focus on OLS regressions.

The results are reported in Table 3.6 for the broad offshoring indicator and in Table 3.7 for the narrow measure. Strikingly, in the regression for manufacturing employment, the coefficient on the interaction between robot exposure and offshoring is always positive and very precisely estimated. This confirms that automation reduces manufacturing employment relatively less in CZs that are initially more reliant on offshoring. To quantify the extent of heterogeneity, we use the estimated (linear and interaction) coefficients on $\Delta Robots_{ct}$ along with the observed distribution of offshoring across CZs in our data. This exercise reveals that the employment effect of robot exposure is negative in the majority of CZs; yet, for a small fraction of high offshoring-intensive CZs (the top 5% by $B\_Offsh_{ct}$ and the top 1% by $N\_Offsh_{ct}$), automation actually leads to an increase in manufacturing employment. In the regression for non-manufacturing employment, the coefficient on the interaction between robot exposure and offshoring is always negative and precisely estimated, consistent with the view that displaced workers reallocate, at least partially, outside of the manufacturing sector.

In the remaining panels, we submit the baseline results to various robustness checks. In panel b, we re-compute the offshoring indicators by excluding imports of machinery made by each industry. This avoids the offshoring measures to be contaminated by robot imports. In panel c, we augment the specification by adding interactions of $\Delta Robots_{ct}$ with all other start-of-period controls included in $\mathbf{X}_{ct}$. This prevents our coefficients of interest from being influenced by differences in other CZ-level characteristics that could interact with automation. Finally, in panel d, we extend the specification by including the four variables measuring exposure to other types of capital, both linearly and interacted with offshoring. This allays the concern that the baseline results could be driven by the correlation between robot adoption and other forms of investment. In all cases, the results confirm that offshoring plays an important role at mediating the employment effects of automation across US local labor markets.

## 5  Conclusions

In this chapter, we have studied the effects of automation, measured by the adoption of industrial robots, in the presence of offshoring. The literature has mostly studied these phenomena in isolation. This is unfortunate, because what we have shown is that offshoring can change the impact of automation in important ways. In particular, when robots affect differentially domestically-produced and foreign-sourced tasks, automation has terms-of-trade effects that redistribute income across countries. This has important implications. While automation replacing foreign workers is necessarily welfare-improving for the domestic

economy, automation replacing domestically-produced tasks can lower the real wage of domestic workers through a deterioration of the terms of trade.

These results underscore the importance of identifying which workers are in more direct competition with robots and motivate the empirical analysis conducted in the chapter. Using US data across industries, occupations and local labor markets, we have studied the interaction between automation and offshoring over the 1990–2015 period. Our results suggest that industrial robots displace US workers from manufacturing industries, but that the effect is weaker in CZs that are more exposed to offshoring. We also found that industrial robots lower the incidence of offshoring and that their negative employment effects are concentrated in occupations performing tasks that are classified as non-offshorable. These results are consistent with the view that automation contributes to the reshoring of economic activity, which in turn tends to mitigate any adverse labor market effects for US workers.

We conclude by discussing some limitations and possible extensions of our analysis. The empirical findings in this chapter are based entirely on US data. However, we consider equally important to study the effect of US automation on low-wage countries. Consistent with our results, some papers tend to find negative effects on labor market outcomes in the developing world (see, for instance, Faber, 2020, Artuc, Christiaensen and Winkler, 2019, Stemmler, 2019, Kugler et al. 2020). Yet, it would be desirable to combine data across countries to directly identify the terms-of-trade effect of automation. We view this as an interesting direction for future research.

From a normative perspective, the result that automation is likely to redistribute income across countries implies that policy makers may have an incentive to promote the adoption of technologies that lower the dependence on foreign inputs. Such an effort can, however, lead to an inefficient equilibrium with excessive automation and too little trade. In fact, we speculate that foreign competition may even be the trigger for the adoption of policies aiming at self-sufficiency. Exploring this scenario and possible remedies goes beyond the scope of this paper but seems another important and interesting avenue for future research.

## Notes

1  We define automation as the replacement of human labor with robots. Robots are programmable machines that have the capability to move on at least three axes. Unlike other pieces of equipment, robots are designed to replicate human actions.
2  Although we study a static model, we follow the literature in referring to the endogenous increase in the supply of robot as "capital deepening". See, for instance, Acemoglu and Restrepo (2021).

3  To measure replaceability, we use the classification of occupations developed by Graetz and Michaels (2018). To measure offshorability, we use the index employed by Autor and Dorn (2013). The two indexes capture different dimensions. For instance, replaceable occupations tend to perform manual and repetitive works, while offshorable occupations do not require face-to-face interaction and physical presence on the job.

4  The model builds on earlier formalizations of automation, such as Zeira (1998), Acemoglu and Restrepo (2019) and Hemous and Olsen (2020); and offshoring, such as Grossman and Rossi-Hansberg (2008), Rodriguez-Clare (2010) and Acemoglu, Gancia and Zilibotti (2015).

5  For instance, they would still apply in a model where automation and offshoring opportuinities are endogenous as in Acemoglu, Gancia and Zilibotti (2015), Grossman and Rossi-Hansberg (2008) or Acemoglu and Restrepo (2018). See Appendix A for more details on the relationship between the model in the text and the task-based approach.

6  This result would change if the supply of robots were not perfectly elastic. In this case, $r$ would also increase with $\kappa$.

7  The Censuses and the ACS are 5% and 1% samples, respectively, of the US population and are representative at the level of micro-regions known as Public Use Microdata Areas (PUMAs). We map PUMAs to CZs using a crosswalk developed by Autor and Dorn (2013). We have also experimented with an extended sample including ACS data for the year 2020. In this case, because the automation data illustrated in the following are available up to the year 2018, we have used data for 2018 to construct automation variables referring to the year 2020. Our main results hold also in this extended sample (available upon request).

8  In particular, imports of industrial robots for multiple uses, lifting, handling, loading or unloading and industrial robot parts are classified in the following HTS codes: 8479899540, 8479500000, 8428900100, 8428908015, 8428900120, 8428900220, 8479909740 and 8479909540.

9  Specifically, we compute US robot imports in industry $j$ and year $t$ as $Rob\_M_{jt} = \omega_{jt} \cdot Rob\_M_t$, where $Rob\_M_t$ is the total value of US robot imports and $\omega_{jt}$ is the share of industry $j$ in total US imports of machinery in year $t$, constructed from the US Import Matrices.

10  We construct $\lambda_{cjt}$ using data from the County Business Patterns (CBP). In the CBP, industries are defined according to the 6-digit level of the 2012 NAICS classification. We map BEA industries into 6-digit NAICS industries using a crosswalk provided with the US Input–Output Tables. In case of missing data on robot imports for some years, we use data for the closest available year. Robot imports are expressed at constant 2005 prices using the US Consumer Price Index.

11  Consistent with this, our main results would continue to hold if robot exposure was constructed using the log change in the IFR stock of robots in place of the log change in robot imports in eq. (12).

12  The eleven European countries are Austria, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden, Switzerland and the UK. In the UN Comtrade database, trade in industrial robots is recorded under code 847950 of the Harmonized System classification.

13  Wright (2014) proposes a plausibly exogenous measure of offshoring, derived using variation in US offshoring to China.

14  In case an index is missing for an occupation, we use information for the corresponding broader occupational group.

15  See, among others, Acemoglu and Restrepo (2019) for additional evidence on the growth in the usage of industrial robots in the US based on data from the IFR.

16  The change in offshoring in a CZ is constructed as $\Delta B\_Offsh_{ct} = \sum_j \lambda_{cjt} \cdot \Delta B\_Offsh_{jt}$, where $\Delta B\_Offsh_{jt}$ is the change in offshoring in industry $j$ over period $t$. For each CZ, Figure 3.5 shows the mean of $\Delta Robots_{ct}$ (map a) and the mean of $\Delta B\_Offsh_{ct}$ (map b) across all available time periods.

17  The proxies for the demographic composition of employment and the share of routine-intensive occupations are constructed following Autor, Dorn and Hanson (2013). Unless otherwise indicated, we control for offshoring intensity using the broad offshoring indicator; the first period with available data on off-shoring is 2000–2005. The proxies for export shocks and for shocks to import competition from China and other countries are defined as changes in a given variable divided by start-of-period employment in the CZ, and are constructed as in Autor, Dorn and Hanson (2013) using trade data from Schott (2008).

18  These variables are constructed analogously to $\Delta Robots_{ct}$, by replacing $\Delta \ln Rob\_M_{jt}$ in eq. (12) with ten-year equivalent log changes in expenditure on software and databases, ICT, machinery and other types of capital and machinery.

19  The proxy for robot exposure based on changes in the stock of robot imports over a given period is constructed as $\Delta Robots\_Stk_{ct} = \sum_j \lambda_{cjt} \sum_{\tau \in t} \ln(1 + Rob\_M_{j\tau})$, where $\tau$ denotes individual years within time period $t$. The other two proxies are constructed analogously to eq. (12).

20  We implement the correction for spatial clustering using the approach presented in Conley (1999). We define the spatial cluster of a CZ as including all other CZs within a range of 660 km or 768 km. These distances ensure that the spatial cluster of the most remote CZ consists of at least 5 or 10 CZs, respectively. The resulting clusters can overlap with each other and can span different states. To define industry similarity, we instead use cluster analysis and group CZs into 25, 50 or 100 groups characterized by a similar industrial structure, as proxied by the industry shares in total CZ employment, $\lambda_{cjt}$. The standard errors are then corrected for clustering within each group of CZs.

21  The Kleibergen-Paap $F$-statistic for excluded instruments easily exceeds the value of 10, which is normally considered as the rule-of-thumb threshold for instrument relevance.

22  In particular, the dependent variables are constructed as follows: $\Delta B\_Offsh_{ct} = \sum_j \lambda_{cjt} \cdot \Delta B\_Offsh_{jt}$ and $\Delta N\_Offsh_{ct} = \sum_j \lambda_{cjt} \cdot \Delta N\_Offsh_{jt}$, where $\Delta B\_Offsh_{jt}$ and $\Delta N\_Offsh_{jt}$ are changes in a given offshoring indicator in industry $j$ over period $t$.

23  The control variables $\mathbf{X}_{ct}$ already include the linear term of $B\_Offsh_{ct}$. When interacting $\Delta Robots_{ct}$ with $N\_Offsh_{ct}$, we use a linear term in $N\_Offsh_{ct}$ in place of the linear term in $B\_Offsh_{ct}$.

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# Appendix A

## A More General Model of Automation and Offshoring

We consider now a more general case in which productivity varies across tasks and factors, as in the models of offshoring and automation in Grossman and Rossi-Hansberg (2008) and Acemoglu and Restrepo (2018). Tasks are allocated to factors so as to minimize costs:

$$p_i = \min\left\{\frac{w_s}{a_{s,i}}, \frac{w_n}{a_{n,i}}, \frac{r}{a_{r,i}}\right\}.$$

Using $p_i$, we can then solve for output of each task:

$$x_{s,i} = \frac{a_{s,i}L_s}{m_s}$$

$$x_{n,i} = \frac{a_{n,i}L_n}{m_n}$$

$$x_{r,i} = \frac{a_{r,i}\Upsilon}{r}.$$

Using these quantities into (1), we obtain (6) where

$$a_x \equiv \exp\left(\int_{i \in N_x} \frac{\ln a_{x,i}}{m_x}\mathrm{d}i\right)$$

is now endogenous and is equal to the average productivity over the tasks $N_x$ performed by factor $x \in \{s, n, r\}$. Equations (7) (8) and (9) are still valid.

In this model, a shock to automation is an increase in some $a_{r,i}$. This can raise $m_r$ (the extensive margin of automation), $a_r$ (the intensive margin of automation), or both. In turn, the change in $m_r$ and/or $a_r$ can affect the allocation of tasks to the other factors too. Holding constant $m_r$, an increase in $a_r$ benefits all factors. This is the most benign form of automation, corresponding to factor-augmenting technical change without any displacement. Holding constant $a_r$, the effects of an increase in $m_r$ are those discussed Section 2.2. This is the case in which automation displaces workers. The general model shows that $m_r$ and $a_r$ may change simultaneously. The result that automation can lower both the relative and the real wage of displaced workers still holds. This is because the effect of displacement on wages is unchanged. However, the productivity effect may be weaker or stronger in the more general model.

# Appenidx B

Additional Results

*Table 3.B1* Robot Exposure and Employment, Additional Results and Robustness

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Δ Total Emp./Pop.* | *Δ Mnfg Emp./Pop.* | *Δ Non-Mnfg Emp./Pop.* | *Δ Total Emp./Pop.* | *Δ Mnfg Emp./Pop.* | *Δ Non-Mnfg Emp./Pop.* |
| | **a) Sample: 1990–2005** | | | **b) Sample: 2005–2015** | | |
| ΔRobots | −0.010 | −0.012** | 0.003 | −0.013*** | −0.019*** | 0.006 |
| | [0.009] | [0.005] | [0.007] | [0.005] | [0.005] | [0.006] |
| Obs. | 1441 | 1441 | 1441 | 1438 | 1438 | 1438 |
| R2 | 0.50 | 0.28 | 0.59 | 0.30 | 0.32 | 0.08 |
| | **c) Placebo, Future Rob_Exp** | | | **d) Excl. CZs in Top 1% of Rob_Exp** | | |
| ΔRobots | 0.001 | −0.001 | 0.001 | −0.004 | −0.018*** | 0.014** |
| | [0.001] | [0.001] | [0.002] | [0.005] | [0.004] | [0.006] |
| Obs. | 3600 | 3600 | 3600 | 1937 | 1937 | 1937 |
| R2 | 0.41 | 0.30 | 0.33 | 0.54 | 0.37 | 0.37 |
| | **e) Exposure to Other Types of Capital** | | | **f) Cumulative Stock of Robot Imports** | | |
| ΔRobots | −0.004 | −0.016*** | 0.012** | −0.0002*** | −0.0003*** | 0.0001 |
| | [0.005] | [0.005] | [0.006] | [0.0001] | [0.0001] | [0.0001] |
| Obs. | 2157 | 2157 | 2157 | 2157 | 2157 | 2157 |
| R2 | 0.54 | 0.37 | 0.37 | 0.53 | 0.36 | 0.35 |
| | **g) Net Robot Imports** | | | **h) Industry Shares of Machinery Purchases** | | |
| ΔRobots | −0.005* | −0.013*** | 0.008** | −0.005* | −0.013*** | 0.008** |
| | [0.003] | [0.003] | [0.004] | [0.003] | [0.003] | [0.004] |
| Obs. | 2157 | 2157 | 2157 | 2157 | 2157 | 2157 |
| R2 | 0.53 | 0.37 | 0.36 | 0.53 | 0.37 | 0.36 |

Notes: The table contains additional results and robustness checks on the OLS regressions reported in Table 3.2. All regressions are estimated on a panel of 722 CZs. The samples used in panels a and b cover two time periods: 1990–2000 and 2000-2005 in panel a; 2005–2010 and 2010–2015 in panel b. In panel c, *Δ Robots* enters with a one-year lead. Panel d excludes CZs in the top percentile of the distribution of *ΔRobots* in each year. Panel e includes four variables measuring the exposure of each CZ to software, ICT, machinery and other types of capital. In panel f, *ΔRobots* is constructed as the weighted average of cumulative sums of log US robot imports across industries, with weights given by the industrial structure of employment in each CZ at the beginning of each period. In panel g, *ΔRobots* is constructed using US net robot imports (imports minus export) rather than US robot imports. In panel h, *ΔRobots* is constructed by apportioning US robot imports to individual industries using industry shares in total (domestic plus foreign) machinery purchases from the US Input-Output Tables, rather than industry shares in machinery imports from the US Import Matrices. The specifications in panels a include state and year fixed effects; the specifications in panels d-h also include the same control variables as in Table 3.2. All regressions are weighted by the initial share of each CZ in total US population. Standard errors, reported in square brackets, are corrected for clustering within states. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

a) Δ Mnfg Emp./Pop.



• Coefficient on Robot Exposure ——— Confidence interval

b) Δ Non Mnfg Emp./Pop.



• Coefficient on Robot Exposure ——— Confidence interval
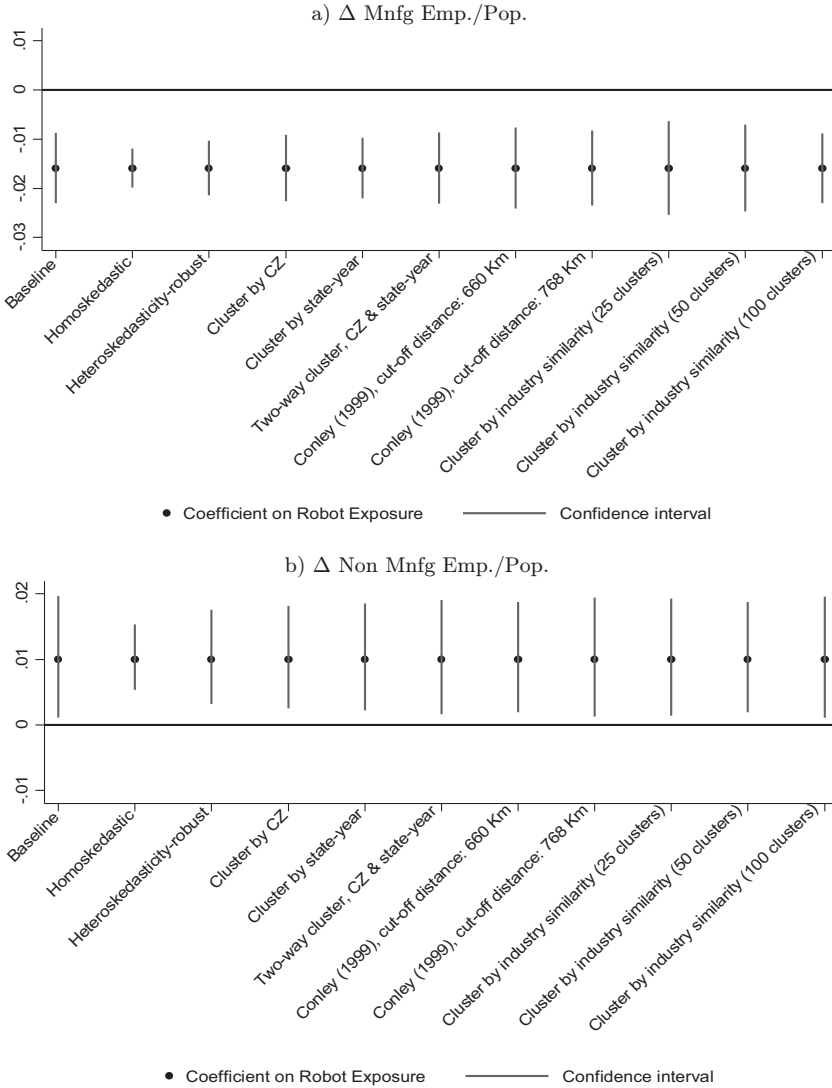
*Figure 3.B1* Robot Exposure and Employment: Alternative Corrections of Standard Errors

Notes: The figure plots the OLS coefficients on Δ*Robots* obtained with the baseline specifications reported in columns (5) and (6) of Table 3.2 (top and bottom graph, respectively), together with 90% confidence intervals corresponding to alternative ways of correcting the standard errors, as indicated on the horizontal axis. The baseline confidence intervals refer to standard errors corrected for clustering within states. The Conley (1999) confidence intervals refer to standard errors corrected for residual correlation among CZs belonging to the same spatial cluster, as defined by the reported cutoff distance. The last three confidence intervals are obtained by first using cluster analysis to create 25, 50 or 100 groups of CZs with a similar industrial structure of employment and then correcting the standard errors for clustering within each group.

# 4 On the Employment Consequences of Automation and Offshoring

## A Labor Market Sorting View

*Ester Faia, Sébastien Laffitte, Maximilian Mayer, and Gianmarco Ottaviano*

## 1 Introduction

Automation and offshoring are two of the most debated global developments with potentially disruptive effects on the labour market and momentous implications for workers' employment opportunities and wages. Understanding their effects, their relative importance and their possible interactions is, therefore, of preeminent relevance and, as such, has attracted a lot of research.[1]

The existing literature highlights that, from a country's point of view, automation and offshoring may affect employment opportunities and wages in two main ways. On the one hand, automating or offshoring some tasks implies that these tasks are not performed by the country's workers any longer so that the demand for their services falls. This is the negative "substitution effect", which may cause employment and wages to fall. On the other hand, reallocating tasks from the country's workers to automated systems or foreign workers may promote production efficiency, which in turn expands production activities with a beneficial impact on employment opportunities and wages. This is the positive "productivity effect", which may cause employment and wages to rise.

In the case of automation, most studies stress capital-labour substitution.[2] This is of primary importance and particularly relevant for automation related to the adoption of robots and machines in production. It may affect different workers differently. With "skill-biased technological change" (SBTC), new technology complements workers with high skills. With "routine-biased technological change" (RBTC), new technology crowds out workers from traditional routine tasks while creating additional jobs involving new complex tasks (see e.g. Acemoglu and Restrepo, 2018b, for a detailed discussion).

Differently from these studies, the present paper investigates the possible existence of an additional negative effect of automation on workers' employment opportunities and wages. This effect is related to what has been called the "paradox of automation" (Bainbridge, 1983). The idea is that, as automation intensifies, the efficient completion of related tasks increasingly requires human operators with specialized knowledge of automated systems involving specific

algorithms, software and machines. Hence, according to the paradox, the more advanced an automated system is, the more crucial the contribution of the specialized human operator may end up being.[3] The associated growing demand for specialized knowledge is conducive to a form of workers' specialization that increasingly matters above and beyond what would be needed by the vertical skill content of tasks or their degree of routineness. In this respect, by fostering tasks' horizontal knowledge differentiation, automation also demands workers' horizontal skill differentiation. We call this "core-biased technological change" (CBTC), whereby new technology requires workers with specialized knowledge ("core competencies") independently of them being high or low skilled, or their tasks being more or less routine intensive.

Our investigation of the possible consequences of CBTC for the labor market emphasizes the challenges workers and firms face in matching the formers' horizontally differentiated skills with the latters' horizontally differentiated tasks in the presence of search frictions and rising match assortativity due to automation (see Shimer and Smith, 2000). In a perfectly competitive labor market, more assortativity would increase the surplus of all equilibrium matches as these take place only between "ideal" partners, that is, between workers and firms with perfectly matched skills and tasks. In contrast, with search costs not all matches necessarily involve ideal partners as some firms or workers may find it optimal to accept less-than-ideal counterparts ("mismatch") in order to avoid incurring the opportunity cost of additional search. When the "paradox of automation" is at work, as automation proceeds the surplus of ideal matches increases relative to that of less-than-ideal matches, amplifying the losses from mismatch and making both firms and workers more selective in choosing their partners. As selectivity increases, firms and workers become more willing to spend time searching for better matches. As a result, unemployment duration rises, mismatch falls and specialized knowledge concentrates more on the tasks specifically requiring it.

One could argue that a similar mechanism may be relevant also for offshoring if interpreted as another form of technological change.[4] For example, the more sophisticated a country's global value chains are, the more crucial may be the contribution of specialized knowledge by the country's workers.[5] Management studies emphasize what they call "offshoring management capability" (Mihalache and Mihalache, 2020). According to Mukherjee, Gaur and Datta (2013), coordination capabilities (e.g. those leveraging IT coordination applications for enterprise resource planning or customer-relationship management software) are important for creating value through offshoring because geographically dispersed knowledge needs to be transferred and integrated. Manning, Massini and Lewin (2008) argue that, to use science and engineering talent at globally dispersed locations, firms need capabilities such as recruiting, developing, and retaining talent, coordinating globally dispersed innovation activities, and collaborating with external partners. Mukherjee et al. (2019) stress the role of contract negotiation skills, the ability to monitor and evaluate the performance of suppliers, or the knowledge of alternative supplier arrangements and their cost structure.

Whether the "paradox of automation" is of any practical relevance, and whether something similar applies also to offshoring is, first of all, an empirical issue. We look for traces of the paradox at the sector-occupation level.[6] We focus on 92 occupations at the 3-digit ISCO-88 level and 16 (out of 21) sectors according to the NACE Rev.2 classification. To make sure that our results are not driven by specific countries or institutional contexts, our dataset covers 13 European countries in the period 1995–2010. We analyze the impact of automation and offshoring on "selectivity" as measured by skill concentration, unemployment duration and educational mismatch. To this end, our dataset combines data on employment from the European Labour Force Survey (EU-LFS) with occupation-level measures of "automatability" as in Acemoglu and Autor (2011) and "offshorability" as in Blinder and Krueger (2013). We find that over the period of observation, sectors with higher initial automatability experienced a differential increase in selectivity. By contrast, we find that sectors with higher initial offshorability experienced a differential decrease in selectivity.

We argue that these findings are consistent with the "paradox of automation" and CBTC in the case of automation, while they are inconsistent with something similar happening in the case of offshoring. We spell out our argument through a growth model that, beyond productivity and substitution effects, features search frictions in the labor market and two-sided heterogeneity of horizontally differentiated skills and tasks. Workers and firms in our model are risk-neutral and maximize lifetime discounted utility in continuous time. They meet through a random matching process governed by a canonical constant return to scale function based on one-to-one relations with congestion externalities for each task (see Mortensen and Pissarides, 1994). For analytical transparency, workers' skills and firms' tasks are assumed to be uniformly and symmetrically distributed around a circle describing the space of their heterogeneous characteristics. Due to search frictions, workers and firms do not match perfectly, but instead search and optimally accept less-than-ideal matches in an interval around their ideal ones. "Mismatch" is measured by the distance between matched skills and tasks along the circle and negatively affects match surplus. We use a numerical implementation based on specific functional forms to show that the empirical patterns we have uncovered in the data can be reproduced by our model as long as match surplus is assumed to be: (i) log-submodular in mismatch and automation, so that matches at shorter distance have a comparative advantage in exploiting automation; (ii) log-supermodular in mismatch and offshoring, so that matches at longer distance have a comparative advantage in exploiting offshoring; (iii) log-supermodular in automation and offshoring so that, for given mismatch, the impact of more automation on match surplus is amplified when there is more offshoring. When these conditions are met, the model predicts that more selectivity is associated with less employment as firms and workers are willing to search longer for the ideal counterpart. It therefore implies that automation and offshoring have opposite effects on employment due to their opposite effects on selectivity. While automation reduces employment by raising selectivity,

offshoring increases employment by reducing selectivity. The model also predicts that more selectivity is associated with more wage inequality between ideal and less-than-ideal matches as the surplus of the former increases relative to the surplus of the latter.

The rest of the chapter is organized as follows. Section 2 offers some anecdotal examples of the "paradox of automation" and discusses survey evidence on specialization trends in occupations. Section 3 introduces the dataset and describes the empirical analysis. Section 4 presents the model, discusses the conditions on assortativity needed to make it consistent with the empirical findings of Section 3, and studies its implications for employment and wage inequality under those conditions. Section 5 concludes.

## 2 Ironies of Automation and Skill Specialization

The notion of "core-biased technological change" (CBTC) emphasizes the positive impact that new technologies may have on the horizontal assortativity of skills and tasks. This notion speaks to what was termed the "paradox of automation" around forty years ago by cognitive psychologist Lisanne Bainbridge in a still influential paper titled *Ironies of Automation* (Bainbridge, 1983). Bainbridge's idea is that, as automation intensifies, the efficient completion by humans of tasks related to the automated systems increasingly requires workers with specialized knowledge of the specific systems. As a result, automation raises the assortativity between workers' specialized skills and firms' specific tasks.

In her paper, Bainbridge notes that the classic aim of automation is to replace human manual control, planning and problem solving by automatic devices and computers. Yet, this may have ironic implications:

> [T]he more advanced a control system is, so the more crucial may be the contribution of the human operator [as] the designer who tries to eliminate the operator still leaves the operator to do the tasks which the designer cannot think how to automate. [In this respect, there] are two general categories of task left for an operator in an automated system. He may be expected to monitor that the automatic system is operating correctly, and if it is not he may be expected to call a more experienced operator or to take over himself. To take over and stabilize the process requires manual control skills, to diagnose the fault as a basis for shut down or recovery requires cognitive skills.

When called to intervene, a more experienced operator may in turn face similar challenges, only at a higher level. In any case, relevant experience requires "special training". A traditional example is the flight deck (Malquist and Rapoport, 2021):

> More automation should mean more training. Today's highly automated planes create surprises pilots aren't familiar with. The humans in the

cockpit need to be better prepared for the machine's quirks. [...] Modern jet aircraft developed using classic methods lead to scenarios that wait for the right combination of events. Unlike legacy aircraft built using only basic electrical and mechanical components, the automation in these modern jets uses a complex series of situations to "decide" how to perform. [...] In the case of the [Boeing] MAX crashes, pilots found themselves in confusing situations, i.e., the automation worked perfectly, just not as expected. [...] Although these challenges can often be "designed out", pilots can't wait for planes that are better-designed. They need to be trained now to understand that an aircraft's response depends on the computer "process model".

The training needed can be extremely specific in terms of "core competencies" (Aviation Voice, 2008):

[Boeing and Airbus] have very different philosophies about their aircraft. [...] Boeing has a traditional control wheel, whereas Airbus has a highly automated system and a side stick. According to Airbus, the absence of the larger yoke ensures much more comfortable flying. It also allows operating the array of computers easier with more space and one free hand. The competitor states that the yoke is an essential tool to handle emergencies. It does not prevent a pilot from overriding the autopilot if necessary and allows for better coordination between the pilot and co-pilot.

Training in aviation is so specific that generally pilots must be "type-rated", that is, they must be certified with additional training beyond the scope of the initial license and aircraft class training, tailored to the aircraft type they are asked to fly (Aviation Voice, 2008):

Pilots type-rated on both Airbus A320 and Boeing 737 say that it took a while for them to get used to a fundamentally different way to operate an aircraft.

The general point is that, if an automated system has an error, the system will multiply the error until the error is fixed or the system is shut down. Fixing the error or shutting down may require system-specific experience. Both fixing the error or shutting down may require that a human takes control who knows immediately and exactly what to do. As the knowledge required is very specific, the human holding it is not readily replaced with another human without appropriate system-specific experience. While the need of all this may be tragically self-evident in the case of a flying aircraft, it may be very important also in other less dramatic situations (Kaufmann, 2012):

Imagine a fully automated production line that makes computer processors that sell for $200. All the human operators have to do is to push a button,

and the production system starts cranking out 2,400 finished products per minute. [. . .] Imagine that a drill used to bore holes in the silicon wafer becomes misaligned, and starts drilling microscopic holes through the middle of the processor core. Every second the system keeps working, 40 chips are ruined. Assume each processor costs $20 in material costs—that means the factory start losing $800 every second the error isn't found. Every minute the system keeps running, the company loses $48,000 in raw materials. And that's just the direct cost—if you take into account that each processor would sell for $200, the company is losing $528,000 a minute: $48,000 in direct costs and $480,000 in opportunity cost. [. . .] When an error happens, operators need to get involved quickly and flawlessly—otherwise, the automated system will amplify the effects of the error until it is fixed.

Having difficulty "finding the right skills or talent" or "filling jobs" is often quoted as one of the main issues raised by employers. For example, the 2018 Talent Shortage Survey by Manpower Group (2018) highlights how talent shortage has been increasing over time, leaving a growing number of jobs unfilled all around the world.[7] The shortage is strongly linked to technology, but does not necessarily depend on a dearth of workers with higher education (Manpower Group, 2018, p.6):

> Most of the top ten in-demand roles today require post-secondary training and not always a full university degree.[. . .] In the digital age, employment will not always require a college degree, but will rely heavily on continual skills development as even the most traditional roles are augmented with new technology.

A wide range of jobs with different education and routine contents are affected across sectors. Higher than average recruitment bottlenecks tend to be reported in manufacturing, ICT and health care for jobs such as skilled trades workers, machine operators, sales representatives, engineers, technicians, ICT professionals, workers in marketing posts, drivers and office support staff (Cedefop Eurofound, 2018).[8] A concern for both firms and workers is that retraining from a known to a different machine can be a costly time-consuming process, making them cautious about potential mismatch. This is consistent with evidence collected by Bartel, Ichniowski and Shaw (2007) and Koren, Csillag and Köllo (2020), according to which workers assigned to new machines or IT-enhanced capital equipment are required to have "better" technical and problem-solving skills. These are likely to be horizontally differentiated and acquired mostly through experience as highlighted by Dauth et al. (2019).[9] Black, Hasan and Koning (2020) report survey evidence that the changing demand of skills has affected how firms search for new hires, in particular through increased firm-driven search for skilled workers.

## 3 Empirical Evidence from Occupational Data

In this section, we look for evidence consistent with CBTC in occupational data. In particular, we are interested in assessing whether and how more automation and offshoring may lead to higher match selectivity, which we measure in terms of longer unemployment duration, less mismatch, and more concentration of specialized knowledge in specific tasks. While matched employer-employee data with detailed information in skills and tasks would arguably be the most natural setup for our investigation, occupational data have the advantage of being available for several countries in a harmonized way, thus allowing us to control for country-specific aspects.

### 3.1 Data and Variables

For our investigation we use occupational data on European countries extracted from the *European Labour Force Survey* (hereafter EULFS). To include the maximum number of available countries and keep a consistent classification of occupations, we restrict our analysis to the years 1995–2010. This leads to a sample of 13 countries with various labor market institutions and economic situations. The countries are: Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, and the United Kingdom.

We focus on 92 occupations at the 3-digit ISCO-88 level and 16 sectors according to the NACE Rev.2 classification. To ensure the stability of the sector definition across years, we group these 16 sectors into 11 sectors.[10] We aggregate worker-level observations into country × sector × occupation × year cells. For each country, sector and occupation we have information on employment, number of employees, number of hours worked and number of unemployed workers (see Appendix A for more details on the data).

We exploit long-differences between 1995 and 2010 assuming that automation and offshoring shocks materialize between these two dates as documented in other studies.[11] Henceforth, the long-difference of any variable $\Upsilon$ between 1995 and 2010 will be simply denoted $\Delta\Upsilon$.

#### 3.1.1 Measuring Automation and Offshorability

The EULFS is merged with data on occupations' exposure to automation ("automatability") and to offshoring ("offshorability"). We use these variables to infer actual automation and offshoring in the subsequent years, which we do not observe. The underlying idea is that automation and offshoring are two general long-run trends whose effects can be assessed in terms of the differential exposure of different occupations to them.

To measure the "automatability" of an occupation we use its *Routine Task Intensity* index (RTI) as computed by Acemoglu and Autor (2011), which has been widely used in previous studies (see among many other Autor, Levy and

Murnane, 2003; Autor and Dorn, 2013; Goos, Manning and Salomons, 2014).[12] The RTI builds on information about the task content of occupations available from the Occupational Information Network (ONET). We use a crosswalk to go from the SOC 2000 classification used in ONET to the 4-digit ISCO-88 classification before aggregating to the 3-digit ISCO-88 classification (see Appendix A for additional details). Comparing our RTI measure with an alternative measure of automatibility constructed by Frey and Osbourne (2013) reveals a large positive correlation between them with only few exceptions for specific occupations.[13]

To measure the "offshorability" of an occupation we adopt the index developed by Blinder and Krueger (2013) (hereafter BK). This index builds on questionnaires as well as qualitative observations, and it is constructed by professional coders based on an occupational classification of workers. Offshorabilty is then reported on a 4-step qualitative scale from *Highly Non-Offshorable* (1) to *Highly Offshorable* (4).[14] A different measure is provided by Acemoglu and Autor (2011), who instead build a quantitative index based on aggregating several ONET indicators. While correlations between these different measures are mostly positive (see Appendix A for additional details), we use the BK index as our benchmark measure of offshorability as Goos, Manning, Salomons (2014) find that this index is more reliable when compared with actual offshoring measures.[15]

While both automation and offshoring may displace workers, it is important to note that they are conceptually quite different. The likelihood of automation is linked to the routineness of a task, hence to the possibility that the task can be performed algorithmically by a computer or a robot. By contrast, offshorability à la Blinder and Krueger (2013) refers to the ability to perform one's work duties, for the same employer and customers, in a foreign country, even though the supply of the good or the service is still based in the home country. Accordingly, while the correlation between our measures of automatability and offshorability is positive, there are important exceptions across occupations (see column 4 and 5 in Table 4.1 and Appendix A for a full picture).

### 3.1.2 Measuring Selectivity

We proxy "selectivity" in terms of unemployment duration, mismatch and concentration of specialized knowledge in specific tasks. We capture the last by the concentration of occupations' employment across sectors. In the wake of Costinot and Vogel (2010) the underlying idea is that, while a sector may cover a rich menu of occupations, these include a submenu of "core" occupations that are disproportionately concentrated in the sector. While the change in concentration is likely determined by many concurrent factors, more concentration triggered by higher automatability or offshorability would still be consistent with the channel of selectivity we are looking for. Specifically, let $\mathcal{O} = \{o_1, \cdots, o_{92}\}$ be the set of occupations, $\mathcal{K} = \{k_1, \cdots, k_{11}\}$ be the set of sectors and $\mathcal{I} = \{i_1, \cdots, i_{13}\}$ be the

set of countries in our sample. Consider occupation $o \in \mathcal{O}$ in sector $k \in \mathcal{K}$ of country $i \in \mathcal{I}$ with employment denoted by $L_{oki}$. Our measure of occupation $o$'s employment concentration across sectors $k \in \mathcal{K}$ in country $i$ is given by the Herfindhal index

$$SSO_{oi} = \sum_{k \in \mathcal{K}} \left( \frac{L_{oki}}{\sum_{k \in \mathcal{K}} L_{oki}} \right)^2, \tag{1}$$

where SSO is a mnemonic for "sectoral selectivity of occupation". Two remarks on eq. (1) are in order. First, as each occupation is not present in every sector, a key feature of SSO is that it is not standardized to account for the number of sectors used in the estimation. To understand this point, assume, for instance, that an occupation is equally observed in five different sectors in 1995, but disappears from one of the sectors in 2010 with previous employment from this sector evenly reallocated to the other four sectors. The distribution of the occupation's employment across sectors is, therefore, uniform both in 1995 and in 2010. A standardized Herfindahl index would be equal to zero in both cases, implying that no change in selectivity would be detected between 1995 and 2010 for this occupation. Second, high SSO implies that few sectors account for a large share of the occupation's employment. Therefore, an increase in SSO corresponds to an increase in concentration and thus more selectivity.

Our second measure of selectivity is based on the consideration that, if either automation or offshoring make specialized skills more salient, then firms may be willing to search longer for the right worker. We use unemployment duration as a proxy for workers' and firms' willingness to wait. This is computed at the occupation level by associating unemployed workers to their last occupation. Given the small number of observations in any given cell, we use occupations defined by the 2-digit ISCO classification. Moreover, when using this selectivity measure, we have to exclude France and the Netherlands from the sample due to data availability constraints.

Finally, our third measure of selectivity is based on the consideration that, if either automation or offshoring make specialized skills more salient, then the mismatch between workers' skills and firms' tasks should decrease. Therefore we use educational mismatch as a proxy for the extent to which workers' skills in given occupations are aligned with the occupations' task content. We consider both over-education and under-education by comparing each worker's years of education with those of her or his peers in a given occupation, sector and country at the time of observation. A worker is considered as over-educated when the worker's educational level is above the average of the worker's 10-year cohort by more than 2 standard deviations; vice versa, a worker is considered as under-educated when the worker's educational level is below the average of her or his 10-year cohort by more than 2 standard deviations (see e.g. Hartog, 2000, for a similar definition). Also in this case, given the small

number of observations in any given cell, we use occupations defined by the 2-digit ISCO classification. However, poor data availability for educational variables restricts our analysis to the years from 1998 to 2010. We then gauge changes in selectivity from changes in the shares of over- and under-educated workers in each occupation × industry × country cell. The underlying idea is that, if automation or offshoring makes firms more selective, we may observe a fall in under-education and possibly a rise in over-education among matched workers in more exposed sectors.

### 3.2 Descriptive Statistics

Table 4.1 presents descriptive statistics on the occupational characteristics aggregated at the 2-digit level for clarity. Occupations are ranked from the least to the most "automatable" (i.e. routine-intensive). Column 1 displays the percentage point change in the share of hours worked between 1995 and 2010. Overall, the change is smaller (or negative) for occupations that are more "automatable". Among the ten most automatable occupations only *Customer Service Clerks* (42) and *Sales and Services Elementary* (91) do not exhibit a fall in the share of hours worked. On the contrary, the share of hours worked in occupations with a low routine content systematically increases. This illustrates the impact of routine-biased technological change on employment trends. Column 2 reports the change in unemployment. The ranking is less clear but the majority of low-RTI occupations experienced a decrease or stability in their unemployment rate.

### 3.3 Automation, Offshoring and Employment

Figure 4.1 looks at the direct effects of automatability on employment and its interplay with offshorability. We collapse observations to the occupation level and divide the 92 occupations into two groups according to median offshorability.[16]

   Overall (dashed line), occupations with a low share of automatable tasks in 1995 experience an increase in total hours worked in subsequent years. Vice versa, occupations with a high share of automatable tasks in 1995 experience a decrease in total hours worked in subsequent years.

   When considering the interaction with offshorability, a more nuanced pattern emerges. While the negative relationship between automatability and employment is confirmed for highly offshorable occupations (solid black line), the observed change in hours worked in occupations with low offshorability (solid grey line) is unrelated to the automatability of their tasks.[17]

### 3.4 Automation, Offshoring and Selectivity

To assess whether selectivity has any role to play in explaining the relative decrease in hours worked in occupations more exposed to automation and

*Table 4.1* Descriptive Statistics: Occupations

| Occupations ranked by Automation Probability | Δ Share of Hours (1) | Δ Unemployment Rate (2) | Routine Task Intensity (3) | Offshorability (BK) (4) | Rank Offshorability (5) |
|---|---|---|---|---|---|
| Corporate managers (12) | 0.10 | -0.03 | -1.83 | -0.19 | 10 |
| Other professionals (24) | 0.43 | 0.18 | -1.71 | 0.09 | 11 |
| General managers (13) | 0.20 | 0.08 | -1.60 | -0.59 | 8 |
| Physical, mathematical, and engineering professionals (21) | 0.40 | -0.45 | -1.33 | 0.96 | 17 |
| Life science and health professionals (22) | 0.02 | -0.46 | -1.23 | -0.87 | 6 |
| Life science and health associate professionals (32) | 0.63 | -0.01 | -0.87 | -0.83 | 7 |
| Other associate professionals (34) | 0.39 | 0.28 | -0.78 | 0.48 | 13 |
| Physical and engineering science associate professionals (31) | 0.12 | 0.01 | -0.05 | 0.61 | 15 |
| Personal and protective service workers (51) | 0.74 | 0.48 | 0.17 | -0.94 | 4 |
| Models, salespersons and demonstrators (52) | -0.57 | 0.30 | 0.21 | -0.95 | 1 |
| Office clerks (41) | -0.26 | -0.33 | 0.27 | 1.56 | 19 |
| Extraction and building trades workers (71) | -0.43 | 0.30 | 0.32 | -0.95 | 3 |
| Metal, machinery and related trade workers (72) | -0.66 | -0.07 | 0.39 | -0.56 | 9 |
| Customer services clerks (42) | 0.02 | 0.60 | 0.68 | 0.56 | 14 |
| Sales and services elementary occupations (91) | 0.46 | 0.32 | 0.95 | -0.91 | 5 |
| Laborers in mining. construction. manufacturing and transport (93) | -0.10 | 0.08 | 1.02 | 0.43 | 12 |
| Precision. handicraft. printing and related trades workers (73) | -0.43 | -0.63 | 1.03 | 1.86 | 20 |
| Drivers and mobile-plant operators (83) | -0.07 | 0.17 | 1.19 | -0.95 | 2 |
| Stationary-plant and related operators (81) | -0.22 | -0.01 | 1.19 | 2.31 | 21 |
| Other craft and related trade workers (74) | -1.52 | -0.11 | 1.46 | 1.02 | 18 |
| Machine operators and assemblers (82) | -1.31 | 0.03 | 1.48 | 0.93 | 16 |

Occupations are ranked from least to most routine-intensive. Δ Share of Hours and Δ Unemployment Rate is the change in hours worked and the unemployment rate between 1995 and 2010 respectively. Data is from the EULFS. Routine Task Intensity is taken from Acemoglu and Autor (2011) and Offshorability from Blinder and Krueger (2013). Both are standardized to have a mean of 0 and a standard deviation of 1.

offshoring documented in Figure 4.1, we estimate the following equation:

$$\Delta \Upsilon_{oki} = \beta_1 RTI_o + \beta_2 Offshor_o + \beta_3 RTI_o \times Offshor_o + Z'_{oki}\mathbf{C} + \mu_{oi} + \epsilon_{oki}. \quad (2)$$

On the left hand side, the dependent variable $\Delta \Upsilon_{oki}$ corresponds to the long-term change in selectivity as captured by our three measures. For SSO and unemployment duration, $\Delta \Upsilon_{oki}$ is the difference between 1995 and 2010, while for under-education or over-education, $\Delta \Upsilon_{oki}$ is the difference between 1998 and 2010. This is due to the limited availability of educational data before 1998 as already mentioned. As SSO measures the concentration of occupation $o$ across sectors $k$, the sample is aggregated at the occupation×country level. On the right hand side of (2), the explanatory variables $RTI_o$ and $Offshor_o$ are the indices of automatability and offshorability respectively, while $Z_{oi}$ is a set of control variables including the initial values of selectivity and of the employment share of the cell. We also include occupation×country fixed effects ($\mu_{oi}$) except when the dependent variable is SSO, in which case we include country fixed effects ($\mu_i$). As the indices of automatability and offshorability are standardized to have a mean of 0 and a standard deviation of 1, $\beta_1$ can be interpreted as the
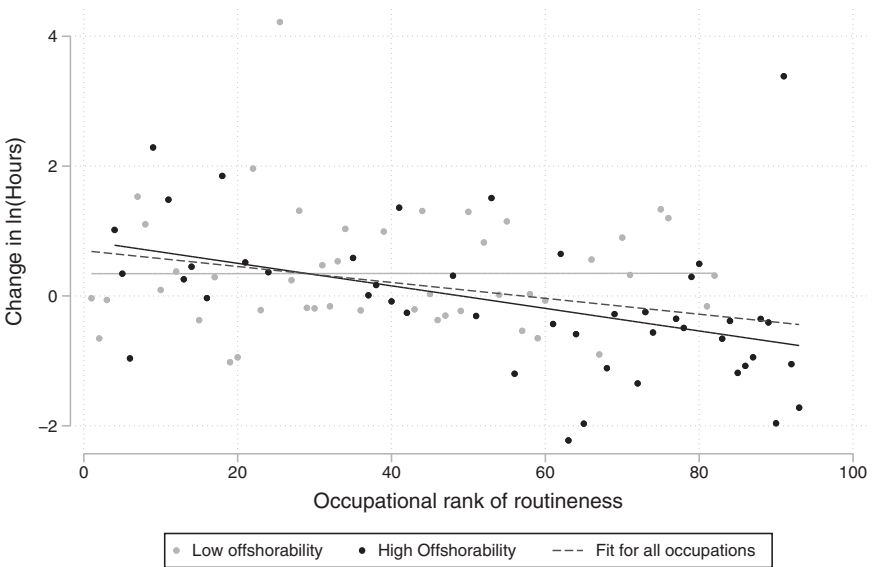


*Figure 4.1* The Impact of Routineness and Offshorability on Labour Hours

Notes: Figure 4.1 plots the change in hours worked from 1995 to 2010 against the occupational rank of routineness. Data on employment is aggregated at the occupation level. Routineness of the occupation is taken from Acemoglu and Autor (2011) and data on offshorability comes from Blinder and Krueger (2013). Occupations belong to the low or high offshorability sample if they are below or above the median offshorability. Occupations with below- (above-) median offshorability are displayed in grey dots (black dots) with the corresponding linear sample fit plotted as the solid grey (black) line. The overall sample fit is plotted as a dashed line.

effect of automatability when offshorability is equal to its average value. Analogously, $\beta_2$ can be interpreted as the effect of offshorability when automatability is equal to its average value. Moreover, the effect of automatability when offshorability is one standard deviation larger than the average is given by $\beta_1+\beta_3$. This is also the effect of offshorability when automatability is one standard deviation larger than the average. Unless specified otherwise, we comment on the effect of a variable when the other is at its average value.

The corresponding estimates are reported in Table 4.2. In this table, column 1 reports the results for SSO. It shows that occupations with higher initial automatability become more selective along the period when offshorability is at its average value. The coefficient is, however, imprecisely estimated and its p-value is slightly above the conventional levels of statistical significance. The effect of offshoring when automatability is at its average value is, instead, precisely estimated and negative. Automation and offshoring have thus opposite effects on the concentration of occupations across sectors. Though the trend of increasing concentration may be driven by other factors, the pattern is in line with an increase in selectivity for occupations more exposed to automation and a decrease in selectivity for occupations more exposed to offshoring. Moreover, as the interaction term between $RTI_o$ and $Offshor_o$ is positive and significant, the increase in concentration for occupations more exposed to automation is more pronounced for those that are also more exposed to offshoring. For instance, when offshorability is larger than its average value by one standard deviation, the effect of automatability on SSO is almost twice as large and significantly different from 0 ($\beta_1+ \beta_3$ = 0.16 with $p\text{–}value$ = 0.016). Column 2 reports the results for unemployment duration. We observe that the occupations more exposed to automation experience a larger increase in unemployment duration when offshorability is at its average value. This effect is reinforced for occupations that have higher degrees of offshorability. On the contrary, the effect of offshorability on unemployment duration is negative and imprecisely estimated. This effect becomes more negative as RTI decreases (i.e. as automatability decreases). Finally, columns 3 and 4 report the results for educational mismatch, looking at the shares of under- and over-educated workers separately. Column 4 shows that under-education falls in more automatable occupations and increases in more offshorable occupations. The interaction between automation and offshoring is negative, in line with the results in columns 1 and 2. By contrast, in column 3 over-education reacts in the opposite direction.

Overall, this empirical investigation reveals empirical patterns in line with increased selectivity in occupations exposed to automation and decreased selectivity in occupations exposed to offshoring. In particular, the patterns observed for automation are in line with the automation paradox, first highlighted by Bainbridge (1983) and discussed in Section 2. The empirical investigation also reveals that the interaction with offshorability generally reinforces the selectivity induced by automatability.[18]

*Table 4.2* Selectivity, Automation and Offshoring.

|  | (1)<br>Δln(SSO) | (2)<br>Δln(Unemp. duration) | (3)<br>Δ Under ed. % | (4)<br>Δ Over ed. % |
|---|---|---|---|---|
| RTI | 0.0802 | 0.0413* | -0.00439*** | 0.00336*** |
|  | (0.0506) | (0.0244) | (0.000685) | (0.000756) |
| Offshor. | -0.123** | -0.0300 | 0.00274*** | -0.00207** |
|  | (0.0525) | (0.0328) | (0.000836) | (0.000923) |
| RTI × Offshor. | 0.0792* | 0.0558* | -0.00236*** | -0.00107 |
|  | (0.0473) | (0.0332) | (0.000729) | (0.000753) |
| Observations | 1,063 | 905 | 1,915 | 1,915 |
| R-squared | 0.148 | 0.189 | 0.172 | 0.246 |
| Fixed effects | Country | Country-Industry | Country-Industry | Country-Industry |

The table reports coefficients of estimating (2). The dependent variable is our proxy for selectivity. *Δln(SSO)* is the log change of the Sectoral Selectivity of an Occupation calculated as the Herfindahl index of occupational employment shares across industries in a country. In Column 1, the dataset is aggregated at the country × occupation level. It is aggregated at the country × sector × occupation level in columns 2 to 4. *RTI* is routine-task intensity as in Acemoglu and Autor (2011) and *Offshor.* measures the offshorability of an occupation as in Blinder and Krueger (2013). Standard errors in parentheses are clustered at the occupation level in column 1 and at the country × occupation level in columns 2 to 4.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

# 4 A Search Model with Core-Biased Technological Change

In this section we rationalize the empirical findings of the previous section in terms of a simple labor-market sorting model that explains how automation and offshoring can affect match selectivity and employment as observed in the data.

Following Becker (1973) and Shimer and Smith (2000), the model relies on two key elements. The first is assortativity between firms' tasks and workers' skills required to perform those tasks, which implies that there exist "ideal" pairings of skill and tasks producing maximum match surplus.[19] The second element is search frictions, which implies that, as the ideal pairings cannot be immediately located, firms and workers sort according to acceptance regions around their ideal matches. The smaller the acceptance regions, the more selective workers and firms are. More selectivity implies less mismatch between tasks and skills, and more concentration of specialized knowledge in specific tasks. It also implies longer unemployment duration as workers and firms are more willing to forego less-than-ideal matches and wait for alternative future matches closer to the ideal ones. The degree of selectivity depends on the differential surplus of ideal matches with respect to less-than-ideal ones. In particular, anything that increases the differential surplus raises selectivity. Vice versa, anything that decreases the differential surplus reduces selectivity.

We show that calibrating the way automation and offshoring affect match surplus allows the model to replicate the empirical patterns highlighted in the previous section. Specifically, increased selectivity in occupations exposed to automation and decreased selectivity in occupations exposed to offshoring require the differential surplus of ideal matches with respect to less-than-ideal ones to be raised by automation and reduced by offshoring. Moreover, the observation that the interaction with offshorability generally reinforces the effect of automatability requires the positive impact of automation on the differential surplus to be enhanced by offshoring. As we will see, these requirements discipline the assortativity properties of the production process.

## 4.1 Matching, Search and Heterogeneity

There are two types of heterogeneous agents: workers and firms. Time is continuous, and in each moment the timing of events is as follows. Firms with heterogeneous tasks decide whether or not to enter the labor market and randomly meet one-to-one with workers with heterogeneous skills. After observing their respective tasks or skills, each firm and the worker it has met decide whether to match or not. If they decide to match, they bargain on the wage as a fraction of the match surplus according to the Nash protocol. The steady state pure strategy of each firm or worker is to decide which workers or firms to match with, taking the strategies of all other firms and workers as given.

All agents are risk-neutral, infinitely lived and maximize the present value of their future income streams, discounted by the common discount factor $\rho$.

Income streams are determined by the match surplus generated by firms and workers through production. Horizontal differentiation in workers' skills and firms' tasks is introduced in terms of different addresses along a characteristics' space represented by a unit circle. Along the unit circle, there is an exogenous measure of domestic workers $L > 0$ with skills indexed $x \in [0, 1]$ clockwise from noon ("skill address"). The distribution of skills across addresses is determined by a uniform p.d.f. $g_w(x)$. Given unit support, there are thus $L$ workers at each address. Likewise, there is a measure of firms with tasks indexed $y \in [0, 1]$ clockwise from noon ("task address"). While the measure of workers $L$ is exogenously given, the measure of firms is endogenously determined by free entry and exit. The distribution of tasks is also governed by a uniform p.d.f. $g_f(y)$. Uniformity is assumed for simplicity as it will lead to the same equilibrium outcome for all addresses.

When a worker with address $x$ and a firm with address $y$ are matched, they produce joint surplus $s(x, y, A, \Omega)$. This surplus depends on the degree of automation $A$, the extent of offshoring $\Omega$ and the distance between the addresses of skill $x$ and task $y$:

$$d(x, y) = \min [x - y + 1, y - x] \tag{3}$$

where the min function selects the shorter arc distance of clockwise and counter-clockwise travels between $x$ and $y$ along the unit circle. An "ideal" match happens for $x = y$ and thus implies $d(x, y) = 0$. We will focus on the symmetric pure strategy steady state with the acceptance region given by the interval $[-d^*, d^*]$ centered around the ideal match $d = 0$ for all $x \in [0, 1]$ and $y \in [0, 1]$. Accordingly, we will leave the dependence of $d$ on $x$ and $y$ implicit, and simply use $s(d, A, \Omega)$ to denote the match surplus at distance $d$ with degree of automation $A$ and extent of offshoring $\Omega$. As the acceptance interval has measure $2d^*$, we will use $1/d^*$ as the model's index of "selectivity".

All agents know their own type and the types of all potential partners they meet. However, due to search frictions, domestic firms and workers are not necessarily all paired in a productive match.[20] Firms can be either producing ($P$) or vacant ($V$). Workers can be either employed ($E$), or unemployed ($U$). By definition, the sum of employed and unemployed workers equals the labour force, $E + U = L$, and we set $L = 1$ by choice of units. Hence, $E + U = 1$ holds both in the aggregate and for each address.

Only vacant firms and unemployed workers engage in search. Meeting rates are set according to a standard random search setup featuring Poisson distributed meeting intervals. We adopt a linear matching technology described by a homogeneous-of-degree-one Cobb-Douglas matching function $M(U, V) = \vartheta U^{\xi} V^{1-\xi}$, where $\vartheta$ is matching efficiency, $U$ is unemployment, $V$ are vacancies and $\xi \in (0, 1)$ is the elasticity of new matches to unemployment.[21] In this setup the Poisson arrival rate can be derived as a function of aggregate labor market tightness $V/U$. We can then define $q_v = M(U, V)/V = \vartheta(U/V)^{\xi}$ as the rate at which vacant firms meet unemployed workers and $q_u = M(U, V)/U = \vartheta(V/U)^{1-\xi}$ as the

rate at which unemployed workers meet vacancies. Matches can be destroyed by separation shocks, which we assume to happen with per-period probability $\delta \in (0, 1)$.

Firms face a cost $c > 0$ of maintaining a job either filled or vacant paid in units of the final good. Match surplus is shared according to the Nash bargaining solution with worker bargaining weight $\alpha \in (0, 1)$. We impose zero outside options for both workers and firms by normalizing the unemployed workers' and vacant firms' income to 0.[22]

The equilibrium of the model is determined as follows. To avoid cluttering the notation, we leave the dependence of variables on automation and offshoring implicit for now. A worker's discounted value of being employed $v_e(d)$ equals the current wage plus the option value of the potential future loss from unemployment:

$$\rho v_e(d) = w(d) - \delta\left(v_e(d) - v_u\right). \tag{4}$$

Given that unemployed workers' income is normalized to 0, a worker's discounted value of being unemployed $v_u$ equals the option value of the potential future gain from employment:

$$\rho v_u = 2q_u \int_0^{d^*} \left(v_e(z) - v_u\right) dz, \tag{5}$$

which takes into account that an unemployed worker meets a vacancy at endogenous rate $q_u$ and converts the meeting into a job if the worker's type falls in the acceptance interval of measure $2d^*$ centered at $d = 0$. The discounted value of a filled vacancy $v_p(d)$ equals what is left of the match surplus after the wage $w(d)$ and the maintenance cost $c$ have been paid plus the option value of the potential future loss from exogenous separation at rate $\delta$:

$$\rho v_p(d) = \left(s(d) - w(d) - c\right) - \delta\left(v_p(d) - v_v\right) \tag{6}$$

The value of an unfilled vacancy $v_v$ satisfies

$$\rho v_v = -c + 2q_v \int_0^{d^*} \left(v_p(z) - v_v\right) dz, \tag{7}$$

where the right-hand side corresponds to the option value of filling the vacancy at endogenous rate $q_v$ in the future net of the maintenance cost $c$.

The set of equilibrium conditions is then completed by the Nash bargaining rule

$$(1 - \alpha)\left(v_e(d) - v_u\right) = \alpha\left(v_p(d) - v_v\right) \tag{8}$$

together with the free entry condition for the value of a vacancy ($v_v = 0$), the zero cutoff value condition for a filled vacancy associated with maximum mismatch $d^*$

$(v_p(d^*) = 0)$, and the steady state flow condition for employment

$$q_u = \frac{\delta E}{2d^*(1 - E)}. \tag{9}$$

The last condition requires job destruction $\delta E$ to be exactly offset by job creation $2q_u d^*(1 - E)$ as an unemployed worker meets a vacancy at rate $q_u$ and matches with the corresponding firm at a rate given by the ratio between the measures of the acceptance interval (equal to $2d^*$) and of the characteristic space (equal to 1).

Using the free entry and zero cutoff conditions, the set of equilibrium conditions can be reduced to a system of the two equations,

$$(1 - \alpha) \frac{2\vartheta^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}}}{\delta + \rho + 2(1 - \alpha)\vartheta^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}} + 2\alpha q_u} \int_0^{d^*} s(z)dz = c \tag{10}$$

and

$$(1 - \alpha) \frac{\delta + \rho + 2\vartheta^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}}}{\delta + \rho + 2(1 - \alpha)\vartheta^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}} + 2\alpha q_u} s(d^*) = c, \tag{11}$$

in employment $E$ and maximum mismatch $d^*$ with match surplus $s(d)$ and meeting rate $q_u$ given by (9).[23] Solving this system gives the equilibrium values of $E$ and $d^*$, which can then be used to evaluate the equilibrium wage of domestic workers as follows:

$$w(d) = \frac{\alpha(\delta + \rho + 2q_u)}{\delta + \rho + 2(1 - \alpha)\vartheta^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}} + 2\alpha q_u} s(d). \tag{12}$$

### 4.2 Automation, Offshoring and Assortativity

Having laid out the search model with two-sided heterogeneity, we can now discuss how assortativity should be affected by automation and offshoring for the model's predictions to be consistent with the empirical patterns discussed in Section 2 and highlighted in Section 3. To this aim we make the dependence of match surplus $s(d)$ on automation and offshoring explicit by rewriting it as $s(d, A, \Omega)$.

There are three requirements that the model's predictions should fullfill in order to be in line with the empirical patterns. First, the differential surplus of ideal matches with respect to less-than-ideal ones should be increased by automation. Second, the differential surplus should be decreased by offshoring. Third and last, the positive impact of automation on the differential surplus should be reinforced by offshoring.

The first requirement is fullfilled by the model's predictions if match surplus $s(d, A, \Omega)$ is log-submodular in $d$ and $A$. Analogously, the second requirement

is fulfilled if match surplus $s(d, A, \Omega)$ is log-supermodular in $d$ and $\Omega$. In words, better matches (i.e. matches at smaller distance $d$) have a comparative advantage in exploiting automation, whereas worse matches (i.e. matches at longer distance $d$) have a comparative advantage in exploiting offshoring. The third and last requirement is met if match surplus $s(d, A, \Omega)$ is log-supermodular in $A$ and $\Omega$. In words, matches with a higher degree of automation have a comparative advantage in exploiting offshoring, and vice versa matches with a larger extent of offshoring have a comparative advantage in exploiting automation. Note that log-submodularity in $A$ and $d$ implies that, as automation proceeds (larger $A$), workers and firms attribute increasingly higher value to ideal matches relative to less-than-ideal ones. This is what we call "core-biased technological change" (CBTC).

We show that these assumptions on log-modularity allow the model to reproduce the observed empirical patterns through a numerical implementation based on a specific microfounded functional form for match surplus $s(d, A, \Omega)$.

### 4.3 A Simple Numerical Example

Assume that production by matched worker $x$ and firm $y$ takes place according to a constant return to scale Cobb-Douglas production function employing capital and labor as inputs with total factor productivity $B > 0$ and capital share $\beta \in (0, 1)$. Output is sold in a perfectly competitive product market at a given price normalized to unity. The worker's productivity is determined by match distance $d(x, y)$, the degree of automation $A$ and the extent of offshoring $\Omega$. Leaving again the dependence of $d$ on $x$ and $y$ implicit, we use $L(d, A, \Omega)$ to denote such productivity, which corresponds also to the worker's efficiency units of labor as the worker is assumed to supply one unit of labor inelastically. The corresponding capital services can be rented in a perfectly competitive capital market at rental rate $\rho > 0$. Match surplus is then obtained by subtracting capital services from production. Given perfect competition, capital services are related to $L(d, A, \Omega)$ by the firm's profit maximizing condition that the value of the marginal productivity of capital equals its rental rate. As a result, match surplus evaluates to:

$$s(d, A, \Omega) = \Phi B^{\frac{1}{1-\beta}} L(d, A, \Omega), \tag{13}$$

with bundling parameter $\Phi \equiv (1 - \beta)(\beta/\rho)^{\frac{\beta}{1-\beta}}$.

Each task consists of subtasks that are differentiated over a two-dimensional continuum in terms of their "automatability" and "offshorability", inversely measured by indices $a \in [0, 1]$ and $\omega \in [0, 1]$ respectively. The two-dimensional representation captures the fact that automatability and offshorability are conceptually and empirically quite different as highlighted in Section 3.1.1. The worker's productivity in performing a subtask with automatability $a$ and

offshorability $\omega$ is given by:

$$l(d, a, \omega) = Fa\omega - \frac{1}{2}(\gamma_a a + \gamma_\omega \omega)d, \tag{14}$$

with $F > 0$. According to (14), in the absence of mismatch ($d = 0$), the worker is more productive in subtasks with low automatability (large $a$) and low offshorability (large $\omega$). Crucially, in the presence of mismatch ($d > 0$), for given $d$, automatability and offshorability affect the mismatch penalty $\gamma_a a + \gamma_\omega \omega$, where $\gamma_a$ and $\gamma_\omega$ are fixed parameters whose signs will play a crucial role in what follows.

The firm first decides which subtasks to automate or offshore; it then looks for a worker whom to assign the remaining tasks to. Given (14), the firm has a stronger incentive to automate subtasks with low $a$ and to offshore subtasks with low $\omega$. Hence, if there are costs of automation and offshoring and these are an increasing function of the measure ("number") of subtasks that are automated and offshored, there will exist thresholds of automatability $A \in [0, 1]$ and offshoring $\Omega \in [0, 1]$ such that subtasks ($a, \omega$) with $a \in [0, A]$ are automated, subtasks with $\omega \in [0, \Omega]$ are offshored, and subtasks with $a \in [0, A]$ and $\omega \in [0, \Omega]$ are both automated and offshored. For the remaining tasks with $a \in [A, 1]$ and $\omega \in [\Omega, 1]$ the firm searches for a worker.[24]

The productivity of a matched worker with skill at distance $d$ from the firm's task can then be evaluated by integrating (14) with respect to $a$ and $\omega$ with $a \in [A, 1]$ and $\omega \in [\Omega, 1]$ to obtain:

$$L(d, A, \Omega) = (1 - A)(1 - \Omega)$$
$$\left\{ \frac{1}{4}F(1 + A)(1 + \Omega) - \frac{1}{4}[\gamma_a(1 + A) + \gamma_\omega(1 + \Omega)]d \right\}, \tag{15}$$

where the term $(1–A)(1–\Omega)$ outside the curly brackets is the measure ("number") of subtasks performed by the worker as they are neither automated nor offshored ("extensive margin"), while the term inside the curly brackets is the worker's average productivity across these subtasks ("intensive margin"). When more subtasks are automated (larger $A$) or offshored (large $\Omega$), there are three effects on the matched worker's productivity (15). First, the extensive margin shrinks as the worker is assigned fewer subtasks. This is the "substitution effect". Second, the productivity of the ideal match ($d = 0$) increases as the matched worker can specialize in subtasks with higher $a$ or higher $\omega$ in which the worker is more productive. This is the "productivity effect". Third, the productivity of less-than-ideal matches ($d > 0$) increases or decreases relative to the ideal match ($d = 0$) depending on the signs of $\gamma_a$ and $\gamma_\omega$. This is the "mismatch penalty effect".

The sign of the mismatch penalty effect is determined by the assumptions on the log-modularity of labor productivity $L(d, A, \Omega)$ and thus of match surplus $s(d, A, \Omega)$, given that by (13) the latter inherits the log-modularity properties of the former. In particular, $L(d, A, \Omega)$—and thus $s(d, A, \Omega)$—is log-submodular in $A$ and $d$ if and only if, for all $d' > d$ and $A' > A$, we have

$s(d', A')/s(d, A')<s(d', A)/s(d, A)$, which is the case for $\gamma_\omega < 0$. Analogously, $L(d, A, \Omega)$—and thus $s(d, A, \Omega)$—is log-supermodular in $\Omega$ and $d$ if and only if, for all $d' > d$ and $\Omega' > \Omega$, we have $s(d', \Omega')/s(d, \Omega')>s(d', \Omega)/s(d, \Omega)$, which is the case for $\gamma_a > 0$. Moreover, for $\gamma_\omega < 0$ and $\gamma_a > 0$, $L(d, A, \Omega)$—and thus $s(d, A, \Omega)$—is also log-supermodular in $A$ and $\Omega$.

Figures 4.2, 4.3 and 4.4 provide graphical representations of the effects of automation and offshoring on the theoretical correlates of our three measures of selectivity. Parameter values are drawn from the literature except for those of the mismatch penalty parameters and productivity of the optimal match, which we treat as free parameters chosen in order to deliver empirically relevant equilibrium rates of unemployment between around 2% and 7%.[25] The concentration of occupations' employment across sectors is proxied in the model by the Herfindahl index of concentration of skills's employment (in efficiency units) across tasks in the acceptance interval:

$$H = \frac{1}{2} \frac{\int_0^{d^*} [L(z, A, \Omega)]^2 dz}{\left[\int_0^{d^*} L(z, A, \Omega)\, dz\right]^2}.$$

Unemployment duration is computed as the inverse of the rate $q_u$ at which unemployed workers meet vacancies. Mismatch is measured by the length $d^*$ of (half) the acceptance interval. Figures 4.2, 4.3 and 4.4 then show that, for the chosen parameter values, selectivity is an increasing function of automation (left panels) and a decreasing function of offshoring (right panels), no matter whether we measure selectivity in terms of employment concentration,
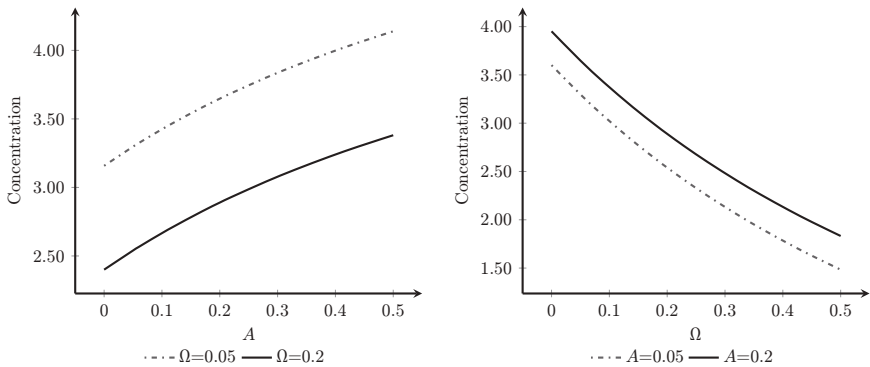


*Figure 4.2* Employment Concentration. This figure plots simulated employment concentration over a range of automation $A$ on the x-axis for $\Omega = 0.05$ (dashed) and $\Omega = 0.2$ (solid) in the left panel and over a range of offshoring $\Omega$ on the x-axis for $A = 0.05$ (dashed) and $A = 0.2$ (solid) in the right panel. Simulations are based on the system of equations (10)–(11) and parameters as specified in Table 4.C1.
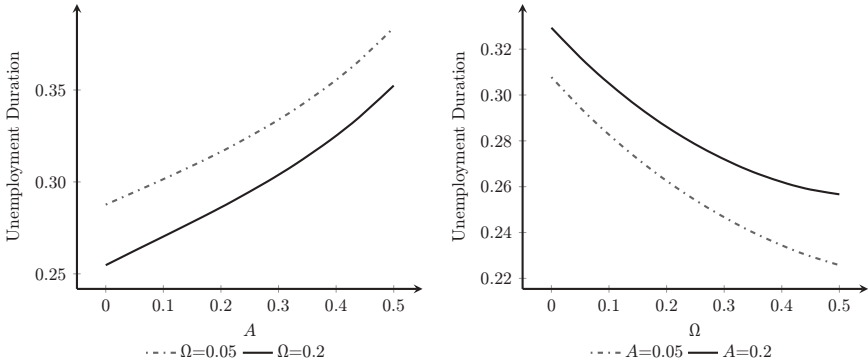
*Figure 4.3* Unemployment Duration. This figure plots simulated unemployment duration over a range of automation *A* on the x-axis for Ω = 0.05 (dashed) and Ω = 0.2 (solid) in the left panel and over a range of offshoring on the x-axis for *A* = 0.05 (dashed) and *A* = 0.2 (solid) in the right panel. Simulations are based on the system of equations (10)–(11) and parameters as specified in Table 4.C1.
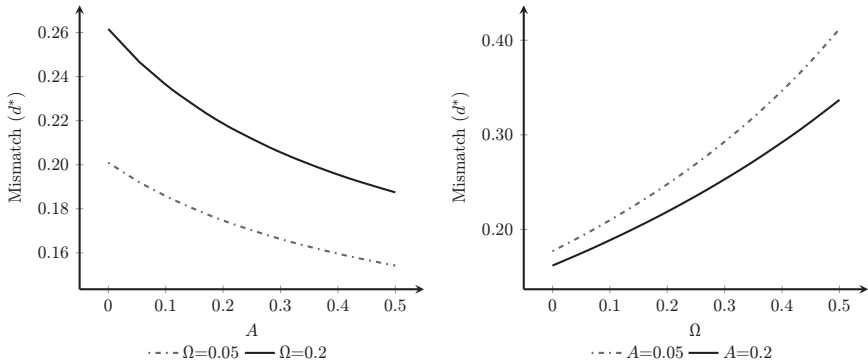


*Figure 4.4* Mismatch. This figure plots simulated mismatch *d\** over a range of automation *A* on the x-axis for Ω = 0.05 (dashed) and Ω = 0.2 (solid) in the left panel and over a range of offshoring Ω on the x-axis for *A* = 0.05 (dashed) and *A* = 0.2 (solid) in the right panel. Simulations are based on the system of equations (10)–(11) and parameters as specified in Table 4.C1.

unemployment duration and mismatch. They confirm that our model is able to qualitatively reproduce the empirical patterns we uncovered in the data.[26]

The parametrized model can then be used to investigate how automation and offshoring may affect workers' employment opportunities and wages, which we do not observe in the data. The results of this investigation, corresponding to the effects on selectivity reported in the previous figures, are shown in Figure 4.5 for employment and Figure 4.6 for wages. Figure 4.5 shows that, for the
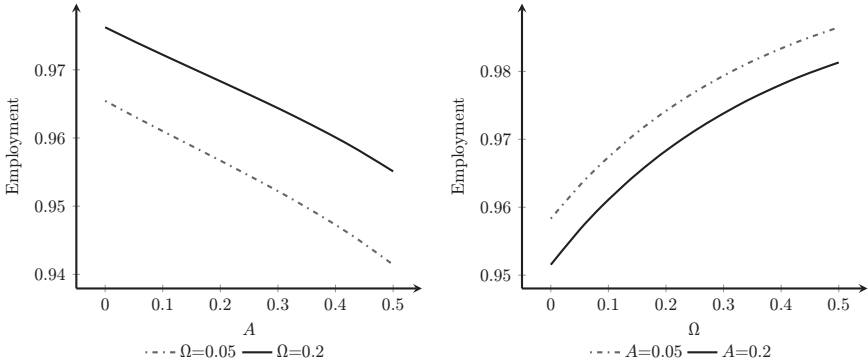
*Figure 4.5* Employment. This figure plots simulated employment rates over a range of automation *A* on the x-axis for Ω = 0.05 (dashed) and Ω = 0.2 (solid) in the left panel and over a range of offshoring Ω on the x-axis for *A* = 0.05 (dashed) and *A* = 0.2 (solid) in the right panel. Simulations are based on the system of equations (10)–(11) and parameters as specified in Table 4.C1.



*Figure 4.6* Relative Wages of Best vs. Worst Match. This figure plots of the wages of the best possible match (*d* = 0) relative to the worst possible match (*d* = d*) over a range of automation *A* on the x-axis for Ω = 0.05 (dashed) and Ω = 0.2 (solid) in the left panel and over a range of offshoring Ω on the x-axis for *A* = 0.05 (dashed) and *A* = 0.2 (solid) in the right panel. Simulations are based on the system of equations (10)–(11) with wages computed as in (12) and parameters as specified in Table 4.C1.

chosen parameter values, equilibrium employment *E* is a decreasing function of automation *A* (left panel) and an increasing function of offshoring (right panel). As for interactions, the figure reveals that employment is log-supermodular in automation and offshoring: the negative impact of automation on employment

is stronger when there is more offshoring.[27] Figure 4.6 shows that automation increases wage inequality between the best ($d = 0$) and worst ($d = d^*$) matches, especially when there is more offshoring.[28]

To summarize, for standard parameter values drawn from the literature, if better matches between firms and workers have a comparative advantage in exploiting automation, our model reproduces the observed effects of automation and offshoring on our three measures of selectivity. The model then implies that automation reduces employment by increasing workers' and firms' selectivity. If worse matches between firms and workers have a comparative advantage in exploiting offshoring, it also predicts that offshoring raises employment by decreasing workers' and firms' selectivity. Lastly, if matches with a higher degree of automation have a comparative advantage in exploiting offshoring, the model predicts that offshorability reinforces the impact of automation. These predictions are consistent with the automation paradox discussed in Section 2 and what we called "core biased technological change".

## 5  Conclusion

Automation and offshoring may affect a country's workers employment opportunities and wages in two main ways. As some tasks are automated or offshored, these tasks are not performed by the country's workers any longer and the demand for their services falls. This is the negative "substitution effect", which leads to reduced employment opportunities and wages. Nonetheless, reallocating tasks from the country's workers to automated systems or foreign workers may also promote production efficiency, which in turn allows production activities to expand with a beneficial impact on employment opportunities and wages. This is the positive "productivity effect", which may cause employment and wages to rise.

With regard to the substitution effect, existing studies mainly focus on the impact of automation on capital-labor substitution, which is particularly relevant for the adoption of robots and machines in production. They have highlighted that different workers are affected differently depending on their education ("skill-biased technological change") or the routineness of their tasks ("routine-biased technological change").

In the present chapter we have investigated the possible existence of an additional negative effect of automation on workers' employment opportunities and wages. As automation intensifies, specialized knowledge ("core competencies") becomes increasingly salient above and beyond what would be needed by the education content of tasks or their degree of routineness. As a result, workers and firms become more selective in matching their specialized skills and tasks. We have called this aspect of automation "core-biased technological change" (CBTC), and argued that something similar could be relevant also for offshoring: the more sophisticated a country's global value chains are, the more crucial may be the contribution of specialized knowledge by the country's workers.

We have looked for evidence consistent with CBTC in occupational data for European industries. We have found that automation reduces employment opportunities. More interestingly for the purposes of our analysis, automation also increases workers' and firms' selectivity as captured by longer unemployment duration, less skill-task mismatch, and more concentration of specialized knowledge in specific tasks. This does not happen in the case of offshoring, though offshoring reinforces the effects of automation.

We have shown that a labor market model with two-sided heterogeneity and search frictions can rationalize our empirical findings as long as one is willing to assume that better matches between firms and workers have a comparative advantage in exploiting automation, worse matches between firms and workers have a comparative advantage in exploiting offshoring, and matches with a higher degree of automation have a comparative advantage in exploiting offshoring. Directly testing these properties has not been possible with the occupational data used in this chapter, and we leave it to future research exploiting matched employer-employee data with detailed information in skills and tasks.

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## A  Data Description

We use the annual files of the European Labour Force Survey (EULFS) made available by Eurostat. This survey combines labour force surveys conducted at the national level in European countries. It has the advantage to provide harmonized information on basic labour markets variables. Our final database corresponds to *country × industry × occupation × year* cells. The information on the sector is based on the broad NACE sectors (21 sectors in the NACE Rev.2 classification) and the information on the occupation is based on the 3-digits ISCO-88 classification. The EULFS is used to derive the number of employed and unemployed workers in each cell by collapsing individual observations using the provided weighting coefficients. We also use the EULFS to compute the unemployment duration in each cell.

**Construction of the variables** We keep the employed people as defined by the ILO criteria and derived by Eurostat. It is less common to compute unemployment at the *sector × occupation* level since workers can be mobile across sectors and occupations. We define unemployment in a given sector and a given occupation as the number of unemployed people who had this precise occupation in this precise sector. This measure corresponds to the true and unobservable unemployment rate at the *sector × occupation* level if workers do not move across sectors and occupations.

**Dataset selection** We restrict our dataset to the 13 following countries: Austria, Belgium, Germany, Denmark, Spain, France, United Kingdom, Greece, Ireland, Italy, Luxembourg, Netherlands and Portugal. This group of countries corresponds to all countries that provided data at least from 1995. It is important to note that France and the Netherlands do not provide enough information to compute the unemployment rate at the cell level. Following Goos, Manning and Salomons (2014), we also drop the following industries: Agriculture, Forestry, Fishing (A); Mining and Quarrying (B), Public Administration and Defence and Compulsory Social security (O); Education (P) and Extra-territorial organizations and bodies (U). These sectors corresponds to public sectors and agricultural sectors. They account for 26% of all jobs in our sample. The following occupations, closely associated to the sectors deleted are also dropped from the sample: Legislators and senior officials (ISCO-88: 11); teaching professionals (ISCO-88: 23); teaching associate professionals (ISCO-88: 33); market-oriented skilled agricultural and fishery workers (ISCO-88: 61); agricultural, fishery and related labourers (ISCO-88: 92).[29] Finally, our data contains information, virtually complete, at the cell level for 92 occupations, in 16 sectors.

Table 4.A1 sums up the coverage of our database relative to official statistics. According to official Eurostat statistics, we cover around 70% of the employment in each country, except for Luxembourg for which we only cover 58.5% of the employment. This is due to the fact that Luxembourg is a small country with a large institutional sector driven by the presence of some European institutions. Our coverage of unemployment is a bit less precise, going from 36.2% of official unemployment numbers in Italy to 69.6% in Denmark. This is principally due to

*Table 4.A1* Database Coverage (in % of official Eurostat figures)

| Country | # of employees | # of unemployed workers |
|---|---|---|
| Austria | 70.9% | 56.1% |
| Belgium | 70.5% | 51.5% |
| Germany | 75.4% | 62.3% |
| Denmark | 73.3% | 69.6% |
| Spain | 70.5% | 61.1% |
| France | 69.1% | - |
| United Kingdom | 74.2% | 59.8% |
| Greece | 61.1% | 42.3% |
| Ireland | 66.5% | 51.1% |
| Italy | 71.8% | 36.2% |
| Luxembourg | 58.5% | 44.0% |
| Netherlands | 68.0% | - |
| Portugal | 69.8% | 38.6% |

the lack of precise reporting of the last job for unemployed people and to dropped industries. Especially the coverage is very low for Portugal in 1995 (around 10%).

The time frame of our analysis corresponds to 1995–2010 in order to include the maximum number of countries. Our analysis stops in 2010 because after this date, a change in the occupation classification (ISCO-88 to ISCO-08) prevents us from accurately representing changes in the time series.

## A.1 Offshorability

Three different measures of offshorability are proposed in the literature: by Blinder (2009), by Blinder and Krueger (2013, hereafter BK) and by Acemoglu and Autor (2011, hereafter AA). In the first two cases, the authors propose a qualitative scale of offshorability, ranking occupations from "Highly Non-Offshorable" (1) to "Highly Offshorable" (4) following Blinder (2009). Blinder then proposes a qualitative ranking of occupations according to their degree of offshorability. BK only provide 4 categories. AA propose a quantitative index of offshorability based on ONET. [30] Their measure aggregates several ONET indicators: Face to face discussions, Assisting and Caring for Others, Performing for or Working Directly with the Public, Inspecting Equipment, Structures, or Material, Handling and Moving Objects, 0.5*Repairing and Maintaining Mechanical Equipment, 0.5*Repairing and Maintaining Electronic Equipment.

While Blinder and BK measures are based on questionnaires and qualitative observations about offshorability; the AA measure is not. The two types of measures are likely to diverge for some occupations. In Table 4.A2, we compute the correlation coefficient between these measures. The correlation between Blinder and BK indices is large while for both indices the correlation with the AA measure is quite low.

*Table 4.A2* Correlation Table between Offshorability Measures

|                          | AA (2011) | Blinder (2009) | BK (2013) |
|--------------------------|-----------|----------------|-----------|
| Acemoglu-Autor (2011)    | 1         | –              |           |
| Blinder (2009)           | 0.34      | 1              | –         |
| Blinder-Krueger (2013)   | 0.25      | 0.94           | 1         |

For instance, Models, Salespersons and Demonstrators (code 52) is an occupation classified among the five most offshorable occupations according to the AA index while it is ranked as Highly Non-Offshorable by Blinder (2009). Teaching professionals (code 23) are also in the same situation. On the contrary, Machine operators and assemblers (code 82) are ranked as offshorable in Blinder (2009) while being ranked as a low offshorability activity by the AA index.

In their data appendix Goos, Manning and Salomons (2014) compare different offshorability index with actual offshorability measures. Blinder/BK types of measures seem more reliable. We consider these two measures as our preferred ones, using the BK index in our baseline regressions.

## A.2 Automatability

We proxy the probability of future automation of an occupation using the RTI measure constructed by Autor and Dorn (2009). This measure correlates with the one provided by Frey and Osbourne (2013). Using the files by Acemoglu and Autor (2011) and the definition of the RTI by Lewandowski et al. (2017) we compute the RTI index based on DOT data.[31] The measure of the RTI is standardized in order to have a mean of zero and a standard error of one. We use a crosswalk to go from SOC 2000 classification to 4-digit ISCO-88 classification and then aggregate it to the 3-digit ISCO-88 classification. At this level the correlation between the RTI ("routineness") and measure by Frey and Osborne ("probability of automation") is 0.77 (see Figure 4.A1). However, the two variables diverge for some occupations.

To assess the evolution of routine jobs across countries and industries, Dao et al. (2017) also use an index of "routineness" fixed for the nine 1-digit ISCO-88 occupations. They then assume that the partition of jobs within 1-digit ISCO occupations is fixed among countries, industries and time. We relax this assumption by only assuming that the RTI of a 3-digit ISCO occupation is fixed. This way we are able to observe the evolution in the automatability by country, industry and occupation.

## A.3 Relation Between Offshorability and Automatability

In this subsection we document that automatability and offshorability are not trivially correlated. First, conceptually the two concepts are different. Offshorability is defined as "the ability to perform one's work duties (for the same

prob_c~388 = .61149 + .86154 rti   $R^2$ = 59.6%

*n* = 109   RMSE = .1983753
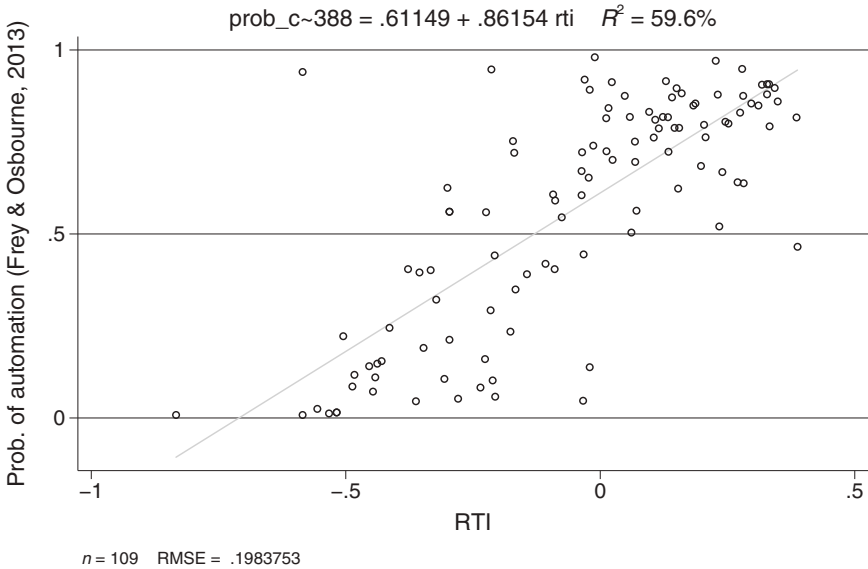
*Figure 4.A1* Correlation between Automation Probability and Routineness

employer and customers) in a foreign country but still supply the good or service to the home market" (Blinder and Krueger, 2009) while the automatability is more strictly linked to the routineness of a task, its possibility to be solved algorithmically, etc. Figure 4.A2 documents the correlation between the two variables. There is a global positive correlation, but the figure also highlights the diversity of RTI/offshorability combinations. Especially some occupations are both offshorable and routine-intensive (42: Customer service clerks; 73: Precision, handicraft, printing and related trades workers; 74: Other craft and related trade workers; 81: Stationary-plant and related operators; 82: machine operators and assemblers). Others are not routine intensive but offshorable (21: Physical, mathematical and engineering science professional) while some are protected from offshorability but at risk of automation (83: Drivers and mobile-plant operators; 91: sales and services elementary occupations; 93: labourers in mining, construction, manufacturing and transport). Finally, some occupations are both protected from automation and from offshorability (12: corporate managers; 13: general managers; 22: life science and health professionals). Note, however, that the scope of occupations that are not routine intensive but offshorable is very limited.

### A.4 Merging Procedure

Our matching strategy could be decomposed as follows: i) We only keep the observations before 2011, ii) we compute the RTI for each 4-digit ISCO-88 using official crosswalks, iii) we average the probabilities of automation when many SOC occupations are matched into a single ISCO occupation, iv) we
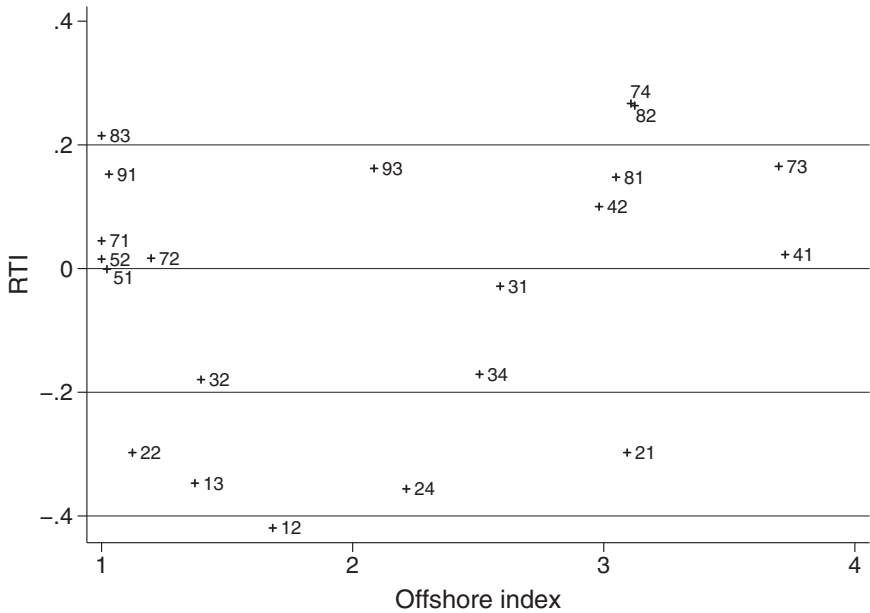
*Figure 4.A2* Automation Probability and Offshorability (BK, 09)

take the unweighted average probability of automation to aggregate our measure at the 3-digit ISCO-88 levels, v) we match each occupation with its RTI, vi) we proceed in the same way to assign RTI and offshorability indexes to occupation reported at the 2-digit ISCO level. Finally, when necessary, we obtain the measure of routine task intensity and offshorability at the 2-digit ISCO level by collapsing (with appropriate weights) all observations at the 3-digit level in their corresponding 2-digit ISCO occupation.

## B Model Solution

This Appendix provides a detailed derivation of (10), (11) and (12) in the main text. The steady state equilibrium is characterized by the following equations:

Surplus function:

$$s(d, A, \Omega) = \Phi B^{\frac{1}{1-\beta}}(1 - A)(1 - \Omega)\left\{\frac{1}{4}F(1 + A)(1 + \Omega)- \quad (16)\right.$$

$$\left. \frac{1}{4}[\gamma_a(1 + A) + \gamma_\omega(1 + \Omega)]d\right\}, \quad (17)$$

where we occasionally omit the dependence on $A$ and $\Omega$ for brevity.

Matching function:

$$M(U, V) = \vartheta U^{\xi} V^{1-\xi}. \tag{18}$$

Resource constraint:

$$E + U = L = 1. \tag{19}$$

Flow condition:

$$2d^* M(U, V) = \delta E. \tag{20}$$

Meeting probabilities:

$$q_v = M(U, V)/V = \vartheta(U/V)^{\xi}. \tag{21}$$

$$q_u = M(U, V)/U = \vartheta(V/U)^{1-\xi}. \tag{22}$$

Optimality conditions:

$$\rho v_E(d) = w(d) - \delta(v_E(d) - v_U), \tag{23}$$

$$\rho v_P(d) = (s(d) - w(d) - c) - \delta(v_P(d) - v_v), \tag{24}$$

$$\rho v_U = 2q_u \int_0^{d^*} (v_E(z) - v_U)dz, \tag{25}$$

$$\rho v_V = -c + 2q_v \int_0^{d^*} (v_P(z) - v_V)dz. \tag{26}$$

Bargaining outcome:

$$(1 - \alpha)(v_E(d) - v_U) = \alpha(v_P(d) - v_V). \tag{27}$$

Free entry condition:

$$v_V = 0. \tag{28}$$

Zero cutoff value condition:

$$v_P(d^*) = 0. \tag{29}$$

From this system of 13 equations in 13 unknowns ($E$, $U$, $V$, $M$, $q_v$, $q_u$, $w$, $v_E$, $v_p$, $v_U$, $v_V$, $s$, $d^*$), (10) and (11) can be obtained as follows. Subtract (25) from (23) to obtain:

$$\int_0^{d^*} (v_E(z) - v_u)dz = \frac{\int_0^{d^*} w(z)dz}{\rho + \delta + 2q_u(\theta)}. \tag{30}$$

Subtract (26) from (24) to obtain:

$$\int_0^{d^*} (v_P(z) - v_V)dz = \frac{\int_0^{d^*} (s(z) - w(z))dz}{\rho + \delta + 2q_v(\theta)}. \tag{31}$$

Substitute into the integral of (27)

$$(1 - \alpha) \int_0^{d^*} (v_E(z) - v_U)dz = \alpha \int_0^{d^*} (v_P(z) - v_V)dz \tag{32}$$

to obtain:

$$w(z) = \frac{\alpha(\delta + \rho + 2q_u(\theta))s(z)}{\delta + \rho + (1 - \alpha)2q_v(\theta) + \alpha 2q_u(\theta)}. \tag{33}$$

Substitute (27) into (26) to obtain:

$$\rho v_V = -c + 2q_v(\theta)\frac{1 - \alpha}{\alpha} \int_0^{d^*} (v_E(z) - v_U)dz. \tag{34}$$

Substitute (33) into (30) to obtain:

$$\int_0^{d^*} (v_E(z) - v_u)dz = \frac{\alpha \int_0^{d^*} s(z)dz}{\delta + \rho + (1 - \alpha)2q_v(\theta) + \alpha 2q_u(\theta)}. \tag{35}$$

Hence (34) and (35) imply:

$$\rho v_V = -c + \frac{(1-\alpha)2q_v(\theta)\int_0^{d^*} s(z)dz}{\delta + \rho + (1-\alpha)2q_v(\theta) + \alpha 2q_u(\theta)} \tag{36}$$

Using (20) and (19) in (22) gives:

$$q_u = \frac{M(U,V)}{U} = \frac{\delta E}{2d^*(L-E)}. \tag{37}$$

Using (20) and (19) gives

$$V = \left(\frac{\delta E}{2d^*\vartheta U^\xi}\right)^{\frac{1}{1-\xi}},$$

which, once substituted into (21), gives:

$$q_v = \vartheta^{\frac{1}{1-\xi}}(\delta E)^{-\frac{\xi}{1-\xi}}(L-E)^{\frac{\xi}{1-\xi}}(2d^*)^{\frac{\xi}{1-\xi}}, \tag{38}$$

or equivalently

$$q_v = \vartheta^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}}. \tag{39}$$

Substituting (39) into (33) gives (12) in the main text:

$$w(d) = \frac{\alpha(\delta + \rho + 2q_u)}{\delta + \rho + 2(1-\alpha)\vartheta^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}} + 2\alpha q_u}\, s(d).$$

Now substitute (39) into (36) to obtain:

$$\rho v_V = -c + \frac{2(1-\alpha)\vartheta^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}}\int_0^{d^*} s(z)dz}{\delta + \rho + 2(1-\alpha)\vartheta^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}} + 2\alpha q_u}. \tag{40}$$

Hence using the free entry condition $v_v = 0$, (40) becomes:

$$\frac{2(1-\alpha)\vartheta^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}}\int_0^{d^*} s(z)dz}{\delta+\rho+2(1-\alpha)\vartheta^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}}+2\alpha q_u} = c, \tag{41}$$

which is (10) in the main text where (17) implies:

$$\int_0^{d^*} s(x,A,\Omega)dx = \Phi B^{\frac{1}{1-\beta}}(1-A)(1-\Omega)\frac{1}{4}d^*$$
$$\left\{F(1+A)(1+\Omega)-\frac{1}{2}[\gamma_a(1+A)+\gamma_\omega(1+\Omega)]d^*\right\}$$

Finally, substitute the free entry condition and (29) into (24) to obtain

$$w(d^*) = s(d^*) - c,$$

which, together with (17) evaluated at $d^*$

$$w(d^*) = \frac{\alpha(\delta+\rho+2q_u)s(d^*)}{\delta+\rho+2(1-\alpha)q_v+2\alpha q_u},$$

gives:

$$(1-\alpha)\frac{\delta+\rho+2q_v}{\delta+\rho+2(1-\alpha)q_v+2\alpha q_u}s(d^*) = c.$$

Substituting (39) gives:

$$(1-\alpha)\frac{\delta+\rho+2\vartheta^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}}}{\delta+\rho+2(1-\alpha)\vartheta^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}}+2\alpha q_u}s(d^*) = c, \tag{42}$$

which is (11) in the main text where

$$s(d^*,A,\Omega) = \Phi B^{\frac{1}{1-\beta}}(1-A)(1-\Omega)$$
$$\left\{\frac{1}{4}F(1+A)(1+\Omega)-\frac{1}{4}[\gamma_a(1+A)+\gamma_\omega(1+\Omega)]d^*\right\}$$

and

$$q_u = \frac{\delta E}{2d^*(1-E)}.$$

given $L = 1$.

## C Parameter Values

Table 4.C1 reports the parameter values used in Section 4

*Table 4.C1* Parameters

| Parameter | Description | Value |
|---|---|---|
| $\alpha$ | Bargaining Weight | 0.5 |
| $\rho$ | Patience | 0.04 |
| $\delta$ | Per-period Separation Shock | 0.05 |
| $\xi$ | Matching Function Elasticity | 0.5 |
| $\vartheta$ | Matching Function Constant | 0.4 |
| $\beta$ | Capital share in CB | 0.33 |
| $c$ | Vacancy Cost | 1 |
| $F$ | Max. Productivity | 115 |
| $B$ | Factor Aug. Technology | 25.5 |
| $\gamma_A$ | Mismatch penalty $A$ | 115 |
| $\gamma_B$ | Mismatch penalty $\Omega$ | -53 |

Notes: Table 4.C1 shows parameter values used for the numerical example in the main text. Parameter values are standard values drawn from Hagedorn, Law and Manovskii (2017) except for the mismatch penalty parameters whose values have been chosen in order to deliver empirically relevant equilibrium rates of employment. As we do not model endogenous separations we choose a higher separation rate compared to Hagedorn, Law and Manovskii (2017) and closer to Fujita and Ramey (2012).

## Notes

1  See, for example, Autor and Dorn (2009), Ottaviano, Peri and Wright (2013), Goos, Manning and Salomons (2014), Graetz and Michaels (2018), Acemoglu and Restrepo (2020a), Dauth et al. (2017) on the empirical side; Acemoglu and Autor (2011), Aghion, Jones and Jones (2017), Acemoglu and Restrepo (2018b) and Acemoglu and Restrepo (2018a), Caselli and Manning (2019) on the theoretical one. Most of these studies tend to focus more on the effects of either automation or globalization (for instance Grossman and Rossi-Hansberg, 2008, Costinot and Vogel, 2010 or Costinot, Vogel and Wang, 2012) than on their interactions. Empirical assessments of their simultaneous effects across US regions can be found, for example, in Autor, Dorn and Hanson (2013, 2015) and with a global perspective, both theoretically and empirically, in, for example, Arkolakis et al. (2018).

2  See, for instance, Acemoglu and Restrepo (2018b) and Acemoglu and Restrepo (2018a) and, on employment, also Bostrom (2014), Brynjolfsson and McAfee (2014), Goos, Manning and Salomons (2014), Ford (2015), Susskind and Susskind (2015), White House (2016), Stone (2016), Frey and Osbourne (2013), Caselli and Manning (2019), Acemoglu and Restrepo (2019), Acemoglu, Lelarge and Restrepo (2020), and Acemoglu and Restrepo (2020b) and Fornino and Manera (2019) regarding the reversability of capital investments.

3  See Section 2 for concrete examples.

4  See, e.g., Grossman and Rossi-Hansberg (2008), Costinot and Vogel (2010), Ottaviano, Peri and Wright (2013), Goos, Manning and Salomons (2014).

5  For example, in the offshoring model by Antras, Garicano and Rossi-Hansberg (2006), cross-country hierarchical teams are formed where less skilled countries specialize in production and more skilled countries specialize in problem solving. In the model of global value chains by Antras, Garicano and Rossi-Hansberg (2006), in which production of the final good is sequential and subject to mistakes, countries with lower probabilities of making mistakes at all stages specialize in later stages of production.

6  In the wake of Costinot and Vogel (2010) the underlying idea is that, while a sector may cover a rich menu of occupations, these include a submenu of "core occupations" that are disproportionately concentrated in the sector.

7  The 2018 Talent Shortage Survey by ManpowerGroup covers 39,195 employers across six industry sectors in 43 countries and territories: Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, China, Colombia, Costa Rica, Czech Republic, Finland, France, Germany, Greece, Guatemala, Hong Kong, Hungary, India, Ireland, Israel, Italy, Japan, Mexico, Netherlands, New Zealand, Norway, Panama, Peru, Poland, Portugal, Romania, Singapore, Slovakia, Slovenia, South Africa, Spain, Sweden, Switzerland, Taiwan, Turkey, UK and USA.

8  In spring 2014 the European Centre for the Development of Vocational Training of the European Union (Cedefop) undertook the first European skills and jobs survey (ESJS), a large-scale primary data collection of about 49,000 adult employees in 28 EU Member States. Cedefop Eurofound (2018) summarizes many of the insights gained by closer empirical scrutiny of this new European data set.

9  Koren, Csillag and Köllo (2020) also find that the productivity of workers assigned to new machines rises and their wages increase but become more unequal.

10 Following Goos, Manning and Salomons (2014), occupations and sectors closely associated with public and agricultural activities are dropped. We also drop 3-digit ISCO occupations that are not precisely reported. These occupations are dropped from the final sample. This corresponds to 1.1% of total hours worked in the sample and this only affects six countries in the sample.

11 For instance, Chiacchio, Petropoulos and Pichler (2018) shows that robot penetration in the EU28 has tripled over this period and particularly between 1995–2007 relative to the years 2007–2015. A similar pattern can be observed for offshoring as measured by foreign direct investment and intermediates trade in the WTO and UNCTAD statistics.

12 We follow the definition of Lewandowski et al. (2017): $RTI_o = ln(\text{Routine Cognitive}_o + \text{Routine Manual}_o) - ln(\text{Non-Routine Analytical}_o + \text{Non-Routine Interpersonnal}_o)$. Throughout we standardize RTI to have a mean equal to zero and a standard deviation of one.

13 The measure used by Frey and Osbourne (2013) builds on the selection of solutions that engineers need to devise for specific occupations to be automated and it is given by the probability of computerization based on a Gaussian process classifier.

14 The index of Blinder (2009) is constructed in the same way, but it reports a qualitative ranking of occupations according to their degree of offshorability.

15 We obtain data from the Princeton Data Improvement Initiative (https://krueger.princeton.edu/pages/princeton-data-improvement-initiative-pdii). The matching procedure of occupations with our automatability and offshorability indices is detailed in Appendix A. Throughout we standardize the BK index to have a mean equal to zero and a standard deviation of one.

16 We aggregate our data at the cell level (country × sector × occupation × year) into occupation × year cells and for each occupation we compute the log change in

hours worked across the countries in our sample: $\Delta ln(Hours_o) = ln(Hours_o^{2010}) - ln(Hours_o^{1995})$.

17  The paper by Bonfiglioli, Crinò, Gancia, and Papadakis (2021) in this volume studies the effect of imported industrial robots on US local labor markets between 1990 and 2015, unveiling empirical patterns consistent with "reshoring" whereby imported robots substitute foreign workers more than US workers. Related to our Figure 4.1, after classifying occupations in terms of their "replaceability" (by robots) and "offshorability", they show in their Table 5 that the employment changes in non-replaceable occupations are uncorrelated with robot exposure regardless of offshorability. This holds also for replaceable occupations if they are also offshorable, whereas the correlation is negative if they are non-offshorable. It should be noted, however, that, while in a robustness check they measure "off-shorability" as we also do, our measure of "automatability" based on routine intensity as in Acemoglu and Autor (2011) is quite different from their measure of "replaceability" based on robot application categories as in Graetz and Michaels (2018). Moreover, "reshoring" seems to be less relevant in Europe than in the US (De Backer et al., 2016; Kinkel, Dewanti and Zimmermann, 2017; Vanchan, Mulhall and Bryson, 2018).

18  The results on educational mismatch may resonate with the implications of traditional models of SBTC, but there is a crucial difference. In those models the demand of workers with higher education rises and the demand of workers with lower education falls in occupations more exposed to technological change. Yet, typically this is not connected to the evolution of over/under education.

19  Matches are one-worker-one-job relationships, and therefore we do not consider the complementarities between workers within the same firm as in Eeckhout and Kircher (2018). While complementarities within the firms are certainly important, they are not immediately relevant for our purposes.

20  In the absence of search or information frictions all workers and firms would be matched to their optimal partner as in Becker (1973).

21  See Mortensen and Pissarides (1994). Our assumption departs from the non-linear matching function employed in models with two-sided heterogeneity à la Shimer and Smith (2000). In particular, our matching technology implies that congestion externalities arise for each task.

22  If the outside option were positive, workers would simply search for longer periods of time.

23  See Appendix B for detailed derivations.

24  While we do not dwell on the determination of $A$ and $\Omega$, it would be straightforward to explicitly endogenize them by specifying the costs of automation and offshoring. Most naturally, $A$ and $\Omega$ would be determined as decreasing functions of those costs. Compative statics results would then be stated with respect to the cost parameters driving the choice of $A$ and $\Omega$ rather than with respect to $A$ and $\Omega$. As this would not add much insight to the analysis, we prefer to keep the costs of automation and offshoring in the background and discuss the comparative statics with respect $A$ and $\Omega$.

25  See Appendix C for additional details.

26  To give some idea about the quantitative consistency of the calibrated model with the motivating evidence, consider deviations from point $A = 0.2$ and $\Omega = 0.2$ in the left panel of Figure 4.2 (i.e. black line). Increasing $A$ to 0.35 corresponds to an increase in concentration of 8% comparable to the estimated increase of 8% in response to a 1 standard deviation increase in automatability (RTI) reported in Table 4.2. Similarly, in the right panel of Figure 2 increasing $\Omega$ to 0.35 (with $A = 0.2$) translates to a 17% decrease in selectivity in the model which is comparable to the estimated 12% drop in *SSO* in response to a 1 standard

deviation increase in offshorability. Similarly, consider decreasing $A$ from 0.2 to 0.05, that is moving from the black to the dotted line in the right panel of Figure 4.2, while keeping $\Omega = 0.35$: selectivity decreases by roughly 30% relative to the case of $A = 0.2$ and $\Omega = 0.2$. This is comparable to empirically predicted drop in *SSO* by 27% when offshorability increases and automatability decreases by 1 standard deviation respectively. A similar exercise based on unemployment duration in Figure 4.3 reveals that the magnitude of the model's predictions roughly aligns with the estimated effects; mapping over- and under-education to a suitable model-analogue for interpretation is, however, difficult.

27  For instance, the left panel of Figure 4.5 clearly shows that, after denoting equilibrium employment by $E(A, \Omega)$, for $A' > A$ and $\Omega' > \Omega$ with $\Omega = 0.05$ and $\Omega' = 0.2$, we have $E(A', \Omega')/E(A', \Omega) > E(A, \Omega')/E(A, \Omega)$. This derives from the fact that $E(A, \Omega')$ is a flatter function of $A$ than $E(A, \Omega)$. While less visible, the same applies to the right panel.

28  For instance, the left panel of Figure 4.6 clearly shows that, after denoting the equilibrium wage ratio by $W(A, \Omega)$, for $A' > A$ and $\Omega' > \Omega$ with $\Omega = 0.05$ and $\Omega' = 0.2$, we have $W(A', \Omega')/W(A', \Omega) > W(A, \Omega')/W(A, \Omega)$. While less visible, the same applies to the right panel of Figure 4.6. In Figure 4.6 the wage of the best match is an order of magnitude larger than the wage of the worst match. While this gap between the two extremes of the wage distribution may look unrealistically large, comparing the 75% and 25% percentiles reveals that the wage in the former percentile is only about twice as large as that in the latter percentile.

29  These occupations respectively account for 0.12%, 0.27%, 0.53%, 0.39% and 0.07% observations in the sectors kept.

30  This index is inspired by Firpo, Fortin and Lemieux (2011)

31  Lewandowski et al. (2017) slightly modify the RTI definition compared to Autor and Dorn (2009) in order to adapt it to the use of ONET data instead of DOT data: $RTI = \ln(\text{Routine Cognitive} + \text{Routine Manual}) - \ln(\text{Non-Routine Analytical} + \text{Non-Routine Interpersonnal})$.

# 5 The Impacts of AI, Robots, and Globalization on Labor Markets

## Analysis of a Quantitative General Equilibrium Trade Model

*Taiji Furusawa, Shoki Kusaka, and Yoichi Sugita*

## 1 Introduction

A generally held view about the complementarity between labor and capital is that workers benefit from increased capital. However, the story can be very different when it comes to a special kind of capital, namely industrial robots, which the International Standard Organization (ISO) defines as 'an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications' (ISO 8373:2012). These industrial robots can perform tasks that factory workers would otherwise perform. Therefore, they may substitute for low-skilled, manual labor.

Technological progress has also occurred in areas that put high-skilled workers' cognitive jobs at risk. In particular, artificial intelligence (AI) continues to advance at an amazing pace. It complements and substitutes for various types of workers in the medical and pharmaceutical industries among others, and changes future perspectives in many industries. Brynjolfsson and McAfee (2011) and Baldwin (2019) argue that robot technology and AI advance at an explosive pace so that only those that can utilize such new technology benefit. Meanwhile, the majority of workers may be left behind with lower pay.

Globalization, defined here as declining costs of trade in goods and services, has contributed to the global spread of robots and AI. World trade in robots has been steadily increasing since approximately 2000, as shown in Figure 5.1, although it still occupies a tiny portion (0.13% in 2018) of the world trade in capital goods. A notable feature of the robot and AI industries is that a small number of countries hold significant shares in world production and exports. Figure 5.2 shows the dominance of Japan and Germany in robot exports in 2018. AI companies are also geographically concentrated in a few countries such as the US, China, the UK, Germany, France, and India (Samoili et al., 2020).

Using a quantitative general-equilibrium trade model, this chapter assesses the impacts of robot/AI technological progress and globalization on labor markets in the world economy. In our model, robots can perform low-skilled labor's tasks and AI high-skilled labor's tasks in the manner of the
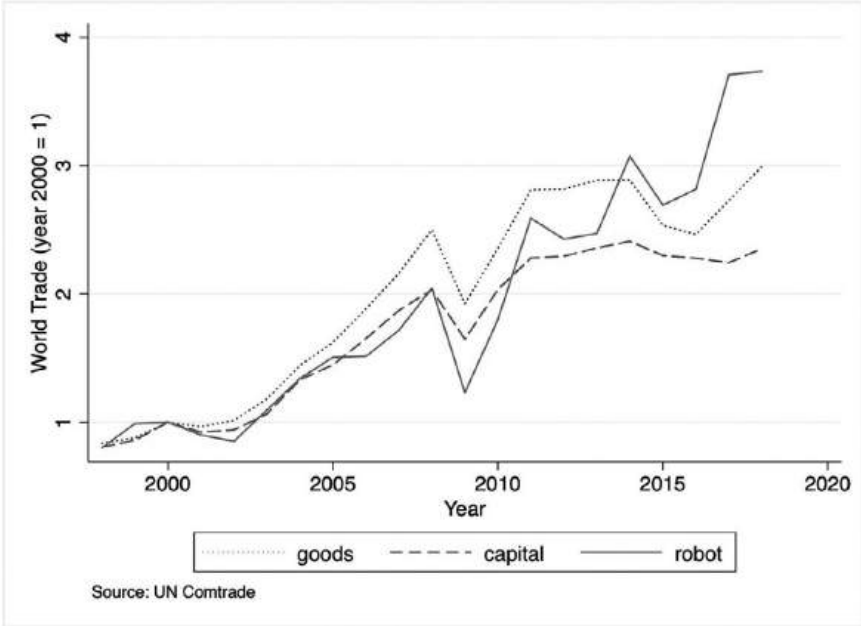
*Figure 5.1* World Trade in Goods, Capital, and Robots
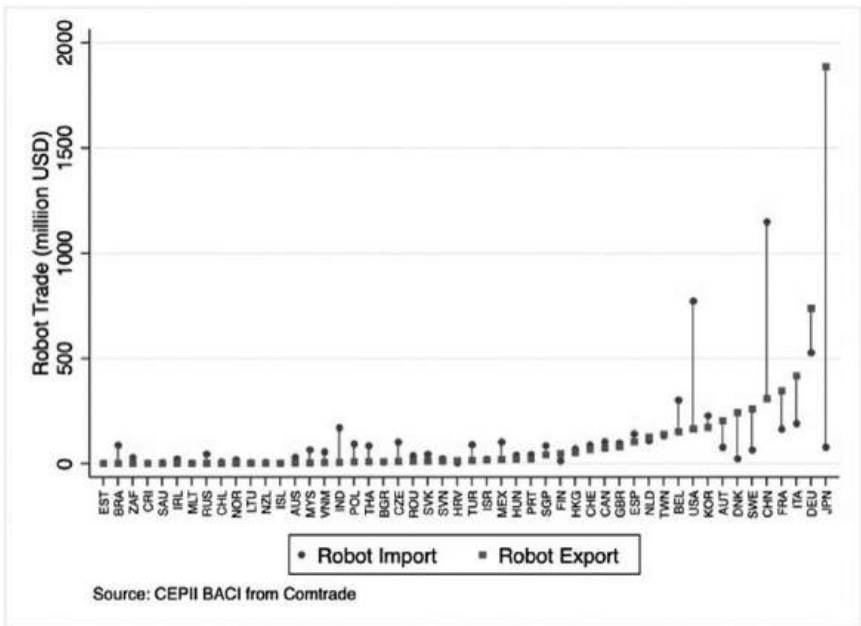


*Figure 5.2* Robot Exports and Imports Across Countries in 2018

task-based approach developed by Acemoglu and Autor (2011), Acemoglu and Restrepo (2018a; 2018b), and Grossman and Rossi-Hansberg (2008, 2012). Following Eaton and Kortum (2002), Caliendo and Parro (2015), Sugita et al. (2019), and Furusawa and Sugita (2020), we also incorporate the important feature of global value chains (GVCs) linking multiple industries in multiple countries. A task-based model with a GVC structure enables us to address a rich set of questions regarding globalization, technology adoption, and income inequality.

In Section 2, we set up a model with robots but not AI and evaluate the effects of past technological progress and globalization. Section 3 presents our unique dataset that includes five production factors: two labor skill groups, robot installation, input-output tables, and bilateral trade for 17 ISIC 2-digit industries and 50 countries. We develop a novel method to use the data and the model's structure, notably the gravity equation of robot trade, in estimating two critical parameters: robot income shares in low-skilled task production in each industry and each country and elasticities of substitution between robots and low-skilled labor in each industry. The robot income shares are sizable in some industries but are generally small at the country level. The elasticities of substitutions are around a moderate number of 2. In Section 4, we first simulate the world economy in 2014, where either robot-related technology or trade costs are assigned their 1993 levels. The effect of advances in robot technology on labor markets is much smaller than that of trade liberalization from 1993 to 2014 despite being sizable in the most affected industries. Our results suggest that the macroeconomic impact of past robot technological progress on labor markets in 2014 was limited. Then, we simulate a future world where the task-productivity of robots becomes ten times its 2014 level. The share of tasks that robots would perform would still be small in most countries as would the impact on the labor market.

Finally, in Section 5, we extend our baseline model with robots to incorporate the substitution of AI for high-skilled labor. With limited data on trade in AI services, we estimate elasticities of substitution between AI and high-skilled labor in 17 industries and conduct a counterfactual analysis on the impact of a tenfold increase in AI task-productivity on labor markets. These elasticities of substitution are smaller than the estimated elasticities of substitution between robots and low-skilled labor. As a consequence, we find that its impact on the labor market is smaller than that of robotics and that advances in AI technology would decrease wage inequality between high-skilled and low-skilled labor.

The effects of automation on the labor market have been studied extensively. Autor et al.(2003) and Autor and Dorn (2013) show that automation replaces workers performing routine tasks, contributing to employment and wage polarization. Industrial robots primarily displace low-skilled production workers in factories. Graetz and Michaels (2018) and Acemoglu and Restrepo (2020) find that robot adoption reduces low-skilled workers' employment share and lowers employment and wages across commuting zones in the US, respectively.

However, they find evidence that robots raise firms' productivity (Acemoglu, Lelarge, and Restrepo, 2020b), which could benefit all workers, including the adversely affected low-skilled workers, by reducing consumer prices. Recent studies on AI also report similar job-replacing and productivity-enhancing effects.[1]

Recent papers by Humlum (2019), Adachi (2021), and Artuc, Bastos, and Rijkers (2020) add new insights to the literature on the labor market impacts of robots in the world economy. Humlum (2019) constructs a dynamic general-equilibrium trade model that incorporates firms' choice of robot adoption and workers' choice of occupation and simulates the model with parameters estimated from Danish data to assess the impact of robot adoption on the Danish labor market. Adachi (2021) develops an open-economy model to analyze the impact of falling robot costs in Japan on the US labor market. He estimates elasticities of substitution between robots and labor across occupations and conducts a counterfactual analysis to assess the contribution of robots to wage polarization in the US. Like our model, Artuc et al. (2020) independently developed a quantitative Ricardian trade model with two-stage production that incorporates substitution of robots and labor. They analyze the effects of robotization in the North on trade patterns, wages, and welfare in the world.

Our analysis contributes to this new strand of the literature by enriching the model of the labor market and global trade structure to analyze the impact of globalization and the adoption of robots and AI on labor markets across the world. It is our contribution to estimate the robot shares of income at the country-industry-year level and use these estimates to estimate the elasticities of substitution between robots and low-skilled labor at the industry level. It is also worth conducting a rigorous model analysis with data and revealing the macroeconomic effect of robots and AI is small relative to the effect of globalization.

## 2 Model

We set up a model that is rich enough to quantify the effect of robotics and globalization on labor markets. The basic structure of our model is similar to those of Caliendo and Parro (2015), Sugita et al. (2019), and Furusawa and Sugita (2020). The fact that only a small number of countries export a large fraction of all robots traded in the world suggests that we need a multi-country model that incorporates differential industrial structures across countries. Building a model that allows differential industrial structures is also important because the use of robots (and AI) is heavily concentrated in some industries as we will see later. The model should also accommodate a GVC structure because its development is a prominent feature of globalization since the 1990s.

### 2.1 Basic Settings

$N$ countries, indexed by $i$, $n \in \{1,..., N\}$, produce $S$ goods and services, indexed by $s$, $k \in \{1,..., S\}$, for infinite time periods, indexed by $t \in \{0,..., \infty\}$. The

industry $S$ represents the robot-producing industry. The model incorporates five factors of production: specific factor ($G$) only in the agriculture and mining industries, low-skilled labor ($L$), high-skilled labor ($H$), non-robot capital ($K$), and robots ($R$). Industry-specific factors and labor are supplied inelastically. Consumers invest and accumulate non-robot capital and robots. Goods are tradable across countries but services and factors are not. Robots and non-robot capital are tradable across countries only at the time of their investment. Once they are installed as capital goods, consumers can only lend them to domestic firms. All goods and factors are traded in perfectly competitive markets.

Each non-robot industry $s \in \{1, .., S-1\}$ produces two types of goods with different usages: final usage and intermediate usage. Final goods, denoted by $f$, are used only as final consumption and investment, whereas intermediate goods, denoted by $m$, are used only as inputs for production. Consumers do not consume robots. Goods of each usage $u \in \{f, m\}$ in industry $s$ consist of a continuum of varieties $\omega^{su} \in [0, 1]$.

Country $n$'s representative consumer has a two-tier utility function with a Cobb-Douglas upper tier and a constant-elasticity-of-substitution (CES) lower tier:

$$U_n = \sum_{t=0}^{\infty} \beta^t \ln Q_{nt}^f, \ \ Q_{nt}^f \equiv \prod_{s=1}^{S-1} (Q_{nt}^{sf})^{\alpha_{nt}^s},$$

$$Q_{nt}^{sf} \equiv \left[ \int_0^1 q_{nt}^{sf}(\omega^{sf})^{\frac{\sigma^{sf}-1}{\sigma^{sf}}} d\omega^{sf} \right]^{\frac{\sigma^{sf}}{\sigma^{sf}-1}}, \tag{1}$$

where $\beta \in (0, 1)$ is the time discount factor, $Q_{nt}^f$ the aggregate final consumption, $Q_{nt}^{sf}$ the industry-level consumption and $\sum_{s=1}^{S-1} \alpha_{nt}^s = 1$. We let $\omega^{sf}$ denote a variety of final good $s$, $q_{nt}^{sf}(\omega^{sf})$ country $n$'s consumption of $\omega^{sf}$ at time $t$, and $\sigma^{sf} > 0$ the elasticity of substitution between varieties of final good $s$.

A firm in industry $s \in \{1,..., S\}$ in country $n$ produces $\Upsilon_{nt}$ units of variety $\omega^{su}$ of usage $u$ with the Cobb-Douglas production function:

$$\Upsilon_{nt} = A_{nt}^s Z_{sn}(\omega^{su}) G_{nst}^{\beta_{Gnt}^s} K_{nst}^{\beta_{Knt}^s} H_{nst}^{\beta_{Hnt}^s} T_{nst}^{\beta_{Tnt}^s} \prod_{k=1}^{S} (M_{nt}^{sk})^{\beta_{nt}^{sk}},$$

$$M_{nt}^{sk} \equiv \left[ \int_0^1 m_{nt}^{sk}(\omega^{km})^{\frac{\sigma^{km}-1}{\sigma^{km}}} d\omega^{km} \right]^{\frac{\sigma^{km}}{\sigma^{km}-1}}, \tag{2}$$

where $\sum_v \beta_{vnt}^s + \sum_{k=1}^S \beta_{nt}^{sk} = 1$, $A_{nt}^s$ is the country-industry specific component of the total factor productivity (TFP), $Z_{sn}(\omega^{su})$ the idiosyncratic component, and $\{G_{nst}, K_{nst}, H_{nst}\}$ the inputs of industry-specific factor, non-robot capital and high-skilled labor, respectively. Factor $T_{nst}$ is a composite input of tasks that

either low-skilled labor or robots may perform, which we explain in detail in Section 2.2. $M_{nt}^{sk}$ is a CES composite of intermediate good $k$ where $m_{nt}^{sk}(\omega^{km})$ is the input of variety $\omega^{km}$ and $\sigma^{km} > 0$ the elasticity of substitution. The idiosyncratic productivity $Z_{sn}(\omega^{su})$ varies across varieties, independently following the Fréchet distribution $F^s(z) = \exp(-z^{-\theta^s})$ with industry-specific parameter $\theta^s$.

Consumers and firms in country $n$ purchase each variety $\omega^{su}$ with the lowest price that is given by $p_{nt}(\omega^{su}) \equiv \min_{i=1}^{N} p_{nit}(\omega^{su})$, where $p_{nit}(\omega^{su})$ is the unit cost of supply from country $i$ to country $n$. There exits trade costs $d_{nit}^{su}$ such that $p_{nit}(\omega^{su}) \equiv d_{nit}^{su} p_{iit}(\omega^{su})$. Trade costs consist of ad valorem tariffs $\tau_{nit}^s$ and iceberg non-tariff barriers $D_{nit}^{su}$ such that $d_{nit}^{su} = (1 + \tau_{nit}^s) D_{nit}^{su}$. Trade costs are assumed to satisfy the triangle inequality $d_{njt}^{su} d_{jit}^{su} \geq d_{nit}^{su}$. Trade costs may differ between final usage and intermediate usage within industries.

## 2.2 Robot and Labor Substitution in Low-Skilled Task Production

We model the substitution of robots for low-skilled labor, following the task-based approach of Acemoglu and Restrepo (2018b; 2020). The task-based model can address that robots substitute labor for particular tasks, while simultaneously complementing workers for other tasks. The input of low-skilled tasks for the production of good $s$, $T_{ist}$, in (2) is given by the Cobb-Douglas composite of a continuum of tasks $v \in [0, 1]$:

$$T_{nst} = \exp\left(\int_0^1 \ln T_{nst}(v)dv\right), \quad T_{nst}(v) \equiv \gamma_{st}(v)R_{nst}(v) + L_{nst}(v), \qquad (3)$$

where $T_{nst}(v)$ is the amount of task $v$ performed by either low-skilled labor or robots and $\gamma_{st}(v)$ represents the task-productivity of robots. Low-skilled labor and robots are perfect substitutes. Tasks are ordered by the comparative advantage of robots so that $\gamma_{st}'(v) < 0$ holds.

For a given low-skilled wage rate $w_{Lnt}$ and robot rental rate $w_{Rnt}$, there exists a threshold task $v_{nst}$ defined by $w_{Rnt}/\gamma_{st}(v_{nst}) = w_{Lnt}$. Robots perform tasks $v \leq v_{nst}$, while low-skilled workers perform $v > v_{nst}$. The threshold $v_{nst}$ can be expressed as a function of the relative factor prices:

$$v_{nst} = v_{st}\left(\frac{w_{Rnt}}{w_{Lnt}}\right) \equiv \gamma_{st}^{-1}\left(\frac{w_{Rnt}}{w_{Lnt}}\right), \qquad (4)$$

where $\gamma_{st}^{-1}$ is the inverse function of $\gamma_{st}$, so that $v_{st}$ is a decreasing function. From the optimal assignment of each task, the task composite (3) becomes

$$T_{nst} = \Gamma_{st}(v_{nst})\left(\frac{R_{nst}}{v_{nst}}\right)^{v_{nst}}\left(\frac{L_{nst}}{1 - v_{nst}}\right)^{1 - v_{nst}}, \qquad (5)$$

where $\Gamma_{st}(x) \equiv \exp\left(\int_0^x \ln\gamma_{st}(v)dv\right)$ captures the productivity advantage of robots over low-skilled labor.

The function $v_{st}$ in (4) is the key function that determines the impact of robots on low-skilled labor's income. As seen in (5), the equilibrium value $v_{nst}$ of function $v_{st}$ determines the income shares of robots and low-skilled labor. In industry $s$ in country $n$ at time $t$, low-skilled workers receive the share $\beta^s_{Tnt}(1 - v_{nst})$ of the industry's revenue, while robots receive the share $\beta^s_{Tnt}v_{nst}$. We will estimate $v_{st}$ in (4) from data.

## 2.3 Robot and Capital Accumulation

A representative consumer invests and accumulates robot capital and non-robot capital, lending them to local firms in their country. The robot stock $R_{nt}$ and the non-robot capital stock $K_{nt}$ in country $n$ are accumulated as follows:

$$R_{nt+1} = I^R_{nt} + (1 - \delta_R)R_{nt} \text{ and } K_{nt+1} = I^K_{nt} + (1 - \delta_K)K_{nt}, \tag{6}$$

where $I^R_{nt}$ and $I^K_{nt}$ are investment in robot and non-robot capital, respectively, and $\delta_R$ and $\delta_K$ are the depreciation rates. For simplicity, the investment technology of non-robot capital is given by the same CES aggregator as the consumption aggregator $Q^f_{nt}$ expressed by (1). Investment in robots is also expressed as a CES aggregate of varieties of robots, $I^R_{nt} \equiv \left[\int_0^1 I^R_{nt}(\omega_R)^{\frac{\sigma_R-1}{\sigma_R}} d\omega_R\right]^{\frac{\sigma_R}{\sigma_R-1}}$, where $\sigma_R > 0$ is the elasticity of substitution and $I^R_{it}(\omega_R)$ is the robot investment of variety $\omega_R$.

A representative consumer's maximization problem can be expressed in two steps. Let $w_{Knt}$ denote the rental rate of non-robot capita. Let $P_{nt}$ and $P^R_{nt}$ be the price index of consumption/capital investment and robot investment, respectively. The upper-tier problem is to choose the aggregate consumption $Q_{nt}$ and investment $(I^R_{nt}, I^K_{nt})$:

$$\max_{\{Q_{nt}, I^K_{nt}, I^R_{nt}\}} \sum_{t=0}^{\infty} \beta^t_n \ln Q_{nt}$$

$$\text{s.t. } P_{nt}(Q_{nt} + I^K_{nt}) + P^R_{nt}I^R_{nt} = w_{Knt}K_{nt} + w_{Rnt}R_{nt} + E_{nt} \text{ and (6)},$$

where $K_{n0}$ and $R_{n0}$ are given, and $E_{nt}$ represents income from other sources including labor income, distributed trade balance, and tariff revenue. We assume that the economy is in a steady state, where $K_{nt} = K_n$, $R_{nt} = R_n$, $Q_{nt} = Q_n$, $I^K_{nt} = \delta_K K_n$, and $I^R_{nt} = \delta_R R_n$. Then, the Euler equation gives us the following expressions for the rental rates of capital:

$$w_{Rnt} = P^R_{nt}(r_n + \delta_R) \text{ and } w_{Knt} = P_{nt}(r_n + \delta_K), \tag{7}$$

where $r_n \equiv (1-\beta_n)/\beta_n$ is the real interest rate.

In the second-tier problem, the consumer chooses demands for individual varieties of goods, taking $\{Q^s_{nt}, I^K_{nt}, I^K_{Rt}\}$ as given. It follows from Eaton and Kortum (2002) that the trade share of country $i$'s products of usage $u$ in industry

*s* in country *n* is given by

$$\pi_{nit}^{su} = \frac{\left(A_{it}^{s}\right)^{\theta_s}\left(c_{it}^{s}d_{nit}^{su}\right)^{-\theta^s}}{\left(P_{nt}^{su}/\gamma^{su}\right)^{-\theta^s}},\tag{8}$$

where $\gamma^{su}$ is a constant, $c_{it}^{s}$ is the value of the Cobb-Douglas function of factor prices and intermediate good price indexes (shown in (17) in the Appendix), and $P_{nt}^{su}$ is the price index for goods of usage $u$ in industry $s$ in country $i$ satisfying

$$\left(\frac{P_{nt}^{su}}{\gamma^{su}}\right)^{-\theta^s} = \sum_{i=1}^{N}\left(A_{it}^{s}\right)^{\theta_s}\left(c_{it}^{s}d_{nit}^{su}\right)^{-\theta^s}.\tag{9}$$

The trade share equation (8) relates trade flows to prices in importing countries and leads to the gravity equation. We exploit this relationship to estimate robot prices from robot trade data.

## 2.4 Equilibrium Conditions for Counterfactual Analyses

Following Dekle et al. (2008) and Caliendo and Parro (2015), we consider a system of equilibrium conditions for changes in variables. We denote the counterfactual change in variable $x$ by $\hat{x}_t \equiv x_t'/x_t$, where $x_t$ is the value of variable $x$ in equilibrium at time $t$ while $x_t'$ is its value in equilibrium of the counterfactual economy. We relegate to the Appendix the description of the system of equilibrium

*Table 5.1* Countries in Our Dataset

| | | |
|---|---|---|
| Argentina | Hong Kong | Korea |
| Australia | Hungary | Romania |
| Austria | India | Russian Federation |
| Belgium | Indonesia | Singapore |
| Brazil | Ireland | Slovakia |
| Bulgaria | Israel | Slovenia |
| Canada | Italy | South Africa |
| Chile | Japan | Spain |
| China | Latvia | Sweden |
| Croatia | Lithuania | Switzerland |
| Czech Republic | Mexico | Taiwan |
| Denmark | Netherlands | Thailand |
| Estonia | New Zealand | Turkey |
| Finland | Norway | United Kingdom |
| France | Philippines | United States |
| Germany | Poland | Vietnam |
| Greece | Portugal | Rest of the world |

conditions and relegate the conditions for changes in variables and our numerical-solution algorithm to the Online Appendix available on the authors' web pages.

# 3 Data and Estimation

## 3.1 Data

We construct a unique dataset for our quantitative general equilibrium analysis. The dataset includes information about bilateral trade in goods and robots, input-output tables, country-industry-year-level output and input allocations, and country-year-level factor prices for: 50 countries and the rest of the world (Table 5.1); 13 good industries and four service industries, which closely follow the 2-digit ISIC (International Standard Industrial Classification) codes; five production factors; and four years (2004, 2007, 2011, 2014).

This section explains the data on robots and labor skill groups. The data sources for other variables are conventional in the literature: the Global Trade Analysis Project (GTAP) database version 10, the Penn World Table, and the International Labour Organization (ILO) stat database. Details on the data construction are relegated to the Online Appendix.

**Robot Stocks, Robot trade, and Robot Prices:** the International Federation of Robotics (IFR) database reports the physical quantity of newly installed industrial robots for 71 countries and 18 industries since 1993. The IFR follows the ISO 8373 definition of robotics, mentioned in the Introduction, and has been used in the literature, e.g., Graetz and Michaels (2018) and Acemoglu and Restrepo (2020). Following the procedure in Graetz and Michaels (2018), we construct robot stocks using the perpetual inventory method with the depreciation rate $\delta_R = 0.1$. We collect bilateral trade in industrial robots from the UN Comtrade database, which contains the category of the 6-digit harmonized system code 847950, "industrial robots for multiple uses". We construct time-series data on the price for robots in Japan, unit robot price in Japan in 2014 calculated from the IFR data, and the time-series robot price indices with the benchmark of the 2015 price collected from the Bank of Japan (BoJ) Corporate Goods Price Index database. The BoJ monthly surveys prices of industrial robots and reports quality-adjusted price indices since 1990, which to our knowledge is the only data on quality-adjusted robot prices in our sample period.

**Labor Skill Groups:** following Weingarden and Tsigas (2010), we aggregate 10 occupations in the International Standard Classification of Occupations (ISCO-08) from the ILO database into two skill categories. The high-skill group includes: (1) Managers, (2) Professionals, and (3) Technicians and Associate Professionals. The low-skill group includes: (4) Clerical Support Worker, (5) Service and Sales Workers, (6) Skilled Agricultural, Forestry, and Fishery Workers, (7) Craft and Related Trades Workers, (8) Plant and Machine Operators and Assemblers, and (9) Elementary Occupations. We removed the category "Armed Forces Occupations" from the data.

## 3.2 Parameter Estimation

**Cobb-Douglas Parameters:** we calibrate the Cobb-Douglas parameters of utility and production functions $\{\alpha_{snt}, \beta_{snt}\}$ from expenditure shares calculated from the data.

**Trade Elasticities** We estimate Fréchet parameters $\theta^s$, also called trade elasticities, by exploiting variations of bilateral tariffs in the gravity model, in the spirit of Caliendo and Parro (2015). Trade costs $d_{nit}^{su}$ are modeled as $\ln d_{nit}^{su} = \ln\left(1 + \tau_{nit}^s\right) + \sum_k TC_{ni,k}\delta_{kt}^{su} + \tilde{\varepsilon}_{nit}^{su}$, where $\tau_{nit}^s$ is the bilateral tariff rate, $\tilde{\varepsilon}_{nit}^{su}$ the idiosyncratic trade costs, and $TC_{ni,\,k}$ the $k$-th variable of the country-pair characteristics commonly used in the gravity analysis.[2] Substituting $\ln d_{nit}^{su}$ into (8) yields the following gravity model with fixed effects:

$$
\ln \pi_{nit}^{su} = \beta^s \ln\left(1 + \tau_{nit}^s\right) + \sum_t \sum_k TC_{ni,k}\left(\beta_{kt}^f + I_{\{u=m\}}\beta_{kt}^m\right)I_{\{year=t\}}
$$
$$
+ ex_{it}^s + im_{nt}^{su} + \varepsilon_{nit}^{su}, \tag{10}
$$

where $I_{\{year\,=\,t\}}$ and $I_{\{u\,=\,m\}}$ are year dummies and intermediate goods dummies, respectively, $ex_{it}^s$ the exporter-time fixed effect, and $im_{it}^{su}$ the importer-time-usage fixed effect.

We estimate (10) by OLS for each tradable-good industry (IFR industry from 1 to 13) separately, pooling all four periods (2004, 2007, 2011, 2014) and excluding observations without tariff information.[3] Table 5.2 reports the estimated elasticities $\theta^s = -\beta^s$ with standard errors clustered at the exporter-importer-year level. The estimates have small standard errors and are generally higher (but within a comparable range) than those in other studies (e.g., Caliendo and Parro (2015)).[4] For non-tradable service industries, we choose the median estimate of 10.582 as their $\theta^s$, because our approach (as in other similar approaches) cannot be applied to non-tradable industries.

*Table 5.2* Estimated Trade Elasticities

| IFR | Description | θ | SE | n.obs |
|-----|-------------|------|------|-------|
| 1 | Agriculture, forestry, and fishing | 4.456 | (1.341) | 15,940 |
| 2 | Mining and quarrying | 18.685 | (5.029) | 15,890 |
| 3 | Food and beverages | 8.429 | (0.759) | 15,952 |
| 4 | Textiles | 6.799 | (0.721) | 15,960 |
| 5 | Wood and furniture | 11.535 | (1.663) | 15,950 |
| 6 | Paper | 17.533 | (1.743) | 15,948 |
| 7 | Plastic and chemical products | 11.142 | (1.087) | 15,962 |
| 8 | Glass, ceramics, stone, and mineral products | 8.913 | (1.172) | 15,958 |
| 9 | Metal | 14.522 | (1.459) | 15,962 |
| 10 | Electrical, electronics, and machinery | 11.228 | (1.212) | 15,962 |
| 11 | Automotive | 10.582 | (0.883) | 15,950 |
| 12 | Other vehicles | 9.198 | (1.621) | 15,934 |
| 13 | All other manufacturing branches | 6.545 | (1.017) | 15,950 |

Notes: Standard errors (SE) are clustered at the exporter-importer-year level. All estimates are statistically significant at 1% level.
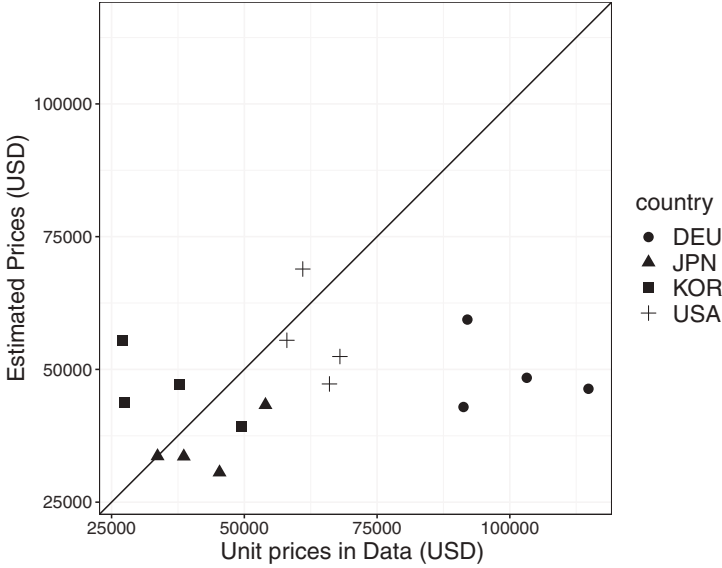
*Figure 5.3* Estimated and Actual Robot Prices

**Robot Prices and Production:** we estimate the prices and production of robots from the gravity equation of trade in industrial robots. Let $X_{nt}^R \equiv X_{nnt}^R + \sum_{i \neq n} X_{nit}^R$ be country $n$'s total expenditure (i.e., investment) on robots. The trade share equation (8) implies the following gravity equation of robot trade:

$$\ln X_{nit}^R = \ln X_{nt}^R + \theta^R \ln P_{nt}^R + \theta^R \ln \left( A_{it}^R / c_{it}^R \right) - \theta^R \ln d_{nit}^R. \tag{11}$$

Modeling trade costs of robots as $\ln d_{nit}^R = \sum_k TC_{ni,k} \delta_{kt} + \tilde{\varepsilon}_{nit}$ as in (10), we estimate the gravity equation with fixed effects:

$$\ln X_{nit}^R = \zeta_{nt}^M + \zeta_{it}^E + \sum_k TC_{ni,k} \beta_{kt} + u_{nit}, \tag{12}$$

where $\zeta_{nt}^M$ is the importer-time fixed effect and $\zeta_{it}^E$ the exporter-time fixed effect.

We estimate (12) by the Poisson pseudo maximum likelihood (PPML), including the observations with zero trade. Choosing Japan as a benchmark country, we drop the constant term and the importer-year dummy $\zeta_{bt}^M$ for the country $b = JAPAN$ for each year.[5] We see from (11) that the estimated coefficient of the importer-time dummy $\tilde{\zeta}_{nt}^M$ equals $\tilde{\zeta}_{nt}^M = \ln X_{nt}^R + \theta^R \ln P_{nt}^R - \left( \ln X_{bt}^R + \theta^R \ln P_{bt}^R \right)$.[6] Rearranging this equation yields the price index of robots in country $n$ relative to the benchmark country $b$:

$$\frac{P_{nt}^R}{P_{bt}^R} = \exp \left[ \frac{1}{\theta^R} \left( \tilde{\zeta}_{nt}^M - \ln \frac{\sum_{i \neq n} X_{nit}^R + X_{nnt}^R}{\sum_{i \neq b} X_{bit}^R + X_{bbt}^R} \right) \right]. \tag{13}$$

*Table 5.3* Robot Income Shares in Low-Skilled Tasks in 2014

| | Industry-Level Shares | | | Aggregate Share |
| Country | Median | Min | Max | |
| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| China | 0.01% | 0.00% | 0.89% | 0.04% |
| Germany | 0.09% | 0.00% | 3.26% | 0.21% |
| India | 0.00% | 0.00% | 1.40% | 0.02% |
| Indonesia | 0.00% | 0.00% | 0.33% | 0.02% |
| Japan | 0.17% | 0.00% | 2.78% | 0.29% |
| Korea | 0.04% | 0.00% | 3.43% | 0.31% |
| Singapore | 0.19% | 0.00% | 5.20% | 0.30% |
| Thailand | 0.02% | 0.00% | 5.21% | 0.24% |
| United States | 0.01% | 0.00% | 1.13% | 0.03% |

We obtain robot prices and robot rental rates from (13). As an estimate of $\theta^R$, we use the estimated trade elasticity in the IFR industry 10 "Electrical, electronics, and machinery" that includes industrial robots. We calculate domestic trade by $X_{nnt}^R = \exp\left[\tilde{\zeta}_{nt}^E + \tilde{\zeta}_{nt}^M - \theta^R \ln d_{nnt}^R\right]$ for each country $n$ where we estimate domestic trade costs $\theta^R \ln d_{nnt}^R$ by the gravity equation (12) for the IFR industry 10 using the domestic trade data.

Using the robot price in Japan $P_{bt}^R$, we can now calculate robot price $P_{nt}^R$ for each country from (13). Figure 5.3 compares the estimated robot prices with the unit prices in the IFR database in the four countries, Germany, Japan, Korea, and the USA. The estimated robot prices are reasonably close to the actual ones, except in Germany.[7] Finally, we calculate the robot rental rate $w_{Rnt}$ from (7), where we collect the real interest rate $r_{nt}$ from the World Development Indicators and choose a depreciation rate of $\delta^R = 0.1$, following Graetz and Michaels (2018).

**Robot Income Shares:** based on the robot-stock data and estimates of the robot rental rates, we calculate the robot income share in the income from low-skilled tasks, $\nu_{nst} = w_{Rnt} R_{nt}^s / \left(w_{Rnt} R_{ns}^s + w_{Lnt} L_{nt}^s\right)$ and report it for selected countries in 2014 in Table 5.3.[8] Columns (1), (2), and (3) report the median, minimum, and maximum shares. Column (4) reports the aggregate robot income share, defined by $\nu_{nt} \equiv \sum_s w_{Rnt} R_{nt}^s / \sum_s \left(w_{Rnt} R_{nt}^s + w_{Lnt} L_{nt}^s\right)$. Table 5.3 illustrates that the income shares of industrial robots in low-skilled tasks are very small in most industries across all countries.[9]

## 3.3 Elasticities of Substitution between Robots and Low-Skilled Labor

We assume that the function $\nu_{st}$ in (4) takes the following logistic function:

$$\nu_{nst} = \nu_{st}\left(\frac{w_{Rnt}}{w_{Lnt}}\right) = \frac{\exp\left(\iota_{st} - (\sigma_s - 1)\ln\frac{w_{Rnt}}{w_{Lnt}} + \epsilon_{nst}\right)}{1 + \exp\left(\iota_{st} - (\sigma_s - 1)\ln\frac{w_{Rnt}}{w_{Lnt}} + \epsilon_{nst}\right)}, \tag{14}$$

*Table 5.4* Elasticities of Substitution Between Robots and Low-Skilled labor

| IFR | Description | $\sigma_s$ | Robust SE | 1st Stage F | n.obs |
|---|---|---|---|---|---|
| 1 | Agriculture, forestry, and fishing | 2.028 | (0.209) | 20.1 | 118 |
| 2 | Mining and quarrying | 1.435 | (0.360) | 15.4 | 82 |
| 3 | Food and beverages | 2.158 | (0.173) | 23.5 | 182 |
| 4 | Textiles | 2.879 | (0.238) | 14.9 | 120 |
| 5 | Wood and furniture | 2.927 | (0.316) | 21.5 | 140 |
| 6 | Paper | 1.947 | (0.200) | 17.9 | 133 |
| 7 | Plastic and chemical products | 1.775 | (0.177) | 25.2 | 189 |
| 8 | Glass, ceramics, stone, and mineral products | 1.995 | (0.171) | 24.5 | 170 |
| 9 | Metal | 2.181 | (0.179) | 25.0 | 189 |
| 10 | Electrical, electronics, and machinery | 2.065 | (0.215) | 20.8 | 176 |
| 11 | Automotive | 1.826 | (0.203) | 21.2 | 175 |
| 12 | Other vehicles | 1.793 | (0.173) | 28.8 | 170 |
| 13 | All other manufacturing branches | 1.906 | (0.173) | 22.8 | 178 |
| 14 | All other non-manufacturing branches | 1.221 | (0.209) | 24.8 | 132 |
| 15 | Electricity, gas, and water supply | 1.724 | (0.152) | 22.0 | 99 |
| 16 | Construction | 1.070 | (0.195) | 26.9 | 145 |
| 17 | Education, research, and development | 1.757 | (0.202) | 20.8 | 175 |

Notes: Standard errors are heteroscedasticity robust standard errors. The first stage F-values differ across industries because of the difference in the sample sizes.

where $\iota_{st}$ and $\epsilon_{nst}$ capture the sector-year specific determinants and the unobserved determinants of the robot demands other than the relative rental rate of robots, respectively.[10] Given that the task production function (5) implies $v_{nst} = w_{Rnt}R_{nt}^s/(w_{Lnt}L_{nt}^s + w_{Rnt}R_{nt}^s) = (w_{Rnt}R_{nt}^s/w_{Lnt}L_{nt}^s)/[1 + (w_{Rnt}R_{nt}^s/w_{Lnt}L_{nt}^s)]$, formulating $v_{st}$ by (14) is equivalent to formulating the relative demand function for robots to be log-linear:

$$\ln \frac{R_{nt}^s}{L_{nt}^s} = \iota_{st} - \sigma_s \ln \frac{w_{Rnt}}{w_{Lnt}} + \epsilon_{nst}, \tag{15}$$

where $\sigma_s$ is the elasticity of substitution between robots and low-skilled labor. It follows from (14) that $\sigma_s > 1$ must hold for $v_{st}$ to be a decreasing function.

Since $\epsilon_{nst}$ may be correlated with $w_{Rnt}$, we use an instrument (IV) for $w_{Rnt}$ that shifts only the supply function. As such an IV, we use country $n$'s geographical access to robot exporters defined by $\zeta_{nt} \equiv \sum_{i \neq n} \left(A_{it}^R\right)^{\theta^R} \left(c_{it}^R d_{nit}^R\right)^{-\theta^R}$ and calculate $\tilde{\zeta}_{nt} = \sum_{i \neq n} X_{nit}^R / X_{nt}^R \left(P_{nt}^R\right)^{\theta^R}$ from the estimated robot gravity equation (12). Since the robot price satisfies $\left(P_{nt}^R/\gamma^R\right)^{-\theta^R} = \zeta_{nt} + \left(A_{it}^R\right)^{\theta^R} \left(c_{nt}^R d_{nnt}^R\right)^{-\theta^R}$ as shown in (9), it is clear that the IV $\zeta_{nt}$ utilizes the variation in the price of imported robots. Moreover, since the exporter-specific component $\left(A_{it}^R\right)^{\theta^R} \left(c_{it}^R\right)^{-\theta^R}$ of $\zeta_{nt}$ is common for all importers at time $t$, trade cost $d_{nit}^R$ is the main source of cross-sectional variation of $\zeta_{nt}$ across countries. The exclusion restriction is that

trade cost $d_{nit}^R$ is uncorrelated with $\epsilon_{nst}$, the unobserved determinants of the robot demand.[11]

We estimate (15) for each industry by the two-stage least squares with $\ln\left(\tilde{\zeta}_{nt}/w_{Lnt}\right)$ an IV for $\ln(w_{Rnt}/w_{Lnt})$. The equation (15) includes only the year fixed effect, but not country fixed effects because the variation of $d_{nit}^R$ in $\zeta_{nt}$ is mostly cross-sectional so that $\zeta_{nt}$ has little time-series variation. Table 5.4 reports estimates of $\sigma_s$ with the heteroscedasticity-robust standard errors. The standard errors are small and the first stage F-statistics are all greater than 10. Point estimates of $\sigma_s$ are greater than 1 in all industries.[12]

The elasticities of substitution in Table 5.4 can be compared with estimates in other studies. Adachi (2021) estimates elasticities of substitution between robots and labor within five occupation groups (production, transportation, other routines, services, abstract) in the US labor market. All of our estimates fall in the range of his estimates from 0.8 (abstract) to 4.29 (transportation). There are also studies that estimate the elasticities of substitution between capital and labor. Most of them report estimates that are smaller than 1 (e.g., Antras (2004)). Our estimates suggest that in many industries, robots and low-skilled labor are more substitutable than general capital and labor. This makes sense since robots generally can perform tasks more flexibly than other types of capital.

## 4 Counterfactual Analysis

We conduct counterfactual analyses to quantify the impact of past and future automation by robotics on the global economy. In Section 4.1, we simulate counterfactual world economies in 2014 where robot-related technology and costs of international trade are set at their levels in 1993. Whereas, in section 4.2, we simulate counterfactual world economies in 2014 where robot technology has advanced from its 2014 level.

### 4.1 The Impacts of Robotics and Globalization from 1993 to 2014

#### 4.1.1 Changes in Trade Costs and Robot Technology from 1993 to 2014

To analyze the effect of progress in robot technology and the reduction in trade cost separately, we consider two counterfactual scenarios: only the robot technology is set at the 1993 level (*Robot effect*), and only trade costs are set at the 1993 level (*Trade effect*).[13] As for the trade effect, we confine ourselves to examining the impact of a change in *international* trade costs relative to domestic trade costs.[14]

**Trade Effect** We estimate changes in trade costs between 1993 and 2014, following Novy (2013). Assuming that trade costs are bilaterally symmetric and common across usages (i.e., $d_{nit}^s \equiv d_{nit}^{sf} = d_{int}^{sf} = d_{nit}^{sm} = d_{int}^{sm}$) and that domestic trade costs remain the same (i.e., $d_{nn2004}^s = d_{nn1993}^s$), a change in trade costs

between 1993 and 2004 can be expressed from (8) as:

$$\hat{d}^s_{nit} = \frac{d^s_{ni1993}}{d^s_{ni2004}} = \left( \frac{X^s_{ii1993} X^s_{nn1993} X^s_{ni2004} X^s_{in2004}}{X^s_{ni1993} X^s_{in1993} X^s_{ii2004} X^s_{nn2004}} \right)^{1/(2\theta^s)}. \tag{16}$$

With the estimates of $\theta^s$ in Table 5.2, we estimate trade costs from the data on international and domestic trade: the CEPII TradeProd database (De Sousa, Mayer, and Zignago, 2012) and the International Trade and Production Database for Estimation (Borchert, Larch, Shikher, and Yotov, 2020).[15]

**Robot Effect** We calibrate the progress in robot-related technology from 1993 to 2014 by matching predicted values of two target variables in the model with the data. The first target is robot density, which is defined as the stock of industrial robots per 1000 workers. According to Graetz and Michaels (2018) and our own calculation from the IFR data, robot density in the world increased by 3.79-fold from 1993 to 2014. The second target is the price index of industrial robots in Japan, which declined from 100 in 1993 to 65.5 in 2014. The model predicts these changes, when the robot task-productivity and TFP for robot production were lower in 1993 than in 2014 by 35% and 31.5%, respectively, i.e., $\hat{\gamma}_{s2014}(v) = \lambda_{s2014} = 0.65$ and $\hat{A}^R_{n2014} = \hat{A}^R_{2014} = 0.685$. These counterfactual changes in robot technology are assumed to be common for all countries.

### 4.1.2 Results

This section reports the results of our counterfactual analyses about the effects on: (1) the relative price of robots to that of low-skilled labor and on robot density, (2) real wage rates for low-skilled and high-skilled workers, and (3) robot-worker replacement.

*Table 5.5* The Impact of Robotics and Globalization from 2014 back to 1993: Robot Price and Robot Density

| | Robot Rental/ Low-Skilled Wage | | Robot Density (per 1000 workers) | | |
|---|---|---|---|---|---|
| | Robot | Trade | 2014 | Robot | Trade |
| Country | (1) | (2) | (3) | (4) | (5) |
| China | +47.1% | +5.0% | 0.221 | -69.0% | -7.3% |
| Germany | +47.1% | +11.4% | 4.793 | -68.3% | -29.1% |
| India | +47.1% | +13.5% | 0.022 | -67.0% | -25.1% |
| Indonesia | +47.1% | -15.8% | 0.039 | -65.8% | +51.2% |
| Japan | +47.1% | +2.2% | 8.386 | -69.5% | -8.3% |
| Korea | +47.1% | +8.2% | 6.331 | -69.8% | -22.0% |
| Thailand | +47.1% | -21.0% | 0.521 | -66.3% | +10.7% |
| United States | +47.1% | -3.0% | 1.525 | -68.6% | +12.5% |
| World | +47.1% | +13.0% | 0.740 | -69.1% | +13.1% |

Notes: Robot density is the number of industrial robots per 1000 workers (including both high-skilled and low-skilled workers). The value of "robot rental/low-skilled wage" in the world is the mean value of the countries in the sample.

*Table 5.6* The Impact of Robotics and Globalization from 2014 back to 1993: Wages

| Country | Real Wage for Low-Skilled | | Real Wage for High-Skilled | | Skill Wage Premium | |
|---|---|---|---|---|---|---|
| | Robot | Trade | Robot | Trade | Robot | Trade |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| China | -0.01% | -4.96% | -0.03% | -5.37% | -0.02% | -0.43% |
| Germany | +0.03% | -5.89% | -0.07% | -5.00% | -0.10% | +0.95% |
| India | -0.00% | -6.37% | -0.01% | -2.37% | -0.01% | +4.28% |
| Indonesia | -0.01% | +0.64% | -0.02% | +0.64% | -0.01% | -0.00% |
| Japan | -0.01% | -2.14% | -0.11% | -1.50% | -0.10% | +0.66% |
| Korea | +0.00% | -4.59% | -0.16% | -4.88% | -0.17% | -0.30% |
| Thailand | +0.00% | +7.28% | -0.11% | +9.99% | -0.11% | +2.53% |
| United States | +0.00% | -0.47% | -0.02% | -0.74% | -0.02% | -0.27% |
| World | +0.01% | -4.15% | -0.04% | -2.92% | -0.04% | +1.16% |

Notes: The values for the World are the mean values of the countries in the sample.

Columns (1) and (2) in Table 5.5 show the effect of robot technology and trade on the relative price of robots to that of low-skilled labor, $w_{Rit}/w_{Lit}$, for selected countries. Column (1) shows that the relative price of robots in 2014 would have been about 47% higher if robot technology was at the 1993 level. Although not shown in the table, our analysis reveals that the change in relative price is almost entirely attributed to the increase in robot rental rate. Column (2) indicates that the impact of trade costs are smaller than those of robot technology and vary across the countries. In most countries, the relative price of robots would have been higher if trade costs were at their 1993 levels. This is partly because a decline in trade costs lowered robot prices from 1993–2014. It is also because trade liberalization benefited low-skilled workers in those countries.

The impact on robot density reflects these changes in the relative price of robots, as illustrated in columns (4) and (5). Robot density would have been 69.1% lower on average in the world if robot technology was at its 1993 level. The impact of robot technology is similar in magnitude across countries, while that of trade costs is heterogeneous. The impact of robot technology and trade is rather large in most countries. Yet, the macroeconomic impact of increases in robot density can still be small, especially in countries with a small robot density in 2014 (see column (3)).

Let us turn to our main counterfactual analysis of the effects on labor markets. Table 5.6 shows the effects of robot technology and trade on the real wage rate for low-skilled labor, $w_{Lit}/P_{it}^f$, the real wage rate for high-skilled labor, $w_{Hit}/P_{it}^f$, and the skill wage premium, $w_{Hit}/w_{Lit}$. Robot installation directly displaces low-skilled labor. This is why the real wage rate for low-skilled labor would have been higher in Germany and the world average if robot technology was set at the 1993 level, though the general price level would have been higher in that case. The real wage rates for low-skilled labor would have been lower in some other countries, albeit only to a small degree. This suggests that robot installation increases

*Table 5.7* The Impacts of Robotics and Globalization from 2014 back to 1993: Robot-Worker Replacement

| | | The most Robot Installing Industry | | |
| | | Robot | Change in Low-Skilled Labor | |
| Industry Name | | Change | Robot | Trade |
| Country | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| China | Automotive | -50,933 | 65,934 | 1,752,039 |
| Germany | Automotive | -85,275 | 11,362 | -149,281 |
| India | Automotive | -5,394 | 26,952 | -138,858 |
| Indonesia | Plastic and chemical products | -1,629 | 1,488 | 600,476 |
| Japan | Electrical, electronics, and machinery | -130,283 | 10,572 | -526,303 |
| Korea | Electrical, electronics, and machinery | -68,512 | 8,872 | -169,508 |
| Thailand | Automotive | -6,972 | 17,055 | -256,422 |
| United States | Automotive | -73,910 | 7,147 | 127,833 |
| World | Automotive | -488,763 | 213,092 | 504,859 |

Notes: The most robot-installing industry is an industry with the largest increase in robot stocks from the counterfactual equilibrium (where both robot and trade costs are set at their 1993 levels) to the 2014 equilibrium. The robot change is the change in the number of industrial robots in the most robot-installing industry. Columns (3) and (4) show the effects of changes in robot technology and trade costs on the number of low-skilled workers in the most robot-installing industry.

productivity, thereby benefiting all the workers regardless of their skill level. The effect of progress in robot technology on the real wage rate for high-skilled labor is positive in every country (as shown as negative numbers in Column (3)), reflecting the productivity effect and the complementarity between the low-skilled and high-skilled tasks. As a result, progress in robot technology increased the skill wage premium in every country in 1993–2014. This effect is relatively large in Japan and Korea, as the real wage rates for the high-skilled labor would have been much lower than in other countries if robot technology was at its 1993 level.

The effect of trade on real wage rates for both high-skilled and low-skilled labor is rather heterogeneous across countries, as shown in Columns (2) and (4). The effect of trade on the skill premium is also heterogeneous. The skill premium would have been lower in China, Korea, and the United States if trade costs were at their 1993 levels, which supports the argument that globalization entails wage inequality. But globalization appears to have mitigated wage inequality in other countries.[16]

The most notable result here, however, is that the impact of trade is generally much greater in size than robot technology. This is because robot shares are still small in 2014 (as shown in Table 5.3), so the impact on the labor market is limited.

Even though robotics has a minor impact on wages on the economy as a whole, it can have a substantial impact on some industries. Table 5.7 shows the industry that is estimated to have installed the largest number of robots

*Table 5.8* Tenfold Increases in Robot Productivity: Robot Usage

| | Robot Task Share ($v_{nst}$) in the most Robot Installing Industry | | | Country-Level Robot Density (per 1000 Workers) | |
| --- | --- | --- | --- | --- | --- |
| | IFR | 2014 | CF | 2014 | CF |
| Country | (1) | (2) | (3) | (4) | (5) |
| China | 10 | 0.001 | 0.012 | 0.22 | 2.03 |
| Germany | 11 | 0.033 | 0.186 | 4.79 | 45.53 |
| India | 11 | 0.014 | 0.087 | 0.02 | 0.16 |
| Indonesia | 7 | 0.003 | 0.015 | 0.04 | 0.26 |
| Japan | 10 | 0.010 | 0.111 | 8.39 | 90.93 |
| Korea | 10 | 0.018 | 0.181 | 6.33 | 64.43 |
| Thailand | 11 | 0.052 | 0.273 | 0.52 | 3.68 |
| United States | 11 | 0.011 | 0.072 | 1.52 | 13.46 |
| World | 10 | 0.002 | 0.021 | 0.74 | 7.31 |

Notes: The most robot-installing industry is an industry with the largest increase in robot stocks from 2014 to the counterfactual equilibrium. Their IFR industry codes are shown in column (1). The values for the World are the mean values of the countries in the sample.

from 1993 to 2014 for each country and the change in the number of low-skilled workers employed in such industries. The automotive industry, plastic and chemical industries, and electrical, electronics, and machinery industries are most affected. The number of low-skilled workers in China, India, and Thailand among others would have been substantially higher in these respective industries if robot technology was at its 1993 level. It is worth emphasizing that in the automotive industry, which is one of the industries that install a large number of robots, robot technology displaced 213,092 low-skilled workers worldwide, while trade liberalization displaced 504,859 workers according to our simulation. In the automotive industry, the labor-displacement effect of robotics is rather large, nearly half the volume of that of trade.

## 4.2 The Impacts of Future Robot Automation

From the counterfactual analysis described in the previous section, we have found, among others, that progress in robot technology made only a minor impact on labor markets as a whole in the period of 1993–2014. This can be simply because the advances in robot technology were still at an early stage in 2014. In this section, therefore, we make a bold assumption that the robot productivity will increase tenfold (i.e., $\lambda_t = \hat{A}_t^S = 10$), from the 2014 level and assess the implications of progress in robot technology of that scale on the labor market.

Table 5.8 shows the change in the share of tasks performed by robots in the most affected industry for each country and the change in the country's overall robot density from the 2014 economy to the counterfactual economy (CF). The worldwide robot task share in the electrical, electronics, and machinery industry would increase approximately tenfold from 0.002 to 0.021. It would

still be too small to make an impact on the macroeconomy, although the shares of the most affected industries would become rather sizable in some countries, such as Germany, Japan, and Thailand. The tenfold increase in robot technology would increase each country's robot share and robot density about tenfold, as columns (4) and (5) illustrate.

Such large changes in robot technology engender a much greater impact on the labor market than observed in the previous section's counterfactual analysis. Table 5.9 presents the aggregate labor market impact, showing the changes in the real wage rates for low-skilled and high-skilled labor and the skill premium. As robot technology advances, high-skilled workers would benefit in all countries. Low-skilled workers would also benefit in all countries in this list. The skill premium would increase in all countries in the list but India. The tenfold increase in robot technology would make sizable positive impacts on the real wage rate for high-skilled labor and hence increase the skill premium by non-negligible percentage points in countries such as Germany, Japan, and Korea. But, as a whole, even the tenfold increase in robot productivity would make only a moderate impact on the global labor market.

We also investigate to what degree low-skilled workers would be relocated as a result of the technological progress, which is reported in column (4). In some countries, such as Germany, Japan, and Korea, a sizable percentage of workers would be relocated.[17] But, we see that the impact of progress in robot technology on the labor market would still not be that large on average.

## 5 AI

This section extends our analysis of robots to AI. We assume here that AI can perform the high-skilled labor's tasks $H_{nst}$ and reformulate the production function (3) in the same manner as robots substitute for the low-skilled workers.

Unlike robots that are a special sort of capital, we treat AI as a service to which user firms subscribe. Thus, we directly calculate each country's expenditure on AI to derive the share of AI in high-skilled tasks. The difficulty, though, is that we do not have data on such expenditures, specifically on AI. AI trades are recorded in the GTAP database as part of trades in the communication sector, which includes postal services, motion pictures, and others.

To find an appropriate share of AI in the communication sector, we make a bold assumption that the world average share of AI in the most AI installing Industry, namely "All other non-manufacturing branches" (IFR industry 14), equals 0.002, the world average share of robots in the most robot-installing industry. Using the World Input-Output Database (WIOD) Release 2016, we calculate the trade shares of "computer programming, consultancy, and the related activities; information service activities" in those in the communication sector. When only 1.5% of those shares are related to AI, the world average share of AI in the most AI installing Industry equals 0.002.

We estimate the elasticities of substitution between AI and the high-skilled labor in 17 IFR industries, in the same manner as we have done with robots.

*Table 5.9* Tenfold Increases in Robot Productivity: Labor Market Impacts

| Country | Real Wage for Low-Skilled | Real Wage for High-Skilled | Skill Wage Premium | Aggregate Low-Skilled Labor Relocation |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| China | +0.55% | +0.90% | +0.35% | 0.32% |
| Germany | +0.60% | +2.04% | +1.44% | 0.94% |
| India | +0.17% | +0.07% | -0.10% | 0.19% |
| Indonesia | +0.30% | +0.47% | +0.17% | 0.30% |
| Japan | +2.12% | +3.30% | +1.16% | 1.01% |
| Korea | +1.74% | +4.41% | +2.62% | 1.38% |
| Thailand | +1.22% | +2.22% | +0.99% | 0.59% |
| United States | +0.19% | +0.47% | +0.28% | 0.20% |
| World | +0.39% | +0.99% | +0.60% | 0.54% |

Notes: The skill wage premium is the ratio of the high-skilled wage rate to low-skilled wage rate. The aggregate low-skilled labor relocation is calculated by $\sum_{s=1}^{S} L_{i2014}^{s\prime} - L_{i2014}^{s}/2L_{i2014}^{s}$ and shown as a percentage, where $L_{i2014}^{s}$ and $L_{i2014}^{s\prime}$ denote the actual and counterfactual numbers of low-skilled workers employed in industry $s$ in 2014, respectively. We divide the sum of changes in employment over the industries by 2 to avoid double counting. The values for the World are the mean values of the countries in the sample.

Table 5.10 shows the results. In every industry, the estimated elasticity is smaller than that of robots and low-skilled labor, suggesting that the high-skilled labor is less substitutable by AI than the low-skilled labor is by robots. Indeed, the estimated elasticities are smaller than 1 in ten industries. In the following simulations of the 2014 economy with enhanced AI productivities, we replace those

*Table 5.10* Elasticities of Substitution Between AI and High-Skilled Labor

| IFR | Description | $\sigma_{AL}$ | Robust SE | 1st Stage F | n.obs |
|---|---|---|---|---|---|
| 1 | Agriculture, forestry, and fishing | 0.958 | (0.087) | 162.61 | 204 |
| 2 | Mining and quarrying | 1.113 | (0.093) | 162.61 | 204 |
| 3 | Food and beverages | 1.026 | (0.071) | 162.61 | 204 |
| 4 | Textiles | 0.936 | (0.077) | 162.61 | 204 |
| 5 | Wood and furniture | 0.873 | (0.078) | 162.61 | 204 |
| 6 | Paper | 1.033 | (0.076) | 162.61 | 204 |
| 7 | Plastic and chemical products | 1.045 | (0.076) | 162.61 | 204 |
| 8 | Glass, ceramics, stone, and mineral products | 0.824 | (0.073) | 162.61 | 204 |
| 9 | Metal | 0.710 | (0.071) | 162.61 | 204 |
| 10 | Electrical, electronics, and machinery | 0.727 | (0.076) | 162.61 | 204 |
| 11 | Automotive | 0.506 | (0.089) | 162.61 | 204 |
| 12 | Other vehicles | 0.740 | (0.0923) | 162.61 | 204 |
| 13 | All other manufacturing branches | 0.828 | (0.073) | 162.61 | 204 |
| 14 | All other non-manufacturing branches | 1.192 | (0.072) | 162.61 | 204 |
| 15 | Electricity, gas, and water supply | 1.189 | (0.088) | 162.61 | 204 |
| 16 | Construction | 0.956 | (0.091) | 162.61 | 204 |
| 17 | Education, research, and development | 1.251 | (0.080) | 162.61 | 204 |

Notes: Standard errors are heteroscedasticity robust standard error. The first stage F-values are identical for all industries because the first stage is common for all industries.

*Table 5.11* Tenfold Increases in AI Productivity: AI Shares

| | *AI Task Share in the most AI Subscribing Industry* | | |
|---|---|---|---|
| | *IFR* | *2014* | *CF* |
| *Country* | *(1)* | *(2)* | *(3)* |
| China | 14 | 0.0007 | 0.0011 |
| Germany | 14 | 0.0031 | 0.0048 |
| India | 17 | 0.0003 | 0.0005 |
| Indonesia | 14 | 0.0006 | 0.0009 |
| Japan | 14 | 0.0020 | 0.0032 |
| Korea | 14 | 0.0011 | 0.0017 |
| Thailand | 14 | 0.0004 | 0.0006 |
| United States | 14 | 0.0007 | 0.0011 |
| World | 14 | 0.0020 | 0.0030 |

Notes: The values for the World are the mean values of the countries in the sample.

elasticities with 1 because our model requires the elasticity to be greater than or equal to 1.[18]

With these estimates of the elasticities of substitutions, we follow the same procedure conducted in the analysis of robots and obtain the estimated impact on labor markets. To isolate the effect of AI on labor markets, we simulate the 2014 economy with the AI productivities (AI's counterpart of $\gamma_{st}$) that is 10 times as large as those in 2014, but leave the robot productivities at 2014 levels. Table 5.11 shows simulated changes in AI task shares. Compared with Table 5.8, resulting changes in the AI shares are much smaller than those in the robot shares when the robot productivity becomes tenfold, reflecting the observation that the elasticity of substitution between AI and high-skilled labor is smaller than that between robots and low-skilled labor in every industry.

Table 5.12 shows the estimated impacts of a tenfold increase in AI productivity on labor markets. As expected, low-skilled workers benefit from the progress in AI technology. The impact on real wage rates for low-skilled labor, however,

*Table 5.12* Tenfold Increases in AI Productivity: Labor Market Impacts

| | *Real Wage for Low-Skilled* | *Real Wage for High-Skilled* | *Skill Wage Premium* |
|---|---|---|---|
| *Country* | *(1)* | *(2)* | *(3))* |
| China | +0.07% | -0.04% | -0.11% |
| Germany | +0.56% | +0.45% | -0.11% |
| India | +0.07% | -0.04% | -0.11% |
| Indonesia | +0.07% | -0.08% | -0.15% |
| Japan | +0.37% | +0.26% | -0.11% |
| Korea | +0.14% | +0.02% | -0.12% |
| Thailand | +0.02% | -0.08% | -0.11% |
| United States | +0.18% | +0.07% | -0.11% |
| World | +0.35% | +0.20% | -0.14% |

Notes: The values for the World are the mean values of the countries in the sample.

are smaller than those of robots on the real wage rate for high-skilled labor, as shown in Table 5.9, due to the smaller elasticities of substitution between AI and high-skilled labor. The impacts are relatively large in Germany and Japan, both of which have relatively large AI task shares both in 2014 and in the counterfactual equilibrium, as shown in Table 5.11. Similarly to the case of robotics, progress in AI productivity increases the real wage rates for high-skilled labor, which AI substitutes, in some countries such as Germany and Japan. Wage inequality would be reduced in all the countries.

## 6  Conclusion

This chapter has quantified the impact of past and future robot/AI progress on labor markets in a general equilibrium trade model with task substitutions between robots and low-skilled labor and between AI and high-skilled labor. Based on our new estimates of robot/AI income shares and elasticities of substitution for labor, the model shows that past technological progress of industrial robots had much smaller macroeconomic impacts on labor markets than the past trade liberalization and that the future impact of tenfold increases in the productivity of robot and AI on would be modest.

As Brynjolfsson and McAfee (2011) emphasize, robot technology advances at an exponential pace. It is likely that the benchmark year of 2014 was still on the verge of rapid technological advances, so our simulation may well have underestimated the future impact of robots and AI. The narrow definition of robotics may also have contributed to the underestimation. Technological progress in AI and robots have indeed been more rapid than we had anticipated. These are likely to reinforce each other in the technology-development stage and also at the stage of industrial usage. As Brynjolfsson and McAfee (2011) and Baldwin (2019) argue, the impacts of AI and robotics on the labor market, and more broadly the global economy, may soon become quite large.

## Notes

1  Acemoglu et al. (2020a) show that establishments whose workers engage in tasks compatible with current AI capabilities increase the hiring of workers in AI positions but decrease non-AI hiring. They also observe no discernible industry-level impact on employment or wages. Frey and Osborne (2017) assess how 702 occupations are susceptible to computerization and find evidence that wages and educational attainment exhibit a negative relationship with the susceptibility of computerization. Felten et al. (2018) assess which occupations are heavily affected by AI advances.

2  $TC_{ni}$ includes the logarithm of distance, dummy variables for contiguity, common language, ever-colonial relationship, and a dummy indicating international trade (i.e., $i \neq n$) as opposed to intranational trade. These variables are from the CEPII datasets.

3  We also estimated (10) by the Poisson pseudo maximum likelihood (PPML) and found the PPML estimates slightly greater than those in Table 5.2.

4  Our estimates of trade elasticities are robust to the removal of observations with small trade shares. The Online Appendix shows the comparison of our estimates with those of some other studies: Caliendo and Parro (2015), Giri et al. (2021), and Shapiro (2016). It also shows the results of the same counterfactual analysis as presented in Section 4.1 but with mean estimates by those studies instead of our own. With smaller trade elasticities, price variation would be greater, and hence the impact of robotics and trade on real wage rates would tend to be greater. But, our main message about the size of the macroeconomic impact of robotics would remain valid.

5  If we included the constant term in (12), we would have to drop one importer-year dummy and one exporter-year dummy for each year to avoid perfect collinearity. Instead, we choose to drop the constant term and the benchmark country's importer-time dummy.

6  From the comparison of the gravity equation (12) with its theoretical counterpart (11), especially when $n = b$, it is apparent that the coefficient of the exporter-time dummy equals $\tilde{\zeta}_{it}^E = \theta^R \ln\left(A_{it}^R / c_{it}^R\right) + \left(\ln X_{bt}^R + \theta^R \ln P_{bt}^R\right)$. By including the exporter-time dummy for all exporting countries without the constant term (which would reflect the benchmark country's importer-time fixed effect), the coefficient of the exporter-time dummy reflects the benchmark country's importer-time fixed effect as well as the exporter-time fixed effect in question.

7  The prices in Germany are underestimated, possibly because German robots are of higher quality. If we remove the data for Germany, the root mean squared errors would be 13,806 dollars, which is slightly lower than one standard deviation of 14,439 dollars in the sample. The correlation between the estimated prices and the prices in the data would be 0.39.

8  The results of this estimation and all subsequent analyses for other countries are reported in the Online Appendix.

9  The estimated income shares of robots are so small partly because the IFR's definition of industrial robots is very narrow. The definition excludes machines that only work in specialized tasks.

10  A limitation of the logistic formulation (14) is that it always predicts a strictly positive $v_{nst} > 0$, even though the data includes $v_{nst} = 0$ for some industries in some countries. In our counterfactual analysis, we deal with this zero robot-use case in the two ways. In the first approach, we set $v_{nst} = 0$ and $\hat{v}_{nst} = 1$, whenever $v_{nst} = 0$. In the second approach, we replace $v_{nst} = 0$ with $\min\{v_{ist} > 0 : i = 1, \cdots, N\}$. We take the first approach in a simulation where robot usage is expected to decrease in the counterfactual scenario and take the second approach otherwise.

11  The exclusion restriction would be violated if, for example, the robot productivity is heterogenous across countries and correlated with the distance to robot exporting countries.

12  They are statistically greater than 1 at 1% level of significance in all but three industries, 2 (Mining and quarrying), 14 (All other non-manufacturing branches), and 16 (Construction).

13  We also examined another scenario to show the *Combined effect*, where both robot technology and trade costs are set at their 1993 levels. The combined effect is not very different from the sum of the two individual effects, suggesting the interaction of the two effects is not large in scale.

14  It is difficult to estimate changes in domestic and international trade costs separately with our data, because the trade share of a country's products in a market, which we use to estimate the elasticities of substitution between input varieties in production, depends on the relative costs of international trade to those of domestic trade but not on them separately.

15  We connect the two datasets in the year 2000. Equation (16) cannot be applied if either $X_{nit}^s$ or $X_{int}^s$ is zero or missing. In such cases, we choose the median trade costs for other products between the same pair of countries.

16  Our model allows countries to have different factor endowments as well as different production technologies. Therefore, part of the heterogeneity of this impact of trade across countries can be explained by the traditional Stolper-Samuelson effect. The effect of trade liberalization on factor prices is complex (see, for example, Grossman and Rossi-Hansberg (2008); and Feenstra (2015), Chapter 4). It is beyond the scope of the chapter to identify the main cause of each specific result as to the effect of trade on real wage rates.

17  In terms of the number of workers, 465,418 workers in Japan and 165,852 workers in the United States, for example, would be relocated.

18  As shown in (14), if the elasticity of substitution is smaller than 1, a decrease in the relative price of AI would decrease the share of tasks that are performed by AI in our model with a Cobb-Douglas production of the composite task as formulated in (3). We imposed the restriction that the elasticity is greater than 1 to prevent such implausible demand responses to the AI price shocks from happening in our simulations.

19  We introduce $O_{nt}$ to match country $n$'s total expenditure with its total income in each year $t$.

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## A  APPENDIX: EQUILIBRIUM CONDITIONS

From the production functions (2), the unit cost index $c_{it}^s$ in (8) is given by

$$c_{it}^s = \xi_i^s w_{Git}^{\beta_{Git}^s} w_{Hit}^{\beta_{Hit}^s} w_{Kit}^{\beta_{Kit}^s} w_{Tit}^{\beta_{Tit}^s} \prod_{k=1}^{S} \left(P_{it}^{km}\right)^{\beta_{it}^{sk}}, \tag{17}$$

where $\xi_i^s$ is a constant, $w_{Git}$ the industry-specific factor price and $w_{Ht}$ the high-skilled labor wage. From (5), the unit cost of the set of low-skilled tasks $w_{Tist}$ in industry $s$ in country $i$ at time $t$ becomes

$$w_{Tist} = \frac{\left(w_{Rit}\right)^{\nu_{ist}} \left(w_{Lit}\right)^{1-\nu_{ist}}}{\Gamma_{st}(\nu_{ist})}. \tag{18}$$

Let $X_{nt}^{su}$ be country $n$'s tariff-inclusive expenditure on usage $u$ in industry $s$. Let $\Upsilon_{nt}^s$ be the tariff-exclusive gross revenue of industry $s$ in country $n$ that satisfies $\Upsilon_{nt}^k = \sum_{i=1}^{N} \frac{\pi_{int}^{kf}}{1+\tau_{int}^k} X_{it}^{kf} + \sum_{i=1}^{N} \frac{\pi_{int}^{km}}{1+\tau_{int}^k} X_{it}^{km}$. The Cobb-Douglas production and utility functions imply

$$\begin{aligned}
X_{nt}^{sm} &= \sum_{k=1}^{S} \beta_{nt}^{ks} \Upsilon_{nt}^k, \\
X_{nt}^{sf} &= \alpha_n^s \left(V_{nt} + TR_{nt} + TD_{nt} - X_{nt}^S\right) \text{ for } s = 1, ..., S-1, \\
X_{nt}^{Sf} &= I_{nt}^R = \delta^R R_{nt} \text{ and } X_{nt}^{Sm} = 0,
\end{aligned} \tag{19}$$

where $V_{nt} \equiv \Sigma_s w_{Hsnt} G_{snt} + w_{Hnt} H_{nt} + w_{Lnt} L_{nt} + w_{Knt} K_{nt} + w_{Rnt} R_{nt}$ is the factor income, $TR_{nt} \equiv \sum_{s=1}^{S} \sum_{i=1}^{N} \frac{\tau_{nit}^s}{1+\tau_{nit}^s}\left(\pi_{nit}^{sf} X_{nt}^{sf} + \pi_{nit}^{sm} X_{nt}^{sm}\right)$ the sum of the tariff revenue, $O_{nt}$ other exogenous income sources, and $TD_{nt} = \sum_{s=1}^{S} \sum_{i=1}^{N} \left(\frac{\pi_{nit}^{sf} X_{nt}^{sf} + \pi_{nit}^{sm} X_{nt}^{sm}}{1+\tau_{nit}^s} - \frac{\pi_{int}^{sf} X_{it}^{sf} + \pi_{int}^{sm} X_{it}^{sm}}{1+\tau_{int}^s}\right)$ the trade deficit exogenously given.[19]

For the production factors, the Cobb-Douglas production function implies

$$\begin{aligned}
&\beta_{Gnt}^s \Upsilon_{nt}^s = w_{Gnst} G_{nst}, \\
&\sum_{s=1}^{S} \beta_{Hnt}^s \Upsilon_{nt}^s = w_{Hnt} H_{nt}, \quad \sum_{s=1}^{S} \beta_{Knt}^s \Upsilon_{nt}^s = w_{Knt} K_{nt}, \\
&\sum_{s=1}^{S} \left(1 - \nu_{st}\left(\frac{w_{Rnt}}{w_{Lnt}}\right)\right) \beta_{Tnt}^s \Upsilon_{nt}^s = w_{Lnt} L_{nt}, \text{ and } \sum_{s=1}^{S} \nu_{st}\left(\frac{w_{Rnt}}{w_{Lnt}}\right) \beta_{Tnt}^s \Upsilon_{nt}^s = w_{Rnt} R_{nst}.
\end{aligned} \tag{20}$$

Since the consumer price index is $P_{nt} = \prod_{s=1}^{S-1} \left( P_{nt}^{sf} \right)^{\alpha_s}$, the Euler equations (7) are written as:

$$\prod_{s=1}^{S-1} \left( P_{nt}^{sf} \right)^{\alpha_s} = \frac{w_{Knt}}{r_n + \delta_K} \quad \text{and} \quad P_{nt}^R = \frac{w_{Rnt}}{r_n + \delta_R}. \tag{21}$$

Conditions (9), (8), (17), (19), (20) and (21) determine the equilibrium allocation.

# 6 Telemigration and Development
## On the Offshorability of Teleworkable Jobs

*Richard Baldwin and Jonathan I. Dingel*

## 1 Introduction

The future of globalisation is changing for one ineluctable reason. The cost of moving weightless things (ideas and data) is falling radically faster than the cost of moving heavy things (goods). Telemigration – namely, working from home when home is abroad – is a small but fast-growing aspect of globalisation's weightless future.

Will telemigration have a measurable impact on development? The answer to this question turns on the answer to a second question: How many service-sector jobs will be offshored from rich nations to emerging markets? Since answering this requires all sorts of unknowable things, economists have tended to focus on a narrower question: How many jobs are offshorable?

More than a decade ago, Alan Blinder (2007) tackled the narrower question by looking at features of jobs in the United States. His answer was based on two vectors. The first vector described the offshorability of each occupation. The second vector was the number of US workers employed in each occupation. The inner product of these vectors yielded the number of US jobs that could be offshored. Blinder's answer was: "I estimate that somewhere between 22% and 29% of all US jobs are or will be potentially offshorable within a decade or two (I make no estimate of how many jobs will actually be offshored)."[1]

One goal of this chapter is to argue that moving from the narrow question to the broader question should involve switching from a focus on the nature of occupations to broader considerations that point to the gravity equation as a way of roughly quantifying the value of work that might be offshored to workers in lower-wage economies. We develop the exercise in Section 3 (theoretical motivation) and Section 4 (quantification exercise).

The conclusion of our rough quantification exercise is that telemigration is starting from too low of a base to allow it to become a major force for development – unless something radical changes. The constant-elasticity gravity model we employ embeds a series of assumptions that limit the impact of modest declines in trade costs. Correspondingly, telemigration should not be much of a threat to the service workers in high-wage nations. This soothing conclusion flies in the face of the anxiety that online offshoring evokes in high-wage nations. For example, David Wessel (2004) wrote in *The Wall Street Journal*:

Much of the American anxiety about outsourcing to India and China can be boiled down to this simple question: Will there be good jobs left for our kids? . . . Tens of millions of increasingly skilled Chinese and Indian workers are joining the global economy at a moment when technology can dispatch white-collar work overseas almost instantly.

What is the source of this mismatch between popular perceptions and our quantification exercise? Is the model we are using missing something, or does the popular anxiety reflect the familiar disconnect between trade economists and the public regarding the role of comparative advantage in general equilibrium? In Section 5, we explore the possibility that the mismatch might be the fault of the model.

Canonical frameworks rule out the possibility that modest changes in trade frictions can generate radical changes in employment patterns. Quantitative Ricardian trade models, starting from Eaton and Kortum (2002), typically assume that the pattern of comparative advantage is symmetric across countries.[2] More broadly, quantitative trade models typically feature a constant trade elasticity, so that the direct effect of a symmetric decline in trade costs is a symmetric increase in exports by both high- and low-wage nations.

In Section 5, we articulate circumstances that allow marginal changes to have radical effects. The analytic framework features both trade in goods and telemigration, which is trade in services. In this simple two-country model of telemigration, a symmetric decline in the costs of trading services internationally can have very asymmetric consequences for the exports of developed and developing economies. The key is to assume that latent comparative advantage takes a different shape than typically assumed in quantitative trade models. In short, it is a model in which telemigration could meaningfully shape low-wage nations' development journeys, with attendant effects on the service-sector employment prospects of workers in high-wage economies.[3]

## 2 Offshored jobs: Beyond the two-vector approach

Blinder's seminal calculations turned primarily on his judgement of the offshorability of particular occupations using a four-way categorisation that ranged from non-offshorable (category IV) to highly offshorable (category I). The judgement was guided by a decision tree illustrated in Figure 6.1.

These judgements were then matched with the number of US workers employed in the relevant occupations. The two vectors he used are shown in Table 6.1. The calculation was done under a "conservative" assumption – scenario Low in the table – that includes all jobs in category I and II occupations, and an "aggressive" assumption – scenario High in the table – that also includes all category III occupations. The inner product of the low scenario vector and the jobs vector yields the answer that about 29 million jobs are offshorable, which was about 22% of the labour force in 2004. The inner product of the high scenario vector with the jobs vector gives the answer that about
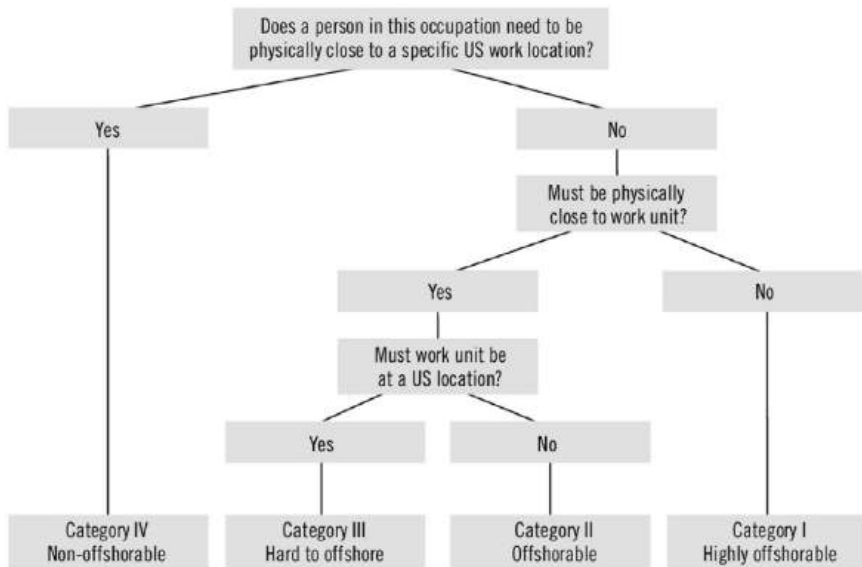
*Figure 6.1* Blinder's Classification Procedure.
Source: Blinder (2007).

38 million jobs might be offshorable (about 29% of all jobs). Blinder refined the first vector, which describes the offshorability of each occupation, in subsequent research (Blinder 2009; Blinder and Krueger 2013).

Some researchers came up with broadly similar results, while others found much lower figures. McKinsey Global Institute (2005) looked at eight representative sectors in various high-wage economies and estimated that about 11% of the jobs were offshorable to developing countries. Bardhan and Kroll (2003) found that about 11% of all US jobs were offshorable, but they limited themselves to occupations where some offshoring was already occurring. Van Welsum and Vickery (2005) gauged that 20% of total US employment was offshorable. Jensen and Kletzer (2010) used a very different approach that leveraged location data inside the US. Geographically concentrated service sectors were more tradable, they suggested, because service consumers tend to be dispersed in proportion to the population. Their work implied that 38% of US workers are in tradable, and therefore offshorable, occupations. In brief, the estimates were never negligible, but some were less than half those of Blinder's original estimate.

### 2.1 *The two-vector approach*

Last year, Dingel and Neiman (2020) took a two-vector approach to answer a question that seems similar to Blinder's: how many jobs can be done at home? Using job traits from the Occupational Information Network (O*NET)

*Table 6.1* Major Occupations ranked by Offshorability Score (OS)

| Occupation | OS | Scenarios | | Workers |
|---|---|---|---|---|
| | | Low | High | |
| Computer programmers | I | 1 | 1 | 389,090 |
| Telemarketers | I | 1 | 1 | 400,860 |
| Computer systems analysts | I | 1 | 1 | 492,120 |
| Billing and posting clerks and machine operators | I | 1 | 1 | 513,020 |
| Bookkeeping, accounting, and auditing clerks | I | 1 | 1 | 1,815,340 |
| Computer support specialists | I and II | 1 | 1 | 499,860 |
| Computer software engineers, applications | II | 1 | 1 | 455,980 |
| Computer software engineers, systems software | II | 1 | 1 | 320,720 |
| Accountants | II | 1 | 1 | 591,311 |
| Welders, cutters, solderers, and brazers | II | 1 | 1 | 358,050 |
| Helpers – production workers | II | 1 | 1 | 528,610 |
| First-line supervisors/managers of production and operating workers | II | 1 | 1 | 679,930 |
| Packaging and filling machine operators and tenders | II | 1 | 1 | 396,270 |
| Team assemblers | II | 1 | 1 | 1,242,370 |
| Bill and account collectors | II | 1 | 1 | 431,280 |
| Machinists | II | 1 | 1 | 368,380 |
| Inspectors, testers, sorters, samplers, and weighers | II | 1 | 1 | 506,160 |
| General and operations managers | III | | 1 | 1,663,810 |
| Stock clerks and order fillers | III | | 1 | 1,625,430 |
| Shipping, receiving, and traffic clerks | III | | 1 | 759,910 |
| Sales managers | III | | 1 | 317,970 |
| Business operations specialists, and all others | IV | | | 916,290 |

Source: Authors' elaboration of information in Blinder (2007), Table 2.

survey, they built the first vector by classifying each occupation as able to be performed remotely or not. The second vector, as with Blinder, contained the number of people working in the corresponding occupations. The inner product of the two provided the answer to the question.

But the Dingel-Neiman and Blinder questions differ in subtle but important ways. Dingel and Neiman (2020) asked how many workers could sit in their homes during the pandemic and perform the same job they were (overwhelmingly) performing at their employers' offices prior to the pandemic. Quite obviously, the main issue is the nature of the jobs: can they be performed remotely? The nature of the workers is irrelevant as far as teleworkability is concerned because the exercise considers whether the same workers could do the jobs from home.

Blinder (2007) answered a very different question. He asked whether, for example, a Uruguayan political analyst could do the same job as an American political analyst by exporting the service to US customers currently serviced by that American analyst. Here both the nature of the job and the nature of the

workers would seem to matter: can the service be provided from another country and are there foreign workers who can provide it? Note that Blinder (2007) explicitly recognises the point, "the task is to estimate the number of jobs that are potentially offshorable, meaning that Americans performing those jobs face potential competition from, say, Indian or Chinese workers."

## 2.2 Additional considerations

Whether an "offshorable" job (in the sense of Blinder 2009) is actually performed offshore depends on a number of other considerations. First, there must be foreign workers who are capable of doing the work. We would want to incorporate data that speaks to the number of potential foreign suppliers in each occupation. Occupations that can be performed remotely tend to be skill-intensive, high-wage jobs in the United States (Dingel and Neiman 2020). As Blinder (2006) discussed, this is part of the concern about the labour-market consequences of emerging markets exporting such services to developed economies. It also means that the potential foreign suppliers are not the total foreign labour force but the number of foreign workers who possess the relevant skills, as revealed by, for example, educational attainment or current occupation.

Second, one must address the fact that domestic and foreign workers are still not perfect substitutes even when they have the same level of educational attainment or occupational title. For example, English-speaking Canadians might be pretty good substitutes for English-speaking Americans in many teleworkable jobs, but Portuguese-speaking Brazilians seem less likely to be able to immediately perform the relevant language-intensive tasks. Even English speakers from different countries may find that their interactions with customers and co-workers are subject to a variety of linguistic and cultural frictions, as captured by the quip that the United States and Great Britain are two countries separated by a common language.

As it turns out, such frictions may be particularly relevant in the kinds of occupations that can be performed remotely. The O*NET surveys that Dingel and Neiman (2020) used to classify occupations as able to be performed remotely also characterize the language intensity and importance of soft skills in each occupation on a scale from 1 to 5. Figure 6.2 shows that teleworkable occupations place much greater importance on command of the English language than those occupations that cannot be performed remotely. The occupation with the highest importance of English language score is public relations specialist (4.96 out of 5). While this job can be performed remotely, it also is an occupation in which linguistic nuance and precision are very important.

More broadly, jobs that can be done remotely tend to rely on soft skills, which embed elements that are specific to particular social and cultural contexts. Deming (2017) documents a rising return to social skills in the United States in recent decades and emphasizes that the fastest growing cognitive occupations have been those requiring significant interpersonal interaction. As shown in Figure 6.3, jobs that can be done remotely are also occupations that typically
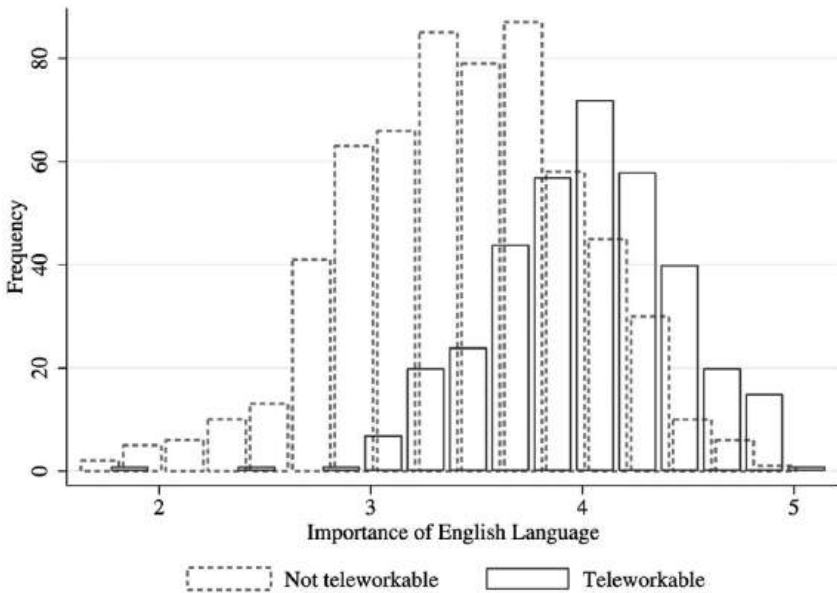
*Figure 6.2* Importance of English Language for Teleworkable versus Non-Teleworkable Jobs

Source: Authors' elaboration of O*NET data. The classification of occupations as teleworkable or not is from Dingel and Neiman (2020).

place greater importance on oral expression and written expression. Figure 6.4 shows that teleworkable jobs also typically place greater importance on persuasion and social perceptiveness. Both sales engineers and mathematical technicians can telework, but they are at opposite extremes in terms of the importance of persuasion (4.25 versus 1.66 out of 5). To the extent that social and cultural contexts vary across countries, this makes it less likely that a public relations specialist or a sales engineer located in Hanoi is a perfect substitute for one located in Seattle.

## 2.3 CAGE distance

One way to articulate the question about the substitutability of workers from different linguistic, cultural, and social contexts is to view it as a matter of "distance" between workers. The metaphoric distance encompasses a variety of dimensions. For example, activities that can be performed remotely but must be performed synchronously will be sensitive to differences in time zones (Bahar 2020). Considering pairs of countries, Ghemawat (2007) dubs differences in these cultural, administrative, geographic, and economic factors the
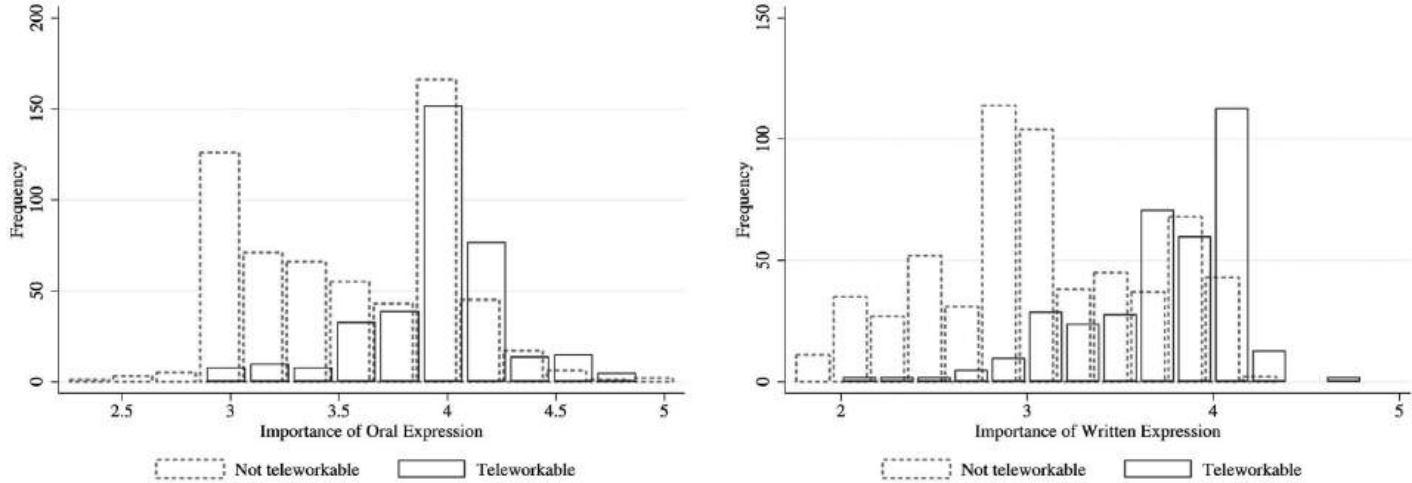
*Figure 6.3* Importance of Oral and Written Expression for Teleworkable versus Non-teleworkable Jobs

Source: Authors' elaboration of O*NET data. The classification of occupations as teleworkable or not is from Dingel and Neiman (2020).
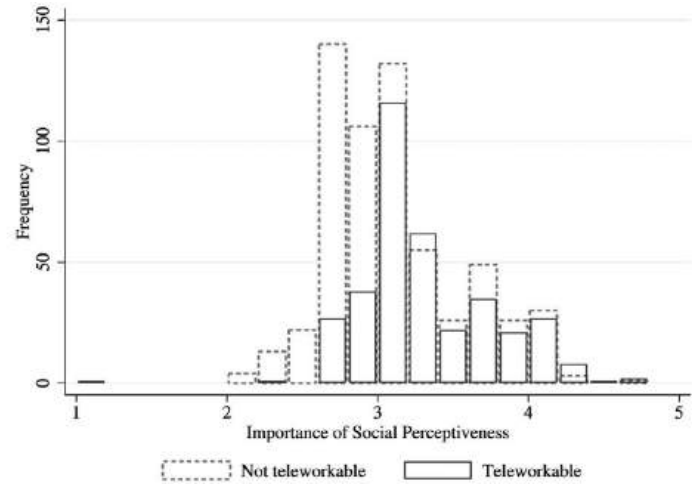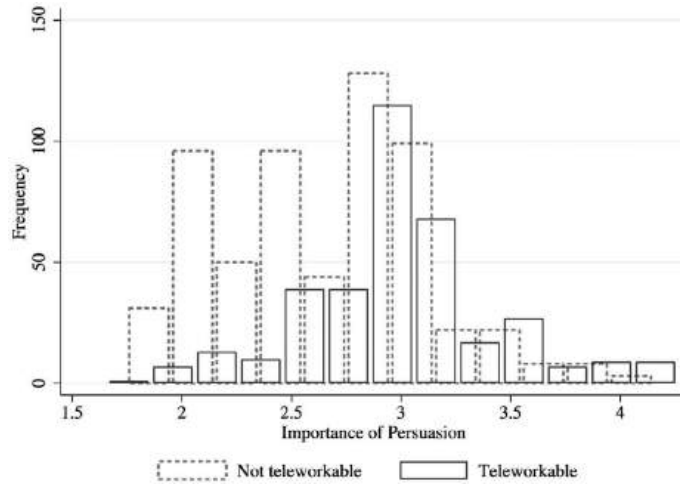
*Figure 6.4* Importance of Persuasion and Social Perceptiveness for Teleworkable Versus Non-teleworkable Jobs

Source: Authors' elaboration of O*NET data. The classification of occupations as teleworkable or not is from Dingel and Neiman (2020).

"CAGE" distance between them. In this sense, French-speaking Canadians in Quebec can be considered "farther" from New York employers than English-speaking Canadians in Calgary, even though Calgary is over 3000 kilometres farther away.

This framing of the substitutability between domestic and foreign workers as a bilateral distance leads immediately to a standard concern in trade – the existence of alternative suppliers. The likelihood of US firms hiring foreign workers from a given country depends not just on the bilateral CAGE distance to that country, but also on the bilateral distances to alternative sources of workers.

Thus, in addition to the two-vector approach that estimates the mass of tele-workable jobs in one nation that might be supplied from abroad, one should consider the mass of potential suppliers in other nations and a measure of "distance" between the two. In moving from the question of "how many developed-economy jobs are offshorable?" to "how many developed-economy jobs could go offshore to emerging markets?", we have added considerations about the exporting nation's economic mass and bilateral impediments to such potential trade in services. That points to the gravity equation for international transactions, a long-standing means of summarizing the expected volume of trade between economies.

### 2.4 Gravity is a hard habit to shake off

The simplest gravity equation predicts that bilateral trade in goods will be proportional to the economic mass of the origin nation times the economic mass of the destination nation divided by the bilateral distance (Head and Mayer 2014). In thinking about occupation-level transactions, one would need the demand for teleworkable tasks in the importing nation, a measure of potential supply in the exporting nation, and a notion of distance. The tally of jobs in the importing nation that can be performed remotely is the relevant importer mass, the population of suitably skilled workers is the relevant exporter mass, and various "CAGE" distances capturing bilateral trade frictions.

As it turns out, estimation using importer and exporter fixed effects addresses the role of competing alternative suppliers and obviates the need to gather data on the mass variables, albeit at the cost of restricting thought experiments about potential supply. Before getting there, it is worth being explicit about how we are thinking about telemigration as trade in services in the context of the gravity equation.

## 3  A first-pass gravity equation for telemigration

To guide our thinking about using gravity to study telemigration, it is useful to lay out the steps in the model's simplest derivation. Here we sketch the gravity model in which all economic activity is in the service sector. This one-sector exposition follows Baldwin and Taglioni (2006).

Suppose that each potential telemigrant provides nationally differentiated labour services (the Armington assumption).[4] Workers in nation $o$ ("origin") charge a price in market $d$ ("destination") of $p_{od}$. The export of services from workers in nation $o$ to nation $d$ is:

$$p_{od}x_{od} \equiv share_{od}E_d$$

where $share_{od}$ is the share of expenditure in market $d$ on services supplied by workers in $o$. $E_d$ is total expenditure on teleworkable jobs in nation $d$. Next, we link shares to relative prices using a CES demand function:

$$share_{od} = \left(\frac{p_{od}}{P_d}\right)^{1-\sigma}, \; where \; P_d = \left(\sum_{k=1}^{R}(p_{kd})^{1-\sigma}\right)^{1/(1-\sigma)}, \; \sigma > 1$$

where $R$ is the number of nations in the world. Assuming perfect competition, the equilibrium price is

$$p_{od} = \tau_{od}w_oa_o$$

where $a_o$ is the unit labour coefficient, $w_o$ is the equilibrium wage, and $\tau_{od}$ is the bilateral iceberg cost. Thus, exports from $o$ to $d$ are:

$$V_{od} = \tau_{od}w_oa_ox_{od} = \left(\frac{\tau_{od}w_oa_o}{P_d}\right)^{1-\sigma}E_d$$

Here $V_{od}$ is the aggregate value of telemigration payments from $o$ to $d$, i.e., the bilateral value of trade in services.

Finally, we use the general equilibrium adding-up condition to solve for prices and wages. Nation $o$ has income $\Upsilon_o = w_oL_o$ (where $L_o$ is the labour supply), which in general equilibrium, must match output, so wages have to adjust such that $\Upsilon_o = \sum_{d=1}^{R} V_{od}$. Thus:

$$\Upsilon_o = (w_oa_o)^{1-\sigma}\sum_{d=1}^{R}\left(\tau_{od}^{1-\sigma}\frac{E_d}{P_d^{1-\sigma}}\right)$$

Solving for the producer price of the services in nation $o$, we get:

$$p_o^{1-\sigma} = \frac{\Upsilon_o}{\Omega_o}, \; where \; \Omega_o \equiv \sum_{i=1}^{R}\left(\tau_{oi}^{1-\sigma}\frac{E_i}{P_i^{1-\sigma}}\right)$$

Here $\Omega_o$ is a measure of market access; the capital-omega is a mnemonic for 'openness' since it measures the openness of nation $o$'s exports to world markets.

Plugging in the solution into the expression for $V_{od}$ is the last step. It yields a first-pass gravity equation for offshoring:

$$V_{od} = \tau_{od}^{1-\sigma} \left( \frac{\Upsilon_o E_d}{\Omega_o P_d^{1-\sigma}} \right)$$

Thus, $\Upsilon_o$ is the total labour income of teleworkers in origin nation $o$, and $E_d$ is the spending in destination nation $d$ on labour in teleworkable jobs. This could be estimated in log-linear form.

The two core messages from Sections 2 and 3 are that 1) offshoring jobs will generate cross-border trade in services, and 2) bilateral trade in services can be empirically modelled using the gravity equation. To illustrate how one may use the gravity-based approach to quantify potential trade in services, we update gravity regressions estimated by Head, Mayer, and Ries (2009). Using Eurostat data covering 1992–2006, they found a strong negative correlation between physical distance and bilateral trade in services.

# 4 Quantifying potential growth in trade in services

The combined forces of rapid technological progress in digital communication tools (Baldwin 2019) and an extended experiment with remote work imposed by the coronavirus pandemic (Dingel and Neiman 2021) may substantially reduce the importance of physical proximity for trade in services relative to the turn of the century. We use the gravity regression to illustrate the scope for greater services trade if physical distance becomes less relevant and discuss the frictions associated with cultural, linguistic, and social differences between trading nations.

Unfortunately, data on trade in services is quite crude relative to data on trade in goods – and extremely crude compared to the occupation-level data used in Blinder (2007) and Dingel and Neiman (2020) and shown in Figures 6.2 through 6.4. There are more than 800 distinct 6-digit occupations in those data sets. The ILO provides employment counts for 40 distinct 2-digit occupational groups for more than 80 countries. By contrast, bilateral trade flows for services are reported for only a dozen or so broad categories of services. Head, Mayer, and Ries (2009) report estimates for only four categories of services trade.

The advantage of using reported flows of services trade is that it allows one to assess the role of international business frictions without having to construct a model of the relevant economic masses. As mentioned, these masses are absorbed in importer-year and exporter-year fixed effects. The consequences of differences in language, cultural, and physical proximity are estimated using variation in services trade across pairs of countries.

## 4.1 Data

We estimate gravity service regressions using data released since Head, Mayer, and Ries (2009) – henceforth HMR – wrote their study. We use trade flows for 12 service sectors in 2005–2019, as reported by the OECD-WTO Balanced

Trade in Services (BaTIS) dataset, and flows for 11 service sectors in 1995–2006, as reported in the previous BaTIS edition (Fortanier et al. 2017; Liberatore and Wettstein 2021). In sharp contrast to the data employed by HMR, these services trade data sets report very few zeros.[5] Following HMR, we include log physical distance, differences in time zones, and dummy variables indicating a colonial relationship, shared language, and a common legal system for each pair of countries.[6]

While one might combine estimates of the frictions impeding international services trade with proxies for latent occupation-level demand and supply for tel-eworkable tasks, here we confine ourselves to discussing the direct effects associated with the estimated elasticities of the gravity regression.

## 4.2 Gravity estimates of bilateral frictions for trade in services

Table 6.2 shows our results for total services. The first five columns are for the 1995–2006 period (corresponding to the original HMR period). The signs and magnitudes of the point estimates are all reasonable in light of their prior

*Table 6.2* Total-Services Gravity Regressions: Various Country Samples, Linear Fixed-Effects Model

|  | (1) Full | (2) EU | (3) OECD | (4) G20 | (5) EU/OECD | 2005–2019 (6) EU/OECD |
|---|---|---|---|---|---|---|
| Distance (log) | −1.155[a] (0.007) | −1.763[a] (0.046) | −1.505[a] (0.034) | −0.746[a] (0.034) | −1.475[a] (0.033) | −1.249[a] (0.025) |
| Distance (log) × trend | −0.009[a] (0.001) | 0.027[a] (0.006) | 0.009[b] (0.004) | −0.004 (0.005) | 0.009[b] (0.004) | 0.003 (0.002) |
| Time zone diff. | 0.080[a] (0.001) | −0.310[a] (0.030) | 0.105[a] (0.006) | −0.026[a] (0.004) | 0.091[a] (0.006) | 0.057[a] (0.004) |
| Shared language | 0.473[a] (0.007) | −0.331[a] (0.058) | 0.037 (0.030) | 0.372[a] (0.036) | 0.089[a] (0.028) | 0.205[a] (0.022) |
| Colonial link | 1.198[a] (0.020) | 0.104[c] (0.054) | 0.192[a] (0.043) | 0.254[a] (0.045) | 0.273[a] (0.040) | 0.344[a] (0.032) |
| Shared legal origin | 0.106[a] (0.004) | 0.360[a] (0.022) | 0.272[a] (0.015) | 0.095[a] (0.023) | 0.228[a] (0.015) | 0.180[a] (0.011) |
| Sample | All | o,d in EU | o,d in OECD | o,d in G20 | o,d in EU/ OECD | o,d in EU/ OECD |
| Obs. | 382,552 | 7,792 | 13,456 | 4,104 | 15,976 | 23,510 |
| $R^2$ | 0.845 | 0.925 | 0.926 | 0.914 | 0.917 | 0.914 |

Notes: Regressions include origin–year and destination–year fixed effects. Statistical significance at the 1%, 5%, and 10% levels is indicated by a, b, and c.

findings. Like HMR, we find that distance has a large, negative coefficient that is more negative than what is typically found for goods trade. Given that the total-services data are such a grab-bag of phenomena – everything from airline tickets and online game playing to pipeline fees and call centres – it is hard to character-ise all the roles bilateral distance may play. It may seem counterintuitive that dis-tance should matter more for trade in services, which is less connected to the transportation of physical objects. Total services, however, includes many flows for which face-to-face interaction may be important for setting up, maintaining, or operating the international exchange. For instance, distribution services, tourism, transportation, and financial services are all major services categories and likely require managers and specialists to move among facilities. The coeffi-cients on time-zone differences, shared language, colonial link, and shared legal origin are all significant in the full sample.

The coefficients vary substantially across estimation samples defined by different sets of countries. This could reflect substantial heterogeneity within the "total ser-vices" set of activities. Trade in services within the EU, for instance, likely has a very different composition than trade among the G20 nations.[7] Beyond such com-positional effects, measurement error and other data features may also vary across the samples. Finally, the relevant elasticities may not be global constants.[8]

The sixth column of Table 6.2 reports estimates for more recent years (2005–2019) for the set of nations where both are in the EU and/or the OECD. The estimated effects of distance, shared legal origin, and timezone are smaller, and the distance trend becomes insignificant, but the effect of shared language more than doubles. The coefficient on the dummy for a colonial link also increases in magnitude. We refrain from overinterpreting these differences in coefficients, since the nature of trade in services shifted considerably between 2005 and 2019, let alone between the 1990s and the later period.

To address some of the concerns about heterogeneity within total services, we present the same regressions for different types of services in Table 6.3. The sample of nations is the EU/OECD sample and the 2005–2019 period, so the first column of Table 6.3 is identical to the sixth column of Table 6.2.

The results show that there is meaningful variation in the point estimates across service categories, but most of them retain the expected sign and not too dissimilar magnitudes. Contrasting Tables 6.2 and 6.3 shows that the sample of countries used has a much greater influence on the estimated coeffi-cients than breaking out total services trade into component categories.

When thinking about telemigration, the category that corresponds most clearly to the model we have in mind is 'Other Business Services' (OBS) shown in column 5. Since the EU/OECD sample does not include India – a key player in telemigration – we present analogous estimates for recent years for a sample of nations that includes all the G20 nations as origin and destination countries in Table 6.4.

The point estimates for the OBS column of Table 6.4 are the ones we use in the quantification exercise. The next step is to think about how to relate the flow of services to jobs.

*Table 6.3* Sectoral Gravity Regressions: Linear Fixed-Effects Model, EU/OECD Sample, 2005–2019.

|  | (1) Total | (2) OCS | (3) Finance | (4) IT | (5) OBS |
|---|---|---|---|---|---|
| Distance (log) | –1.249[a] (0.025) | –1.285[a] (0.030) | –1.517[a] (0.039) | –1.253[a] (0.035) | –1.219[a] (0.033) |
| Distance (log) × trend | 0.003 (0.002) | 0.006[b] (0.003) | –0.001 (0.004) | 0.012[a] (0.004) | –0.002 (0.003) |
| Time zone diff. | 0.057[a] (0.004) | 0.063[a] (0.005) | 0.114[a] (0.007) | 0.023[a] (0.006) | 0.058[a] (0.006) |
| Shared language | 0.205[a] (0.022) | 0.188[a] (0.025) | 0.226[a] (0.039) | –0.000 (0.032) | 0.197[a] (0.030) |
| Colonial link | 0.344[a] (0.032) | 0.234[a] (0.037) | 0.220[a] (0.051) | 0.295[a] (0.045) | 0.163[a] (0.042) |
| Shared legal origin | 0.180[a] (0.011) | 0.190[a] (0.013) | 0.226[a] (0.020) | 0.199[a] (0.017) | 0.234[a] (0.016) |
| Sample | o,d in EU/ OECD | o,d in EU/ OECD | o,d in EU/ OECD | o,d in EU/ OECD | o,d in EU/ OECD |
| Obs. | 23,510 | 23,503 | 22,396 | 23,263 | 23,355 |
| $R^2$ | 0.914 | 0.891 | 0.843 | 0.851 | 0.859 |

Notes: Regressions include origin-year and destination-year fixed effects. Statistical significance at the 1%, 5%, and 10% levels is indicated by a, b and c. The service sectors are Other Commercial Services (OCS, which is non-government services that are not transportation or travel), Finance (financial services including those delivered locally by foreign branches, etc), IT (includes telecommunications and software services), and Other Business Services (OBS, which is trade-related services, operational leasing/rentals, and miscellaneous business, professional and technical services such as legal, accounting, management consulting, public relations services, advertising, market research and public opinion polling, research and development services, architectural, engineering, and other technical services, agricultural, mining and on-site processing).

### 4.3 Translating services flows into jobs

Embracing the bold approximation that OBS services imports are payments to foreign service workers, the bilateral service trade flow can be interpreted as the "wage bill" for telemigrants between pairs of countries. This is crude, but it allows us to tackle order-of-magnitude questions when it comes to the impact of making telemigration easier.

Put simply, emerging economies currently export very modest volumes of other business services. In 2019, China and India's total OBS exports were $68 billion and $51 billion, respectively. These small initial volumes would need to expand massively to be associated with meaningful numbers of new telemigrant jobs. If telemigrants earned $10,000 per year ($5 an hour for 2000 hours per year), a doubling of OBS exports would only create a few million telemigrants in these economies.

*Table 6.4* Sectoral Gravity Regressions: Linear Fixed-Effects Model, G20 Sample, 2005–2019

|  | (1) Total | (2) OCS | (3) Finance | (4) IT | (5) OBS |
|---|---|---|---|---|---|
| Distance (log) | –0.775[a] | –0.696[a] | –0.831[a] | –0.901[a] | –0.707[a] |
|  | (0.026) | (0.028) | (0.039) | (0.032) | (0.029) |
| Distance (log) × trend | 0.004 | 0.003 | 0.001 | 0.009[a] | 0.004 |
|  | (0.003) | (0.003) | (0.004) | (0.003) | (0.003) |
| Time zone diff. | –0.011[a] | –0.014[a] | 0.007 | –0.003 | –0.001 |
|  | (0.003) | (0.003) | (0.005) | (0.004) | (0.003) |
| Shared language | 0.431[a] | 0.477[a] | 0.558[a] | 0.384[a] | 0.396[a] |
|  | (0.024) | (0.027) | (0.039) | (0.035) | (0.029) |
| Colonial link | 0.185[a] | 0.054 | –0.150[b] | 0.087[b] | –0.036 |
|  | (0.034) | (0.042) | (0.059) | (0.042) | (0.035) |
| Shared legal origin | 0.067[a] | 0.074[a] | –0.046[b] | 0.126[a] | 0.173[a] |
|  | (0.015) | (0.020) | (0.023) | (0.021) | (0.021) |
| Sample | o,d in G20 | o,d in G20 | o,d in G20 | o,d in G20 | o,d in G20 |
| Obs. | 5,130 | 5,130 | 5,119 | 5,130 | 5,129 |
| $R^2$ | 0.926 | 0.925 | 0.913 | 0.910 | 0.921 |

Notes: Regressions include origin–year and destination–year fixed effects. Statistical significance at the 1%, 5%, and 10% levels is indicated by a, b, and c. For service sector definitions, see notes of previous table.

Consider how many jobs might come from increased bilateral exports to the US or EU as a result of lower service trade costs. Since physical distance is the canonical shifter of bilateral trade costs, we consider the consequences of reducing its negative impact on bilateral services trade. Per Table 6.4, the estimated impact of distance on trade became less negative during 2005–2019. However, this trend is neither statistically nor economically significant. The estimated coefficient on the interaction of log distance and a linear time trend (0.004) is less than 1% of the log-distance coefficient (-0.707). At that rate, decades would have to pass for an appreciable change in trade volumes to arise. Rather than tracing out the impact of this trend, we choose to consider the consequences of a more radical shift.

Our thought experiment is to consider the numbers of emerging-market jobs that might be created by a 25% decline in the bilateral distance between economies. Imagine the reduced cost of physical distance applying to one pair of countries in isolation. For example, it is about 14,000 kilometres from Palo Alto to Bangalore; slicing off a quarter of this distance would put Bangalore near Taipei. The distance elasticity of -0.707 implies exports would be about 18% higher. We then translate this change in export value into a number of telemigrants by our crude assumption about wages. This calculation overstates the increase in bilateral exports and the number of telemigrants to the extent that

*Table 6.5* Increases in Telemigration Associated with 25% Reduction in Bilateral Distance

|  | Canada | Brazil | China | India |
|---|---|---|---|---|
| *Telemigrants selling to US* | | | | |
| US OBS imports in 2019 (billions USD) | 11.37 | 3.19 | 8.85 | 11.13 |
| Hourly wage | 30.00 | 3.96 | 12.45 | 2.34 |
| Base jobs (millions) | 0.19 | 0.40 | 0.36 | 2.38 |
| Percent increase in US imports of OBS | 0.18 | 0.18 | 0.18 | 0.18 |
| Jobs increase (millions) | 0.03 | 0.07 | 0.06 | 0.42 |
| *Telemigrants selling to EU* | | | | |
| EU OBS imports in 2019 (billions USD) | 5.52 | 4.18 | 22.31 | 18.32 |
| Hourly wage | 30.00 | 3.96 | 12.45 | 2.34 |
| Base jobs (millions) | 0.09 | 0.53 | 0.90 | 3.91 |
| Percent increase in EU imports of OBS | 0.18 | 0.18 | 0.18 | 0.18 |
| Jobs increase (millions) | 0.02 | 0.09 | 0.16 | 0.69 |

Notes: This table computes the jobs increases associated with the bilateral export increases implied by bilateral distance declining by 25%. OBS imports in 2019 are from WTO data. The distance elasticity is from Table 4.3 column 5. We assume 2,000 hours of work per year. Remaining numbers are authors' calculations.

it neglects substitution between export destinations and general-equilibrium effects on wages that would dampen the response.

The first line of Table 6.5 reports the value of US OBS imports in 2019 from four partners: China, India, Brazil, and Canada. The United States is the largest destination for Brazilian, Canadian, and Indian exports of OBS. It is China's second largest destination after Hong Kong. The figures are all very modest: about $11 billion from India and Canada and even less from China and Brazil. Thus, any export growth will be starting from low initial values. Consolidated across all EU members, China and India do export more OBS to the EU, but these values are again modest. These small flows explain why even seemingly large changes in the impact of distance on OBS flows will have rather modest effects on jobs.

We convert the import values to a baseline of foreign jobs using a proxy for the relevant foreign wage: the average hourly wage of an IT worker. US workers in computer and mathematical occupations average $41.51 per hour (Dingel and Neiman 2020). Canadian wages are about three-quarters of that, while those in Brazil, China, and India are notably lower.[9] The resulting numbers of telemigrant jobs suggested by the calculation are 190,000 in Canada, 400,000 in Brazil, 360,000 in China, and 2.38 million in India.

As a result, the jobs increases associated with an 18% increase in US OBS imports are very modest. For India, the number is 420,000 more telemigrant jobs. The figure is less than 70,000 for the three other economies. The job increases associated with increased exports to the EU are similarly modest.

The headline result from these calculations is that the job-impact numbers are very small when we compute growth from initially small bilateral export values. India's labour force is in the region of a half-billion workers. The job impact

suggested by the rough calculations in Table 6.5 is tiny compared to that. The job increases for Brazil and China are similarly modest.

Of course, physical distance is not the only source of trade costs. New digital tools and organizational practices might diminish the frictions associated with time-zone or linguistic differences. One could compute such consequences similar to our previous distance-driven scenario. But an important reason the jobs numbers in Table 6.5 are small is that the 2019 exports of other business services are small, implying a small number of new telemigrants associated with any modest shift in trade costs.

### 4.4 Modest changes are insufficient for a big development impact

Our rough quantification exercise could be greatly refined, but refinements of the elasticities estimated in Section 4.2 are essentially immaterial to the basic conclusion. The current volume of service trade of the type that could be construed as representing payments to telemigrants is just too small for a doubling or tripling to have meaningful consequences for emerging markets' development trajectories. A radical increase in trade flows would be necessary to produce many new service-sector jobs in emerging markets. This is not impossible.[10] For example, between 2005 and 2019, the nominal value of Other Business Services exported by China and India both had annual growth rates of 12%. Such growth also reflects supply shifts, not merely declining trade costs.

The next section explores the economic logic of a model in which modest changes in the frictional barriers to trade in services could lead to more radical changes than those suggested by our quantification exercise.

## 5  A simple model of telemigration: could comparative advantage work differently with services?

Telemigration evokes anxiety in rich nations. "This year's mass experiment with remote working has, for some, triggered a prickling sense of unease: if I can do my job from home in London, Brooklyn or Canberra, could someone else do it more cheaply from Sofia, Mumbai or Manila?" wrote Sarah O'Connor (2020) in the *Financial Times*. The fear is that digitally enabled telemigration will be asymmetric: it will expose tens of millions of office workers based in rich nations to foreign competition without providing them additional, offsetting export opportunities.

Is this anxiety well-founded? The conventional gravity approach would suggest that it is not. In these quantitative models, the elasticity of trade flows with respect to trade costs is constant. As a result, the direct effect of a common decline in the costs of trading services is a common proportionate increase in the exports of services by all economies. Even neglecting developed economies' potential export expansion, the quantification of their increased imports from emerging economies suggests that the number of jobs at stake is modest. There is some nuance in terms of general-equilibrium effects, but the assumptions of the gravity equation that make the pattern of comparative advantage symmetric

and the trade elasticity constant essentially rule out highly asymmetric responses to a common decline in trade costs. On the other hand, we have little evidence to support restricting attention to these particular functional forms.

Two intriguing empirical patterns suggest that it may be fruitful to build a model that allows us to illustrate the possibility behind the anxiety. First, most rich nations run a trade surplus in services and so would seem to have a comparative advantage in services (WTO 2019, Figure B.9). Specifically, developed nations account for about 75% of global service exports, and they export more than they import. Most of this services trade, about 70%, takes place in so-called traditional services. Specifically, these are distribution services (20% of world total), financial services (19%), telecommunications, computer and audio-visual services (13.2%), transportation (12%), and tourism (8%).[11] Correspondingly, developing countries as a whole are net importers of services. In a conventional gravity model, a decline in the cost of trading services would reinforce this initial pattern of comparative advantage.

The second fact is that developing economies have the edge in office and professional services that are exported via digital platforms (ILO 2021). These categories are currently much smaller than traditional services (Other Business Services and professional services account for 4% and 3% of world services trade, respectively), but they are growing faster. The fact that rich nations are running trade deficits in one of the fastest-growing service-trade segments raises the possibility that further advances in digital technology may not simply reinforce past patterns of trade in services.

To evaluate the possibility that the future expansion of service trade may be asymmetric, we need a general-equilibrium trade model that allows us to address two key questions. Why are today's services exports largely "running uphill," from high-wage nations to low-wage nations? Why is there a presumption that reducing the costs of telemigration will lead to an asymmetric rise in cross-border flows that reverses this pattern? Along the way, the model will allow us to consider a few other issues such as: "How do low trade costs for goods interact with higher trade costs for services?" and "If international relative wages are mostly determined today by things like international labour productivity differences and country size, what happens to relative wages when telemigration gets much easier?"

To address these questions, we use the Dornbusch, Fischer, and Samuelson (1977) – henceforth DFS – model as a basis for thinking about telemigration. The model is familiar, so we move through the analysis quickly. To fix ideas and introduction notation, we first present the well-known DFS model for trade in goods.

## 5.1 The DFS model for goods

The world economy has two nations (North and South). Markets are perfectly competitive. There is a continuum of goods, indexed by $z$. Production employs only labour and exhibits constant returns to scale. Labour endowments

in North and South are L and L*, respectively. Unit costs for good $z$ are:

$$wa(z), \ w^*a^*(z), \ z = 0, \dots, 1$$

where $a(z)$ and $a^*(z)$ are the unit labour input coefficients for North and South, and $w$ and $w^*$ are their respective wages. North, as the rich nation, is assumed to have an absolute advantage in every sector, but only relative efficiencies, $a^*(z)/a(z)$, matter for the pattern of trade (Ricardo, 1817). Indexing the sectors so that North's productivity advantage is greatest in low-$z$ sectors, we have:

$$A(z) = \frac{a^*(z)}{a(z)} > 1, \ A'(z) < 0, \ \omega = \frac{w}{w^*}, \ z = 0, \dots, 1$$

North's wage relative to South's wage is $\omega$. Preferences are identical across people and nations, and are Cobb-Douglas with $b(z)$ as the expenditure share for good z. Also, $B(z') = \int_0^{z'} b(z)dz$ and $B(1) = 1$.

## Adding trade costs

Trade is subject to symmetric, iceberg trade costs, so firms must ship $\tau > 1$ units to sell one unit in the other nation; domestic trade is costless. Since North goods pay $\tau$ to get inside South's market, the South-market threshold or borderline good, which we label as $z_S$, is defined by the equal price condition $\tau wa(z_S) = w^*a^*(z_S)$; likewise the North-market threshold good, $z_N$, is defined by $wa(z_N) = \tau w^*a^*(z_N)$.

Closing the model requires the relative wage, and this is determined by the North labour market clearing condition. Given the preferences, it is: $wL = w^*L^*B(z_S) + wLB(z_N)$ because North consumers buy North-made goods in the 0, . . ., $z_N$ range while South consumers spend only on North export goods, 0, . . ., $z_S$. To recap, the three equilibrium conditions are:

$$\tau\omega = A(z_S), \ \omega = \tau A(z_N), \ \omega = \frac{B(z_N)}{1 - B(z_S)} \frac{L^*}{L} \tag{1}$$

It is convenient to have a simple, two-dimensional diagram, so we collapse the 3-equation system into a 2-equation system by assuming explicit functional forms. We assume $A(z)=1/z$, and $b(z)=1$ for all z, so $B(z') = z'$. Additional simplification comes from supposing $L=L^*$. With these, $z_N = z_S\tau^2$ and the equilibrium conditions are:

$$\omega = \frac{\tau}{z_F}, \ \omega = \frac{z_F}{1 - z_F}\tau^2 \tag{2}$$

The equilibrium $\omega$, $z_F$ are defined by the intersection of the two conditions in the left panel of Figure 6.5.

The right panel shows the classic non-traded goods analysis in DFS. The upward sloped line is the ratio of North to South production costs; it is linear due to $A(z)=1/z$.
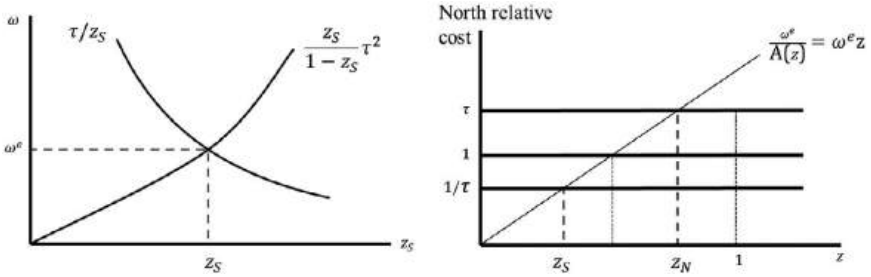
*Figure 6.5* DFS Model and Non-traded Goods
Source: Authors' elaboration.

- When North's relative cost is low enough, it is competitive inside the South market despite the trade cost. This is true for the range zero to $z_S$; North exports these goods.
- When North's relative cost is high enough, South goods are competitive in North despite the trade costs. This is true for the range from $z_N$ to unity; South exports these goods.
- Goods between the two thresholds are non-traded.

Note that neither of the two key questions is clarified by this diagram. The trade is not particularly "uphill" (exports and imports necessarily balance in value terms), and a reduction of $\tau$ would bring forth more North and more South exports in the same proportion (an outcome that is indeed guaranteed by the equilibrium conditions).

We laid out this goods-only model to fix ideas and notation. It also gives us a departure point where most trade is in goods, so $\omega$ is predominately determined by goods trade.

## 5.2  A simple model of telemigration: adding services and service-linked trade costs

Adding services is simple if we embrace a two-tier Cobb-Douglas preferences structure with $\gamma$ as the expenditure share on goods (gamma is a mnemonic for goods). Here we are taking the task approach to services akin to the model of Grossman and Rossi-Hansberg (2006).

We label the relative productivity curve for service "tasks" as:

$$S(t) = \frac{s^*(t)}{s(t)} > 1, \ S'(t) < 0, \ \tau_S \omega = S(t_S), \ \omega = \tau_S S(t_N)$$

where $s(t)$ and $s^*(t)$ are the unit labour input coefficients for North and South service "tasks" (s and t are mnemonics for services and tasks respectively). The final two expressions define the threshold tasks, $t_N$ and $t_S$, which

delineate the non-traded services range. The new labour clearing market condition, which now must include spending on services, is: $wL = \gamma\{w^*L^*z_S + wLz_N\} + (1-\gamma)\{w^*L^*t_S + wLt_N\}$. This simplifies to:

$$\omega = \frac{\gamma z_S + (1-\gamma)t_S}{1 - \{\gamma z_N + (1-\gamma)t_N\}}$$

### *Assumptions reflecting the peculiarities of services trade: the "hockey stick"*

We add two elements to the model to adapt it to the services context. First is that the trade costs in services are very high – so high that there is little cross-border trade in services (compared to the size of the sector). This echoes the fact that service provision often requires, or is much easier, when the service provider and buyer are in the same room at the same time (and moving humans is expensive compared to moving goods). Second, we assume that the pattern of comparative advantage explains the fact that much of this "mode-1" services trade consists of Northern exports of highly sophisticated services (finance, engineering, communications, etc.).

The first feature – high service trade costs – does not require a modification of the model, just the application of a different parameter value. To get the second feature, however, requires more substantial changes. Specifically, we assume the $1/S(t)$ curve has the "hockey-stick" shape shown in Figure 6.6.

Before thinking about the microfoundations of the hockey stick shape, consider what the S(t) curve would look like under Eaton and Kortum (2002) assumptions.[12] When $1/s(t)$ and $1/s^*(t)$ are Fréchet distributed, as in Eaton and Kortum (2002), the $S(t)$ curve has the shape shown in Figure 6.7. Note that since the support of the Fréchet distribution is unbounded, there will
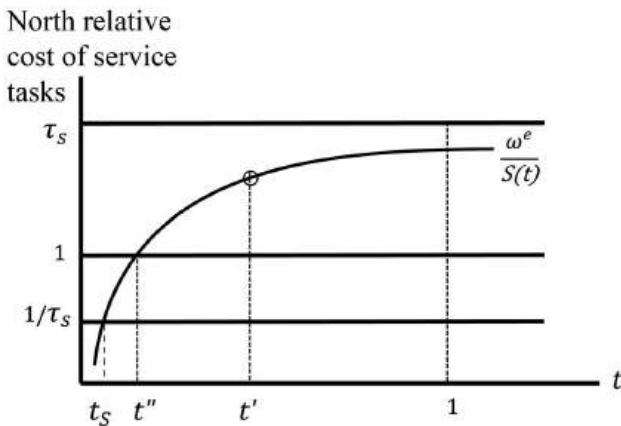


*Figure 6.6* Non-traded Service Tasks in the "Service-Enabled" DFS Model
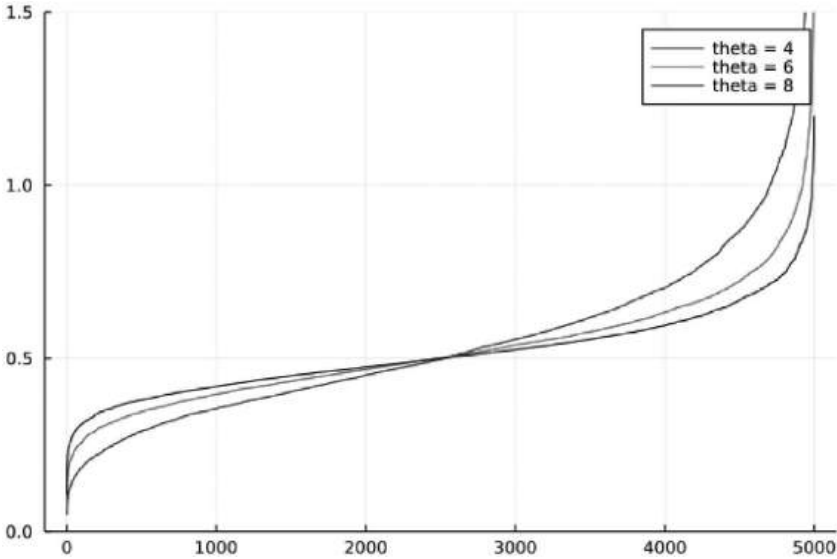Source: Authors' elaboration.

*Figure 6.7* The Relative Efficiency Curve with Eaton-Kortum Assumptions

Source: Authors' elaboration; the Fréchet distributions are $F(s) = e^{-2s^{-\theta}}, F(s^*) = e^{-2s^{*-\theta}}$ $s$, $s^* \geq 0$. We randomly sample 5,000 draws from these Fréchet distributions, compute the unit-cost ratios, and plot those ratios in rank order.

always be extreme values that can overcome any finite level of trade costs. Thus, every country is predicted to exports some tasks, regardless of sectoral-level average productivities. To put it more graphically, the *S(t)* generated by the Fréchet assumption has two blades: one pointing up and one pointing down.[13] Moreover, the patterns of manifest comparative advantage (in tasks actually traded) and latent comparative advantage (in non-traded tasks) are the same. That assumption delivers a constant trade elasticity.

By contrast, we consider the single-blade pattern of relative productivities depicted in Figure 6.6. Why might relative productivities exhibit this "hockey-stick" shape? We briefly step outside the model to think about continuous technological diffusion that tends to narrow extreme productivity differences across economies on a task-by-task basis.

Without innovation, there is a natural tendency for the seepage of know-how to flatten the relative productivity curve. Imagine that products and processes are invented in the advanced economy, so *a(z)* tends to be less than *a\*(z)*, but the cross-sectional differences will tend to fade in a Vernon (1966)-like fashion. That is, things such as good roads, institutions, and trust can explain why German workers are more productive than, say, Turkish workers in every sector, but unless German industry keeps innovating, the German-Turkish productivity ratios will tend towards a constant in all sectors. In other words, this mechanism allows for persistent absolute advantages but only shorter-lived

comparative advantages. The disappearance of comparative advantage is accelerated if the pace of know-how seepage increases with the size of the productivity gap. In this conceptualisation, the $A(z)$ curve gets its slope from the fact that German industry innovates faster in high-technology sectors. The left part of the $A(z)$ curve is continuously pulled upward by fresh innovations even as the gap between $a(z)$ and $a^*(z)$ is continuously narrowed by technological diffusion. In this story, Germany has a comparative advantage in its most innovative sectors.

### Why might S(t) look like a hockey stick in services but not goods?

Moving this line of thinking to the service sector, things change since innovation in the service sector is famously slow. This leads to what is known as Baumol's cost disease. A recent University of Chicago Booth School of Business survey of leading economists framed it as: "Because labour markets across different sectors are connected, rising productivity in manufacturing leads the cost of labour-intensive services to rise." Nordhaus (2008) documents the fact.

The point is that slow innovation results in a very flat relative productivity curve as the slow innovation gives technological diffusion enough time to reduce differences in the cross-sector profile of relative labour productivities (i.e., to flatten the S-curve). The exceptions to this are those service tasks that are high-tech. They involve rapid innovation and coordination of many complex things. This is what turns what otherwise would be a "baseball-bat" shaped $1/S(t)$ curve into a "hockey-stick" shaped $1/S(t)$ curve. In particular, it adds the "blade" that indicates that the North has a marked comparative advantage in sophisticated services where innovation is rapid.

### Implications of the hockey-stick productivity profile

It would take substantial empirical investigation to verify that the relative productivity profile has a "hockey-stick" shape. Before economists invest in such research, however, it is useful to show that if it were true, then it would imply intriguing possibilities relative to the standard logistic-shaped curve that is assumed in the conventional gravity model analysis. To that end, we resume the analysis taking the hockey-stick shape as given.

The equal price conditions that define the threshold tasks, $t_N$ and $t_S$, are $\tau w s(t_S) = w^* s^*(t_S)$ and $w s(t_N) = \tau w^* s^*(t_N)$, which imply:

$$\tau_S \omega = S(t_S), \quad \omega = \tau_S S(t_N)$$

As drawn in Figure 6.6, the North's productivity edge is only high enough to overcome the services barriers for a small range of services tasks. Thus, North exports services tasks indexed by zero to $t_S$. The inverse $S(t)$ curve, however, flattens out, so the lower South wage (which is largely determined by goods market conditions) is not low enough to allow South service providers to be competitive inside the North market. In other words, South exports no services to the North

because $\omega > \tau_S S(1)$: there are no services tasks where the South's relatively low wage is low enough to overcome its productivity disadvantage given the high trade costs. Thus, South exports some goods, and it imports goods and services from North.

The goods sector is crucial to this story. Obtaining the asymmetric trade in services result requires a goods sector where trade is fairly free and comparative advantage is fairly symmetric. Without this, the usual "Ricardian wage equilibration" would drive the relative wage to a point where both North and South were competitive in some service tasks.

The final change is to adapt the equilibrium labour-market condition to incorporate services. For the general case, where both North and South export some service tasks, we will have two service thresholds. In the Figure 6.6 case, however, there is only one, so: $wL = \gamma\{w^* L^* z_S + wL z_N\} + (1 - \gamma)\{w^* L^* t_S + wL\}$, which simplifies to:

$$\omega = \frac{\gamma z_S + (1 - \gamma) t_S}{\gamma(1 - z_N)} \tag{3}$$

When $t_S$ is small, the second expression shows that the relative wage is mostly determined by trade in goods as in the classic DFS model.

## 5.3 Telemigration and development

Here we use the model to guide thinking about how telemigration could affect the future of globalisation. In the initial situation, South service tasks are not competitive inside North, but there is an incipient arbitrage opportunity. If a North firm could – via some new digital technology – purchase tasks in South without incurring the trade costs, they would do so for most tasks. For example, if something held the relative wage fixed, but the $\tau_S$ became unity for a particular service-producing firm in the North, that firm would find it cheaper to source all tasks from t″ to 1 in the South (see Figure 6.6). This could be the source of the anxiety that is often associated with telemigration. Based on partial-equilibrium thinking, which takes relative wages as fixed, digital technology that makes telemigration easier would seem to bring many more service-sector workers in high-wage nations into direct wage competition with low-wage service workers.

### Trade consequence of lower service trade costs

Figure 6.8 shows what a substantial reduction in the service trade costs would do to the services trade pattern. The dashed lines show the new situation with $\tau_s$ falling to $\tau_s'$. This would greatly expand South service exports and only slightly increase North service exports, so the relative demand for North labour would fall – bringing the equilibrium relative wage down from $\omega^e$ to $\omega^{e'}$.

A twist on this thought experiment that may have some additional contact points with reality considers asymmetric changes in telemigration frictions.
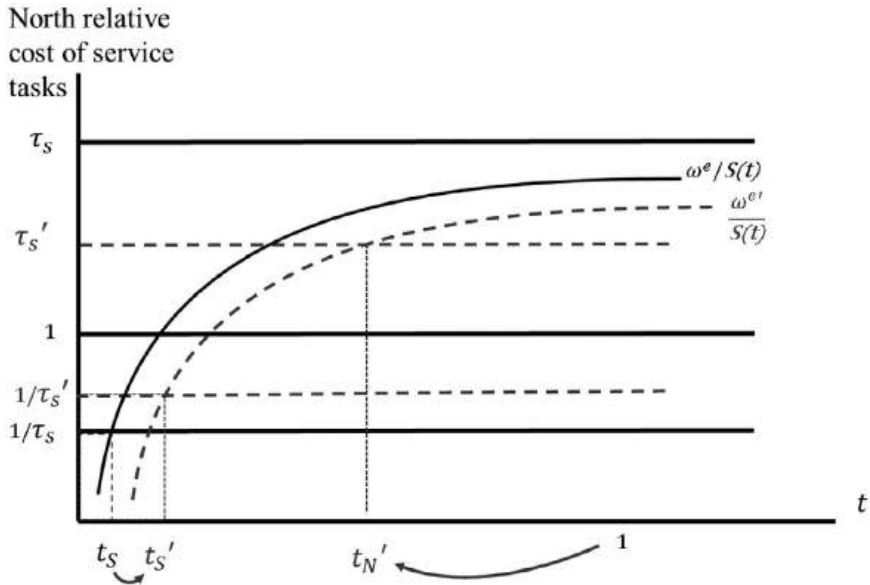
*Figure 6.8* Asymmetric Expansion of Service Exports
Source: Authors' elaboration.

Consider the impact of an asymmetric adoption of the necessary digital technology by North firms but not South firms. For example, we might imagine that the general economic and digital conditions in the North make it easy for South workers to telemigrate Northwards, but the "digital divide" makes it hard for North workers to telemigrate Southwards. In this case, it becomes much easier for South to exports services since, for instance, the North digital coverage and sophistication makes it easier for North firms to integrate remote workers in their service value chains.

The main message from this model is that digital technology could open much greater export opportunities for South-based telemigrants than North-based telemigrants. In other words, the anxiety in the popular debate can be rationalised by a profile of comparative advantage in services of the hockey-stick shape.

Given this pattern of productivities, for many office workers and professionals in high-wage nations, telemigration would be a new source of competition, while it would be a new source of opportunities for rather fewer high-wage workers. With the "twin-blades" model of Figure 6.7, rapid technological advances that made remote workers less remote create vast new export opportunities. In other words, if the pandemic-induced experience of "work from home" portends a shift to "work from anywhere" but substantially increased trade in services mimics the current pattern of trade in services, then developed economies will experience substantial services export growth.

For completeness, we solve for the equilibrium when there is costless trade in both goods and services.[14]

## 6  Concluding remarks

The COVID-19 pandemic has introduced huge numbers of employers and employees to remote work. Remote-work arrangements that had been technologically feasible for years but not broadly employed were rapidly adopted in the absence of any alternative. As the economy returns to normal, employers are likely to re-evaluate the kinds and numbers of workers that they employ. Some may return to their pre-pandemic practices, but massive disruptions produce opportunities to pivot, and some temporary shocks have permanent consequences. Some investments in remote work capacity are very likely to stick (Barrero, Bloom, and Davis 2021).

It seems inevitable that some of the tasks that can be done remotely will be done by telemigrants rather than domestic workers. Again, this will not be due to a massive change in the frontier of possibilities – telemigration is already widespread in sectors like web design and customized software development. It will, if it happens, be due to many more firms changing practices to adopt these technologies. In short, it would seem that the pandemic has brought forward the date of the "Next Industrial Revolution" that Alan Blinder (2006) famously contemplated a decade and a half ago.

This chapter is an attempt to think about how we might evaluate the size of the increased offshoring of office and professional jobs from high-wage to low-wage nations. The starting point is to recognize that many jobs that can be performed remotely require soft skills that make domestic and foreign workers imperfect substitutes. The equilibrium number of telemigrants, therefore, depends on the number of potential foreign suppliers of these tasks and the bilateral frictions that impede trade in these services.

Our quantification is based on two simple ingredients. The first is interpreting trade in certain services as payments to telemigrants so that the gravity equation for trade flows can be used to describe how the volume of transactions will respond to lower trade costs. We updated gravity regressions estimated by Head, Mayer, and Ries (2009) to ballpark these magnitudes. The second ingredient is to assess the development potential of this trade by crudely translating trade flows into numbers of jobs using average wages and the approximation that payments for these services are mainly payments to workers. This is clearly not true for some types of services trade – fees for using oil pipelines, for instance – but it seems sensible for categories like Other Business Services, which contains many of the activities that would be transformed by remote work going global.

Our quantification exercise yields a simple message: the number of offshored jobs is unlikely to be transformative when it comes to the development paths of most emerging economies. This conclusion stems from a point of fact and a point of economic logic. First, the current baseline of trade in Other Business Services is very small. Multiplying these flows by a factor of two or three

would not translate to many jobs in emerging markets. Second, quantitative trade models that assume constant elasticities cannot generate very large responses to modest declines in trade costs. There are no "tipping points" in canonical structural gravity models.

The final contribution of our chapter is to propose a simple model of telemigration in which modest changes in trade costs can have large effects. The key ingredient is that the pattern of comparative advantage has a hockey-stick shape rather than the symmetric shape typically assumed in quantitative trade models. In this account, emerging markets have tremendous potential to export services that is not evident in the current pattern of trade flows.

Our chapter raises many questions for future research. It suggests that making the optimistic case for telemigration-led development will be harder than one might have thought. At the very least, it suggests that making the case would require substantial departures from the standard gravity-based account typically employed in empirical exercises.

## Notes

1  The quotation is from the abstract of Blinder (2007). The paper was published as Blinder (2009).
2  In Eaton and Kortum (2002), productivity follows a Fréchet distribution. This distribution's location parameter, which governs absolute advantage, is country-specific. Its shape parameter, which governs comparative advantage, is common across countries.
3  The possibility of a disruptive outcome is the focus of Baldwin (2019).
4  The assumption that workers in different nations produce imperfect substitutes is merely a convenient shortcut to obtain a constant-elasticity gravity equation. The substantive assumption is that the aggregate import demand system is CES. For example, Eaton and Kortum (2002) provide a Ricardian model in which workers in different nations compete to produce the same set of goods that yields a constant-elasticity gravity equation.
5  See Liberatore and Wettstein (2021) for a detailed description of the relevant data construction and imputation procedures underlying the BaTIS data.
6  We obtain the distance, colonial, and language covariates from the CEPII website associated with Head, Mayer, and Ries (2010) and Head and Mayer (2014). We obtain the legal-origin covariate from La Porta, Lopez-de-Silanes, and Shleifer (2008). We use time-zone data posted by Herman Wong.
7  The G20 countries include members of the European Union, the G7 (France, Germany, Italy, Britain, US, Canada, and Japan), and the BRICS (Brazil, Russia, India, China, and South Africa), plus Argentina, Australia, Indonesia, South Korea, Mexico, Saudi Arabia, and Turkey.
8  Indeed, the notably smaller distance elasticity for the G20 sample is driven by observations in the left tail of the bilateral-distance distribution, suggesting a rejection of the constant-elasticity specification.

9 Hourly wages for "natural and applied sciences and related occupations" in Canada are 37.87 CAD (StatCan Table 14–10–0340–01 for 2019 full-time employees). Average monthly earnings for information, communication, financial, and professional occupations in Brazil were 3,445 BRL in 2019 (Q27 in Pesquisa Nacional Por Amostra De Domicílios contínua, Instituto Brasileiro de Geografia e Estatística, 2012–2020). Urban male "technicians & associate professionals" in India average 28,923 INR per month (Table 55, Annual Report, Periodic Labour Force Survey, 2019–20). Average earnings for "information transmission, software, and information technology" workers in China were 161,352 CNY per year in 2019 (Table 4–15, China Statistical Yearbook 2020). We convert these to US dollars at (roughly) 1 CAD = 0.79 USD, 1 BRL = 0.19 USD, 1 CNY = 0.15 USD, and 1 INR = 0.013 USD. We assume 2,000 hours of work per year.

10 Indeed, Kehoe and Ruhl (2013) emphasize the contribution of growth in previously least-traded goods to total trade growth in episodes of structural transformation and trade liberalization.

11 2017 values from Figure B.2 of WTO (2019).

12 Eaton and Kortum (2002) note that the Kortum (1997) and Eaton and Kortum (1999) models of innovation and diffusion deliver a Fréchet distribution of productivities. Costinot, Donaldson, and Komunjer (2012) and Caliendo and Parro (2015) provide multi-sector models in which productivities within each sector follow the Fréchet distribution. These models generate constant-elasticity gravity equations for sectoral trade flows.

13 When $\frac{1}{s(t)}$ and $\frac{1}{s^*(t)}$ are Fréchet distributed with the same shape parameter, then the log difference in unit costs, $\ln(S(t))$, follows the logistic distribution.

14 With free trade, there is only one threshold in goods and one in services, which we label as $z^e$ and $t^e$. The equilibrium conditions are: $\omega^e = A(z^e)$, $\omega^e = S(t^e)$, $\omega^e = \frac{\gamma z^e + (1-\gamma) t^e}{1 - \{\gamma z^e + (1-\gamma) t^e\}}$. To provide closed-form solutions we can assume that the S(t) curve takes the form $S(t) = 1/\sqrt{t}$. This does not fully reflect the hockey stick shape, but it makes calculations simple and thus transparent. Imposing functional forms: $\omega^e = \frac{1}{Z^e}, \omega^e = \frac{1}{(t^e)^{1/2}}, \gamma = \frac{1}{2}$.

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# 7 Immigration and Regional Specialization in AI

*Gordon Hanson*

## 1 Introduction

There is immense academic and policy interest in how artificial intelligence (AI) will affect labor markets. Given the disruptive impacts of technological change on earnings and employment in recent decades, such interest is understandable. The rapid pace of skill-biased technical change after 1980 is credited with raising the earnings premia for workers with college degrees (Katz & Autor, 1999), which contributed to greater income inequality in many high-income countries. Amid these changes, the automation of routine tasks shifted employment away from middle-skill jobs, leaving a more hollowed-out earnings distribution in its wake (Autor & Dorn, 2013; Goos *et al.*, 2014). The expanding use of industrial robots (Acemoglu & Restrepo, 2020) and employment of contract workers via Uber-like platforms (Abraham *et al.*, 2019; Chen *et al.*, 2019) are the most recent ways in which new technology is upending the world of work. With the potential for AI to convert many job tasks into algorithmic routines that can be performed by machines, yet another wave of disruption may be on the horizon (Autor *et al.*, 2020).

In this chapter I turn my attention not to the labor-market consequences of AI but to the forces governing where AI itself is being created. Three innovations have helped make AI possible (Varian, 2018). One is new approaches to machine learning, another is advances in high-speed and special-purpose computing, and a third is the proliferation of very large data sets in digital format. Machine learning combines techniques from statistics and computer science to predict outcomes or learn patterns from raw data. When embedded in a system that feeds in data, applies domain expertise, and governs learning, AI is the result (Taddy, 2018). This process requires specialized teams of computer scientists, data scientists, electrical and computer engineers, network systems analysts, and software programmers, as well as workers with knowledge of the domains in which AI will operate. The need for high-speed computing arises from the non-linearity and high dimensionality of prediction models, which require large data sets for training, validation, and testing. Of the key inputs to AI, it is the final stage of machine learning and systems engineering that appears to be the most location specific. Creating AI involves computer hardware manufactured elsewhere, data collected from disparate sources, and teams of specialists who tend to work in close proximity.

If AI comes anywhere close to its forecasted potential, there will be an enormous market for AI-related goods and services. Just as employment in new technology tends to be highly geographically concentrated (Moretti, 2012, 2019; Bloom *et al.*, 2020), it is natural to expect AI-related activities to exhibit strong patterns of spatial agglomeration. Understanding emerging comparative advantage in jobs related to AI is therefore important for evaluating how the technology will change national and global trade patterns. Trade in AI-related services is poorly measured, both because it is new and because revenue flows from trade in technology services are hard to detect in conventional data. To study what comparative advantage in the production of AI might look like, I take US commuting zones as my unit of analysis (Tolbert & Sizer, 1996). A regional focus allows me to measure comparative advantage via abundantly available employment data rather than via poorly documented trade flows. Because the US is at the frontier of innovations in AI and IT, it is where regional comparative advantage in new technology is likely to manifest itself first. Even with this focus, the newness of AI creates measurement challenges. I study the occupations that appear to encompass AI-related activities, recognizing that such categories will also include jobs in IT that do not necessarily involve AI. The analysis is therefore subject to the maintained hypothesis that the spatial allocation of employment in AI will resemble that in non-AI jobs that require AI-like skills.

My aim is to understand regional changes in US AI-related employment over the last two decades. Although machine learning dates to the 1950s (Cockburn *et al.*, 2018), the field did not begin to flourish until the 1990s. It was not until after 2000, and especially after 2010, that it came into widespread use (Taddy, 2018). The first step in the analysis is to identify occupations likely to be involved in the production of AI. Within occupations associated with STEM disciplines, I select the occupational codes that are likely to contain AI-producing jobs based on their associated Census-defined job titles having at least one term from each of the two following sets: computer, data, or software; and design/designer, engineer, research/researcher, or science/scientist. This procedure identifies 30 occupational titles out of 707 total titles in the broader STEM category, as being AI-related. The selected job titles include, for example, "artificial intelligence specialist" and "information scientist." Using a wider filter identifies 146 AI-related titles. Because employment can be measured at the occupational code but not at the title level, I focus on the codes that contain these titles. Within these codes, I use results in Lin (2011) to identify the occupational titles that were created after 1990, which is when advances in AI began to accelerate. Following his work, I interpret new job titles as evidence of the creation of new types of work.[1] The creation of new work in AI-related occupations is a signal of AI-related innovations in employment. To measure employment growth in AI jobs over 2000 to 2018, I weight employment growth in AI-related occupations over the period by the share of job titles within an occupation that were new as of 2000. By varying the restrictiveness of the filters used to define AI-related jobs, I check the robustness of the findings to the definition of AI-related activities.

An alternative way to measure employment in AI would be to use job postings that explicitly mention the application of artificial intelligence. A rapidly emerging literature takes this approach to examine changes in labor-market outcomes for the occupations that appear likely to be disrupted by AI (see, e.g., Brynjolfsson *et al.*, 2018; Felten *et al.*, 2018; Acemoglu *et al.*, 2020; Bloom *et al.*, 2020; Webb, 2020). Less work is devoted to figuring out which jobs are involved in the creation of AI and its applications. Acemoglu *et al.* (2020) use job-posting data from Burning Glass to measure the expansion of jobs in AI-producing activities. The advantage of these data is that job postings contain explicit mention of skills related to AI (e.g., computer vision, deep learning, machine learning).[2] Disadvantages include job postings being unavailable in complete form until 2010 and a lack of information on the ultimate number of hires that result from postings. My focus on employment growth in AI-related jobs since 2000 explains my choice to define AI-related occupations using the the Census Bureau list of occupational titles.

The second step in the analysis is to examine regional specialization in AI-related occupations. Two patterns stand out in the data. One is that regional specialization in AI-related jobs is greatest in commuting zones that became hubs for technology jobs in the 1980s or 1990s. These CZs include Austin, Boston, Oakland, San Jose, Seattle, and Washington, DC. Their specialization in AI-related occupations was already substantial in 2000 and became more substantial still by 2018. These are the same cities in which high-tech startups and patenting in high-tech domains are also concentrated (Chatterji *et al.*, 2014; Moretti, 2019). A second pattern is that increased specialization in AI-related jobs in tech-oriented CZs is due primarily to the employment of foreign-born men. Whereas the CZs in which native-born workers are most concentrated in AI-related jobs include cities specialized in government-funded military research (Colorado Springs, CO; Alexandria, VA) and space research (Melbourne, FL; Huntsville, AL), those in which foreign-born men are most concentrated in AI-related fields account for the largest AI employment clusters and are the ones in which private firms dominate the high-tech landscape. Looking across the origin countries of these foreign-born workers, there is wide variation in revealed comparative advantage in AI-related jobs. Comparative advantage in AI-related occupations is strongest for workers born in East and South Asia and weakest for workers born in Latin America and the Caribbean and the US. Although women account for a relatively small share of employment in AI-related occupations, their revealed comparative advantage in AI by country of birth is similar to that for men.

It is well known that across occupations specialization varies among foreign-born workers by their country of origin and that immigrants from specific countries tend to concentrate in specific US cities (see, e.g., Patel & Vella 2013; Hanson & Liu 2017; Burstein *et al.* 2020). These regularities are also manifest in the case of AI-related activities. Because the skills required to create artificial intelligence and related innovations in information technology are scarce and because some countries seem better than others at producing workers capable

of acquiring the required skills, the regions that are best positioned to attract high-skilled foreign-born workers appear to be the ones most likely acquire comparative advantage in AI. Over the period 2000 to 2018, foreign-born workers accounted for 54.6% of the increase in hours worked in AI-related activities.

The third step in the analysis is to identify the factors behind regional employment growth in AI-related jobs. Motivated by the importance of highly educated foreign-born workers in AI-related employment, I model changes in regional specialization in AI as a function of the change in college-educated immigrant labor supply confronting each region. I estimate the change in the CZ share of employment of prime-age college-educated workers in AI-related occupations over the 2000 to 2018 period as a function of the projected local increase in college-educated immigrants. Inspired by the shift-share approach of Altonji & Card (1991) and Card (2001), I predict the increase in the supply of college-educated immigrants in a CZ using national growth in college-educated immigrants from each origin country (outside of the CZ) and the initial-period share of the CZ in the employment of college-educated immigrants from each origin country (outside of AI-related jobs). For men, the immigrant supply shock is strongly positively correlated with employment growth in AI-related occupations. This effect comes entirely from increased employment of the foreign born. The impact of the immigrant labor-supply shock on the employment of native-born men is small and imprecisely estimated, indicating that arriving foreign-born workers neither crowd-in nor crowd-out the native-born in AI-related activities. Results are similar for the employment of women in AI-related occupations, though coefficient magnitudes are smaller, consistent with relatively weaker specialization in AI-related jobs on the part of foreign-born females. I find similar results whether using worker counts or hours worked to measure employment and whether using a narrow or a broad definition of AI-related occupations.

Whereas in earlier decades computer power and data availability were binding constraints on the advancement of AI, today computer power and data availability are vastly improved. The supply of workers sufficiently skilled to design the computing architecture, devise the learning algorithms, apply the domain science, and construct the business systems necessary to create AI is likely to be a constraining factor. Not surprisingly, building successful teams involves a global search for talent (Hanson & Slaughter, 2018). My results suggest that the US regions that are best positioned to attract foreign talent are those that are acquiring a stronger comparative advantage in AI-related activities. Three important actors in the global talent search are the US government, which regulates the supply of visas to high-skilled immigrants (Lazear, 2021); US universities, which admit many future US foreign-born tech workers as students (Bound *et al.*, 2017, 2021); and US technology companies, whose recruitment strategies also help bring skilled foreign workers to the US (Kerr & Lincoln, 2010). The interdependent choices of these actors create a business ecosystem in which innovation in AI has been able to flourish. However, it does not

appear to be the only ecosystem that is conducive to such innovation. To create AI, China is taking a more state-directed approach, including trade protection for domestic technology firms (Goldfarb & Trefler, 2018) and is relying mostly on domestic talent. In terms of academic journal publications and awarded patents, its approach has had some success (Xie & Freeman, 2020). When it comes to projecting my results to the world as a whole, one needs to address how these different ecosystems will fare in global competition with each other, a subject on which my analysis is silent.

The empirical results connect to several bodies of literature. A first is analysis of the labor market consequences of regional labor-supply shocks related to immigration. My finding that arriving immigrant workers neither crowd in nor crowd out native-born workers in AI-related jobs is consistent with results in Burstein *et al.* (2020) across all occupations dedicated to tradable activities.[3] Because arriving immigrant workers can be absorbed into the production of exports (i.e., AI routines), they need not displace existing native-born workers. A second body of related work addresses the occupational comparative advantage of immigrants. Foreign-born workers from non-English-speaking countries tend to avoid jobs that are intensive in communication-based tasks (Dustmann & Fabbri, 2003; Peri & Sparber, 2009; Oreopoulos, 2011), and to specialize in STEM fields (Hunt & Gauthier-Loiselle, 2010), especially those related to computing and engineering (Hunt, 2015). Specialization in STEM may account for the over-representation of the foreign-born among US inventors (Kerr & Lincoln, 2010; Hunt, 2011; Bernstein *et al.*, 2018) and for the positive correlation between growth in college-educated immigrant labor supply and regional productivity growth (Peri *et al.*, 2015). The concentration of foreign-born workers in AI-related activities is the latest manifestation of the propensity for immigrant labor to specialize in technology-oriented fields in the US labor market.

My analysis does not address why immigrants with skills applicable to AI are drawn to the US. The concentration of leading IT firms in the US is one explanation for the attraction. Another is that the highly educated are drawn to the US because it offers rewards to skill that are large relative to other high-income destination countries (Grogger & Hanson, 2011). Nor does my work account for why workers from particular countries appear to excel in AI fields. Hanson & Liu (2021) find that immigrants specializing in jobs more intensive in abstract and quantitative reasoning tend to come from countries that deliver higher quality K-12 education, as evidenced by their students achieving higher PISA exam scores. Similar forces may be at work regarding specialization in AI. It is also unclear whether the specialization of foreign-born workers in AI will translate into a comparative advantage in AI in their countries of origin. Whereas China is both a major source of AI talent to the US labor market and the home to leading AI firms, India checks the first box but not the second (at least as far as conventional data reveal). By implication, the presence of firms with core capabilities in computing (or protection from foreign firms with such capabilities) may be necessary for AI to develop.

In Section 2, I describe how I measure AI-related employment; in Section 3, I present descriptive evidence on specialization in AI-related jobs across US commuting zones; in Section 4, I present empirical analysis of how immigrant labor-supply shocks affect regional employment in AI-related occupations; and in Section 5, I conclude.

## 2  Measuring Employment in AI-Related Occupations

Artificial intelligence distinguishes itself by requiring technical skills in computer science, engineering, math, and related disciplines, and by being new (or at least new at a scale to become detectable by employment surveys). My approach to measuring employment in AI-related occupations keys on both of these features: the technical definitions of occupations and their newness. Of course, new work in AI-related fields may include new work in IT that is not exclusive to AI. I therefore refer to my measures as capturing growth in "AI-related" jobs rather than in jobs that are solely dedicated to AI.

### 2.1  Defining AI-Related Occupational Categories

The Census Bureau defines occupational codes by grouping together workers who perform similar tasks on the job. Over time, it modifies the codes, with most major revisions occurring during census years. To measure employment growth for a uniform set of occupations over a multi-decade period, I use Census occupational codes for 1990, as harmonized by Dorn (2009), Autor & Dorn (2013), and Deming (2017).[4] Each occupational code has an attached set of jobs, which are defined in the *Census Alphabetical List of Occupation Titles*. I use these titles to create filters to capture AI-related job growth.

The creation of AI combines the efforts of workers with training across a wide range of technical disciplines, including computer engineering, computer science, data science, and software engineering. Supporting the workers who construct machine-learning algorithms and design their implementation on dedicated computer hardware are specialists who create and manage large databases, provide expertise in relevant domains (e.g., oncologists and radiologists for the use of AI to detect cancer), and develop and market AI products, among other tasks. In order to focus on jobs that are core to innovations in AI, I target the first group of occupations and not the second.

I define the universe of potential AI-related occupations as those in STEM, using the STEM definition in Hanson & Slaughter (2018). They take the Census Bureau categorization of STEM jobs and remove those in which a relatively high fraction of workers lack a college degree (e.g., lab technicians, computer support staff, drafters). The resulting set of occupations includes all computer programmers, computer scientists, engineers, mathematical scientists, network systems analysts, and life and physical scientists.[5]

To define AI-related jobs, I apply a progressively finer set of filters to these broad STEM categories, which creates four versions of occupations:

- V.0 (version 0) occupations: I remove occupation codes from the Hanson & Slaughter (2018) definition that appear to be related to administrative or supportive roles or that are tied to scientific disciplines that appear to be far removed from AI.[6] The resulting set of modified STEM occupations had 707 titles in 2000, of which 137 were added between 1990 and 2000, as seen in Table 7.2.
- V.1 occupations: I select from V.0 occupations those whose titles have at least one of the following terms: analyst (subject to restrictions), architect, designer/design, developer, engineer, programmer, researcher/research, scientist, or statistician/statistical. The resulting set of potential AI occupations had 325 titles in 2000, of which 68 were added after 1990.
- V.2 occupations: I select from V.1 occupations those whose titles have at least one of the following terms: designer/design, developer, programmer, researcher/research, scientist, and statistician/statistical; and engineer plus computer, data, or software. The resulting set had 146 titles across 18 occupation codes in 2000, of which 48 titles were added after 1990. This version is my broad definition of AI-related jobs.
- V.3 occupations: I select from V.2 occupations those that have at least one term from the group {designer/design, researcher/research, scientist, or statistician/statistical} and one term from the group {computer, data, software}. The resulting set has 30 titles across five occupation codes in 2000, of which 16 titles were added after 1990. This version is my narrow definition of AI jobs and is the baseline for the analysis. V.3 codes and titles appear in Appendix Table A.1.

Table 7.1 describes the application of the V.0 to V.3 filters to modified Census 1990 occupation codes and shows the total number of job titles as of 2000 for each version. In the empirical analysis, I use V.2 and V.3 occupations only.[7] Throughout the text, for notational clarity, I refer to the sets of *occupations* that contain AI titles as $V.0_t$–$V.3_t$ for each version in a given year $t$. Similarly, the sets of *occupation titles* are denoted $V.0.T_t$–$V.3.T_t$.

Appendix Table 7A.1 lists job titles for V.3 occupations. This narrow definition includes five Census 1990 occupations: computer hardware engineers, computer scientists and systems analysts, computer software engineers, network systems and data communications analysts, and statisticians.[8] The 30 AI-related job titles include artificial intelligence specialist, information scientist, computer research, computer systems engineer, and software applications engineer. Whereas the first two of these are AI-specific jobs, the latter three are likely to span AI and non-AI-specific activities. Other job titles also appear likely to include AI and non-AI specific jobs (e.g., software requirements engineer, systems analyst engineer, computer engineer). By targeting job titles created after 1990, as I discuss in the next section, my approach helps narrow the focus on AI-related activities, but may do so imperfectly. The resulting measures of AI-related employment growth are therefore likely to include some non-AI jobs in information technology that nonetheless require AI-like skills. On the

_Table 7.1_ Occupation Title Filters for AI-Related Jobs

| Version: | V.0 | V.1 | V.2 | V.3 |
|---|---|---|---|---|
| # Identified Titles: | 707 | 325 | 146 | 30 |
| **Occupation title filters** | Analyst | Analyst | | |
| | Scientist | Scientist | Scientist | Scientist + Software/ Data/Computer |
| | Administration/administrator | | | |
| | Researcher/research | Researcher/research | Researcher/research | Researcher/research + Software/ Data/Computer |
| | Designer/design | Designer/design | Designer/design | Designer/design + Software/ Data/Computer |
| | Architect | Architect | | |
| | Technician | | | |
| | Programmer | Programmer | Programmer | |
| | Developer | Developer | Developer | |
| | Integrator | | | |
| | Engineer | Engineer | Engineer + Software/ Data/Computer | Engineer + Software/ Data/Computer |
| | Statistician/statistical | Statistician/statistical | Statistician/statistical | |
| | Manager | | | |
| | Planning/planner | | | |
| | Health | | | |
| | Consultant | | | |
| | Specialist | | | |
| | Supervisor | | | |
| | Tester | | | |
| | Installer | | | |
| | Coordinator | | | |
| | Officer | | | |
| | Operator | | | |
| | Investigator | | | |
| | etc. | | | |

This table reports keywords used to define versions V.0 to V.3 of occupational titles. These keywords act as inclusion criteria, subject to discretion. In particular, "analyst" is used in a wide variety of occupation titles, mandating many exclusions (e.g., "forms analysts"). V.0 applies no keyword filters; its associated column reports representative keywords that appeared in many of its occupation titles. The V.1 to V.3 filters are based on the listed keywords. They exclude engineering occupations that appear unconnected to AI (agricultural, biomedical, chemical, civil, environmental, industrial, marine, materials, mechanical, mining and geological, petroleum, and other engineers).

other hand, one may be concerned that designating just 30 job titles as being AI-related is too narrow. For this reason, I also use the broader V.2 definition of AI titles as a robustness check in the empirical analysis.

## 2.2 AI-Related Employment

Although AI as a concept has been around for well over half a century, AI-specific occupations did not become prominent enough to merit their own job titles in public surveys until more recently. After slow progress in the 1970s and 1980s, advances in the field began to accelerate in the 1990s (Cockburn *et al.*, 2018).[9] I use the creation of new job titles after 1990 as an indication of the intensity of innovation across occupations.

The Census Bureau tracks how jobs change over time. To account for changes, it adds and subtracts job titles from occupational codes, where a title defines a specific job performed within an occupation. When the Census adds new titles to occupation codes, it indicates that there are new lines of work within an occupation that appear at sufficient frequency to merit official mention. Within my V.3 definition of AI-related jobs, after 1990 the Census added titles for artificial intelligence specialist and information scientist to the computer scientists and systems analysts occupational category (see Table 7A.1), which signified the expansion computer science jobs to include these fields. Lin (2011) uses the addition of new titles to measure the creation of new work at the level of an occupation code. Using his categorization, I define new AI-related work within an occupation using the job titles that were created after 1990 (by his designation) and that are AI-related (by my designation).[10]

For occupation codes that register new titles in AI-related activities after 1990, Table 7.2 reports 1990 occupation categories in the first column, the total number of job titles for the occupation in 2000 in the second column, the number of titles for V.0 to V.3 occupations in 2000 in the next four columns, and the number of potentially AI-related titles added after 1990 for V.0 to V.3 occupations in the final four columns. After 1990, there were 48 new AI-related job titles added in V.2 occupations, representing a 50.0% $(= \frac{|V.2.T_{2000}| - |V.2.T_{1990}|}{|V.2.T_{1990}|} = \frac{48}{146-48})$ increase in job titles in the category, and 16 new AI-related job titles in V.3 occupations, representing a 114.3% $(= \frac{|V.3.T_{2000}| - |V.3.T_{1990}|}{|V.3.T_{1990}|} = \frac{16}{30-16}))$ increase in job titles in the category. For both definitions, the largest increase in job titles was for computer scientists and systems analysts.

## 2.3 Alternative Approaches to Measuring AI

To provide context for my analysis, I discuss other approaches to measuring AI-related production and work activities. Bloomk *et al.* (2020) use earnings conference calls and patent filings to document the rollout of 20 new technologies

*Table 7.2* Occupation Codes and Numbers of Associated Titles

| Occupation | Total # Occupation Titles | # AI Titles | | | | # New, AI Titles | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | V.0 | V.1 | V.2 | V.3 | V.0 | V.1 | V.2 | V.3 |
| Computer programmers | 22 | 22 | 18 | 18 | 0 | 11 | 10 | 10 | 0 |
| Computer systems analysts and computer scientists | 162 | 97 | 52 | 34 | 24 | 65 | 32 | 24 | 15 |
| Operations and systems research-ers and analysts | 24 | 24 | 9 | 1 | 0 | 6 | 2 | 0 | 0 |
| Engineers and other professionals, n.e.c. | 58 | 58 | 13 | 4 | 0 | 12 | 5 | 2 | 0 |
| Atmospheric and space scientists | 19 | 19 | 17 | 17 | 0 | 3 | 3 | 3 | 0 |
| Marine engineers and naval architects | 13 | 13 | 10 | 2 | 0 | 2 | 1 | 1 | 0 |
| Electrical engineers | 60 | 60 | 54 | 9 | 3 | 9 | 5 | 3 | 1 |
| Petroleum, mining, and geological engineers | 36 | 36 | 0 | 0 | 0 | 5 | 0 | 0 | 0 |
| Mathematicians and statisticians | 27 | 27 | 13 | 10 | 3 | 3 | 0 | 0 | 0 |
| Industrial engineers | 46 | 46 | 0 | 0 | 0 | 5 | 0 | 0 | 0 |
| Mechanical engineers | 41 | 41 | 40 | 9 | 0 | 4 | 4 | 2 | 0 |
| Chemical engineers | 23 | 23 | 16 | 2 | 0 | 2 | 2 | 1 | 0 |
| Physicists and astronomers | 29 | 29 | 20 | 20 | 0 | 2 | 2 | 2 | 0 |
| Biological scientists | 53 | 53 | 11 | 11 | 0 | 2 | 0 | 0 | 0 |
| Civil engineers | 54 | 54 | 0 | 0 | 0 | 2 | 0 | 0 | 0 |
| Management analysts | 31 | 31 | 7 | 0 | 0 | 1 | 0 | 0 | 0 |
| Aerospace engineers | 42 | 42 | 37 | 9 | 0 | 1 | 0 | 0 | 0 |
| Other financial specialists | 27 | 11 | 8 | 0 | 0 | 2 | 2 | 0 | 0 |
| Metallurgical and materials engineers | 21 | 21 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

This table reports the following values for each occupation that contains job titles in the V.0 to V.3 definitions: the total number of occupation titles as of 2000 (column 2), the number of column 2 titles that are potentially related to AI (columns 3-6), and the number of column 3-6 titles that were new as of 2000 (columns 7-10). The final two metrics are shown for V.0 (STEM occupations), V.1 (potential AI occupations), V.2 (broad AI-related occupations), and V.3 (narrow AI-related occupations) categories. The remaining, unlisted 310 occupations had zero potentially AI-related titles.

between 2002 and 2020. For the 10 most-cited U.S. patents in each year between 1976 to 2016, they apply text analysis to identify the most common technical bigrams (e.g., word pairs) that appear in the filings for these patents. From the resulting bigrams, they identify those that appear most frequently in corporate earnings calls over 2002 to 2020 and then collect these terms into 20 technology groups. Of these 20, one is artificial intelligence (whose associated keywords are artificial intelligence, machine learning, neural networks, deep learning, predictive analytics, and language processing). Three other new technologies include applications of AI (driverless, machine vision, virtual reality), while two others are computing technologies that are used to create AI (cloud, disk drive).

Using this categorization, they calculate the exposure of firms and occupations to new technologies, where exposure to a specific technology is defined as the share of all technical bigrams that appear in earnings calls for a firm (from 2002 forward) or Burning Glass job postings for an occupation (from 2010 forward) that are comprised of the bigrams associated with that technology. These data allow Bloom *et al* (2020) to track exposure to new technologies across U.S. industries, occupations, and regions. For AI, firm exposure increased modestly from 2010 to 2015 and rapidly thereafter. As a technology diffuses over time, the desired education level listed in job postings tends to decline.[11]

For my purposes, their measure of technology exposure, which is not yet publicly available, represents a shock to labor demand that may be difficult to sign. For instance, the two most exposed occupations to virtual reality are computer hardware engineers and fine artists. One may imagine that the technology represents a strongly positive shock for engineers but an ambiguous shock for fine artists (e.g., positive for those working in digital media and negative for those working in non-digital media).

Other work focuses on identifying occupations exposed to the job-displacing impacts of AI. The measure in Felten *et al.* (2019) combines the Electronic Frontier Foundation AI Progress Measurement dataset, which tracks technological progress across categories of AI activities (e.g., image recognition), with crowdsourced assessments of how well these categories apply to O*NET ability scales (e.g., depth perception), to measure the vulnerability of occupations to AI, based on the importance of each ability scale to an occupation. In two related approaches, Brynjolfsson *et al.* (2019) use crowdsourcing to evaluate the suitability of machine learning for detailed work activities in O*NET, and then construct an occupation-level measure of exposure to AI based on occupation intensities in these activities, while Webb (2020) defines occupation-level exposure by identifying the overlap between Google Patents Public Data and O*NET tasks. Acemoglu *et al.* (2020) calculate exposure to AI at the establishment level by using the establishment intensity of employment across occupations for each of these three AI occupation-exposure measures.

These advances in measuring occupation or establishment-level exposure to the disruptive impacts of AI are welcome. None, however, appears to be directly useful for detecting which occupations are most likely to be engaged in producing AI.

# 3  Preliminary Analysis

In this section, I examine which U.S. commuting zones are most specialized in AI-related activities, in which commuting zones are AI-related activities most concentrated, and how revealed comparative advantage in AI-related activities varies across workers according to their region of birth. I focus on prime-age workers (ages 25 to 54) who have at least four years of college education. I measure employment as hours worked (weeks worked last year × usual hours worked per week × sampling weight) for individuals who are not in group quarters and who had positive earnings in the previous year. Data are from the 2000 Census, the 2005–2009 ACS five-year sample (which I ascribe to 2009), and the 2014-2018 ACS five-year sample (which I ascribe to 2018).

## *3.1  CZ Specialization in AI-Related Occupations*

Figure 7.1 shows the share of hours worked by the college-educated in AI-related occupations for the V.3 definition across commuting zones. Specifically, letting $L_{oct}^{g,f}$ refer to hours worked in a given occupation $o$, CZ $c$, year $t$, and by gender $g$ and foreign born status $f$, this share is given by the expression,

$$100 * \frac{\sum_o s_{V.3.T,o} * L_{oct}^{g,f}}{\sum_f \sum_o L_{oct}^{g,f}},$$
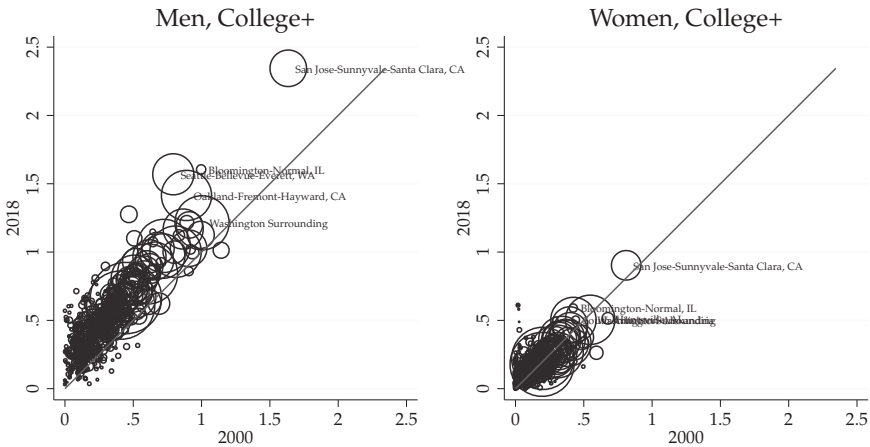


*(a)* All Workers

*Figure 7.1*  Share of Hours Worked in AI-Related Occupations by Commuting Zone

The figures show the share of hours worked (in percentage terms) in AI-related occupations (V.3 definition) for prime-age, college-educated men or women in a given CZ for 2000 and 2018. AI hours worked is measured as hours worked in a given AI-related occupation times the share of all 2000 jobs titles in that occupation that were created after 1990 and that were AI-related. Shares are for all workers in panel (a), foreign-born workers in panel (b), and native-born workers in panel (c).
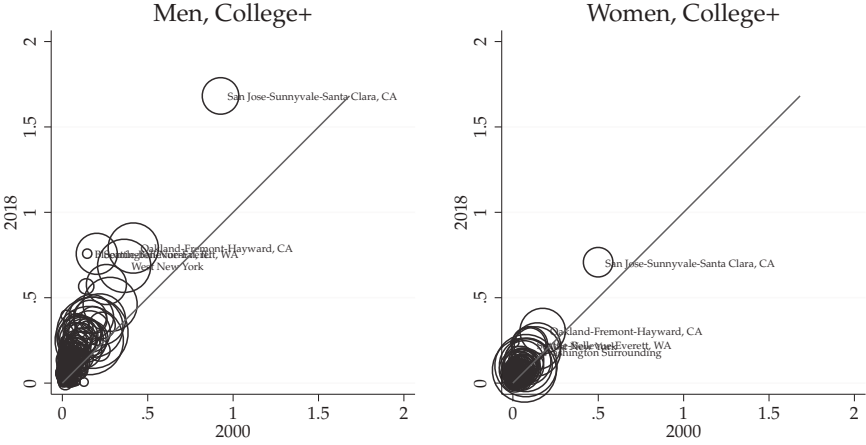
*(b)* Foreign-born Workers
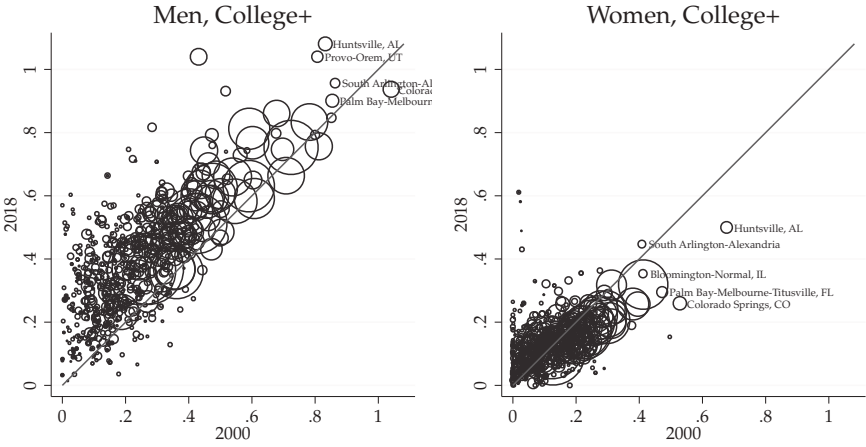


*(c)* Native-born Workers

*Figure 7.1*   (*Continued*)

where $s^o_{V.3.T} = \frac{|V.3.T^o_{2000}| - |V.3.T^o_{1990}|}{|V.3.T^o_{2000}|}$ is the share of titles in a given occupation $o$ that are new and related to AI, thus proxying for the fraction of hours worked in a given occupation that is devoted to new AI-related work. Unreported figures for the V.2 definition of occupations are very similar. The first panel shows the share of all CZ workers employed in AI-related occupations, first for men and then for women; the second panel shows foreign-born workers employed in

AI-related occupations as a share of total CZ employment; and the third panel shows native-born workers employed in AI-related occupations as a share of total CZ employment.[12] In each graph, the share of CZ employment in AI-related jobs for 2018 appears on the vertical axis and the corresponding share for 2000 appears on the horizontal axis. To help identify the individual CZs in the figures, Appendix Table 7A.2 lists the top 20 CZs in each of the six plots. Unreported plots for employment shares using worker counts are very similar.

Three patterns are apparent in the data. The first is that there is persistence in which CZs are specialized in AI-related activities. In each figure, there is a strong positive correlation between the share of CZ employment in AI-related jobs in 2000 and 2018, as indicated by the clustering of points along the 45-degree line. Most points are modestly to substantially above the line, indicating a strengthening of regional specialization in AI-related activities over time. The second is that across CZs and over time, specialization of men in AI-related activities tends to be much stronger than that for women. Male AI employment shares tend to be two to three times as large as those for women. This pattern is consistent with the relatively greater specialization of men in STEM-related jobs across occupations (e.g., Hanson & slaughter, 2018).

The third pattern relates to differences in native-born and foreign-born specialization in AI-related activities across CZs. When considering all workers together in the first panel, specialization in AI-related activities is strongest in three types of CZs: hubs for high-tech industry (e.g., San Jose, CA), university towns (e.g., Bloomington, IL), and cities specialized in government or military research (e.g., Colorado Springs, CO). When I separate foreign-born and native-born workers, we then see that when it comes to specialization in AI-related activities the two groups of workers tend to cluster in different places. The share of foreign-born workers specialized in AI-related activities as a share of CZ total employment is largest in conventional high-tech hubs (San Jose, CA; Oakland, CA; Austin, TX; Boston, MA; Seattle, WA), and major cities (New York, NY; Washington, NY; Dallas, TX). For the native-born, by contrast, the share of their employment in AI-related activities as a share of CZ total employment is highest in locations that have government, military, or space-related research facilities (Colorado Springs, CO; Alexandria, VA; Melbourne, FL; Huntsville, AL) or that are university towns (Bloomington, IL; Provo, UT). For both men and women, the overlap of the top 10 CZs in terms of AI specialization by the foreign-born and native-born includes just two commuting zones, Washington, DC, and Raleigh, NC. Because government and military research tends to require higher-level security clearances, it may be that native-born workers are better positioned to take these types of jobs. Foreign-born workers appear to excel in taking up jobs in CZs populated by private employers and non-governmental research entities.

### 3.2 Concentration of AI-Related Employment in Tech-Oriented CZs

Figure 7.2 shows the share of commuting zones in national hours worked by the college-educated in AI-related occupations by the V.3 definition, where figures
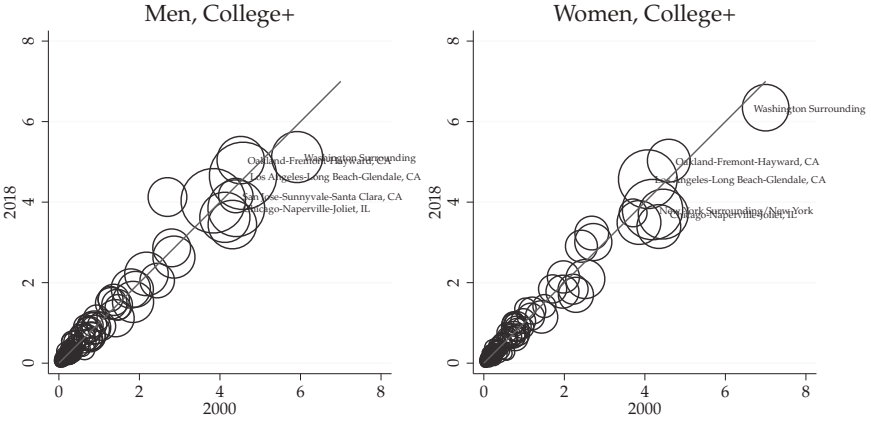
*(a)* All Workers
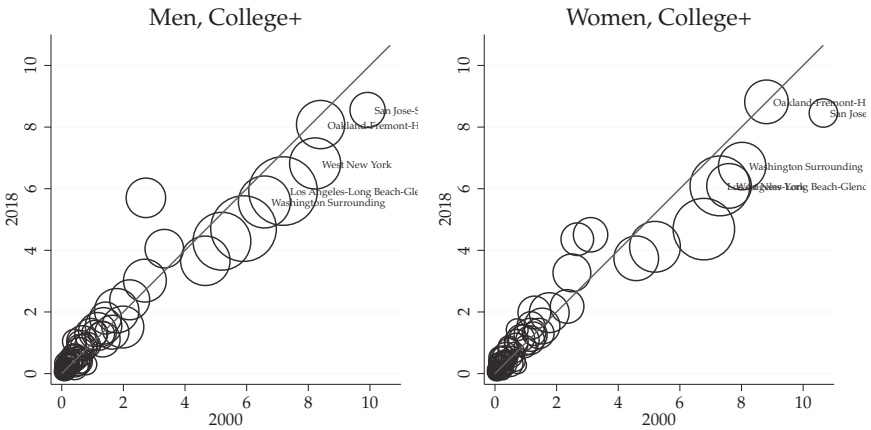


*(b)* Foreign-born Workers

*Figure 7.2* Share of CZ in National Hours Worked in AI-Related Occupations

The figures show the share of a commuting zone in national hours worked (in percentage terms) in AI-related occupations (V.3 definition) for prime-age, college-educated men or women in a given CZ for 2000 and 2018. AI hours worked is measured as hours worked in a given AI-related occupation times the share of all 2000 jobs titles in that occupation that were created after 1990 and that were AI-related. Shares are for all workers in panel (a), foreign-born workers in panel (b), and native-born workers in panel (c).

Men, College+   Women, College+

*(c)* Native-born Workers
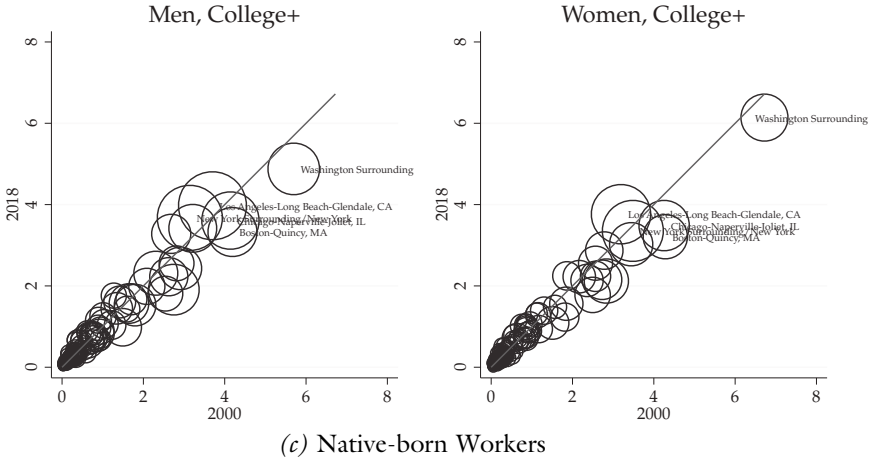
*Figure 7.2*   (*Continued*)

for the V.2 definition are very similar. The first panel includes all workers, first for men and then for women; the second panel includes foreign-born workers only; and the third panel includes native-born workers only. In each graph, the CZ share of national employment in AI-related jobs for 2018 appears on the vertical axis and the corresponding share for 2000 appears on the horizontal axis. Following notation from Section 3.1, the expression for these shares is given by,

$$100 * \frac{\sum_o s_{V.3.T,o} * L_{oct}^{g,f}}{\sum_c \sum_o s_{V.3.T,o} * L_{oct}^{g,f}}.$$

To help identify the individual CZs in the figures, Appendix Table 7A.3 shows the top 20 CZs in each of the six figures. Unreported plots for employment shares using worker counts are very similar.

The largest hubs account for a substantial share of US AI-related employment. These patterns are persistent over time, as indicated by the concentration of data points along the 45-degree line. The top five hubs (Washington, Los Angeles, Oakland, Chicago, San Jose) accounted for 23.1% of male AI-related employment in 2018 and the top 10 (top five plus Boston, New York, West New York, Atlanta, Dallas) accounted 40.9% of male AI-related employment in that year. Figures for women are similar, as are the CZs in which their employment is concentrated. Consistent with overall patterns of spatial agglomeration in high-tech activities (Moretti, 2012, 2019; Bloom *et al.*, 2020), US employment in jobs that require AI-like skills are highly geographically concentrated.

As with regional specialization in AI-related jobs, it is again the case that the commuting zones that account for the largest clusters of AI-related employment differ depending on whether one is examining foreign-born or native-born workers. For foreign-born men, San Jose (8.6% in 2018) and Oakland (8.1% in 2018) are the largest clusters of AI-related employment, whereas for native-born men San Jose

(1.8% in 2018) and Oakland (3.4% in 2018) are ranks 12 and five, respectively. For native-born men, Washington, DC (4.9% in 2018) and Boston (3.3% in 2018) are the largest clusters of AI-related employment, whereas for foreign-born men Washington, DC (5.6% in 2018) and Boston (3.7% in 2018) are ranks five and eight, respectively. This provides further evidences of differences in specialization patterns of the foreign and native-born when it comes to AI-related jobs.

### 3.3 Revealed Comparative Advantage in AI-Related Occupations

In this section, we consider the extent to which foreign and native-born workers differ in their specialization in AI-related jobs. Existing literature indicates that across all STEM-related occupations, the foreign-born show stronger patterns of specialization than do the native-born (Hanson & Liu, 2017; Hanson & Slaughter, 2018). Here, we narrow the focus to the revealed comparative advantage of the two groups in jobs that are related to AI. Of course, the specialization of foreign-born workers in AI-related occupations indicates comparative but not absolute advantage in these jobs. Immigrant specialization in AI may represent an absolute advantage in the activity. On the contrary, US-born workers may have an absolute advantage in all occupations, but end up specializing in non-STEM sectors because of a relatively strong advantage in tasks that require communication and social skills, which may be relatively important in non-STEM activities.

To begin, Figure 7.3 shows the share of hours worked by the prime-age and college-educated in AI-related occupations (V.3 definition) by worker place of birth. I group birth countries into eight regions based on similarities in education levels and specialization in STEM occupations: the US; Africa and the Middle East; China and Hong Kong; Europe, Australia and New Zealand; India; Korea, Japan, and Taiwan; Latin America and the Caribbean; and Other Asia.[13] For men, the share of AI-related jobs (V.3 definition) held by those born in the US declined from 75.2% in 2000 to 65.2% in 2018. This drop was due almost entirely to the increased employment of men born in India, whose share of AI-related employment rose from 7.8% in 2000 to 16.9% in 2018. Over 2000 to 2018, foreign-born workers accounted for 54.6% of the increase in employment in AI-related jobs, with workers born India alone accounting for 63.7% (or 35.3% of the nationwide increase) of this increase. Patterns for women are similar. The share of native-born women in AI-related employment fell between 2000 and 2018 (from 78.1% to 65.1%), with rising shares for women born in India (from 4.8% to 16.4%) accounting for most of this decline.

To characterize specialization in AI-related jobs, one needs to adjust for the overall presence of a national origin group in the economy. I do so by calculating revealed comparative advantage in AI-related employment among workers in the U.S. labor market:
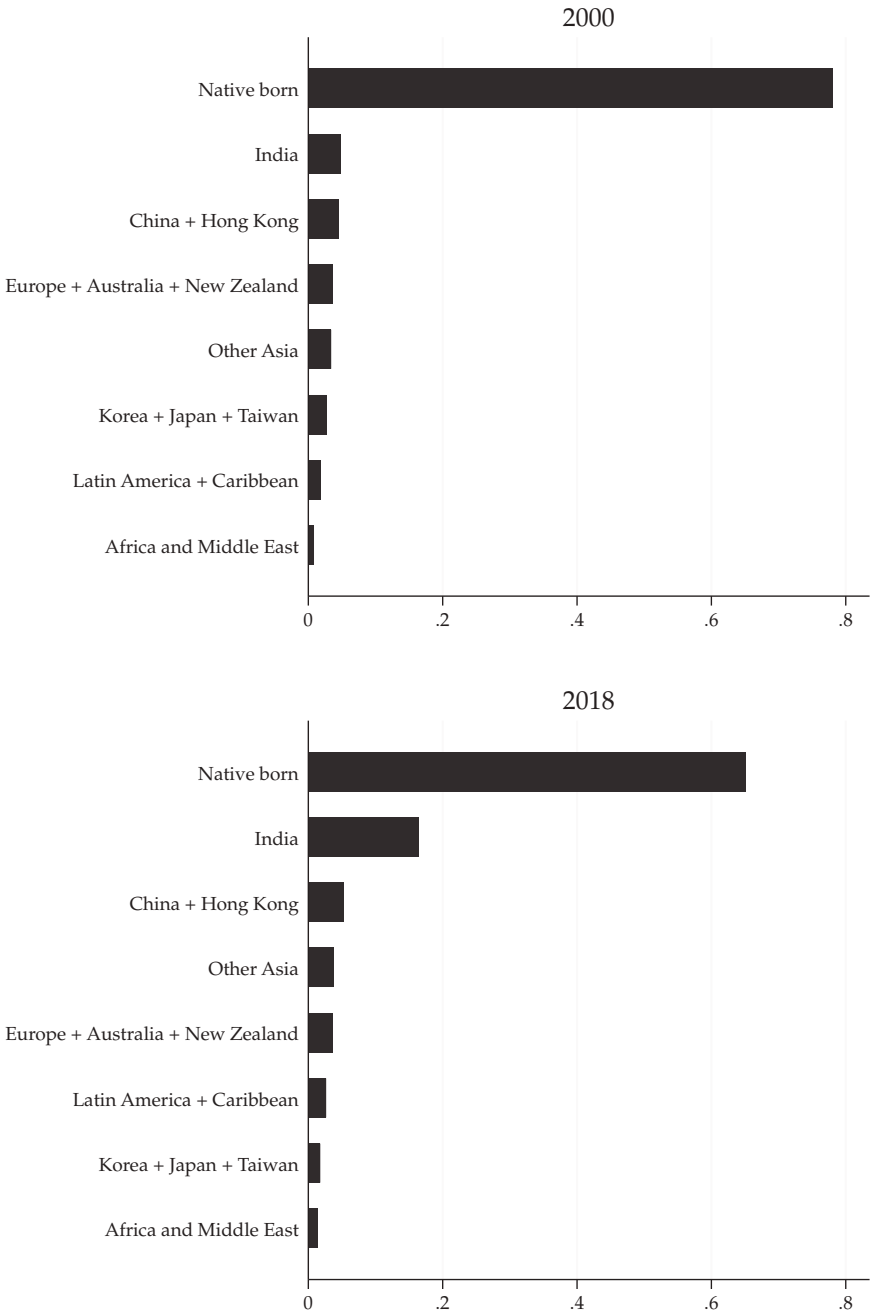
$$RCA_n = \ln\left(\frac{L_n^{ai}/L^{ai}}{L_n/L}\right),$$
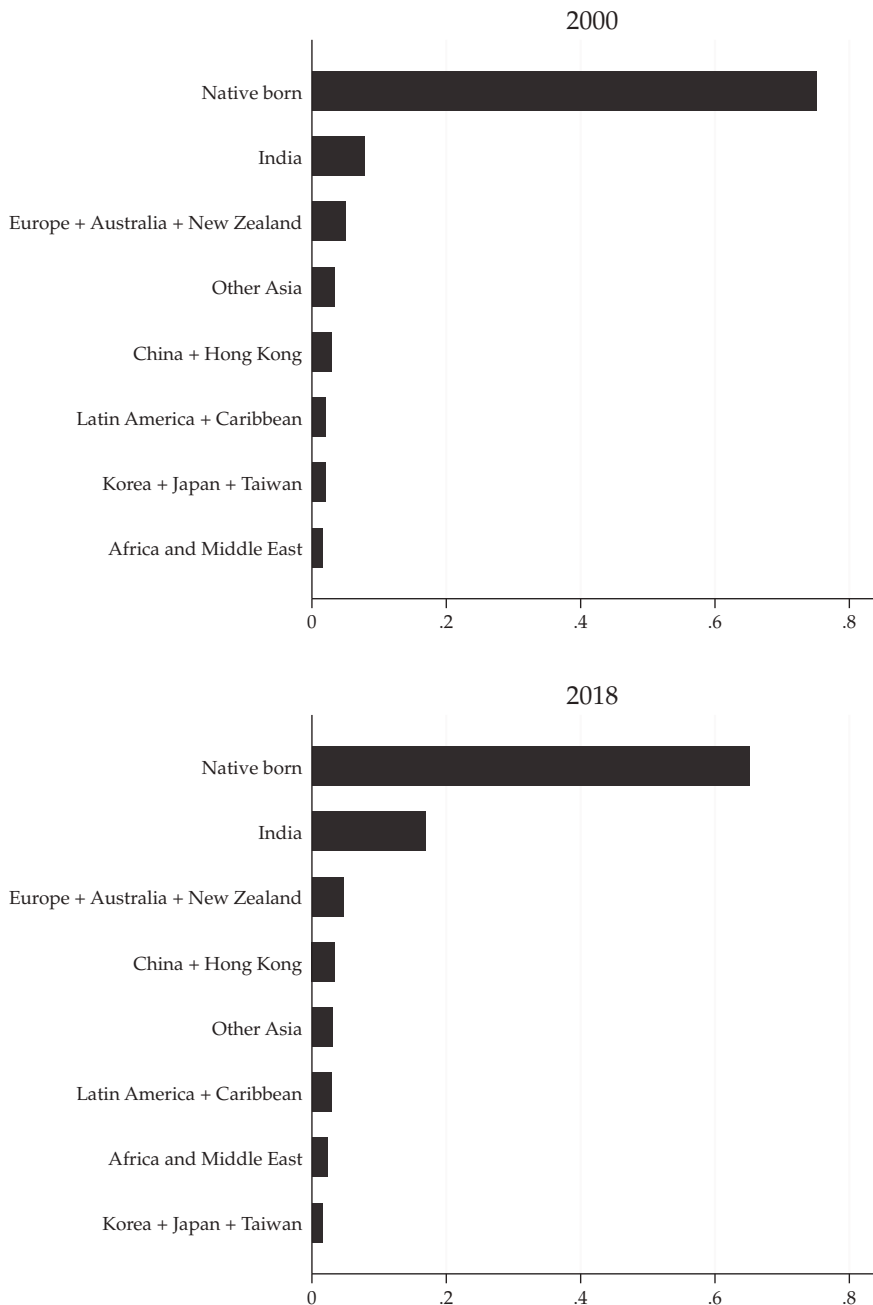
*(a)* Men

*Figure 7.3* Share of Hours Worked by the College Educated in AI-Related Occupations by Worker Region of Birth

## 2000



## 2018



*(b)* Women

*Figure 7.3*   (*Continued*)

where $L_n^{ai}/L^{ai}$ is the share of national-origin group $n$ in US employment (of the college educated) in AI-related occupations (which is shown in Figure 7.3) and $L_n/L$ is the share of national-origin group $n$ in national employment (of the college educated) across all occupations. RCA values for men and women in 2000 and 2018 appear in Figure 7.4. Workers born in India display the strongest revealed comparative advantage in AI-related employment. The log RCA value for Indian men of 1.37 in 2018 indicates that their employment share in AI was 3.9 (= $\exp(1.37)$) times their employment share across all occupations in the US. Women born in India display an even stronger revealed comparative advantage in AI-related activities. For both men and women, China and Hong Kong is the region with the next strongest RCA in AI-related jobs. Robustly negative log RCA values for individuals born in the US and Latin America and the Caribbean indicate that among the college educated, their employment shares in AI-related activities were substantially below their employment shares across all occupations.

Does revealed comparative advantage on the part of Indian and Chinese workers in AI-related occupations simply reflect a generic comparative advantage across all jobs that are related to STEM disciplines? Appendix Tables 7A.4 to 7A.8 show employment shares and log RCA values for national origin groups using the V.0 definition of STEM-related jobs (707 titles), the V.1 definition of potentially AI-related jobs (325 titles), and the V.2 broad definition of AI-related jobs (146 job titles). These categories represent substantially larger employment levels than the 30 AI-related job titles in the V.3 definition. In 2018, workers born in India accounted for 4.3% of total employment of college-educated men in the US, 10.9% of employment in V.0 occupations, 12.1% of employment in V.1 occupations, and 14.6% of employment in V.2 occupations, as compared to their 16.9% of employment in V.3 occupations. A similar patterns holds for women born in India, whose employment shares rise from 2.2% among all college-educated workers to 9.3% in V.0 occupations and to 16.4% in V.3 occupations. As we narrow the definition of jobs related to AI, the revealed comparative advantage of workers from India in these occupations intensifies. For men born in China or Hong Kong, their 2018 employment shares rise from 1.4% across all occupations to 2.7% in V.0 occupations and to 3.4% in V.3 occupations, while for women born in the region their employment shares rise from from 1.4% across all occupations to 4.3% for V.0 occupations and to 5.3% for V.3 occupations. For workers born in India and China, specialization in narrowly defined AI-related jobs is much stronger than specialization in STEM-related occupations overall.

Which factors account for the revealed comparative advantage of workers from China and India in AI-related activities? One possibility is that immigrant specialization in AI is a result, not of an absolute disadvantage among US-born workers in these jobs, but of an overwhelming absolute advantage of the U.S.-born workers in non-AI fields. If, for instance, non-AI jobs place a higher premium on social and communication skills (which may be relatively unimportant in producing AI) and the U.S. educational system (including K-12 schooling) is
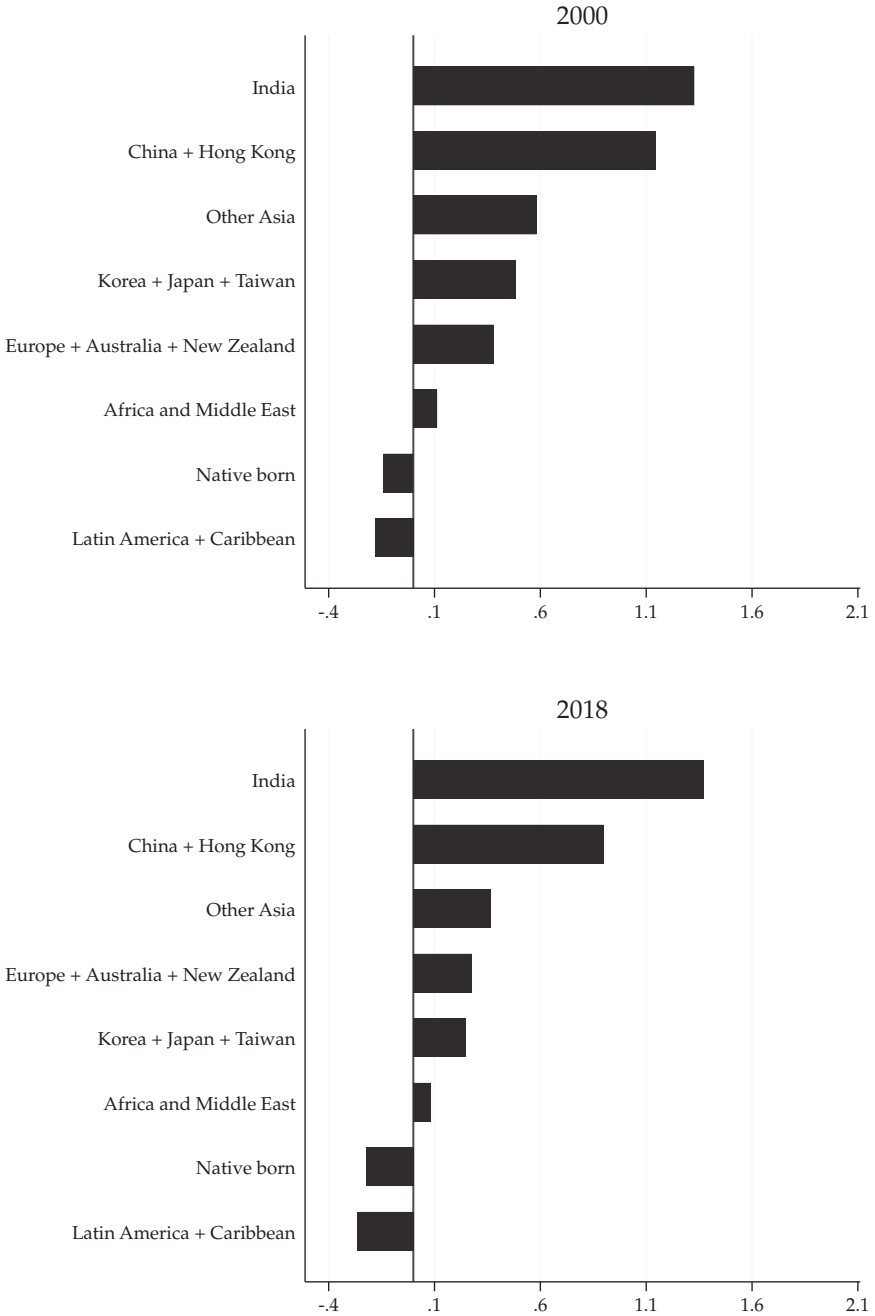
*Figure 7.4* Revealed Comparative Advantage in AI-Related Occupations for College-Educated Workers by Region of Birth

2000



2018
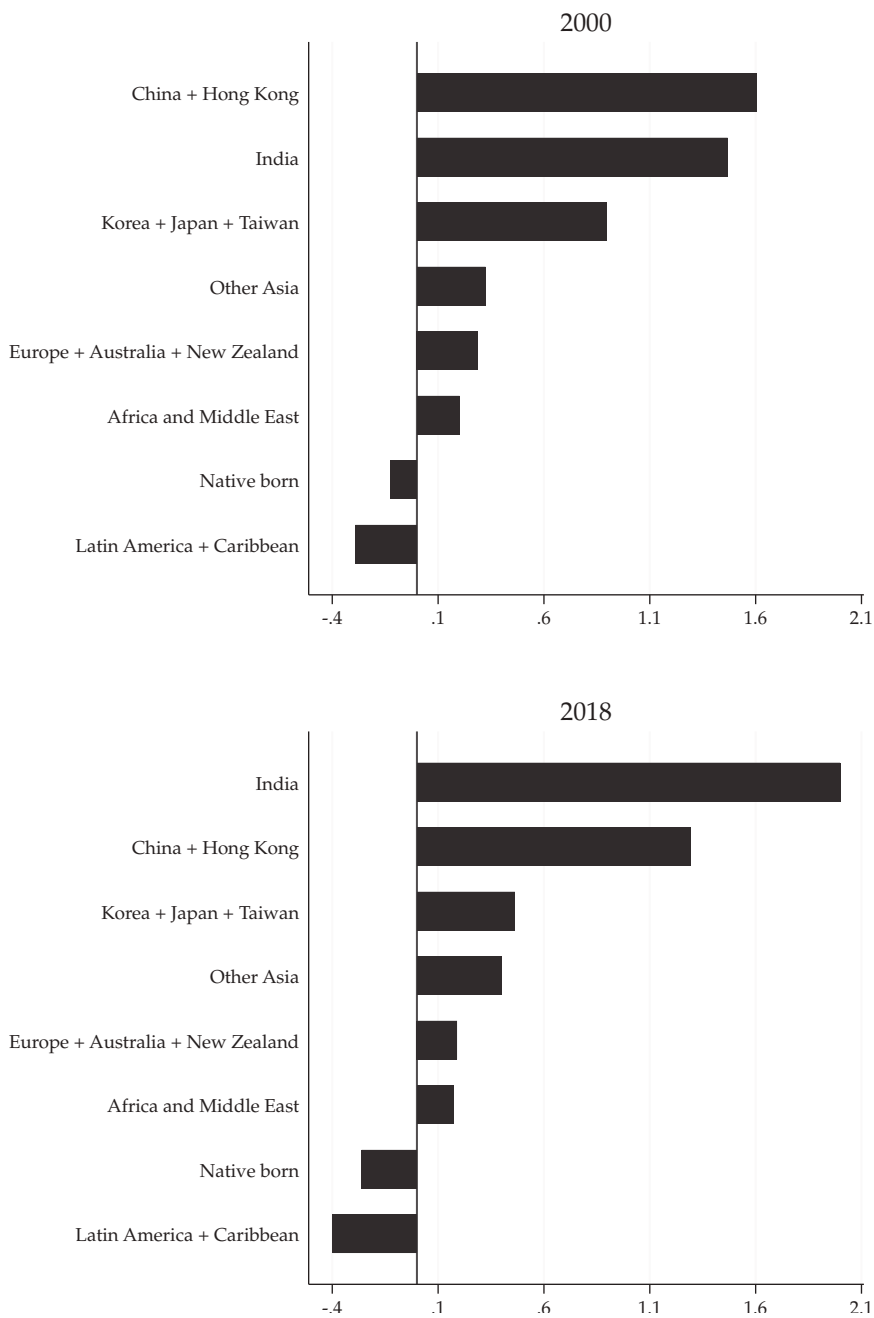


*(b)* Women

*Figure 7.4*   (*Continued*)

particularly adept at imparting these skills, then workers born in the US may specialize in non-AI occupations (and non-STEM occupations in general), despite having an absolute advantage across all trades. For Chinese immigrants, language barriers may put them at a further disadvantage in non-STEM positions.[14]

A second factor may be the quality of technical training in engineering and math in the two countries. China has invested heavily in its university training in STEM (Xie & Freeman, 2020), while India's technical institutes excel in engineering and math. Strong engineering and math skills may have left workers from the countries well-positioned to move into AI, as the field has expanded.[15] A related factor, which may be both a result of and a contributor to the countries' revealed occupational comparative advantage in computer science and engineering, is the relatively strong capabilities of Indian and Chinese firms in technology fields. Indian firms, such as Infosys, Tata Consultancy Services, and Wipro, are among the leading providers of technology-related services globally. Because Alphabet, Amazon, Apple, Facebook, Microsoft, and other major US tech companies appear to excel in all stages of technology production and distribution, Indian firms may have an incentive to specialize in the relatively narrow category of software programming and related technology services, which are used intensively in AI. Indian tech firms may offer training for workers who wish to obtain visas to work in the US technology sector. For its part, China has developed a set of national technology companies in Alibaba, Baidu, Tencent, and others, which occupy similar market niches as the big five US tech firms. Because of barriers to entry in China, the two groups of companies tend not to compete head to head in their national markets. Like Indian companies, these firms may provide a training ground for workers seeking to break into the US job market.

A final factor may be US immigration policy. Prior to 1990, there were few individuals of Indian or Chinese origin in the US. As a result, few US residents would have been able to sponsor individuals from these countries for family-based immigration visas, which by law account for the strong majority of permanent visas that the US government gives out each year. Their primary means of obtaining a US permanent legal residence visa, or green card, has been through employer-sponsored visas, the supply of which equal a legally mandated 15% of all restricted visas (i.e., visas other than those awarded to immediate family members of US residents) awarded in a given year. The need to obtain employer-sponsored green cards may have meant that the Indian and Chinese immigrants selected for admission have been disproportionately likely to reflect the types of high-skilled workers in most demand by US companies, including those in high tech.

H-1B visas, which were introduced in 1990 and allow workers to hold a job in the US for three years and to renew the visa for a second three-year stay, are claimed overwhelmingly by workers in technology-related fields (Bound *et al.*, 2017, 2021). These visas operate as queues for employer-sponsored green cards. One pathway to an employer sponsored green card is first to obtain an H-1B temporary work visa, which allows a worker to demonstrate her talents to a US employer before that employer undertakes the time-consuming task of

employment sponsorship. A second and related pathway is to obtain a student visa, complete an undergraduate or graduate degree in the US, and then secure an H-1B visa. The need for many Chinese and Indian immigrants to obtain an H-1B visa to gain entry to the US may create a selection mechanism that favors workers who excel in jobs that require skills applicable to AI.

## 4 Regression Analysis

In this section, I present the core empirical results of the chapter. I estimate the change in CZ specialization in AI-related activities as a function of the immigrant labor-supply shock confronting the CZ, defined as local exposure to national growth in the number of college-educated immigrants. The estimation covers the long-period change 2000 to 2018; results for stacked first differences over 2000 to 2009 and 2009 to 2018 are shown in the appendix. This time period spans the slower growth in AI-related activities of the early 2000s and the acceleration in growth after 2010. All specifications control for regional business cycles and initial-period CZ demographic composition and exposure technological change, manufacturing decline, and globalization.

Before presenting the specification, it is worth articulating the implicit experiment that underlies the analysis. After 2000, US technology firms began to invest more heavily in AI (due to technological breakthroughs). Their footloose nature left them free to locate where they saw fit. Also after 2000, the US had substantial inflows of highly educated foreign-born workers. Because of historical patterns of immigrant settlement, workers from specific origin countries tended to congregate in specific US commuting zones; and because of historical patterns of occupational specialization, workers from specific origin countries were drawn to specific types of jobs. The quasi-experiment I evaluate is whether CZs seeing larger inflows of foreign-born workers with a proclivity to work in AI—where these inflows were the combined byproduct of historical settlement and specialization patterns—became more specialized in AI-related activities. For the quasi-experiment to be valid, inflows of foreign-born workers to a CZ must not have been caused by investments of local firms in AI. A challenge for the estimation is to construct the immigrant supply shock so as to minimize the potential for such reverse causality.

How would the immigrant labor supply shock affect employment of different types of workers? We would expect the direct effect to be expanded employment of foreign-born workers in AI-related jobs. The magnitude of this impact may differ between foreign-born men and women, if the two groups differ in their tendencies to specialize in AI. The indirect impact of the shock on native-born workers in a CZ is of indeterminate sign. On the one hand, AI-producing firms may expand employment of native-born workers, either because foreign and native-born workers are complements in production or because of agglomeration economies that induce AI firms to expand employment of all factors. On the other hand, if native and foreign-born workers in AI-related jobs are substitutes, firms may be inclined to replace native-born workers with foreign-born

workers, if the latter has a comparative advantage in AI-related tasks. Because AI is a tradable, this crowding-out effect may be attenuated. When studying the adjustment of native-born employment to immigrant labor supply shocks across all occupations, Burstein *et al.* (2020) found neither crowding in nor crowding out—on net, arriving immigrant workers do not displace native-born workers within occupations whose services are tradable. With these alternative adjustment mechanisms in mind, I allow the impact of the immigrant labor supply shock to differ between men and women and between the native and foreign-born.

### 4.1 Empirical Specification

The core empirical specification takes the form,

$$\Delta \Upsilon_{cg\tau}^{v} = \beta_{g0} + \beta_{g1}\Delta z_{cg\tau}^{v} + \beta X_{cg\tau} + \epsilon_{cg\tau}, \tag{1}$$

where $\Delta \Upsilon_{cg\tau}^{v}$ is the change in the share of employment for prime-age, college-educated workers of gender $g$ (female, male) in commuting zone $c$ (722 CZs in the continental US) in AI-related occupations of type $v$ (V.3, V.2) over time period $\tau$ (2000-2018).[16] I use hours worked to measure employment in the baseline analysis; results using worker counts appear in the appendix. I estimate equation (1) separately for men and women. I measure the employment change in the numerator of the dependent variable to be, alternatively, for all workers, foreign-born workers, and native-born workers (such that the estimated $\beta_{g1}$ values for the latter two groups sum to that of the first group).

The immigrant labor-supply shock, $\Delta z_{c\tau}^{v}$, is defined as follows (where all values are gender-group specific and hereafter I suppress the gender-group index):

$$\Delta z_{c\tau}^{v} = \sum_{n} \underbrace{\frac{\left(\sum_{c'} L_{c'\,2000}^{nv}\right) - L_{c2000}^{nv}}{\left(\sum_{c'} L_{c'\,2000}^{n}\right) - L_{c2000}^{n}}}_{A} * \underbrace{\frac{L_{c,2000}^{n} - L_{c2000}^{nv}}{\left(\sum_{c'} L_{c'\,2000}^{n}\right) - \left(\sum_{c} L_{c'\,2000}^{nv}\right)}}_{B} * \underbrace{\frac{\left[\left(\sum_{c'} L_{c'2018}^{n} - L_{c'2018}^{n}\right) - \left(\sum_{c'} L_{c2000}^{n} - L_{c2000}^{n}\right)\right]}{L_{c2000}}}_{C} \tag{2}$$

This shock, which follows the logic of shift-share instruments for immigrant labor supply developed by Altonji and Card (1991) and Card (2001), is the product of three terms. Term $C$ is the change in the employment of prime-age, college-educated individuals of a given gender for national-origin group $n$ outside of CZ $c$ over period $\tau$ (e.g., the change in the number of college-educated Indians in the US living outside of Austin between 2000 and 2018), normalized by the employment of prime-age, college-educated individuals in CZ $c$ in the initial period. By leaving out quantities of CZ $c$ in the numerator of this term, I utilize information on immigration of group $n$, excluding those migrants who chose CZ $c$ as their destination (and may have been motivated by economic conditions in the CZ in making their emigration decision). This value therefore summarizes the generic attraction of college-educated immigrants of national origin group $n$ to the US over time period $\tau$. An assumption needed for identification is that labor-demand shocks in CZ $c$ did not affect immigrant inflows in other CZs.[17]

Term $B$ is the share of workers from national-origin group $n$ employed outside of AI-occupation-group $v$ that resided in CZ $c$ in the year 2000. Excluding AI-related occupations in this share captures the initial-period attraction of CZ $c$ to college-educated immigrants from origin $n$ that is generic to the CZ and not specific to AI-related activities. Term $A$ is the share of college-educated workers of national origin group $n$ outside of CZ $c$ that worked in AI occupation group $v$ in the initial time period. Excluding CZ $c$ from this value captures the generic specialization of national origin group $n$ in AI-related activities. Multiplying terms $A$, $B$, and $C$, and then summing across national origin groups produces the imputed inflow of immigrant workers in AI-related occupations to a CZ, which is based on the specialization of immigrants in AI-related occupations (outside of the CZ), the concentration of different immigrant groups in the CZ (outside of AI-related activities), and national growth in immigrant populations (outside of the CZ). The specification in (1) is therefore equivalent to a first-stage regression in which the CZ employment of workers in AI-related occupations is the endogenous variable and the projected change in CZ immigrant labor supply is the instrument.

The vector of control variables $X_{cg\tau}$ includes state fixed effects (to control for regional business cycles); the sum of the shares in (2) (i.e., $\sum_n A_{cn} B_{cn}$ which follows the recommendation of Borusyak *et al.* (2020) when using shift-share shocks as regressors); and CZ shares for the year 2000 of the college educated in the population, the foreign-born in the population, women in total employment, employment in manufacturing (to control for secular trends in the sector), employment in routine-intensive jobs (to control for exposure to automation and related forms of skill-biased technological change), and employment in offshorable jobs (to control for exposure to globalization). The third group of controls follows those used by Autor *et al.* (2013) in their analysis of local-labor-market adjustment to trade-related, labor-demand shocks. I cluster standard errors by state and weight regressions by CZ total employment (of prime-age, college-educated workers of the given gender group) in the initial period. Summary statistics for the dependent variables and immigration-shock measures used in the analysis appear in Appendix Table 7A.9.

It is important to state what the specification in (1) does and does not allow us to identify. As a difference-in-difference regression, it allows us to compare changes in specialization in CZs with larger versus smaller immigrant labor supply shocks. Any common impact of immigration on specialization in AI across all CZs is absorbed by the constant term (and cannot be recovered without imposing further structure on the estimation). I am thus able to study relative changes in specialization due to relative differences in immigrant inflows, and not the aggregate impact of immigration on AI employment.

## 4.2 Baseline Estimation Results

The baseline estimation results appear in Table 7.3, where AI-related occupations are defined for the narrow V.3 job titles. All coefficients except those for

*Table 7.3* Long Difference (2000–2018): Immigration Impact on CZ Specialization in AI-Related Occupations (V.3)

|  | Men | | | Women | | |
|---|---|---|---|---|---|---|
|  | Foreign-born | Native-born | All | Foreign-born | Native-born | All |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
| Immigrant shock (v3) | 1.927 (0.411) | −0.242 (0.324) | 1.684 (0.658) | 0.776 (0.393) | 0.107 (0.262) | 0.883 (0.626) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 722 | 722 | 722 | 717 | 717 | 717 |
| Adj. R-squared | 0.797 | 0.380 | 0.541 | 0.695 | 0.528 | 0.304 |
| DV Mean | 0.076 | 0.063 | 0.139 | 0.019 | −0.018 | 0.001 |
| DV 25th percentile | 0.032 | 0.026 | 0.107 | 0.005 | −0.040 | −0.020 |
| DV 75th percentile | 0.088 | 0.090 | 0.167 | 0.027 | −0.002 | 0.017 |

$$DV : 100 \times \frac{10}{\Delta t} \times \Delta \frac{AI\ (v3)\ hours\ worked\ by\ nativity\ group}{total\ hours\ worked}$$

The dependent variable is the change in the share of hours worked in AI-related occupations (V.3 definition) for the long difference 2000–2018 for men (columns 1–3) and women (4–6), shown separately for all workers (columns 5 and 6), foreign-born workers (columns 1 and 2), and native-born workers (columns 3 and 4). The immigrant shock for AI-related occupations (V.3 definition) is defined in equation (2). The sample is individuals 25 to 54 years old with at least a bachelor's degree residing in one of the 722 commuting zones in the continental US. All regressions include a constant, the summed product of the weights used in the immigration shock, state fixed effects, and initial-period shares of the college educated in the population, the foreign-born in the population, females in total employment, employment in manufacturing, employment in routine-intensive jobs, and employment in offshorable jobs. Standard errors (in parentheses) are clustered by state. Regressions are weighted by CZ employment (of prime-age, college educated workers of the designated gender) in the initial period.

the immigration shock are suppressed. Consider first the results for all men, shown in column 3 of the first panel. The coefficient estimate of 1.68 (t-value = 2.56) implies that when comparing CZs at the 75th and 25th percentiles of exposure to the immigrant labor-supply shock, the more exposed CZ would have a 0.08 (= 1.68 × (0.08 – 0.03)) larger annual percentage-point increase in the share of college-educated men employed in AI-related activities. This increase represents a full standard-deviation change in the dependent variable.

Columns 1 and 2 decompose the dependent variable in column 3 into two terms: the portion due to the increase in CZ employment of the foreign-born and the portion due to the increase in CZ employment of the native-born. By construction, coefficients in columns 1 and 2 sum to that in column 3. The highly precise coefficient estimate of 1.93 (t-value = 4.69) in column 1 implies that when comparing CZs at the 75th and 25th percentiles of exposure to the immigrant labor-supply shock, the more exposed CZ would have a 0.09 (= 1.93 × (0.08 – 0.03)) larger annual percentage-point increase in the share of college-educated men who are employed in AI-related activities and who are foreign born, which represents a 1.2 standard-deviation increase in the

dependent variable. By contrast, in column 2 when the dependent variable is the change in native-born men employed in AI, the coefficient on the immigration shock is small, negative, and imprecisely estimated ($\beta$ = −0.24, t-value = 0.75). This means that an immigrant labor-suppy shock at the CZ level works to expand employment in AI-related activities entirely through increased employment of the foreign born. The shock neither crowds in nor crowds out the employment of native-born men in a CZ's AI-related occupations.[18]

The concentrated impact of CZ-level immigrant labor-supply growth on foreign-born AI employment is notable because nationally, foreign and native-born workers have contributed roughly equally to the increase in AI employment. Of the mean change in the share of men employed in AI over 2000 to 2018 in Table 7A.9, 54.6% is due to greater employment of the foreign-born and 45.4% is due to greater employment of the native-born. Despite this similar contribution, the two groups have responded quite differently to localized high-skilled immigrant labor-supply shocks. Consistent with the descriptive evidence in Figures 7.1, the factors driving expanded AI-related regional employment for the foreign-born appear to be distinct from those for the native-born.

It is important to note that the results in Table 7.3 are not mechanical. CZs exposed to a larger *overall* increase in college-educated immigration experience larger employment growth *specific* to AI-related activities. Because AI-related occupations account for a very small share of total employment, there is no automatic connection between the expanded supply of college graduates in a CZ and greater specialization in AI-related activities. The results for women, to which I now turn, confirm this reasoning.

Estimation results for women appear in the second panel of Table 7.3. Impacts of the immigration supply shock on AI-related employment of all college-educated women, shown in column 6, are positive but imprecisely estimated ($\beta$ = 0.88, t-value = 1.41). This overall effect combines a positive but small and imprecise impact on the AI employment of native-born women in column 5 ($\beta$ = 0.11, t-value = 0.42) and a larger, positive, and more precisely estimated impact on the AI employment of foreign-born women in column 4 ($\beta$ = 0.78, t-value = 1.98). Given the differential specialization of men and women in AI-related jobs—over 2000 to 2018, employment shares in AI-related occupations rose by 0.14 percentage points annually for men but just 0.001 percentage points annually for women—the immigration labor-supply shock has substantially larger impacts on male versus female employment. By the same token, the specialization of foreign-born men in AI-related activities means that increased access to college-educated male immigrants drives a region to specialize relatively more strongly in AI-related activities.

Burstein *et al.* (2020) provide a theoretical framework that explains how exogenous increases in the supply of foreign-born workers to specific occupations need neither crowd in nor crowd out the employment of native-born workers, at least in jobs whose output is tradable. Tradability implies that firms can absorb immigrant workers in an occupation (e.g., using machine learning to create AI) by expanding exports to other regions. As long as a region is small

in the sense of its output changes having minimal impacts on prices in national or global markets, then the expansion in the employment of the foreign born need not displace any native-born workers, even where foreign and native-born workers are perfectly substitutable on the job. Because AI-related occupations are highly tradable, the results in Table 7.3 appear to be consistent with Burstein *et al.* (2020) logic.

Beyond the tradable-sector adjustment mechanism, there may be other factors at work that affect how foreign and native-born workers sort themselves across jobs related to AI. AI has many applications in national defense, national intelligence, and space-related research (Allen and Chan, 2017). Jobs in these applications, whether they be for private employers, universities, non-profit research organizations, or the government, often require a security clearance. Native-born workers may be better positioned to acquire such clearances. Although Census and ACS data do identify whether or not workers are employed by government entities, the data are not sufficiently granular to identify which private employers are engaged in activities related to national security. One task for future research is to evaluate whether greater access to high-skilled immigrant labor leads a region to adjust the types of AI activities in which it engages.

Additionally, native-born workers with strong cognitive skills may be drawn to highly-paid jobs in finance and away from AI. Because many jobs in investment banking appear to involve deal making, which may draw on communication and social skills, native-born workers may have an advantage in securing them. Hanson and Liu (2021) report that in terms of intensity in abstract and quantitative reasoning, financial managers rank 5th out of 30 occupations, just behind engineers, mathematicians, and scientists. By contrast, when it comes to intensity of interpersonal communication on the job, financial managers rank 11th, engineers rank 23rd, and scientists and mathematicians rank 28th.

## 4.3 Robustness Checks

Next, I explore the robustness of the empirical results in three dimensions. First, I use alternative measures of employment. Appendix Table 7A.10 displays results using worker counts, rather than hours worked, to measure employment. For men and women and all nativity groups, the results in Table 7A.10 are very similar to those in Table 7.3. The implication is that the immigration shock has comparable impacts on the intensive margin (hours worked) and extensive margin (worker counts) of AI employment.

Second, I adjust the definition of time periods used in the analysis. Instead of the 2000 to 2018 long difference, I organize the data in stacked first differences over two time periods, 2000 to 2009, during which growth in AI was relatively slow, and 2009 to 2018, during which growth in AI was relatively rapid (Bloom *et al.*, 2020). The results, which appear in Appendix Table 7A.12, are very similar in terms of coefficient signs and magnitudes to those in Table 7.3. Shortening the time periods and expanding the sample size allows for more precision in the coefficient estimation. For women, the impact of the immigration shock

on employment in AI-related occupations is now positively and strongly precisely estimated for all women and for foreign-born women. The impact on native-born women remains small and imprecisely estimated.

Finally, I broaden the definition of AI-related occupations. The V.3 measure I have used so far in the estimation defines AI jobs to comprise 30 job titles, of which 16 were created after 1990. The broader V.2 definition includes 146 job titles, of which 48 were created after 1990. Table 7.4 reports results for V.2 AI-related occupations using employment measured as hours worked, and the 2000 to 2018 long difference. Appendix Tables 7A.11 and 7A.13 show corresponding V.2 results for employment measured using worker counts and stacked first differences over 2000 to 2009 and 2009 to 2018, respectively. For men, the results in Tables 7.3 and 7.4 are qualitatively similar. For either measure, the high-skilled immigration shock has a strongly positive impact on employment in AI-related occupations, which is due entirely to the expanded employment of the foreign born. The results differ in terms of magnitudes. The coefficient on the immigration shock for V.3 occupations is twice as large (1.95 = 1.93/0.99) as for V.2 occupations. For women, the change in coefficient

*Table 7.4* Long Difference (2000-2018): Immigration Impact on CZ Specialization in AI-Related Occupations (V.2)

|  | *Men* | | | *Women* | | |
|---|---|---|---|---|---|---|
|  | *Foreign-born* | *Native-born* | *All* | *Foreign-born* | *Native-born* | *All* |
|  | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* |
| Immigrant shock (v2) | 0.989 (0.260) | 0.217 (0.278) | 1.206 (0.476) | 0.280 (0.283) | 0.119 (0.153) | 0.400 (0.352) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 722 | 722 | 722 | 717 | 717 | 717 |
| Adj. R-squared | 0.675 | 0.478 | 0.398 | 0.637 | 0.534 | 0.466 |
| DV Mean | 0.102 | –0.037 | 0.065 | 0.003 | –0.130 | –0.128 |
| DV 25th percentile | 0.027 | –0.145 | –0.045 | –0.029 | –0.190 | –0.196 |
| DV 75th percentile | 0.141 | 0.046 | 0.157 | 0.028 | –0.067 | –0.065 |

$$DV : 100 \times \tfrac{10}{\Delta t} \times \Delta \tfrac{AI\ (v2)\ hours\ worked\ by\ nativity\ group}{total\ hours\ worked}$$

The dependent variable is the change in the share of hours worked in AI-related occupations (V.2 definition) for the long difference 2000–2018 for men (columns 1–3) and women (4–6), shown separately for all workers (columns 5 and 6), foreign-born workers (columns 1 and 2), and native-born workers (columns 3 and 4). The immigrant shock for AI-related occupations (V.2 definition) is defined in equation (2). The sample is individuals 25 to 54 years old with at least a bachelor's degree residing in one of the 722 commuting zones in the continental US. All regressions include a constant, the summed product of the weights used in the immigration shock, state fixed effects, and initial-period shares of the college educated in the population, the foreign-born in the population, females in total employment, employment in manufacturing, employment in routine-intensive jobs, and employment in offshorable jobs. Standard errors (in parentheses) are clustered by state. Regressions are weighted by CZ employment (of prime-age, college educated workers of the designated gender) in the initial period.

magnitudes is even more substantial. The immigration shock coefficient for foreign-born women in Table 7.4 is only one-third ($0.36 = 0.78/0.28$) as large as in Table 7.3 and is quite imprecisely estimated (t-value = 0.99).

One interpretation of the finding that the high-skilled immigration shock has a larger impact on employment shares in narrow versus broad AI-related occupations is that the supply of skilled labor is a more binding constraint for former than for the latter. Relaxing this constraint would then generate larger adjustment in V.3 than in V.2 occupations. Because narrow V.3 job titles are associated with the more skilled jobs than the broad V.2 titles, this interpretation appears plausible.

## 5  Discussion

The frenzy over artificial intelligence rivals that surrounding the space race of the 1950s and 1960s. With applications of AI still in its early stages, observers are free to make bold claims about how the technology will cause widespread job loss, usher in a future of driverless transportation, render language barriers obsolete, or bring forth other massive disruptions. Whatever the future of AI, it is likely to inspire heavy investments in new ventures for some time to come. Where these investments occur will help determine the future spatial distribution of activities in IT. Because AI is the current frontier of IT, which locations host its creation is of enormous interest to government and industry alike.

In the US, the regions that are best able to attract the computer scientists, data scientists, and computer systems engineers who are most adept at machine learning and related activities are likely to be the ones that acquire a comparative advantage in AI. Globalization has made it possible to obtain advanced computer hardware just about anywhere. Advances in digital communications now allow data to flow freely across space. Because these two key AI ingredients are footloose, the location of their production may have little bearing on the location of AI production. The technical talent that creates AI is also footloose. In the US, much of this talent is foreign born—and from India and China in particular. The location choices of newly arrived immigrants, whether low-skilled or high-skilled, tend to follow the location choices of previous generations of workers from their origin countries. So too has it been in the case for AI-related workers. US commuting zones that were most exposed to increases in the supply of college-educated immigrants—based on the previous specialization patterns of these regions and their historical attraction to foreign-born arrivals—have seen the largest increase in the share of employment devoted to AI-related jobs. The lesson from this regularity is that access to high-skilled immigration relaxes the talent constraint that limits the expansion of AI. The US government, by regulating the volume and composition of high-skilled labor inflows from abroad, in effect regulates the pace of growth in AI.

The US model of innovation in AI—in which private-sector firms competing in open markets make their own investment decisions and hire talent from around the world—stands in contrast with that of China. China's tech

firms enjoy protection from foreign competition, receive subsidies for R&D and other performance measures, and benefit from the government's appetite for facial recognition and other AI applications (US firms, for their part, also receive government subsidies, at least in indirect form through public funding of basic and applied research and possibly in direct form through government procurement). One presumes that the talent constraint in AI production applies in China, just as in the US. What remains to be seen is whether the relative openness of the US to immigration gives it an advantage in the sector.

## Notes

1 For literature that examines the creation of new work across all occupations and over longer time spans, see Atalay *et al.* (2020) and Autor *et al.* (2020).
2 *Bloom et al.* (2020) develop a conceptually related approach to identify new technology by tracking the presence of key words or phrases in company earnings calls and Burning Glass job postings.
3 See *Borjas and Doran* (2012) for evidence on how arriving Russian mathematicians displaced US scholars working in subfields of mathematics in which Soviet-era research was relatively specialized.
4 These codes were modified slightly to accommodate work in military-related occupations.
5 To this list, I add financial and management analysts, which may include workers engaged in quantitative finance (an active area of AI). These categories are dropped in V.2, which contains broad AI titles.
6 The excluded occupations, based on their 2000 Census codes, are: computer and information systems managers, engineering managers, financial specialists (all other), computer support specialists, database administrators, network and computer systems administrators, engineering technicians, computer operators, data entry keyers, and computer control programmers and operators. Among life and physical scientists, I exclude agricultural and food scientists, chemists and materials scientists, conservation and forestry scientists, and surveyors, cartographers, and mapping scientists.
7 In unreported results, I perform analysis for V.0 and V.1 occupations and obtain similar results.
8 Note that the 30 job titles designated to be AI-related exclude many other titles within the five occupation codes that appear to be support roles, e.g., as indicated by the terms analyst, consultant, developer, integrator, planner, specialist, tester, or writer.
9 Perhaps the signature AI achievement of the decade was IBM's Deep Blue machine-learning-based system defeating world champion Gary Kasparov in chess in 1997.
10 Ideally, one would like to track the creation of new occupational titles separately for each decade. Such an exercise is unfortunately beyond the scope of this chapter.
11 An amalgam of their approach and mine would be to use Burning Glass data to measure the share of new jobs for each job title within a Census occupation code, which would improve upon my somewhat crude metric of effectively treating the number of jobs per title as the same across titles.

12 The shares in the second and third panels add to the total shares shown in the first panel.
13 See Appendix Tables 7A.6 and 7A.8 for the values reported in these figures as well as values for the V.2 definition of AI-related jobs.
14 If countries whose spoken languages are more distant from English are better at technical straining, then language may confound analysis of the impact of education quality on occupational comparative advantage in the U.S. One measure of the quality of a country's educational instituions in imparting cognitive skills is test scores from the Program for Internatoinal Student Assessment (PISA). *Hanson and Liu* (2021) report that the correlation between PISA math scores and linguistic distance to the U.S. is just 0.17.
15 This would not explain the specialization of Chinese and Indian workers in AI over STEM in general.
16 Both the dependent variable, $\Delta \Upsilon_{cg\tau}^{v}$, and the immigration labor-supply shock, $\Delta z_{cg\tau}^{v}$, are expressed in decadalized terms by multiplying them by $10/\triangle t$, where $\triangle t$ is the length of time period $\tau$.
17 This approach to identification is analogous to assuming "exogeneity of the shifts" as defined by Borusyak *et al.* (2020) for shift-share instruments. An alternative would be to assume "exogeneity of the shares" as elaborated by Goldsmith-Pinkham *et al.* (2020).
18 This finding mirrors the Burstein *et al.* (2020) result on how native-born employment in tradable occupations (such as AI) adjusts to an immigrant labor supply shock.

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*Table 7A1* Job Titles Associated with AI-Related Occupations (V.3 definition)

| Occupation | Occupation Title | V.3 AI | New |
|---|---|:---:|:---:|
| Computer scientists and systems analysts | Analyst \ n.s. | | |
| | Artificial intelligence specialist | ✓ | ✓ |
| | Business systems analyst | | |
| | Computer analyst | | |
| | Computer consultant \ n.e.c. or n.s. | | |
| | Computer research | ✓ | ✓ |
| | Computer scientist | ✓ | |
| | Computer systems analyst | | |
| | Computer systems design analyst | ✓ | ✓ |
| | Computer systems designer | ✓ | |
| | Computer systems, planning | | |
| | Computing systems analyst | | |
| | Consultant, systems, computer or data processing | | |
| | Data processing consultant | | |
| | Data processing systems analyst | | |
| | Data processing systems project planner | | |
| | Digital computer systems analyst | | |
| | Engineering systems analyst | | |
| | Health systems analyst, computer | | |
| | Information scientist | ✓ | |
| | Information systems consultant | | |
| | Information systems specialist | | |
| | Information technology specialist, general or n.s. | | |
| | Information technology specialist, systems analysis | | |
| | Methods analyst, computer | | |
| | Scientific systems analyst | | |
| | Software consultant \ n.e.c. | | |
| | Supervisor, computer analyst | | |
| | Systems analyst, computer systems | | |
| | Systems analyst, data processing | | |
| | Systems architect | | |
| | Technician, computer or computer laboratory | | |
| Computer software engineers | Applications developer | | |
| | C.N.E. (certified Novell engineer) | ✓ | ✓ |
| | Computer applications developer | | |
| | Computer programmer analyst | | |
| | Computer specialist, software | | |
| | Engineer, Microsoft certified systems (MCSE) | ✓ | ✓ |
| | Engineer, computer applications | ✓ | |
| | Engineer, computer software \ n.e.c. | ✓ | |

(*Continued*)

Table 7A1 (Continued)

| Occupation | Occupation Title | V.3 AI | New |
|---|---|---|---|
| | Engineer, computer software applications | ✓ | ✓ |
| | Engineer, computer software systems | ✓ | ✓ |
| | Engineer, computer systems | ✓ | |
| | Engineer, software \ n.e.c. | ✓ | |
| | Engineer, software applications | ✓ | ✓ |
| | Engineer, software requirements | ✓ | ✓ |
| | Engineer, software systems | ✓ | ✓ |
| | Engineer, system | ✓ | |
| | Engineer, system EDP | ✓ | ✓ |
| | Engineer, systems analyst | ✓ | ✓ |
| | Info. technology specialist, software engineering,applications | | |
| | Inf. technology specialist, software engineering,systems | | |
| | M.C.S.E (Microsoft certified systems engineer) | ✓ | ✓ |
| | Program analyst | | |
| | Programmer analyst | | |
| | Quality assurance specialist, applications | | |
| | Quality assurance specialist, systems software | | |
| | Software QA tester | | |
| | Software applications specialist | | |
| | Software designer | ✓ | |
| | Software developer | | |
| | Software development specialist | | |
| | Software installer | | |
| | Software specialist, systems | | |
| | Software writer | | |
| | Supervisor, software engineering | | |
| | Tester, software | | |
| Network systems and data communications analysts | Chat room host/monitor | | |
| | Communications consultant | | |
| | Computer consultant, networks | | |
| | Computer integration | | |
| | Data communications analyst | | |
| | Engineer, network | | |
| | Info. technology specialist, internet | | |
| | Info. technology specialist, network services | | |
| | Internet developer | | |
| | Intranet developer | | |
| | Manager, website | | |

*Table 7A1*  (Continued )

| Occupation | Occupation Title | V.3 | AI New |
|---|---|---|---|
| | Multimedia telecom. systems integrator | | |
| | Network analyst | | |
| | Network architect | | |
| | Network consultant | | |
| | Network designer | ✓ | ✓ |
| | Network specialist | | |
| | Network support | | |
| | Network systems analyst | | |
| | Network systems integrator | | |
| | Software consultant, data communications | | |
| | Software consultant, networks | | |
| | Systems integrator | | |
| | Systems planner | | |
| | Telecommunications specialist | | |
| | Web designer | ✓ | ✓ |
| | Web developer | | |
| | Web specialist | | |
| | Webmaster | | |
| Statisticians | Analytical statistician | | |
| | Applied statistician | | |
| | Biometrician | ✓ | |
| | Biostatistician | ✓ | |
| | Engineer, statistical | ✓ | |
| | Mathematical statistician | | |
| | Sampling expert | | |
| | Statistician | | |
| | Survey statistician | | |
| | Time study statistician | | |
| Computer hardware engineers | Computer designer | | |
| | Computer layout | | |
| | Computer tester | | |
| | Engineer, computer \n.e.c. or n.s. | ✓ | ✓ |
| | Engineer, computer hardware | ✓ | |
| | Engineer, design \ n.s. | ✓ | |
| | Engineer, installation, computers exc. PCs | | |
| | Microchip specialist | | |

This table lists all occupation titles that correspond to Census occupation codes that have at least one AI-related title by the V.3 definition. Column 3 (4) indicates whether a title is AI-related (added after 1990).

*Table 7A2* Top 20 CZs in Terms of Share of CZ Hours Worked in AI-Related Occupations, 2000

| | All Workers | | Foreign-Born Workers | | Native-Born Workers | |
|---|---|---|---|---|---|---|
| Rank | *Men* | *Women* | *Men* | *Women* | *Men* | *Women* |
| 1 | San Jose-Sunnyvale-Santa Clara, CA | San Jose-Sunnyvale-Santa Clara, CA | San Jose-Sunnyvale-Santa Clara, CA | San Jose-Sunnyvale-Santa Clara, CA | Colorado Springs, CO | Huntsville, AL |
| 2 | Colorado Springs, CO | Huntsville, AL | Oakland-Fremont-Hayward, CA | Oakland-Fremont-Hayward, CA | South Arlington-Alexandria | Colorado Springs, CO |
| 3 | Washington Surrounding | Colorado Springs, CO | West New York | West New York | Palm Bay-Melbourne-Titusville, FL | Martinsville, VA |
| 4 | Bloomington-Normal, IL | Washington Surrounding | Washington Surrounding | Washington Surrounding | Bloomington-Normal, IL | Palm Bay-Melbourne-Titusville, FL |
| 5 | Raleigh-Cary, NC | Martinsville, VA | Dallas Surrounding | Seattle-Bellevue-Everett, WA | Huntsville, AL | Washington Surrounding |
| 6 | Palm Bay-Melbourne-Titusville, FL | Palm Bay-Melbourne-Titusville, FL | Austin-Round Rock, TX | Edison, NJ | Raleigh-Cary, NC | Bloomington-Normal, IL |
| 7 | South Arlington-Alexandria | Raleigh-Cary, NC | Boston-Quincy, MA | Dallas Surrounding | Provo-Orem, UT | South Arlington-Alexandria |
| 8 | Austin-Round Rock, TX | South Arlington-Alexandria | Edison, NJ | Pike County, KY | Binghamton, NY | Raleigh-Cary, NC |
| 9 | Binghamton, NY | Oakland-Fremont-Hayward, CA | Seattle-Bellevue-Everett, WA | Raleigh-Cary, NC | Denver-Aurora, CO | Denver-Aurora, CO |
| 10 | Denver-Aurora, CO | Bloomington-Normal, IL | Raleigh-Cary, NC | Boston-Quincy, MA | Washington Surrounding | Binghamton, NY |
| 11 | Huntsville, AL | Binghamton, NY | Chicago-Naperville-Joliet, IL | Wilmington, DE-MD-NJ | San Jose-Sunnyvale-Santa Clara, CA | Austin-Round Rock, TX |
| 12 | Oakland-Fremont-Hayward, CA | Denver-Aurora, CO | Los Angeles-Long Beach-Glendale, CA | Houston Surrounding | Rockingham. Strafford County, NH | Baltimore Surrounding |

(*Continued*)

*Table 7A2*  (Continued )

| | All Workers | | Foreign-Born Workers | | Native-Born Workers | |
|---|---|---|---|---|---|---|
| Rank | *Men* | *Women* | *Men* | *Women* | *Men* | *Women* |
| 13 | Dallas Surrounding | Dallas Surrounding | Atlanta Surrounding | Los Angeles-Long Beach-Glendale, CA | Austin-Round Rock, TX | San Jose-Sunnyvale-Santa Clara, CA |
| 14 | Provo-Orem, UT | Seattle-Bellevue-Everett, WA | Miami-Miami Beach-Kendall, FL | Columbus, OH | Rochester, MN | Dallas Surrounding |
| 15 | Boston-Quincy, MA | Boston-Quincy, MA | San Diego-Carlsbad-San Marcos, CA | Goldsboro, NC | Dallas Surrounding | Hagerstown-Martinsburg, MD-WV |
| 16 | Rockingham. Strafford County, NH | Austin-Round Rock, TX | Houston Surrounding | Chicago-Naperville-Joliet, IL | Omaha-Council Bluffs, NE-IA | Seattle-Bellevue-Everett, WA |
| 17 | Seattle-Bellevue-Everett, WA | Baltimore Surrounding | New York Surrounding/New York | New York Surrounding/New York | Baltimore Surrounding | Boston-Quincy, MA |
| 18 | West New York | Wilmington, DE-MD-NJ | Columbus, OH | Atlanta Surrounding | Seattle-Bellevue-Everett, WA | Madison, WI |
| 19 | Atlanta Surrounding | Columbus, OH | Bloomington-Normal, IL | Sullivan County, MO | Boston-Quincy, MA | Chaffee County, CO |
| 20 | Rochester, MN | West New York | Wilmington, DE-MD-NJ | Kirksville, MO | Winchester, VA-WV | East Charlotte |

This table reports the top 20 commuting zones in terms of the share of CZ hours worked in AI-related occupations (V.3 definition) for prime-age, college-educated men and women in 2000. AI hours worked are measured as hours worked in a given AI-related occupation times the share of all 2000 jobs titles in that occupation that were created after 1990 and that were AI-related.

*Table 7A3* Top 20 Commuting Zones in Terms of CZ Share of National Hours Worked in AI-Related Occupations

| | All Workers | | Foreign-Born Workers | | Native-Born Workers | |
|---|---|---|---|---|---|---|
| Rank | Men | Women | Men | Women | Men | Women |
| 1 | Washington Surrounding | Washington Surrounding | San Jose-Sunnyvale-Santa Clara, CA | San Jose-Sunnyvale-Santa Clara, CA | Washington Surrounding | Washington Surrounding |
| 2 | Los Angeles-Long Beach-Glendale, CA | Oakland-Fremont-Hayward, CA | Oakland-Fremont-Hayward, CA | Oakland-Fremont-Hayward, CA | Boston-Quincy, MA | Boston-Quincy, MA |
| 3 | Oakland-Fremont-Hayward, CA | Chicago-Naperville-Joliet, IL | West New York | Washington Surrounding | Chicago-Naperville-Joliet, IL | Chicago-Naperville-Joliet, IL |
| 4 | Chicago-Naperville-Joliet, IL | Boston-Quincy, MA | Los Angeles-Long Beach-Glendale, CA | West New York | Los Angeles-Long Beach-Glendale, CA | New York Surrounding/New York |
| 5 | San Jose-Sunnyvale-Santa Clara, CA | New York Surrounding/New York | Washington Surrounding | Los Angeles-Long Beach-Glendale, CA | Oakland-Fremont-Hayward, CA | Oakland-Fremont-Hayward, CA |
| 6 | Boston-Quincy, MA | Los Angeles-Long Beach-Glendale, CA | New York Surrounding/New York | New York Surrounding/New York | New York Surrounding/New York | Los Angeles-Long Beach-Glendale, CA |
| 7 | West New York | West New York | Chicago-Naperville-Joliet, IL | Chicago-Naperville-Joliet, IL | Atlanta Surrounding | West New York |
| 8 | New York Surrounding/New York | San Jose-Sunnyvale-Santa Clara, CA | Boston-Quincy, MA | Boston-Quincy, MA | Denver-Aurora, CO | Atlanta Surrounding |
| 9 | Atlanta Surrounding | Atlanta Surrounding | Dallas Surrounding | Seattle-Bellevue-Everett, WA | West New York | Philadelphia, PA |
| 10 | Dallas Surrounding | Seattle-Bellevue-Everett, WA | Seattle-Bellevue-Everett, WA | Dallas Surrounding | Seattle-Bellevue-Everett, WA | Denver-Aurora, CO |
| 11 | Seattle-Bellevue-Everett, WA | Philadelphia, PA | Atlanta Surrounding | Atlanta Surrounding | Dallas Surrounding | Seattle-Bellevue-Everett, WA |
| 12 | Denver-Aurora, CO | Dallas Surrounding | Houston Surrounding | Houston Surrounding | San Jose-Sunnyvale-Santa Clara, CA | Warren-Farmington Hills-Troy, MI |

(*Continued*)

*Table 7A3*   (Continued )

| Rank | All Workers | | Foreign-Born Workers | | Native-Born Workers | |
|---|---|---|---|---|---|---|
| | Men | Women | Men | Women | Men | Women |
| 13 | Philadelphia, PA | Warren-Farmington Hills-Troy, MI | Warren-Farmington Hills-Troy, MI | Philadelphia, PA | Philadelphia, PA | Dallas Surrounding |
| 14 | Minneapolis-Bloomington, MN-WI | Denver-Aurora, CO | Philadelphia, PA | Warren-Farmington Hills-Troy, MI | Minneapolis-Bloomington, MN-WI | Minneapolis-Bloomington, MN-WI |
| 15 | Warren-Farmington Hills-Troy, MI | Minneapolis-Bloomington, MN-WI | Miami-Miami Beach-Kendall, FL | Miami-Miami Beach-Kendall, FL | Warren-Farmington Hills-Troy, MI | Baltimore Surrounding |
| 16 | Houston Surrounding | Houston Surrounding | San Diego-Carlsbad-San Marcos, CA | Minneapolis-Bloomington, MN-WI | Baltimore Surrounding, | Houston Surrounding |
| 17 | Raleigh-Cary, NC | Baltimore Surrounding | Minneapolis-Bloomington, MN-WI | Raleigh-Cary, NC | Houston Surrounding | San Jose-Sunnyvale-Santa Clara, CA |
| 18 | Baltimore Surrounding | Raleigh-Cary, NC | Denver-Aurora, CO | San Diego-Carlsbad-San Marcos, CA | Raleigh-Cary, NC | Raleigh-Cary, NC |
| 19 | Hartford, CT | Hartford, CT | Austin-Round Rock, TX | Hartford, CT | Hartford CT | Hartford, CT |
| 20 | San Diego-Carlsbad-San Marcos, CA | Phoenix-Mesa-Scottsdale, AZ | Hartford, CT | Baltimore Surrounding | Phoenix-Mesa-Scottsdale, AZ | Phoenix-Mesa-Scottsdale, AZ |

This table reports the top 20 commuting zones in terms of the CZ share of national hours worked in AI-related occupations (V.3 definition) for prime-age, college-educated men and women in 2000. AI hours worked are measured as hours worked in a given AI-related occupation times the share of all 2000 jobs titles in that occupation that were created after 1990 and that were AI-related.

*Table 7A4* Share of Hours Worked in All Occupations among Prime-Age, College-Educated Workers by Region of Birth

|  | 2000 | 2004–09 | 2014–18 |
|---|---|---|---|
| **Men** |  |  |  |
| Native born | 86.5 | 83.1 | 81.5 |
| Latin America + Caribbean | 2.5 | 3.7 | 3.9 |
| Africa and Middle East | 1.4 | 1.8 | 2.1 |
| China + Hong Kong | 0.9 | 1.2 | 1.4 |
| India | 2.1 | 3.1 | 4.3 |
| Korea + Japan + Taiwan | 1.3 | 1.4 | 1.3 |
| Other Asia | 1.9 | 2.2 | 2.1 |
| Europe + Australia + New Zealand + Canada | 3.4 | 3.6 | 3.5 |
| **Women** |  |  |  |
| Native born | 88.4 | 85.6 | 84.5 |
| Latin America + Caribbean | 2.5 | 3.6 | 4.0 |
| Africa and Middle East | 0.7 | 0.9 | 1.2 |
| China + Hong Kong | 0.9 | 1.2 | 1.4 |
| India | 1.1 | 1.6 | 2.2 |
| Korea + Japan + Taiwan | 1.1 | 1.3 | 1.1 |
| Other Asia | 2.5 | 2.7 | 2.5 |
| Europe + Australia + New Zealand + Canada | 2.7 | 3.1 | 3.0 |

Each cell reports the fraction of hours worked by a particular national origin group for men and women with at least a college education and who are 25 to 54 years old. The data are from the 2000 Census and the 2005–2009 and 2014–2018 five-year ACS samples.

*Table 7A5* Share of Hours Worked in V.O and V.I Occupations among Prime-Age, College-Educated Workers by Region of Birth

|  | V.O Hours | | | V.I Hours | | |
|---|---|---|---|---|---|---|
|  | 2000 | 2004–09 | 2014–18 | 2000 | 2004–09 | 2014–18 |
| **Men** |  |  |  |  |  |  |
| Native born | 80.2 | 75.7 | 72.9 | 78.8 | 74.2 | 71.4 |
| Latin America + Caribbean | 1.9 | 2.5 | 3.0 | 1.9 | 2.4 | 2.9 |
| Africa and Middle East | 1.5 | 1.8 | 2.1 | 1.5 | 1.7 | 2.1 |
| China + Hong Kong | 2.1 | 2.5 | 2.7 | 2.4 | 2.8 | 2.9 |
| India | 5.0 | 7.8 | 10.9 | 5.7 | 8.9 | 12.1 |
| Korea + Japan + Taiwan | 1.7 | 1.9 | 1.5 | 1.8 | 2.0 | 1.6 |
| Other Asia | 2.9 | 3.2 | 2.6 | 3.0 | 3.3 | 2.7 |
| Europe + Australia + New Zealand + Canada | 4.6 | 4.7 | 4.3 | 4.8 | 4.7 | 4.3 |
| Women |  |  |  |  |  |  |
| Native born | 80.6 | 75.9 | 73.1 | 79.0 | 73.9 | 71.8 |
| Latin America + Caribbean | 2.0 | 2.7 | 3.0 | 2.0 | 2.8 | 3.1 |
| Africa and Middle East | 0.8 | 1.1 | 1.3 | 0.8 | 1.2 | 1.3 |
| China + Hong Kong | 3.5 | 4.2 | 4.3 | 4.0 | 4.7 | 4.5 |
| India | 3.3 | 6.0 | 9.3 | 3.8 | 7.0 | 10.2 |
| Korea + Japan + Taiwan | 2.3 | 2.1 | 1.6 | 2.6 | 2.3 | 1.7 |
| Other Asia | 3.3 | 3.6 | 3.3 | 3.4 | 3.9 | 3.5 |
| Europe + Australia + New Zealand + Canada | 4.2 | 4.4 | 4.0 | 4.2 | 4.4 | 3.8 |

Each cell reports the fraction of hours worked by a particular national origin group for men and women with at least a college education and who are 25 to 54 years old in V.0 or V.1 occupations. Data are from the 2000 Census and the 2005–2009 and 2014–2018 five-year ACS samples.

*Table 7A6* Share of Hours Worked in V.2 and V.3 Occupations among Prime-Age,
College-educated Workers by Region of Birth

| | V.2 Hours | | | V.3 Hours | | |
|---|---|---|---|---|---|---|
| | *2000* | *2004–09* | *2014–18* | *2000* | *2004–09* | *2014–18* |
| **Men** | | | | | | |
| Native born | 76.6 | 71.3 | 67.5 | 75.2 | 68.8 | 65.2 |
| Latin America + Caribbean | 2.0 | 2.4 | 2.9 | 2.1 | 2.4 | 3.0 |
| Africa and Middle East | 1.6 | 1.8 | 2.2 | 1.6 | 1.9 | 2.3 |
| China + Hong Kong | 2.7 | 3.2 | 3.4 | 3.0 | 3.3 | 3.4 |
| India | 6.6 | 10.4 | 14.6 | 7.8 | 12.6 | 16.9 |
| Korea + Japan + Taiwan | 2.0 | 2.2 | 1.7 | 2.0 | 2.1 | 1.6 |
| Other Asia | 3.4 | 3.6 | 3.1 | 3.4 | 3.7 | 3.0 |
| Europe + Australia + New Zealand + Canada | 5.2 | 5.2 | 4.6 | 5.0 | 5.2 | 4.7 |
| **Women** | | | | | | |
| Native born | 76.4 | 70.3 | 65.1 | 78.1 | 70.8 | 65.1 |
| Latin America + Caribbean | 1.9 | 2.2 | 2.8 | 1.9 | 2.2 | 2.7 |
| Africa and Middle East | 0.9 | 1.2 | 1.4 | 0.8 | 1.2 | 1.4 |
| China + Hong Kong | 4.9 | 5.7 | 5.6 | 4.5 | 5.5 | 5.3 |
| India | 4.7 | 9.2 | 15.4 | 4.8 | 10.2 | 16.4 |
| Korea + Japan + Taiwan | 2.9 | 2.4 | 1.8 | 2.8 | 2.2 | 1.8 |
| Other Asia | 3.6 | 4.3 | 4.1 | 3.4 | 3.9 | 3.8 |
| Europe + Australia + New Zealand + Canada | 4.7 | 4.7 | 3.9 | 3.7 | 4.0 | 3.6 |

Each cell reports the fraction of hours worked by a particular national origin group for men and women with at least a college education and who are 25 to 54 years old in V.2 or V.3 occupations. Data are from the 2000 Census and the 2005–2009 and 2014–2018 five-year ACS samples.

*Table 7A7* Revealed Comparative Advantage in V.O and V.I Occupations by Worker Region of Birth

| | V.O Hours | | | V.I Hours | | |
|---|---|---|---|---|---|---|
| | 2000 | 2004–09 | 2014–18 | 2000 | 2004–09 | 2014–18 |
| **Men** | | | | | | |
| Native born | -0.08 | -0.09 | -0.11 | -0.09 | -0.11 | -0.13 |
| Latin America + Caribbean | -0.27 | -0.39 | -0.26 | -0.25 | -0.42 | -0.28 |
| Africa and Middle East | 0.05 | -0.00 | -0.01 | 0.03 | -0.04 | -0.01 |
| China + Hong Kong | 0.82 | 0.76 | 0.67 | 0.94 | 0.85 | 0.75 |
| India | 0.89 | 0.94 | 0.93 | 1.02 | 1.07 | 1.04 |
| Korea + Japan + Taiwan | 0.29 | 0.28 | 0.19 | 0.36 | 0.33 | 0.23 |
| Other Asia | 0.44 | 0.36 | 0.23 | 0.48 | 0.39 | 0.25 |
| Europe + Australia + New Zealand + Canada | 0.30 | 0.26 | 0.20 | 0.34 | 0.28 | 0.20 |
| Women | | | | | | |
| Native born | -0.09 | -0.12 | -0.15 | -0.11 | -0.15 | -0.16 |
| Latin America + Caribbean | -0.23 | -0.28 | -0.26 | -0.22 | -0.26 | -0.25 |
| Africa and Middle East | 0.17 | 0.17 | 0.12 | 0.19 | 0.20 | 0.12 |
| China + Hong Kong | 1.35 | 1.29 | 1.10 | 1.49 | 1.39 | 1.13 |
| India | 1.08 | 1.35 | 1.43 | 1.23 | 1.50 | 1.53 |
| Korea + Japan + Taiwan | 0.70 | 0.51 | 0.36 | 0.83 | 0.60 | 0.43 |
| Other Asia | 0.28 | 0.27 | 0.27 | 0.34 | 0.35 | 0.32 |
| Europe + Australia + New Zealand + Canada | 0.43 | 0.34 | 0.30 | 0.44 | 0.34 | 0.26 |

Calculation is:

$$RCA_{kgst} = ln(\frac{\sum_{o \in \mathcal{O}^v}\left(L_{kgost}\right)/\sum_{o \in \mathcal{O}^v}\left(L_{gost}\right)}{\sum_{o \in \mathcal{O}}\left(L_{kgost}\right)/\sum_{o \in \mathcal{O}}\left(L_{gost}\right)})$$

where $L$ is hours worked and $O^v$ is the set of occupations with a positive share of new STEM or potential AI work according to V.0 or V.1. This is calculated for each year *(t)*, gender (g), and national origin group *(k)* among either men or women 25 to 54 years old with at least a college education. Data are from the 2000 Census and the 2005–2009 and 2014–2018 five-year ACS samples.

*Table 7A8* Revealed Comparative Advantage in V.2 and V.3 Occupations by Worker
Region of Birth

| | V.2 Hours | | | V.3 Hours | | |
|---|---|---|---|---|---|---|
| | 2000 | 2004–09 | 2014–18 | 2000 | 2004–09 | 2014–18 |
| **Men** | | | | | | |
| Native born | -0.12 | -0.15 | -0.19 | -0.14 | -0.19 | -0.22 |
| Latin America + Caribbean | -0.21 | -0.43 | -0.27 | -0.18 | -0.42 | -0.27 |
| Africa and Middle East | 0.09 | 0.02 | 0.04 | 0.11 | 0.07 | 0.08 |
| China + Hong Kong | 1.06 | 0.99 | 0.90 | 1.14 | 1.03 | 0.90 |
| India | 1.15 | 1.22 | 1.22 | 1.33 | 1.42 | 1.37 |
| Korea + Japan + Taiwan | 0.46 | 0.42 | 0.31 | 0.48 | 0.38 | 0.25 |
| Other Asia | 0.58 | 0.48 | 0.37 | 0.58 | 0.52 | 0.36 |
| Europe + Australia + New Zealand + Canada | 0.43 | 0.37 | 0.26 | 0.38 | 0.37 | 0.27 |
| Women | | | | | | |
| Native born | -0.15 | -0.20 | -0.26 | -0.12 | -0.19 | -0.26 |
| Latin America + Caribbean | -0.27 | -0.48 | -0.35 | -0.29 | -0.50 | -0.40 |
| Africa and Middle East | 0.21 | 0.26 | 0.18 | 0.20 | 0.25 | 0.17 |
| China + Hong Kong | 1.67 | 1.59 | 1.35 | 1.60 | 1.56 | 1.29 |
| India | 1.45 | 1.77 | 1.94 | 1.47 | 1.87 | 2.00 |
| Korea + Japan + Taiwan | 0.95 | 0.65 | 0.46 | 0.89 | 0.56 | 0.46 |
| Other Asia | 0.38 | 0.44 | 0.47 | 0.32 | 0.35 | 0.40 |
| Europe + Australia + New Zealand + Canada | 0.54 | 0.42 | 0.26 | 0.29 | 0.26 | 0.19 |

Calculation is:

$$RCA_{kgst} = ln(\frac{\sum\limits_{o\in\mathcal{O}^v}\left(L_{kgost}\right)/\sum\limits_{o\in\mathcal{O}^v}\left(L_{gost}\right)}{\sum\limits_{o\in\mathcal{O}}\left(L_{kgost}\right)/\sum\limits_{o\in\mathcal{O}}\left(L_{gost}\right)})$$

where $L$ is hours worked and $\mathcal{O}^v$ is the set of occupations with a positive share of new STEM or potential AI work according to V.2 or V.3. This is calculated for each year *(t)*, gender (g), and national origin group *(k)* among either men or women 25 to 54 years old with at least a college education. Data are from the 2000 Census and the 2005–2009 and 2014–2018 five-year ACS samples.

*Table 7A9* Summary Statistics for Dependent Variables and Immigration Shocks

| Variable | Obs | Mean | Std. Dev. | P25 | P75 |
|---|---|---|---|---|---|
| **Male hours worked** | | | | | |
| **V.3** | | | | | |
| All | 722 | .139 | .078 | .107 | .167 |
| Foreign born | 722 | .076 | .073 | .032 | .088 |
| Native born | 722 | .063 | .052 | .026 | .09 |
| Immigrant shock | 722 | .052 | .035 | .027 | .076 |
| **V.2** | | | | | |
| All | 722 | .065 | .178 | −.045 | .157 |
| Foreign born | 722 | .102 | .131 | .027 | .141 |
| Native born | 722 | −.037 | .158 | −.145 | .046 |
| Immigrant shock | 722 | .153 | .101 | .078 | .219 |
| **Male employment** | | | | | |
| **V.3** | | | | | |
| All | 722 | .144 | .08 | .113 | .173 |
| Foreign born | 722 | .08 | .076 | .033 | .096 |
| Native born | 722 | .064 | .054 | .024 | .094 |
| Immigrant shock | 722 | .068 | .045 | .035 | .101 |
| **V.2** | | | | | |
| All | 722 | .058 | .187 | −.055 | .155 |
| Foreign born | 722 | .106 | .139 | .028 | .157 |
| Native born | 722 | −.048 | .166 | −.156 | .035 |
| Immigrant shock | 722 | .2 | .131 | .104 | .296 |
| **Female hours worked** | | | | | |
| **V.3** | | | | | |
| All | 722 | .001 | .033 | −.02 | .017 |
| Foreign born | 722 | .019 | .022 | .005 | .027 |
| Native born | 722 | −.018 | .032 | −.04 | −.002 |
| Immigrant shock | 717 | .032 | .024 | .014 | .048 |
| **V.2** | | | | | |
| All | 722 | −.128 | .104 | −.196 | −.065 |
| Foreign born | 722 | .003 | .053 | −.029 | .028 |
| Native born | 722 | −.13 | .098 | −.19 | −.067 |
| Immigrant shock | 717 | .114 | .084 | .049 | .168 |
| **Female employment** | | | | | |
| **V.3** | | | | | |
| All | 722 | .005 | .031 | −.015 | .02 |
| Foreign born | 722 | .019 | .022 | .006 | .026 |
| Native born | 722 | −.015 | .031 | −.034 | 0 |
| Immigrant shock | 717 | .034 | .025 | .015 | .051 |
| **V.2** | | | | | |
| All | 722 | −.115 | .101 | −.18 | −.053 |
| Foreign born | 722 | .005 | .054 | −.023 | .029 |
| Native born | 722 | −.12 | .094 | −.173 | −.063 |
| Immigrant shock | 717 | .118 | .088 | .052 | .176 |

This table reports means of the outcome variables and immigration shocks used in the regression analysis. The outcomes are changes employment shares (hours worked, worker counts) by gender group (male, female) in AI-related occupations (V.3, V.2) by nativity group (all workers, foreign-born, native-born) over 2000 to 2018. The immigration shock (defined in equation (2)) is the projected change in the supply of workers (by gender, employment definition) in AI-related occupations (by AI definition) relative to total initial-period labor supply in the CZ over 2000 to 2018. All variables are multiplied by 100 and decadalized (multiplied by 10 divided by the number of years between time periods). The sample includes individuals 25 to 54 years old with at least a bachelor's degree. Results are weighted using CZ total employment of prime-age, college-educated workers of the gender group in the initial period.

*Table 7A10* Long difference (2000-2018): Immigration Impact on CZ Specialization in AI-Related Occupations (V.3)

| | Men | | | Women | | |
|---|---|---|---|---|---|---|
| | Foreign-Born | Native-Born | All | Foreign-Born | Native-Born | All |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Immigrant shock (v3) | 1.529 (0.341) | −0.269 (0.267) | 1.259 (0.553) | 0.872 (0.373) | 0.027 (0.220) | 0.899 (0.561) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 722 | 722 | 722 | 717 | 717 | 717 |
| Adj. R-squared | 0.787 | 0.397 | 0.520 | 0.705 | 0.544 | 0.319 |
| DV Mean | 0.080 | 0.064 | 0.144 | 0.019 | −0.015 | 0.005 |
| DV 25th percentile | 0.033 | 0.024 | 0.113 | 0.006 | −0.034 | −0.015 |
| DV 75th percentile | 0.096 | 0.094 | 0.173 | 0.026 | −0.000 | 0.020 |

$$DV : 100 \times \frac{10}{\Delta t} \times \Delta \frac{AI\ (v3)\ employment\ of\ nativity\ group}{total\ employment}$$

The dependent variable is the change in the share of workers employed in AI-related occupations (V.3 definition) for the long difference 2000–2018 for men (columns 1–3) and women (4–6), shown separately for all workers (columns 5 and 6), foreign-born workers (columns 1 and 2), and native-born workers (columns 3 and 4). The immigrant shock for AI-related occupations (V.3 definition) is defined in equation (2). The sample is individuals 25 to 54 years old with at least a bachelor's degree residing in one of the 722 commuting zones in the continental US. All regressions include a constant, the summed product of the weights used in the immigration shock, state fixed effects, and initial-period shares of the college educated in the population, the foreign-born in the population, females in total employment, employment in manufacturing, employment in routine-intensive jobs, and employment in offshorable jobs. Standard errors (in parentheses) are clustered by state. Regressions are weighted by CZ employment (of prime-age, college educated workers of the designated gender) in the initial period.

*Table 7A11* Long difference (2000–2018): Immigration Impact on CZ Specialization in AI-Related Occupations (V.2)

| | Men | | | Women | | |
|---|---|---|---|---|---|---|
| | Foreign-Born | Native-Born | All | Foreign-Born | Native-Born | All |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Immigrant shock (v2) | 0.763 (0.224) | 0.088 (0.247) | 0.851 (0.422) | 0.382 (0.270) | 0.091 (0.145) | 0.473 (0.334) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 722 | 722 | 722 | 717 | 717 | 717 |
| Adj. R-squared | 0.667 | 0.494 | 0.390 | 0.648 | 0.530 | 0.476 |
| DV Mean | 0.106 | –0.048 | 0.058 | 0.005 | –0.120 | –0.115 |
| DV 25th percentile | 0.028 | –0.156 | –0.055 | –0.023 | –0.173 | –0.180 |
| DV 75th percentile | 0.157 | 0.035 | 0.155 | 0.029 | –0.063 | –0.053 |

$$DV : 100 \times \frac{10}{\Delta t} \times \Delta \frac{AI \ (v2) \ employment \ of \ nativity \ group}{total \ employment}$$

The dependent variable is the change in the share of workers employed in AI-related occupations (V.2 definition) for the long difference 2000–2018 for men (columns 1–3) and women (4–6), shown separately for all workers (columns 5 and 6), foreign-born workers (columns 1 and 2), and native-born workers (columns 3 and 4). The immigrant shock for AI-related occupations (V.2 definition) is defined in equation (2). The sample is individuals 25 to 54 years old with at least a bachelor's degree residing in one of the 722 commuting zones in the continental US. All regressions include a constant, the summed product of the weights used in the immigration shock, state fixed effects, and initial-period shares of the college educated in the population, the foreign-born in the population, females in total employment, employment in manufacturing, employment in routine-intensive jobs, and employment in offshorable jobs. Standard errors (in parentheses) are clustered by state. Regressions are weighted by CZ employment (of prime-age, college educated workers of the designated gender) in the initial period.

*Table 7A12* Stacked First Differences (2000–2009 and 2009–2018): Immigration Impact on CZ Specialization in AI-Related Occupations (V.3)

| | Men | | | Women | | |
|---|---|---|---|---|---|---|
| | *Foreign-Born* | *Native-Born* | *All* | *Foreign-Born* | *Native-Born* | *All* |
| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* |
| Immigrant shock (v3) | 1.835 (0.260) | –0.203 (0.232) | 1.631 (0.444) | 0.729 (0.242) | 0.285 (0.181) | 1.014 (0.369) |
| State × Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 1444 | 1444 | 1444 | 1438 | 1438 | 1438 |
| Adj. R-squared | 0.719 | 0.453 | 0.564 | 0.550 | 0.420 | 0.388 |
| DV Mean | 0.092 | 0.112 | 0.203 | 0.023 | 0.002 | 0.025 |
| DV 25th percentile | 0.031 | 0.065 | 0.142 | 0.004 | –0.019 | –0.005 |
| DV 75th percentile | 0.109 | 0.139 | 0.244 | 0.034 | 0.022 | 0.044 |

$$DV : 100 \times \frac{10}{\Delta t} \times \Delta \frac{AI\ (v3)\ hours\ worked\ by\ nativity\ group}{total\ hours\ worked}$$

The dependent variable is the change in the share of hours worked in AI-related occupations (V.3 definition) for stacked first differences over 2000–2009 and 2009–2018 for men (columns 1–3) and women (4–6), shown separately for all workers (columns 5 and 6), foreign-born workers (columns 1 and 2), and native-born workers (columns 3 and 4). The immigrant shock for AI-related occupations (V.3 definition) is defined in equation (2). The sample is individuals 25 to 54 years old with at least a bachelor's degree residing in one of the 722 commuting zones in the continental US. All regressions include a constant, the summed product of the weights used in the immigration shock, state fixed effects, and initial-period shares of the college educated in the population, the foreign-born in the population, females in total employment, employment in manufacturing, employment in routine-intensive jobs, and employment in offshorable jobs. Standard errors (in parentheses) are clustered by state. Regressions are weighted by CZ employment (of prime-age, college educated workers of the designated gender) in the initial period.

*Table 7A13* Stacked First Differences (2000–2009 and 2009–2018): Immigration Impact on CZ Specialization in AI-Related Occupations (V.2)

| | Men | | | Women | | |
|---|---|---|---|---|---|---|
| | Foreign-Born | Native-Born | All | Foreign-Born | Native-Born | All |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Immigrant shock (v2) | 1.099 (0.199) | 0.202 (0.209) | 1.300 (0.350) | 0.279 (0.239) | 0.333 (0.150) | 0.612 (0.284) |
| State × Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 1444 | 1444 | 1444 | 1438 | 1438 | 1438 |
| Adj. R-squared | 0.566 | 0.398 | 0.375 | 0.429 | 0.371 | 0.362 |
| DV Mean | 0.116 | 0.045 | 0.161 | 0.007 | –0.083 | –0.076 |
| DV 25th percentile | 0.013 | –0.078 | 0.052 | –0.035 | –0.142 | –0.143 |
| DV 75th percentile | 0.169 | 0.154 | 0.251 | 0.038 | –0.029 | –0.009 |

$$DV : 100 \times \frac{10}{\Delta t} \times \Delta \frac{AI\ (v2)\ hours\ worked\ by\ nativity\ group}{total\ hours\ worked}$$

The dependent variable is the change in the share of hours worked in AI-related occupations (V.2 definition) for stacked first differences over 2000–2009 and 2009–2018 for men (columns 1–3) and women (4–6), shown separately for all workers (columns 5 and 6), foreign-born workers (columns 1 and 2), and native-born workers (columns 3 and 4). The immigrant shock for AI-related occupations (V.2 definition) is defined in equation (2). The sample is individuals 25 to 54 years old with at least a bachelor's degree residing in one of the 722 commuting zones in the continental US. All regressions include a constant, the summed product of the weights used in the immigration shock, state fixed effects, and initial-period shares of the college educated in the population, the foreign-born in the population, females in total employment, employment in manufacturing, employment in routine-intensive jobs, and employment in offshorable jobs. Standard errors (in parentheses) are clustered by state. Regressions are weighted by CZ employment (of prime-age, college educated workers of the designated gender) in the initial period.

# 8 Robots and Trade

## Implications for Developing Countries

*Erhan Artuc, Paulo Bastos,*
*Alexander Copestake, and Bob Rijkers*

## 1. Introduction

Modern industrial robots can perform a variety of repetitive tasks with consistent precision and are increasingly used in a wide range of industries and applications. The global operational stock of industrial robots reached a record high of 2.7 million units last year (IFR, 2020) and robot adoption is projected to grow steadily. The accelerating automation of industrial production has stoked concerns that large swaths of the workforce, especially the unskilled, may suffer wage and job losses (e.g., Bloom et al., 2018). These fears are in part predicated on the experience of OECD countries, where robot adoption has contributed to productivity growth at the expense of the employment share and wages of low-skilled workers (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). Recent estimates suggest that around 14% of jobs across the OECD area are at risk of disappearing because of automation, while another 32% are likely to see significant changes (OECD, 2018).

While robotization has been especially pronounced in advanced economies, workers in developing countries could also be at risk. Low-skilled workers, for whom robots substitute particularly well, are disproportionately located in developing countries. Robotization might move production closer to consumers in high-income markets and undermine prospects for industrialization and export-led development (Rodrik, 2018; Hallward-Driemeier and Nayyar, 2019). Developing countries are particularly exposed to automation-induced trade declines, since reduced trade and communication barriers have allowed the offshoring of repetitive and labor-intensive tasks to low-wage countries (Grossman and Rossi-Hansberg, 2008; Antras, 2015; World Bank, 2020). Low-income countries may lack the skills and infrastructure that are needed to meaningfully participate in emerging global value chains, as automation diminishes the importance of low labor costs as a determinant of international competitiveness (Rodrik, 2018).

In this chapter, we first use a Ricardian framework to examine the impact on developing countries of robotization in developed countries. Drawing on Artuc, Bastos and Rijkers (2018), in Section 2 we present theory and evidence indicating that robot adoption in the high-wage advanced economies promoted trade

between developed and developing countries. We highlight that such adoption can ultimately benefit workers in developing countries, particularly through lower prices and increased demand for intermediate inputs. The impact of robotization is shown to depend on the initial degree of robotization. In Section 3, we extend this framework by adding China explicitly to the calibrated model, noting that its robot stock has expanded rapidly in recent years to become by far the world's largest (in absolute terms). We analyze the impact of China's subsidies for robotization, as described in Cheng et al. (2019), and find ambiguous effects on wages of Chinese workers depending on the size of the subsidy. Interestingly, as China increasingly subsidizes industrial robots, its pattern of comparative advantage becomes more similar to that of OECD countries, which reduces its total trade with them. The opposite conclusion applies to trade between China and developing countries.

The Ricardian framework we adopt focuses on long-run and aggregate effects and abstracts from adjustment costs. In the short run, workers cannot move freely across sectors, regions and occupations. In Section 4 we consider broader empirical evidence on the impacts of robotization in developed countries on workers in developing countries. Alongside support for the long-run predictions of the Ricardian model, we catalog evidence of negative short-run employment effects in the local labor markets of some middle-income countries, particularly for the least mobile workers previously performing tasks that can now be executed by robots. These adverse impacts on local labor markets highlight the role for policy to alleviate distributional issues arising from frictions during the automation transition. We also look beyond comparative statics and note that developed-country automation could exacerbate 'premature de-industrialization' (Rodrik, 2016) by discouraging investment in sectors with the highest growth potential. This in turn may help explain the emergence of robot subsidies in some developing economies, particularly China.

Furthermore, robot adoption may be driven by factors other than just the relative prices of robots and workers. Within each country, larger and typically less labor-intensive firms are more likely to be able to afford the fixed costs of upgrading production technology, while firms engaged in complex production networks may attach higher value to the increased precision and reliability enabled by robotics. In Section 5 we therefore move beyond relative prices to provide new evidence on firm-level drivers of adoption in developing countries, while in Section 6 we consider the impact of this adoption on firm-level outcomes. Our empirical analysis draws on firm-level data from ten developing countries. We find support for both the scale and precision hypotheses, aligning with firm-level evidence from developed countries. After adopting robots, these initially larger and more globally connected firms tend to expand further. These firm-level mechanisms help to explain why we observe more and earlier robot adoption in developing countries than our stylized Ricardian model would predict. But they also add a firm-side element to the earlier distributional concerns: it is not just relatively disadvantaged workers who are most threatened by robotization, but also smaller, less productive, less internationally active firms. Given that

low-skilled workers are also disproportionately more likely to work in these firms, the dual threat is a key issue for policymakers to consider.

We conclude by surveying these opportunities and challenges for developing countries raised by automation. In the long run, industrial robots in developed countries could promote trade between advanced and developing countries, and enhance global welfare. And while China's growing robotization (driven in part by subsidies) might reduce productivity differences with advanced economies, and thereby the gains from inter-industry trade with them, it need not hinder future prospects for industrialization and export-led growth in lower-income countries. However, technological change, both in advanced and developing countries, necessitates labor-market adjustment and can create severe distributional tensions, which are not limited to the transition period. As robots catch up with humans in many abilities, so policy must keep pace with adoption.

## 2. Implications of robotization in advanced economies for developing countries

Drawing on Artuc, Bastos and Rijkers (2018), we first use a Ricardian framework to examine the impact on developing countries of robotization in developed countries. We start by inspecting drivers of robot adoption at the country and industry level (see Figure 8.1). High-wage rich countries tend to use more robots (panel A), suggesting that the potential for cost savings is an important determinant of adoption. There is wide variation across industries in the proportion of jobs that are replaceable (calculated using the share of occupations involving tasks that can potentially be performed by robots, following Graetz and Michaels 2018), and this indeed predicts realized robot density (panel B).

Motivated by these patterns, the multi-country, multi-sector Ricardian model features: (i) a higher cost of labor in the North, and (ii) an industry-specific robotization frontier (i.e., the range of tasks for which humans are substitutable by robots varies across sectors).[1] The model features two-stage production, with intermediate goods produced in the first stage and final goods produced in the second stage. In the production process, robots can take over some tasks previously performed by humans.[2]

In the model, a subset of tasks required in the production of intermediate and final goods can be executed either by workers or robots, while other tasks can only be performed by humans. The range of tasks that can be performed by robots varies across sectors. The industry-specific robotization frontier, relative factor prices and productivity determine the extent of robot use within sectors. Production of each final-good variety further requires a composite intermediate good from the same industry. In equilibrium, varieties of intermediate inputs and final goods are sourced from the country that supplies at the lowest price. Thus, there are two layers of competition: (1) between robots and workers in factor markets; and (2) between countries in sector-specific product markets for inputs and outputs.[3] Relative production costs (driven by factor prices and technology) determine country-specific robotization and trade patterns.

Panel A: Robot adoption is higher in richer countries
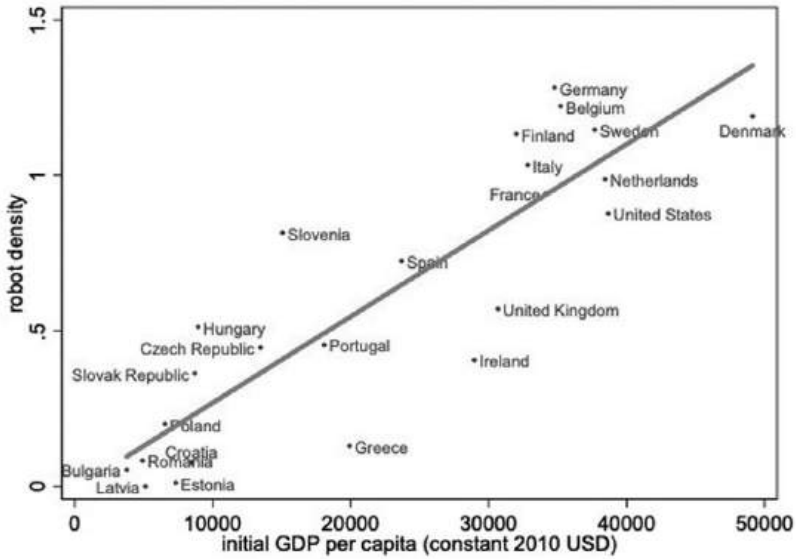


Panel B: Sectors in which automation is feasible adopt more robots
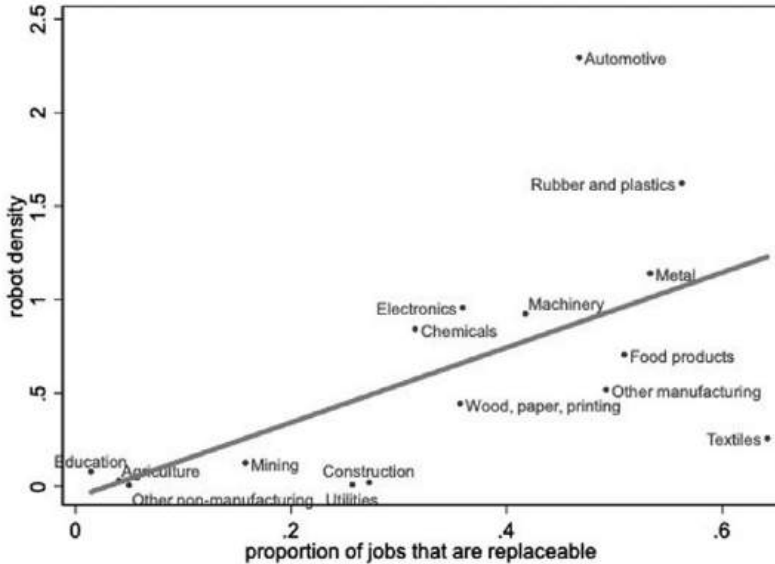


*Figure 8.1* Robotization Across Countries and Sectors

Notes: Panel A depicts the relationship between average robot density by country (averaged across years) and the initial GDP per capita. Panel B depicts the relationship between average robot density by sector (averaged across countries and years) and the share of replaceable jobs in the industry, as measured in Graetz and Michaels (2018), using the distribution of hours worked across occupations and industries from the 1980 US Census. Robot density is defined as the log of one plus the number of robots in use per million worker-hours.

Source: Artuc, Bastos and Rijkers (2018).

With many countries in the model, a fall in the global price of industrial robots initially induces robotization in Northern countries, defined as those with a higher initial cost of labor.[4] This shift impacts relative production costs between countries, and therefore trade patterns. Producers substitute robots for domestic labor in automatable tasks, leading to lower costs of production in Northern countries, and hence to an increase in exports to Southern countries.[5] The more striking growth in same-sector imports from Southern countries reflects the sum of two competing forces. On one hand, lower costs in Northern countries make domestic producers and input suppliers there more competitive relative to foreign ones, which lowers the demand for goods produced abroad as consumers and producers substitute them with domestic goods. On the other hand, the increased scale of production in Northern countries also leads to an overall surge in the demand for intermediate inputs. If these are sourced from abroad, imports from lower-wage Southern countries in these industries can rise.

The two-stage production structure helps us to differentiate comparative advantage patterns for intermediate inputs and final goods, as well as the differences in the demand. Robotization in Northern countries increases productivity of North in both stages of production but does not necessarily reduce the demand for intermediate inputs produced by South, since the scale effect can potentially dominate the substitution effect.

Between 1995 and 2015, the production expansion effect seems to have dominated. Indeed, empirical results in Artuc, Bastos and Rijkers (2018) show that the robot-induced surge in Northern imports from the South is concentrated in intermediate inputs such as parts and components. To gauge the relationship between robotization and North-South trade, the empirical analysis combined robot stock data from the International Federation of Robotics, labor hours data from EU KLEMS, and trade data for 1995–2015 from CEPII BACI. The following baseline specification was estimated:

$$Trade_{nmit} = \beta Robots_{nit} + \Psi_{nmt} + \Lambda_{it} + \epsilon \qquad (1)$$

where $Trade_{nmit}$ denotes the log of (1+exports) from developed country $n$ to developing country $m$ in sector $i$ and year $t$ or alternatively the log of (1+imports) sourced from developed country $n$ in sector $i$ and year $t$; $Robots_{nit}$ denotes a measure of robot usage in country $n$ in sector $i$ in year $t$; $\Psi_{nmt}$ denotes a fixed effect by exporter-importer-year; $\Lambda_{it}$ denotes an industry-year fixed effect; and $\epsilon$ the error term. Equation (1) includes exporter-importer-year fixed effects both to allow for pair-specific shocks (such as fluctuations in relative income and exchange rates) and to control for country pair specific determinants of trade (e.g., distance, having a common language etc.). It further includes industry-year fixed effects to account for factors that are specific to each industry in each year. Standard errors are clustered by developed country. To address the possibility of reverse causality in the relationship between robotization and trade, as well as potential biases caused by omitted variables or measurement error, an instrumental-variables

approach was followed. Specifically, the analysis uses the triple interaction between the (pre-determined) share of workers engaged in replaceable tasks in each sector, the country's initial income per capita, and the global stock of robots as an instrument for robotization.[6]

The instrumental-variables estimates reveal that a 10% increase in robot density in a robotizing industry in the North boosts its exports to the South by 11.8%. Surprisingly, it also induces a 6.1% increase in its imports from the South within the same broad sector. The latter effect is primarily driven by imports of parts and components.[7] These empirical results can be explained by two key features of the Ricardian trade model with a multi-stage production technology: (1) productivity effects of robotization in the North, such that replacing workers with (cheaper) robots increases output and exports; and (2) trade in intermediate goods, such that an expansion in Northern final production can increase imports of inputs from the South within the same broad sector.[8]

Given these patterns, how are further reductions in robot prices likely to impact global trade, wages and welfare? To answer this question, the Ricardian model was calibrated with three countries and three sectors. In particular, the quantitative model features a representative high-income Northern country, a representative country in the South, and a group of other (lower-income) developed countries.[9,10] Among the three sectors considered, two sectors are tradable, and the other sector is non-tradable. Production is subject to robotization in just one of the tradable sectors, consisting of the automotive, rubber and plastic, electronics, chemicals, metal and machinery industries. The non-robotized tradable sector consists of all other manufacturing industries, including food and textiles, agriculture, mining and utilities. The non-tradable sector consists of construction and services.

Simulating the impact of future reductions in robot prices offers several insights, which are illustrated in Figure 8.2. As robot prices decline, producers in the North, who face higher wages, will adopt progressively more robots (panel A). When prices decline even further it also becomes profitable for less developed countries, where producers face lower labor costs, to robotize production. Robot adoption is associated with an initial reduction in the number of jobs in the automating sector (panel B). Yet once all tasks that can be automated are performed by robots, further reductions in robot prices boost the demand for labor in the robotized sector because they make workers in those sectors more productive. The impact of automation on jobs is thus state-dependent: while industrial robots compete with workers in the early stages of adoption, they complement them in subsequent stages, since we assume that the range of automatable tasks is fixed. This also explains the U-shaped relationship between robot prices and wages in North and "Other" (panel C).[11] Interestingly, lower robot prices also gradually raise the wages of workers in the South.[12] As robot prices fall, aggregate welfare increases in all countries but more so in the countries that adopt more robots (panel D).

Turning to trade flows, as Northern producers in the robotized industry demand progressively more intermediate inputs to enable their expansion of

Panel A: Robot use in robotized industry
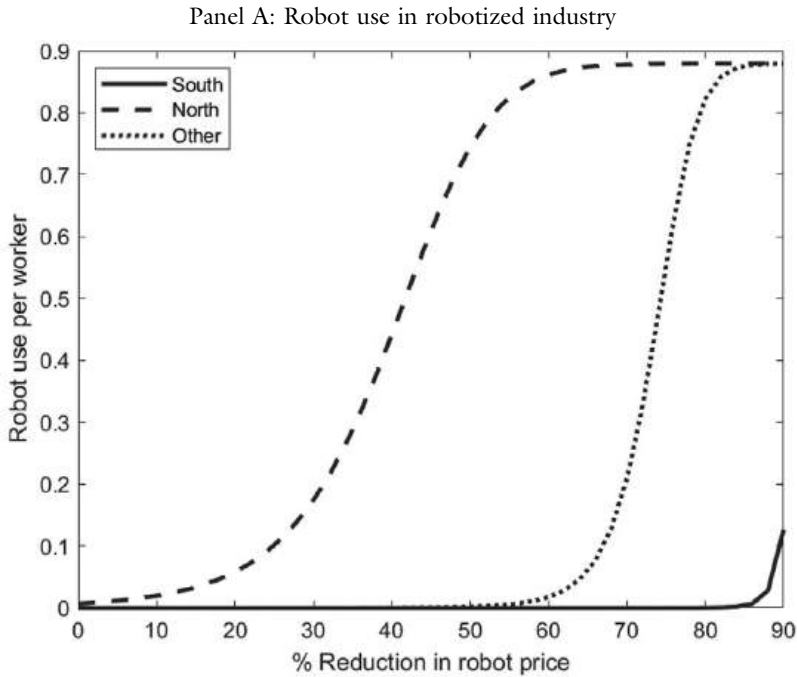


*Figure 8.2* Effects of Robot Price Reductions

Notes: This figure presents results from simulations of the effects of lower robot prices on robot use, labor allocation, wages and welfare. As robot prices fall, initially only North adopts robots (panel A for a 0–60% reduction in robot price), then Other also adopts (60–85%). Eventually these are both fully robotized; beyond 85% all effects are driven by Southern robotization.

Source: Artuc, Bastos and Rijkers (2018).

production (shown in Figure 8.3 panel A), their demand for Southern exports of intermediates surges (panel B).[13] Underlying this increased demand are two forces, decomposed in panel C. The scale effect is the increase in Northern demand resulting from their higher productivity when using robots. This is offset by a substitution effect, in which the increased productivity of Northern producers raises the share of total demand that they supply (e.g., a reduction in the share of goods imported), which necessarily implies a lower share for Southern producers.[14] The same two forces also apply to Southern exports of final goods to the North (Panel D). In this case the scale effect is weaker because it only includes higher Northern demand for final goods – i.e., it excludes the extra demand for intermediate inputs caused by the expansion of Northern final-good producers. Nonetheless, in both cases the scale effect dominates, causing a rise in total Southern exports to the North.[15]

We also investigate the dependence of these results on the specific parameters chosen for the model. Figure 8.A1 in the Appendix repeats Figure 8.3 panels C and D for different values of the trade elasticity.[16] All the results are qualitatively robust, with only the size of the effects changing. For instance, while substitution

Panel B: Labor use in robotized industry
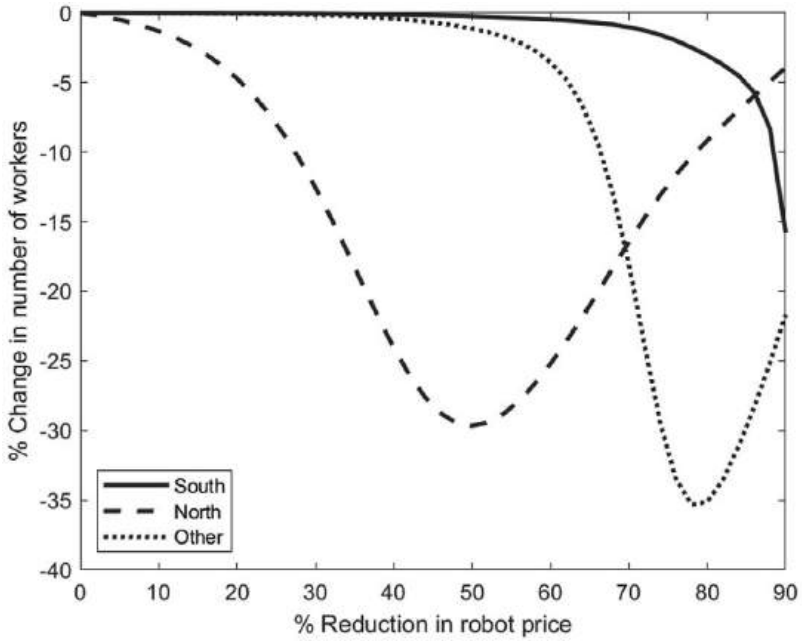


*Figure 8.2* (*Continued*)

Panel C: Wages



*Figure 8.2* (*Continued*)

Panel D: Welfare (Real GDP)
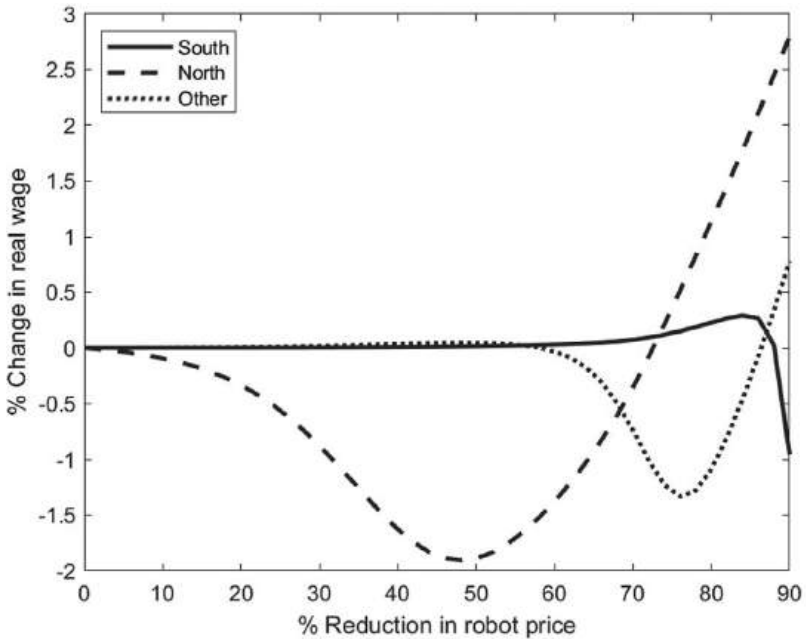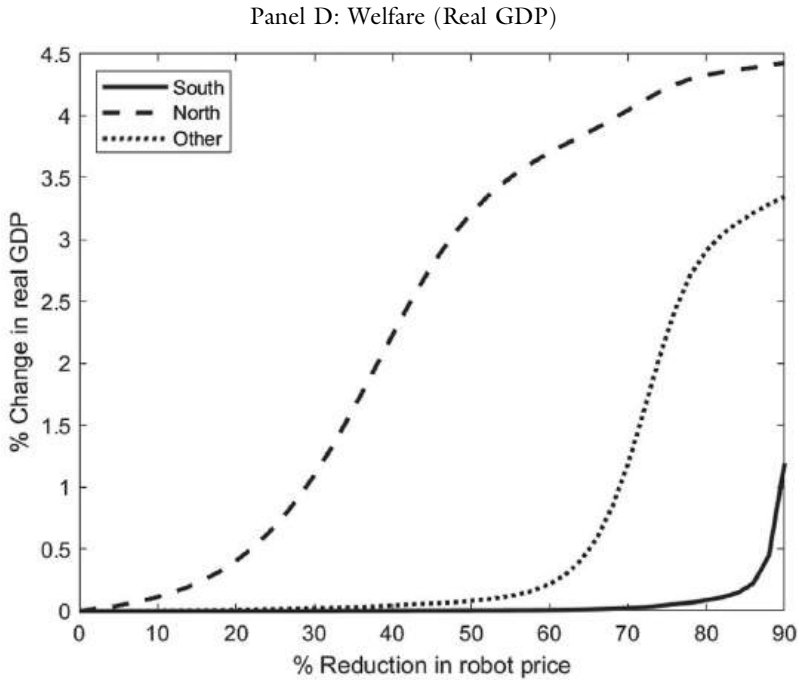


*Figure 8.2    (Continued)*

effects are very large in the high-trade-elasticity case, the scale effect always dominates.[17] In contrast, Figure 8.A2 repeats the baseline simulations with a lower elasticity of substitution between robots and workers, such that robots are modelled as being more similar to conventional capital.[18] Compared to Figure 8.2, we see that investment in robots is more gradual as their prices fall (panel A), and Northern producers in the robotized industry actually increase their total labor use for large price reductions (panel B). Since workers are less easily substitutable, wages rise almost monotonically in North (panel C), in stark contrast to the baseline U-shaped relationship in which Northern wages initially fall substantially as robots displace workers. Nonetheless, Southern wages fall, along with South's exports to the North in the robotized sector (panel D). The substitution effect is now much stronger than the scale effect, so exports of final goods collapse in the robotized sector. Thus, our stated conclusions are specific to automation *per se*, as opposed to capital investments that complement Northern workers. The key characteristic of robots, that they substitute particularly well for human workers for a sizable subset of tasks in manufacturing industries, is critical in generating state-dependent comparative statics.

## *Robustness, indirect effects and heterogeneity*

Artuc, Bastos and Rijkers (2018) run extensive robustness checks on the core empirical predictions of the model, which analyze bilateral trade flows as a function

Panel A: North's exports to South
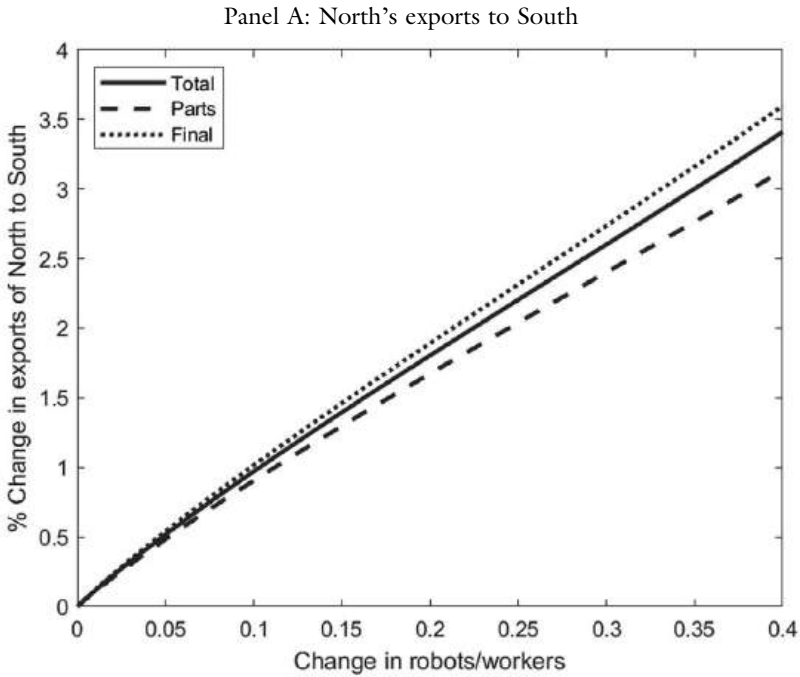


*Figure 8.3* Effects of Robot Adoption on Trade in the Robotized Industry

Notes: This figure presents results from simulations of the effects of increased robot density (resulting from lower robot prices, as per Figure 8.2 panel A) on North-South trade in the robotized industry. Panels C and D decompose the mechanisms underpinning the impacts in panel B, on South's exports of intermediate and final goods respectively.

of automation in developed countries.[19] Yet such automation could also have indirect effects by increasing competition in developing countries' other export markets. If North automates, and so increases its exports to Other, this could displace Southern exports to Other. A commonly held concern is that automation in developed countries could shut developing countries out of global value chains.

In the calibrated model, however, such effects are small. Figure 8.2 shows that automation in developed countries (corresponding to a 0%–60% reduction in robot prices in panel A) leads to only a very small reduction in labor use in the robotized industry in South (panel B). We evaluate whether this prediction is realistic using World KLEMS data (Jorgenson, 2017) that allow us to move beyond bilateral trade flows.[20] We regress industry $i$ log employment or value added $y_{mit}$ in developing country $m$ on its exposure to developed-country automation, measured by robot intensity in developed countries $n$, weighted by their share of $m$'s baseline exports:

$$y_{mit} = \beta \cdot \ln\left(1 + \sum_{k \in n} \omega_{mkit_0} Robots_{kit}\right) + \Psi_{mt} + \Lambda_{it} + \epsilon_{mit} \qquad (2)$$

Panel B: South's exports to North
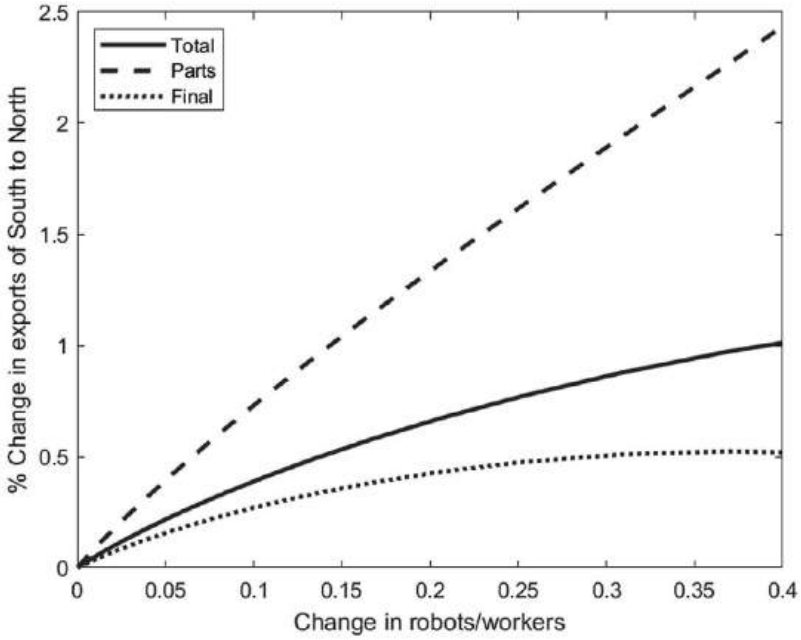


*Figure 8.3   (Continued)*

Panel C: South's exports to North, parts only



*Figure 8.3   (Continued)*

Panel D: South's exports to North, final only
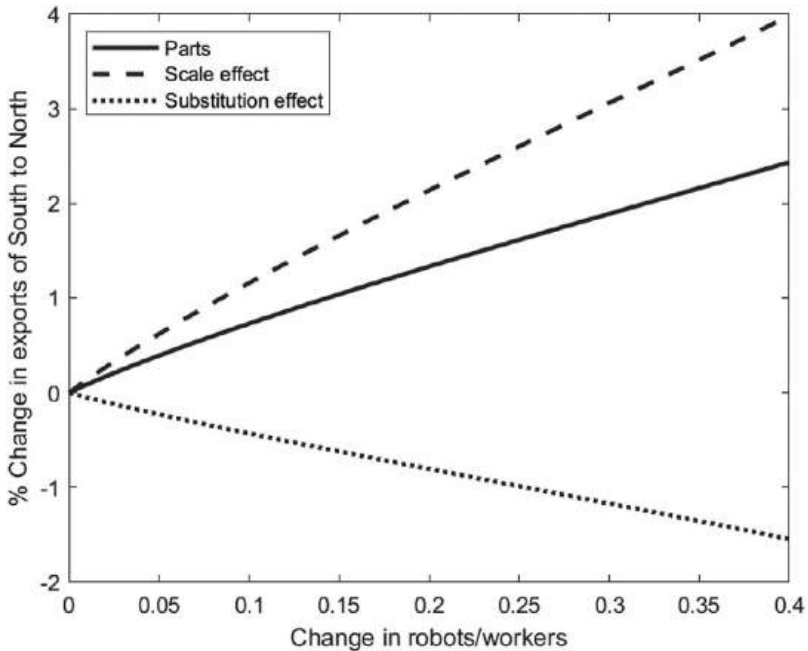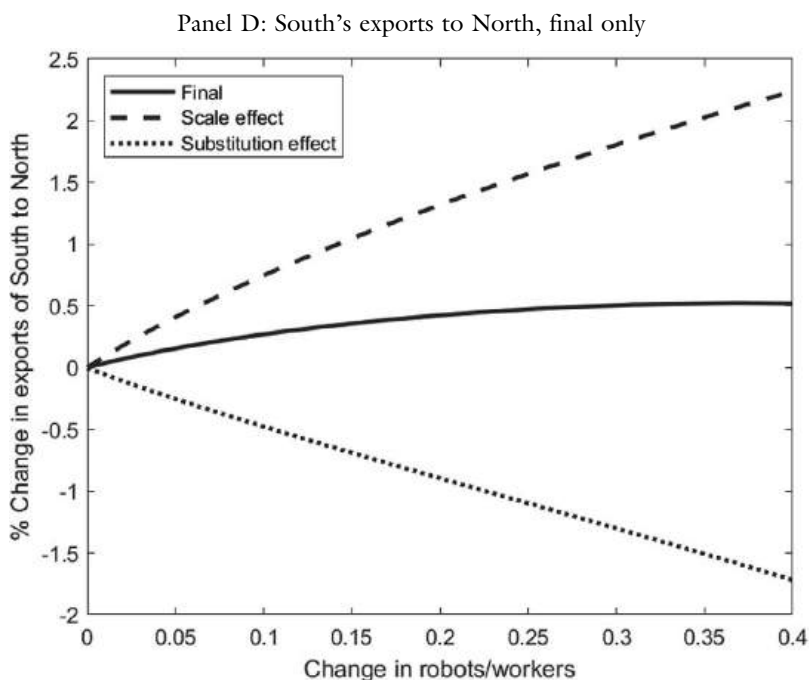


*Figure 8.3   (Continued)*

where $\omega_{mkit_0}$ is baseline exports in industry $i$ from $m$ to $k$, as a share of total exports of $i$ from $m$ to all $n$, and $Robots_{kit}$ is the number of robots per million worker hours in country-industry $ki$. Table 8.1 shows only a weak negative relationship between exposure to foreign robotization and value added as well as employment. These results are robust to instrumenting exposure to developed country-automation with the log of the baseline-weighted product of replace-ability, initial GDP per capita and the global robot stock (as described for regression (1) previously). While data availability limits the sample substantially relative to the regressions with bilateral trade flows, these results are consistent with the those from the calibrated model. Indirect effects do not seem to play an important role; the key conclusion – that Northern automation increases Southern imports and exports – is not affected.

These average impacts may mask heterogeneity across different types of developing countries. Whilst the available input-output data used to quantify trade models do not make it possible to credibly simulate fine-grained country-level heterogeneity across a wide range of developing countries, we can use the empirical approach outlined previously to examine how different types of countries are impacted by automation. In a new extension, we run the previous model separately within sub-samples by income level and region.

The results are shown in Figure 8.4. First, we find robust effects on imports at all income levels (panel A): in each case, robotization significantly raises both

*Table 8.1* Exposure to Foreign Robotization, Employment and Value Added

| | ln Value Added | | ln Employment | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Exposure to developed-country robotization | –0.107 | –0.261 | 0.295 | –0.663 |
| | (0.233) | (0.495) | (0.976) | (1.858) |
| Observations | 1,676 | 1,169 | 1,676 | 1,169 |
| Specification | OLS | 2SLS | OLS | 2SLS |
| Kleibergen-Paap rk Wald-F | | 14.218 | | 14.218 |
| Country-Year FE | Y | Y | Y | Y |
| Industry-Year FE | Y | Y | Y | Y |

Notes: Standard errors in parentheses, clustered at the country-industry level. (Insufficient variation to cluster at country- or industry-level alone.) ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Unbalanced panel of industry-level data between 1980 and 2016. Models (2) and (4) instrument exposure with the log of the baseline-weighted product of replaceability, initial GDP per capita and the global robot stock.

Source: World KLEMS.

Panel A: Heterogeneity across income levels of importers
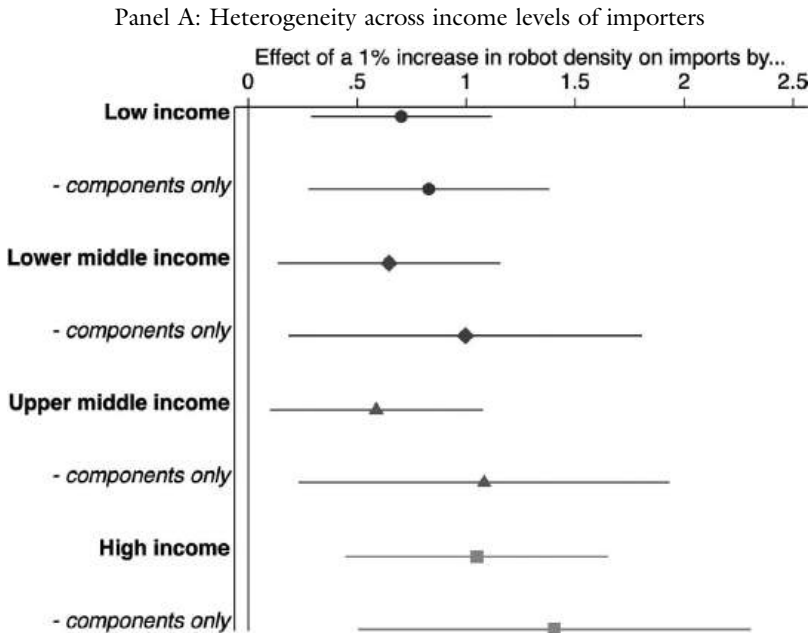


*Figure 8.4* Heterogeneity of Effects of Northern Robotization on North-South Trade

Notes: this figure presents IV estimates of the heterogeneous effects of increased robot density in the OECD on imports from developing countries, using the empirical approach outlined in equation (1).

Panel B: Heterogeneity across regions

Effect of a 1% increase in robot density on imports from...
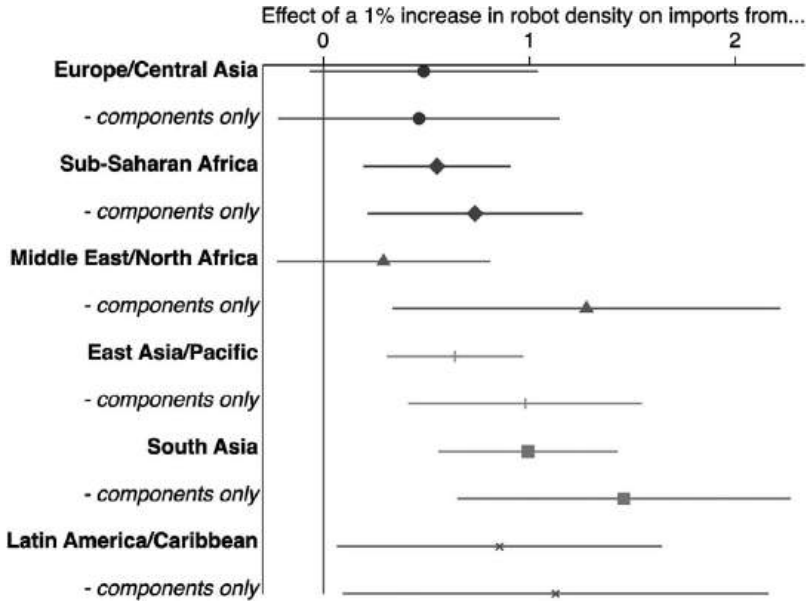


*Figure 8.4* (*Continued*)

total imports and imports of parts and components from developing countries. The scale effect of robotization on imports from developing countries thus appears to consistently outweigh the substitution effect within sectors. Second, we examine the effect of developed-country robotization on imports from developing countries in particular regions. We find that the effects are strongest in South and East Asia and Latin America, with slightly less of an effect in sub-Saharan Africa, a mixed picture in the Middle East/North Africa, and no significant effect in Europe and Central Asia. This points to factors beyond relative prices driving the heterogeneity – particularly regional trade linkages and global value chain participation, which are particularly strong in South and East Asia. These mechanisms are investigated in more detail in Section 5.

## 3. Implications of growing robotization in China

While global robot use has been increasing steadily, adoption of industrial robots has been especially rapid in China – particularly in the last few years (see Figure 8.5). This adds an extra dimension to the mechanisms described previously. Rather than technological progress leading to an exogenous fall in robot prices, which encourages high-wage countries to automate, China's robotization has been supported by large subsidies and a plethora of government programs. Faced with a rapidly ageing population, robotization has been promoted by various levels of government (Cheng et al., 2019). The Ministry of Industry and Information
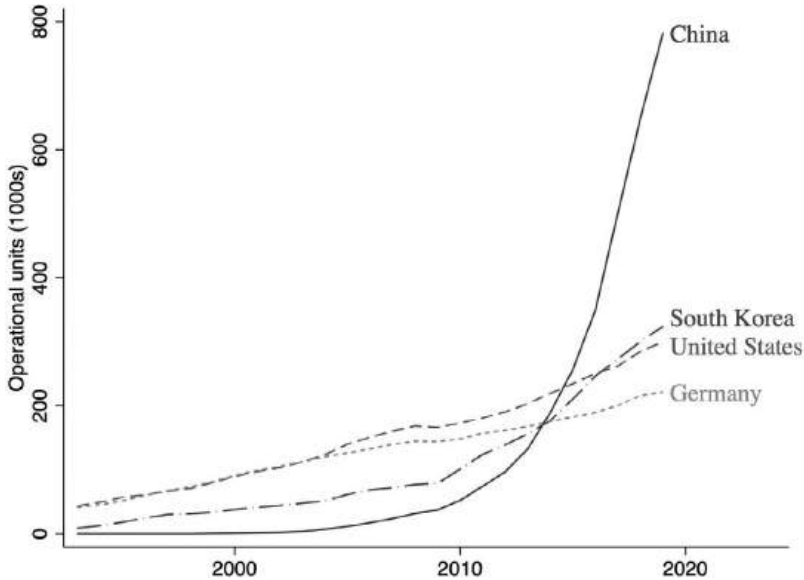
*Figure 8.5* China's Robot Stock has Grown Rapidly

Notes: This figure shows the operational stock of robots over time for leading countries. China's robot stock has expanded rapidly, such that it is now the largest of any country. Note, however, that the robot stock per manufacturing worker in China continues to be considerably smaller than in the OECD. Source: International Federation of Robotics.

Technology (MIIT) released its 'Guidance on the Promotion and Development of the Robot Industry' in 2013, which aimed for a robot density of 10 per 1000 workers in factories. Subsequently, the 2015 'Made in China 2025' program raised this to 15; the Robotics Industry Development Plan released in 2016 by the MIIT, National Development and Reform Commission, and Minister of Finance further encouraged robot use in a broader range of sectors, including services. At a regional level, examples of automation-promoting initiatives include the government of Guangdong Province's USD150 billion fund to invest in automation technology (Yang, 2017).

To study the impact of automation subsidies in China, we use the framework of Artuc, Bastos and Rijkers (2018) with four countries.[21] The simulations include: (i) a representative country for the South (an average of Turkey, Taiwan, Mexico, Indonesia, India, Brazil, Mexico), (ii) a representative country for the North (an average of high automation counties, USA, Denmark, etc. excluding the outliers of Korea and Japan), (iii) the large 'Other' country, containing the totality of the OECD, and (iv) China. Everything in the model operates as before, except we now include a subsidy such that the robot price in China is $(1 - subsidy) \times price$.[22] This therefore increases robot investment in China in an analogous way to the global price reductions modelled in Figure 8.2 panel A.

Panel A: Labor use in robotized industry
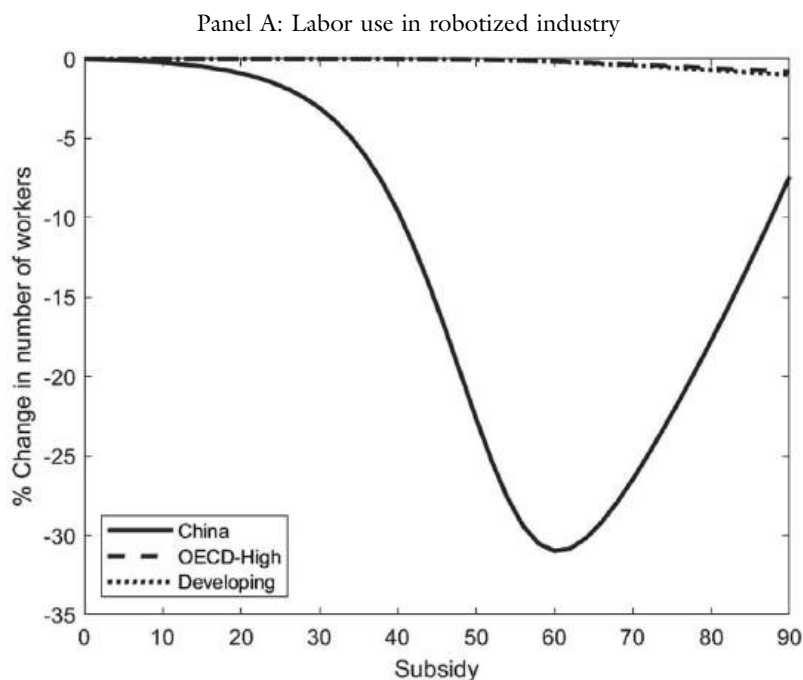


*Figure 8.6* Simulated Effects of Increased Chinese Robot Subsidies

Notes: This figure presents results from simulations of the effects of Chinese robot subsidies on labor use in the robotized industry, wages and trade. Everything in the model operates as before, except that there is now an extra country, calibrated to fit China, which subsidizes robots such that the robot price there is $(1 - subsidy) \times price$.

In the quantified model, China's robot subsidies now push them closer to the comparative advantage profile of developed countries and away from that of developing countries. Specifically, we find that robotization increases significantly with subsidies, so labor use in the robotized industry in China initially declines as the subsidy rises (first part of Figure 8.6 panel A).[23] This reduces labor demand, and so lowers wages (first part of panel B). However, beyond a threshold level – approximately a 60% subsidy in the figures – further subsidies increase labor demand and wages. Once all automatable tasks are performed by robots instead of humans, additional subsidies simply lower production costs and expand output. In other words, there is a robotization frontier beyond which further declines in robot prices are unambiguously beneficial for workers. From this point, further subsidies encourage additional investment in a technology that is now complementary to the remaining human workers.[24]

Turning to trade flows, exports by China's robotized sectors increase unambiguously with subsidies, while China's imports in those sectors decrease unambiguously. As China's robot subsidies push it closer to the relative productivity profile of high-income countries (and further away from that of low-income

Panel B: Wages



*Figure 8.6   (Continued)*

Panel C: Trade with high income countries
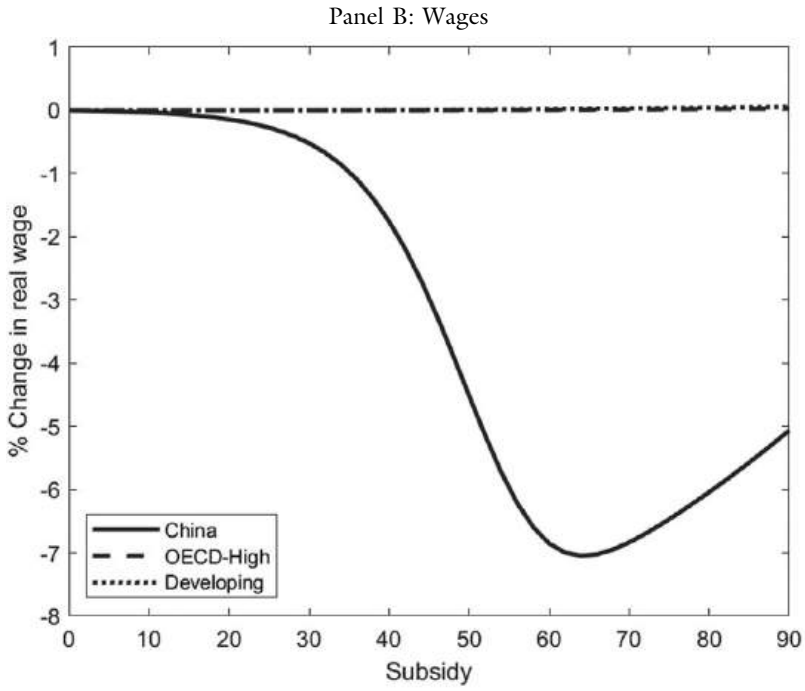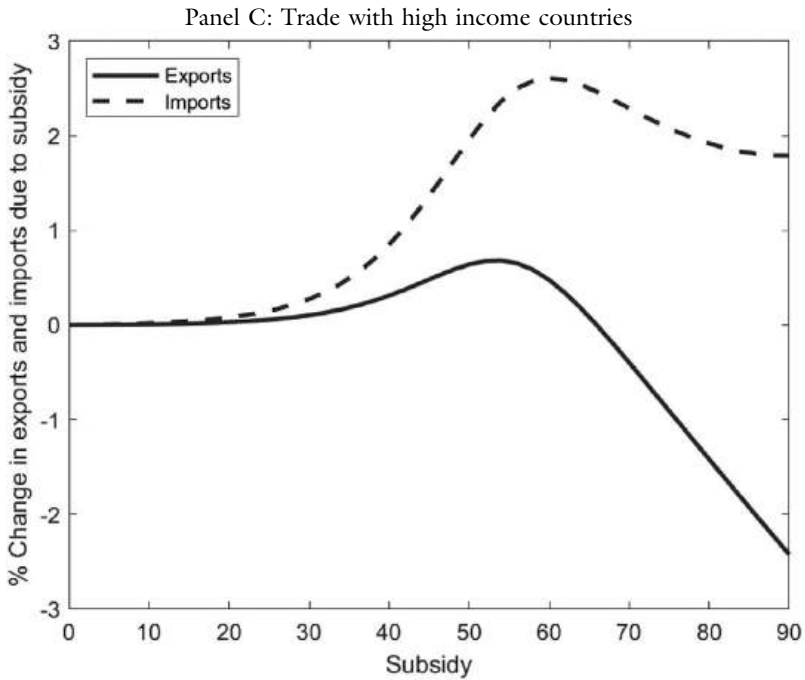


*Figure 8.6   (Continued)*

Panel D: Trade with developing countries
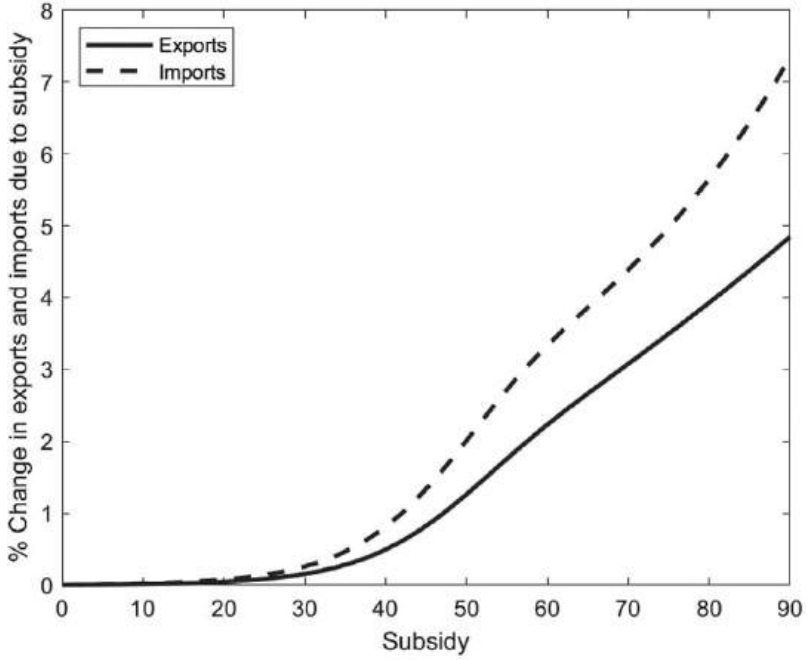


*Figure 8.6* (*Continued*)

Panel E: Rob. ind. imports from South, parts



*Figure 8.6* (*Continued*)

Panel F: Rob. ind. imports from South, final
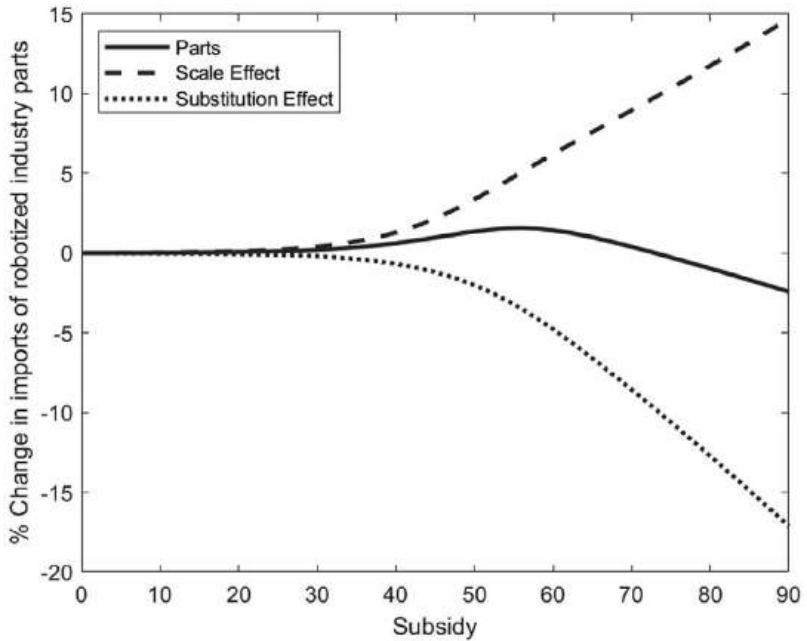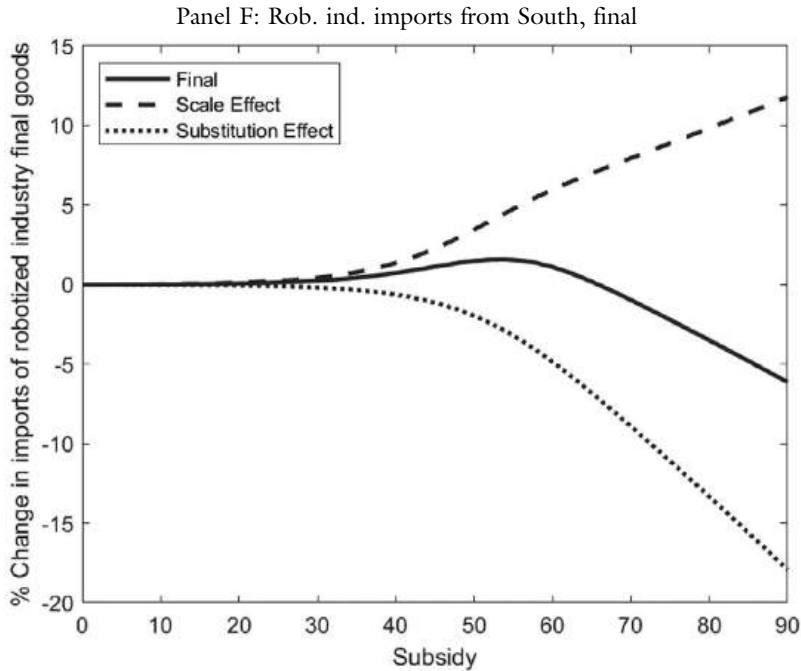


*Figure 8.6*    (*Continued*)

countries), classical comparative advantage discourages trade with high-income countries and encourages it with low-income countries. We see in panel C that China's trade with the North may increase for lower subsidy levels, but will probably decline over time as subsidies continue and China's specialization patterns become more similar to those in the OECD. In contrast, China's trade with the South increases unambiguously (panel D), because subsidies make China more different to other developing countries, as its comparative advantage moves to robot-intensive sectors.

Once again, these aggregate effects result from several interacting mechanisms. Consider, for instance, total Chinese imports of goods produced in the robotized sector in the South (panels E and F). Subsidies in China increase Chinese productivity and output in this sector, which increases imports from the South through both elements of the scale effect (i.e. general consumption plus higher demand for intermediate goods). Yet subsidies also further reduce the relative competitiveness of Southern producers in the robotized sector, reducing Chinese imports from the South (the substitution effect). For large subsidies (approximately greater than 60%), the substitution effect increasingly outweighs the scale effect, so total Chinese imports of robotized-sector goods from the South fall. Once again, this is most pronounced in final goods – since the offsetting scale effect is larger for parts because they benefit from both elements of the scale effect.[25]

Interestingly, other countries' wages and labor allocations are hardly impacted by China's subsidies. The subsidy increases both total imports from and exports to developing countries, which nets out the impact on wages. The impact on labor use in the automatable sector is noticeable, but small, since developing country labor markets are only indirectly exposed to robotization in China through international trade. Therefore, the subsidy in China causes a modest labor shift in developing countries from automatable industries to non-automatable industries, with only marginal impacts on wages.

Accounting for continued population ageing in China would strengthen these results. As documented by Acemoglu and Restrepo (2021), middle-aged workers have a comparative advantage over older workers in manual production tasks, such that demographic changes that reduce their share of the population raise labor costs in manufacturing. Thus continued ageing would further increase the relative attractiveness of robots, paralleling and reinforcing the impacts that we find for a robot subsidy.

## 4. Broader evidence: global value chains, frictions and de-industrialization

Our findings dovetail with empirical evidence from other recent studies. Robotization by Spanish firms increased their demand for inputs from developing countries and also led them to increase their number of affiliates in developing countries (Stapleton and Webb, 2020).[26] Robot usage has also promoted greenfield FDI from high-income countries to low-income countries (Hallward-Driemeier and Nayyar, 2019). This evidence is particularly informative about future trends because greenfield FDI decisions are a forward-looking indicator of where production is expected – unlike trade flows, which reflect past investment decisions. In contrast to fears of automation driving mass reshoring, there is reason to be cautiously optimistic that the positive scale/productivity effect of developed country automation on offshoring may outweigh the negative substitution effect.

However, the focus of our Ricardian model is on long-run and aggregate effects. In the short run, workers cannot move freely across sectors or between subnational regions. Sector-specific skills, frictions and sunk investments could drive transitional unemployment and growing inequality; workers in robot-competing sectors and localities could lose out from Northern robotization. Recent studies find evidence for such effects. To gauge the impact of US robots on employment in Colombia, Kugler et al. (2020) use employer-employee matched data from social security records. They measure exposure to US robotization by combining baseline Colombian local labor market-industry employment shares with industry-time robot adoption in the US and find that such exposure reduces employment and earnings in Colombia. Their estimates imply that, between 2011 to 2016, the adoption of 70,000 new robots in the US led to the cumulative loss of between 63,000 and 100,000 Colombian jobs. The negative effects are largest for women, older and middle-aged workers, and those employed in small

and medium-size businesses – groups which may be least mobile across locations or industries to find new employment.

Similarly, Faber (2020) examines the impact of US robotization on employment in Mexican local labor markets between 1990 and 2015. He combines initial Mexican local labor market-industry employment shares with a measure of offshorability and changes in US robot intensity and again finds a sizeable negative impact on Mexican employment. Although Mexico also automated industrial production in this period, and the coarse industry-level robots data make it difficult to distinguish between the effects of robotization in the US and at home, he finds that the burden of robotization falls most heavily on low-educated machine operators in the manufacturing sector – again, a group likely to be less mobile across locations and occupations. Also focusing on Mexico, but over 2004–2014 Artuc, Christiaensen and Winkler (2019) find less of an effect of US robotization on Mexican regional exports and local labor markets. They find evidence that the informal sector expands, acting as an 'employment buffer' as in Dix-Carneiro et al. (2019), but that automation nonetheless hits the unskilled and other already-disadvantaged workers hardest. Wage inequality thus increases, especially in the local labor markets most exposed to foreign automation. Taken together, this evidence suggests that while robotization could promote trade and increase real wages in developing countries in the medium and long run, in the short run governments will need to be attentive to those workers and regions that are most vulnerable in the transition.

Furthermore, long-run risks are non-negligible. The model described previously focuses on static gains from trade. Over time, developed-country robotization could also push developing economies away from some sectors with higher long-run potential for learning-by-doing or technology transfers. This could compound existing difficulties in trying to grow technology-intensive 'infant industries' to a competitive scale, and exacerbate 'premature de-industrialization' (Rodrik, 2016). Such dynamics may help explain why some developing countries, such as China, have opted to subsidize robots.

## 5. Robot adoption in developing countries: beyond relative prices

The Ricardian model described previously abstracts from firm-level heterogeneity in order to emphasize country- and sector-level effects. In reality, many factors beyond robot prices, wages and subsidies will influence the incentives to adopt robots. First, we can conceptualize robotization as a one-off or per-period fixed cost that lowers marginal production costs. In this case, we might expect only larger, more productive, export-oriented firms to undertake such investment, in the spirit of Melitz (2003) and Bustos (2011). Alternatively, robotization could be conceptualized as an upgrade to product quality – for instance, by allowing greater precision and reliability, as discussed in Verhoogen (2008) and Rodrik (2018). These attributes may be most valued

by firms that are tightly integrated into complex production networks, involving the coordination and assembly of many interdependent components (Kremer, 1993; Verhoogen, 2008; Demir et al., 2021). The cost of producing a defective widget compounds rapidly if its failure negates all the other inputs into a complex final product. By this reasoning, we might then expect more automation in firms that are tightly integrated into global value chains, where the costs of errors (or the payoffs to quality) are highest. Such mechanisms will drive some robot adoption within developing countries, despite the availability of cheap labor. A first glance at high-level cross-country correlations do indeed point to a positive association between GVC participation and robot adoption (Figure 8.7).

To investigate such relationships further, we use the near-universe of firm-level trade transactions from ten developing countries, identifying automation events from imports of industrial robots.[27] The shares of firms that have ever imported robots are shown in Figure 8.8. Consistent with the patterns presented in Section 2, the electronics and automotive sectors have the highest shares of robot use. Defining 'automators' as firms that import robots at some point in the sample period, we regress automator status on a range of
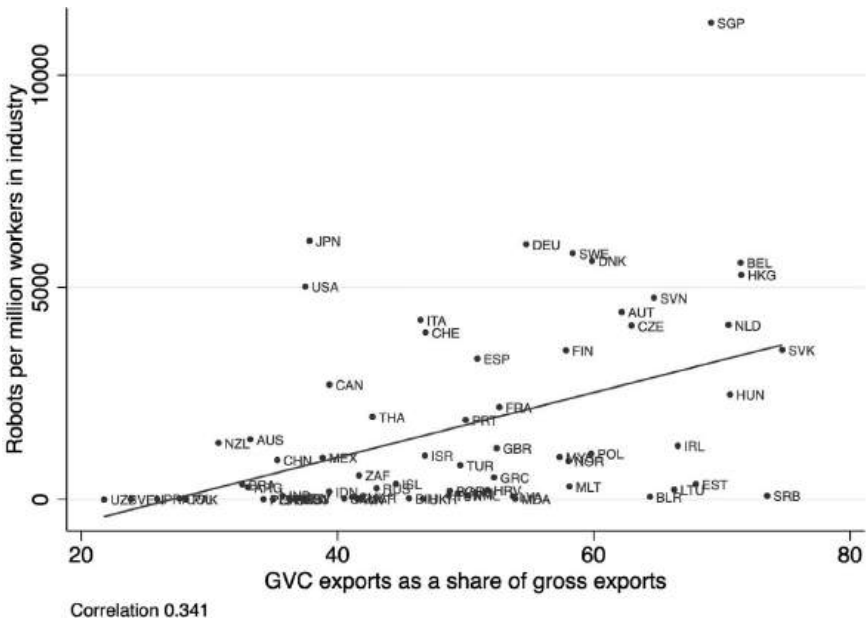


Correlation 0.341

*Figure 8.7* Robot Use and Participation in Global Value Chains

Notes: This graph shows the correlation between robot density and GVC participation in 2015, using the data and methodology outlined in the World Development Report 2020 (World Bank, 2020). GVC exports are defined as those crossing more than one border. One outlier (Republic of Korea) is excluded from the graph for clarity, but is included in the correlation calculation.
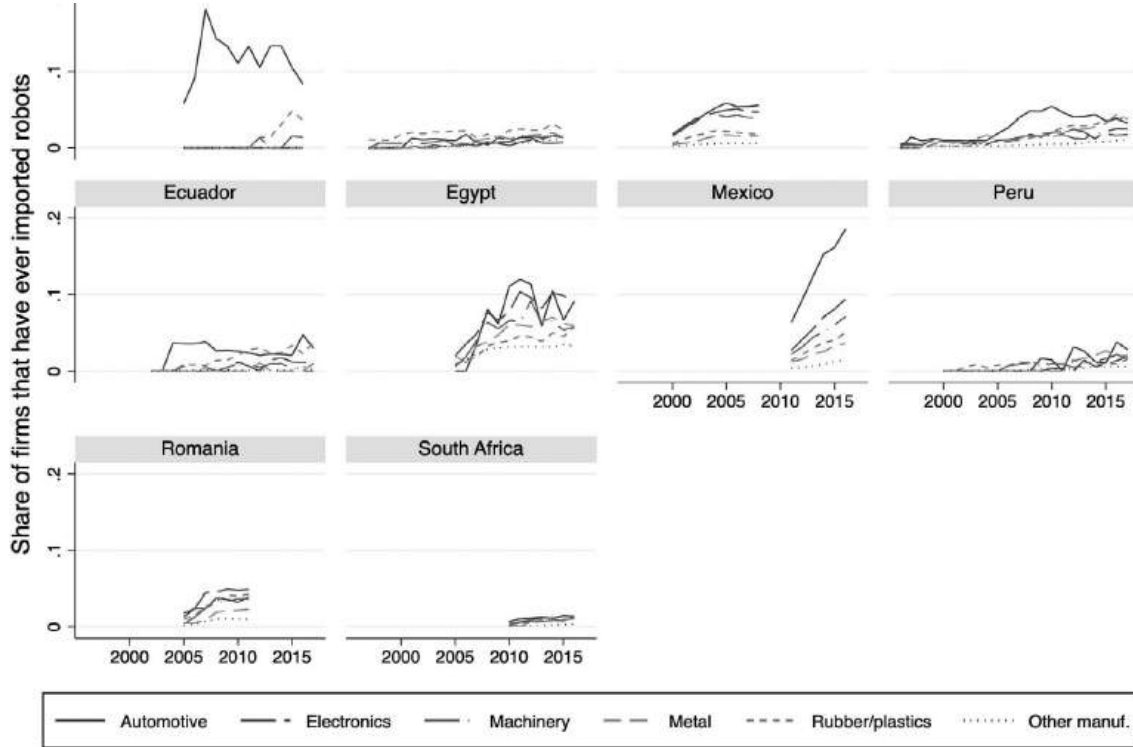
*Figure 8.8* Share of Firms that Imported Robots by Country and Industry

Notes: The figure draws on data from the World Bank's Exporter Dynamics Database, which covers all trade transactions except those of oil and arms. We use data from importer-exporters in Bangladesh, Chile, China, Colombia, Ecuador, Egypt, Mexico, Peru, Romania and South Africa, which contain 10,312 separate robot purchases by 4,646 distinct firms. Note that the range of years displayed for each country varies, according to the current availability of customs data in the EDD.

firm characteristics, using only observations prior to the first observed robot purchase by each firm.[28] The resulting ex-ante correlations are shown in Figure 8.9.[29] Firms adopting robots are larger, more diversified across products (yet simultaneously more specialized in their core products), and more integrated with GVCs. This resonates with the literature on technology adoption. Firms adopting robots in developed countries are generally larger, more productive and growing faster (Humlum, 2019; Koch et al., 2019; Acemoglu et al., 2020; Bonfiglioli et al., 2020). In China, firms that adopt robots also tend to be larger, have more capital per worker, pay higher wages, and are less likely to be state-owned (Cheng et al., 2019).

We supplement this evidence with detailed firm-level data from the Vietnam Technology and Competitiveness Surveys 2010–14. These data record explicitly whether a firm uses computer-operated machines, and are also not restricted to firms that trade internationally. Table 8.2 shows summary statistics for automating vs. non-automating firms. The patterns are similar: in general, automators are larger, pay higher wages, are more likely to export and to be foreign owned. Moving to partial correlations in Table 8.3, and accounting for province, industry and year fixed effects, we find that automators have more assets, earn higher
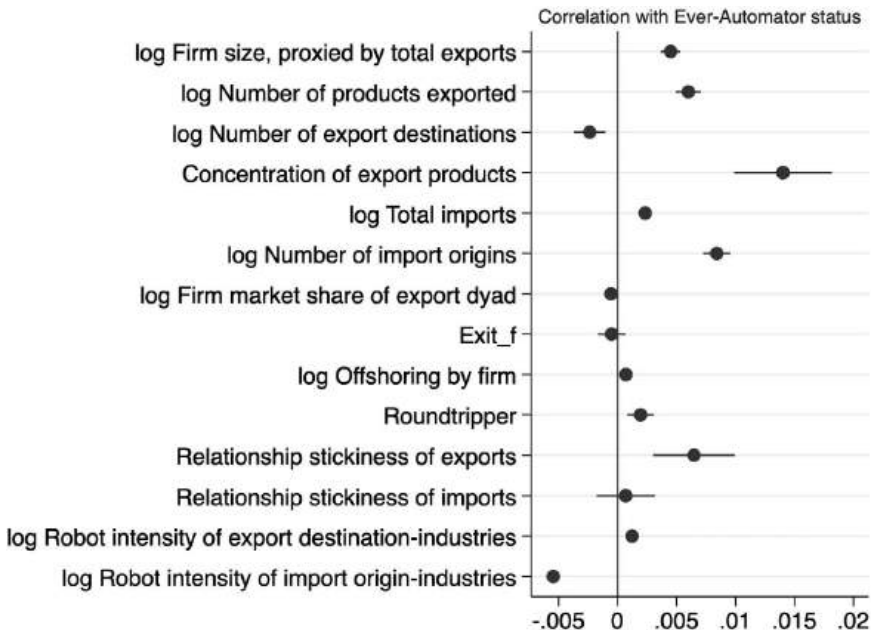


*Figure 8.9* Ex-ante Correlates of Automation

Notes: Confidence intervals shown for 95% significance level. Fixed effects: industry-year, country-year. Standard errors clustered at the firm level. Source: the World Bank's Exporter Dynamics Database.

*Table 8.2* Summary Statistics for Automating vs. Non-automating Firms in Vietnam

|  | *(1) Computer Operated Machines = 0* | | | | *(2) Computer Operated Machines = 1* | | | | *(1)–(2)* | |
|---|---|---|---|---|---|---|---|---|---|---|
|  | *Mean* | *SD* | *Min* | *Max* | *Mean* | *SD* | *Min* | *Max* | *Diff* | *S.E.* |
| log employment | 4.092 | 1.367 | 0.693 | 10.091 | 4.907 | 1.413 | 0.693 | 9.429 | −0.814*** | (0.027) |
| log avg. wage | 3.401 | 0.632 | 0.000 | 10.085 | 3.736 | 0.599 | 0.065 | 8.405 | −0.335*** | (0.011) |
| Exporter | 0.391 | 0.488 | 0.000 | 1.000 | 0.609 | 0.488 | 0.000 | 1.000 | −0.218*** | (0.009) |
| log revenues | 9.580 | 1.989 | 0.000 | 16.604 | 10.952 | 2.046 | 0.000 | 16.952 | −1.372*** | (0.038) |
| log leverage | 0.420 | 0.194 | 0.000 | 0.693 | 0.430 | 0.179 | 0.000 | 0.693 | −0.010** | (0.003) |
| log fixed assets | 8.363 | 2.073 | 0.000 | 17.279 | 9.990 | 2.134 | 0.000 | 16.395 | −1.627*** | (0.040) |
| State-owned | 0.435 | 0.496 | 0.000 | 1.000 | 0.330 | 0.470 | 0.000 | 1.000 | 0.105*** | (0.009) |
| Privately-owned | 0.370 | 0.483 | 0.000 | 1.000 | 0.265 | 0.441 | 0.000 | 1.000 | 0.105*** | (0.008) |
| Foreign-owned | 0.195 | 0.396 | 0.000 | 1.000 | 0.405 | 0.491 | 0.000 | 1.000 | −0.210*** | (0.009) |
| N (obs.) | 28,097 | | | | 3,141 | | | | 31,238 | |

Notes: Standard errors in parentheses, clustered by firm. Data for the 2010–2013 period. Leverage is normalized to lie between 0 and 1.

Source: Vietnam Technology and Competitiveness Surveys.

*Table 8.3* Firm-Level Correlates of Automation in Vietnam

*Dep. Variable: Firm with Computer-Operated Machines*

|  | (1) | (2) |
|---|---|---|
| log employment | -0.001 | 0.003 |
|  | (0.003) | (0.004) |
| log avg. wage | 0.025*** | 0.017*** |
|  | (0.004) | (0.004) |
| Exporter | 0.014 | 0.012 |
|  | (0.007) | (0.008) |
| log revenues | 0.008*** | 0.007** |
|  | (0.002) | (0.002) |
| log leverage | -0.041** | -0.039** |
|  | (0.013) | (0.013) |
| log fixed assets | 0.022*** | 0.022*** |
|  | (0.002) | (0.002) |
| State-owned | 0.006 | 0.001 |
|  | (0.005) | (0.005) |
| Foreign-owned | 0.031** | 0.030** |
|  | (0.010) | (0.011) |
| Province-Industry FE | N | Y |
| Industry FE | Y | N |
| Year | Y | Y |
| N (obs.) | 31,233 | 31,109 |
| R2 | 0.077 | 0.145 |
| F-stat | 72.458 | 59.066 |

Notes: Standard errors in parentheses, clustered by firm. Firm-level data for the 2010–2013 period. Leverage is normalized to lie between 0 and 1.

Source: Vietnam Technology and Competitiveness Surveys.

revenues, pay higher wages, are more likely to be foreign-owned, and have higher levels of labor productivity.

Surveying this evidence, it seems likely that domestic robot adoption will primarily help the largest, most productive and most globally integrated firms in developing countries. Smaller and less productive firms miss out, in line with Rodrik (2018) and Goger et al. (2014).

## 6. Firm-level implications

Larger, internationally active firms are more likely to adopt robots. How do they change ex-post? Drawing on firm-level data for ten developing countries, we address this question using an event study approach (based on Bessen et al., 2020). We estimate[30]:

$$\ln Y_{ft} = \sum_{s \neq -1, s = -2}^{2} \beta_s \times AutoEvent_{ft-s} + \alpha \cdot X_{ft} + \alpha_{ct} + \alpha_{it} + \alpha_f + \epsilon_{ft} \quad (3)$$

where $X_{ft}$ controls for firm age. An automation event is defined as a period in which the firm spends more than three times its average cost-share on robots,

not including robot purchases in the current period. Specifically:

$$AutoEvent_{f\tau}$$

$$= 1 \left\{ \frac{RobotPurchases_{f,t=\tau}}{TotalNonRobotImports_f} \geq 3 \times \frac{\overline{RobotPurchases}_{f,t\neq\tau}}{TotalNonRobotImports_f} \right\} \quad (4)$$

To mitigate selection effects, for example, automators being particularly well-managed, we restrict our main sample to only firms that do, at some point, automate. Thus the relevant counterfactual, against which the effect captured by β is measured is the trend in firms that do automate, but not in the same period as the firm under consideration. We find that after adopting robots, firms increase their exports and market share, and expand their range of export products and destinations (Figure 8.10). Robotizing firms are not only larger ex-ante; their adoption of robots also coincides with a further expansion ex-post.[31]

   In other words, we have evidence consistent with robotization boosting the growth of initially larger firms in developing countries. Robotization could thus contribute to increasing the average firm size in developing countries, and thereby raise aggregate productivity (Hsieh and Klenow, 2014). Yet this evidence also adds a firm-side element to the earlier distributional concerns: it is not just more disadvantaged workers who are most threatened by robotization, but
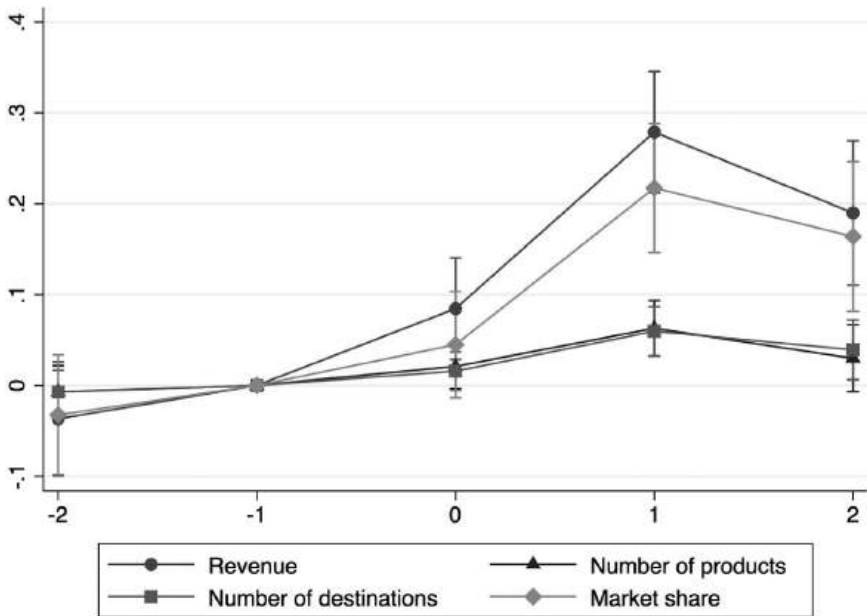


*Figure 8.10* Impact of Robot Adoption on Firm Export Outcomes

Notes: All variables in logs. Confidence intervals shown for 95% significance level. Standard errors clustered at the firm level.

Source: the World Bank's Exporter Dynamics Database.

also smaller, less productive, less internationally active firms.[32] Given that low-skilled workers are also more likely to work at such firms, this dual threat is a key issue for policymakers to consider. As Rodrik (2018) notes, a key objective will be to "disseminate throughout the rest of the economy the capabilities already in place in the most advanced parts of the productive sector". In the meantime, robot adoption may place temporary support systems – whether state welfare systems, social networks or the informal sector (Dix-Carneiro et al., 2019; Dix-Carneiro and Kovak, 2019) – under increasing strain. Reaping the benefits of robot adoption at home and abroad, whilst mitigating the downsides, will be a key policy challenge.

## 7. Conclusion

Industrial robots will place conflicting pressures on developing countries. In the long run, robot adoption in developed countries will most probably catalyze international trade and enhance global welfare. This conclusion is likely to be reinforced by the fact that other new technologies – such as high-speed internet and digital platforms – will further reduce the costs of trading and coordinating across borders (Brynjolfsson et al., 2019; Freund and Weinhold, 2002, 2004) and will create entirely new products and tasks (Acemoglu and Restrepo, 2018; Nakamura and Zeira, 2018). Furthermore, China's growing robotization (driven in part by subsidies) might reduce productivity differences with advanced economies (and thereby the gains from inter-industry trade with them) and need not hinder prospects for industrialization and export-led growth in lower-income countries.

At the same time, trade and technological change will necessitate labor market adjustment and could create severe distributional tensions both during and after the transition to automated production. Robot adoption in developing countries could exacerbate disparities between, on the one hand, the more advanced internationally active firms that account for a large share of exports, and on the other hand, the small-scale, informal firms that account for a large share of low-skilled and manual employment. These firm-level disparities may also accentuate income disparities across households in developing countries. Furthermore, over time developed-country automation could discourage developing countries from investing in some sectors with high growth potential, contributing to 'premature de-industrialization' (Rodrik, 2016). Weighing these risks against the potential gains from specializing in labor-intensive exports will be a difficult balancing act. Informing policies that harness the growth potential of globalization and technological progress while ensuring the attendant gains are equitably shared is thus an important task for future research.

# Appendix

This section provides an overview of the model; further details can be found in Artuc et al. (2018). The task-based Ricardian framework combines several ideas from the literature: productivity differences across countries and sectors (Eaton and Kortum, 2002), two-stage production with trade in intermediates and final goods (Yi, 2003; Caliendo and Parro, 2015) and feasible robotization of some tasks previously performed by humans (Acemoglu and Restrepo, 2020).

We denote countries by $m$ and $n$, sectors by $i$, and production stages by $s$, where $s = 1$ refers to intermediate inputs (first stage) and $s = 2$ refers to final goods (second stage). Workers are mobile across stages and sectors, but not across countries. Robots are equally available in all countries, at the same (exogenous) rental rate, and are owned by residents of the country that robotizes production. The representative household in country $n$ maximises Cobb-Douglas utility

$$U^n = \prod_i (Q_2^{n,i})^{\gamma^{n,i}}$$

where $Q_2^{n,i}$ is the amount of composite final good from sector $i$ demanded by consumers in country $n$, and $\gamma^{n,i}$ is a constant with $\sum_i \gamma^{n,i} = 1$. The composite final good $Q_2^{n,i}$ results from the aggregation of final stage varieties by consumers, as described in detail in the following.

A continuum of varieties $\omega \in [0,1]$ is produced in each sector $i$ of country $n$. These varieties can be produced either as intermediate inputs in the first stage or as final goods in the second stage. We define the set of first and second stage varieties in industry $i$ respectively as $S_1^i$ and $S_2^i$, such that $S_1^i \cup S_2^i = \{0,1\}$. The production function for varieties $\omega$ is:

$$q^{n,i}(\omega) = z^{n,i}(\omega)(F_s^{n,i}(\omega))^{\alpha_F^{n,i}} (Q_1^{n,i}(\omega))^{\alpha_M^{n,i}} (T^{n,i}(\omega))^{\alpha_T^{n,i}}$$

where $Q_1^{n,i}$ is a first stage composite, $F_s^{n,i}(\omega)$ is a fixed factor specific to the industry-stage, $T^{n,i}(\omega)$ is a composite task input, and $z^{n,i}(\omega)$ is productivity drawn from a Frechet distribution with shape parameter $\theta$. Aggregation of stage $s$ varieties $\omega \in S_s^i$ then yields the stage $s$ composite good $Q_s^{n,i}$.

The production of the composite task input $T^{n,i}$ for variety $\omega$ requires performing a range of tasks $k \in [0,1]$. We assume that tasks from 0 to $K^i$ can be performed by robots or humans, while tasks between $K^i$ and 1 can only be performed by workers. In some industries, robotization is not feasible, and hence $\exists i : K^i = 0$. The subset of tasks that can be robotized is thus given by $K^i$, while the subset of tasks that cannot be robotized is given by $1 - K^i$. The robotization frontier and the productivity of robots are assumed to be industry specific, but not stage specific.

To perform one unit of task $k$ of variety $\omega$ within industry $i$, $\phi_L^i \zeta_L(k)$ labor units are required. If $k < K^i$, $\phi_R^i \zeta_R(k)$ robot units can perform the same task. $\zeta_R(k)$ and $\zeta_L(k)$ are distributed Weibull with shape parameter $v$. Thanks to the distributional assumptions, the optimal set of tasks performed by robots is then given by the expression

$$K_R^{n,i} = \frac{(\phi_R^i w_R)^{-v}}{(\phi_R^i w_R)^{-v} + (\phi_L^i w_L^n)^{-v}} K^i$$

and depends upon the automation frontier $K^i$, the elasticity of substitution between robots and workers $1+v$, and the productivity-adjusted relative price of workers versus robots $\phi_L^i w_L^n / \phi_R^i w_R$. The average unit cost of tasks from 0 to $K^i$ is given by the standard CES function

$$w_{T_A}^{n,i} = \psi_3^i \left( (\phi_R^i w_R)^{-v} + (\phi_L^i w_L^n)^{-v} \right)^{-\frac{1}{v}}$$

and depends on wages $w_L^n$, the unit cost of robots $w_R$ and the elasticity of substitution between robots and workers.[33] Similarly, the unit cost of tasks from $K^i$ to 1 is $w_{T_N}^{n,i} = \psi_3^i \phi_L^i w_L^n$. Combining these expressions, the cost of producing a task with robots, relative to the cost of producing it without robots, is:

$$\Omega^{n,i} = 1 - K^i + K^i \left( 1 - \frac{K_R^{n,i}}{K^i} \right)^{\frac{1}{v}}$$

Intuitively, robots bring no cost benefit (i.e. $\Omega^{n,i} = 1$) if there is no potential for robotization in an industry ($K_i = 0$), while the relative cost is minimized (i.e. $\Omega^{n,i}$ is close to zero) if robots are free to rent ($w_R = 0$) and can be used for all tasks ($K_i = 1$). Analogously, labor demand per task is

$$\Xi^{n,i} = 1 - K^i + K^i \left( 1 - \frac{K_R^{n,i}}{K^i} \right)^{1+\frac{1}{v}}$$

such that labor demand is lower when robots (i) are cheaper or (ii) can be used more widely.

We can use $\Omega^{n,i}$ to express the unit price of output under robotization:

$$c_s^{n,i} = \psi_4^{n,i} \left(r_{s,F}^{n,i}\right)^{\alpha_F^{n,i}} \left(P_1^{n,i}\right)^{\alpha_M^{n,i}} \left(\Omega^{n,i} w_L^n\right)^{\alpha_T^{n,i}}$$

where $P_1^{n,i}$ is the price of (first-stage) inputs. A larger cost reduction from robotizing (i.e., $\Omega^{n,i}$ closer to zero) lowers output prices. This in turn raises the probability that country $n$ is the lowest-priced provider of a stage $s$ variety to country:

$$\pi_s^{m,n,i} = \left( \frac{\psi_{s,4}^{n,i} \, \tau^{m,n,i} \left(r_{s,F}^{m,i}\right)^{\alpha_{s,F}^{m,i}} \left(P_1^{n,i}\right)^{\alpha_{s,M}^{n,i}} \left(\Omega^{n,i} \, w_L^n\right)^{\alpha_{s,T}^{n,i}}}{P_s^{m,i}/\psi_2^i} \right)^{-\theta}$$

In other words, robotization at home increases exports to other countries. In the calibrated model, initial higher wages lead the richer Northern countries $n$ to adopt more robots than Southern countries $m$. Declines in robot prices then induce further robotization, which disproportionately lowers production costs in the North and thus increases exports to the South and to the third country ('Other').

In contrast, the effect of Northern robotization on imports sourced from the South is theoretically ambiguous. On the one hand, robotization makes Northern producers more competitive at home (i.e. $\pi_s^{n,n,i}$ is larger), which implies that some varieties that were previously imported from the South are now sourced domestically. On the other hand, robotization leads to an expansion in the scale of production, which raises demand for first-stage varieties sourced from the South (i.e. $Q_1^{m,i}$ is larger).

Panel A: Parts only, high trade elasticity
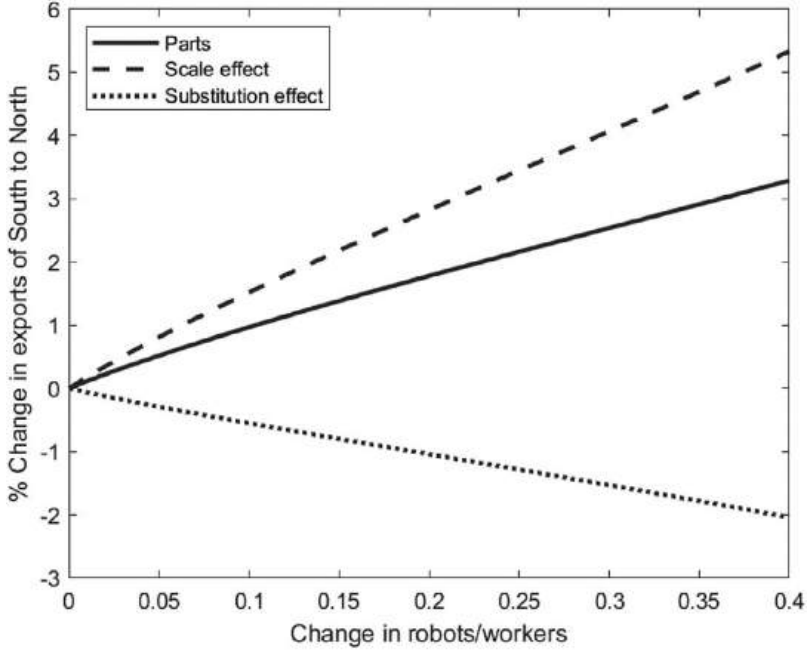


*Figure 8.A1* South's Exports to North in the Robotized Industry

Notes: This figure presents results from simulations of the effects of lower robot prices (and so increased robot usage) on Southern exports to North in the robotized industry, for a range of trade elasticities. Panels A and B show results for a trade elasticity of 10 (versus 4 in Figure 3 in the main text), while panels C and D use a trade elasticity of 2. The results are qualitatively robust across all cases, with only the size of the effects changing. For full discussion, see Section 2 in the main text. Note the differential scaling of the y-axes for the different scenarios.

Panel B: Final goods only, high trade elasticity



*Figure 8.A1*   (*Continued*)

Panel C: Parts only, low trade elasticity



*Figure 8.A1*   (*Continued*)

Panel D: Final goods only, low trade elasticity



*Figure 8.A1* (*Continued*)

Panel A: Robot use in robotized industry
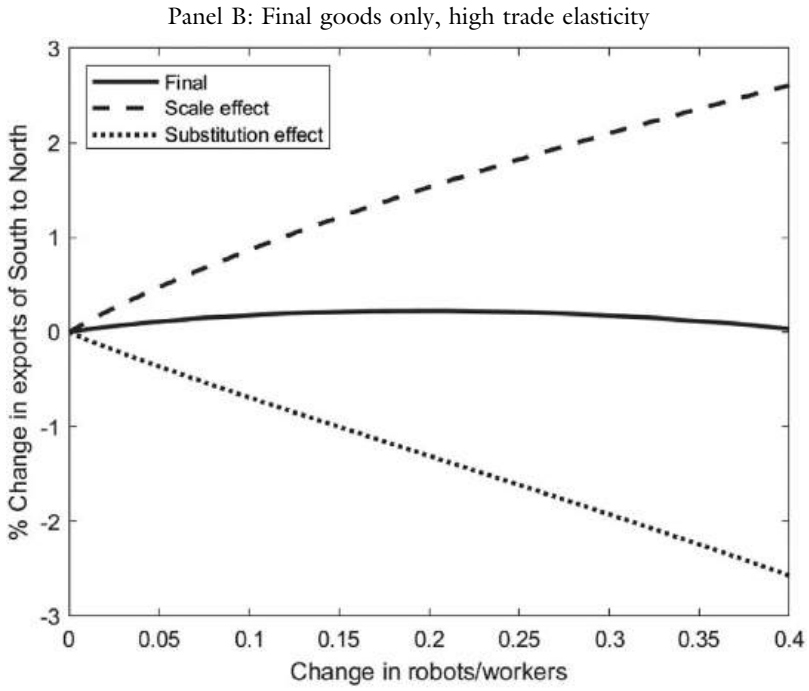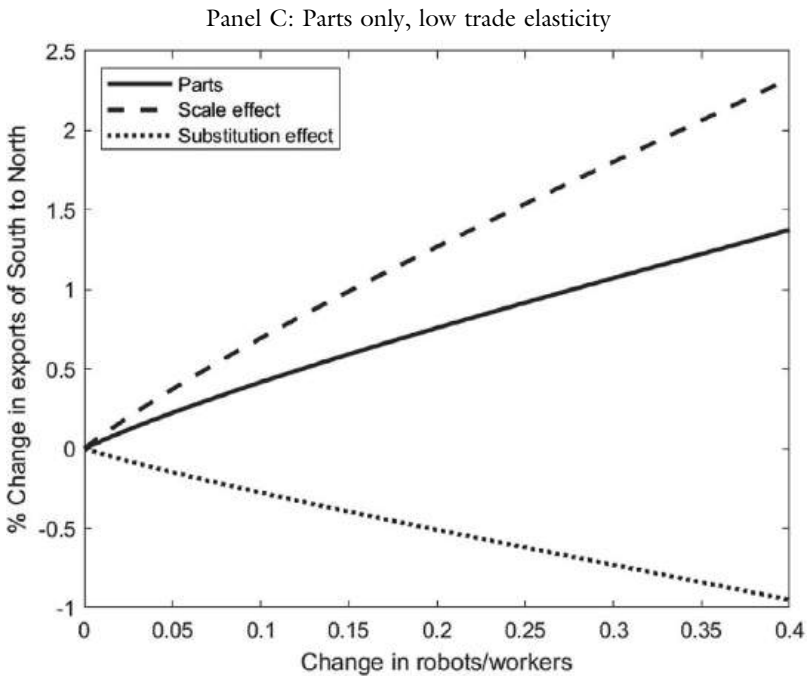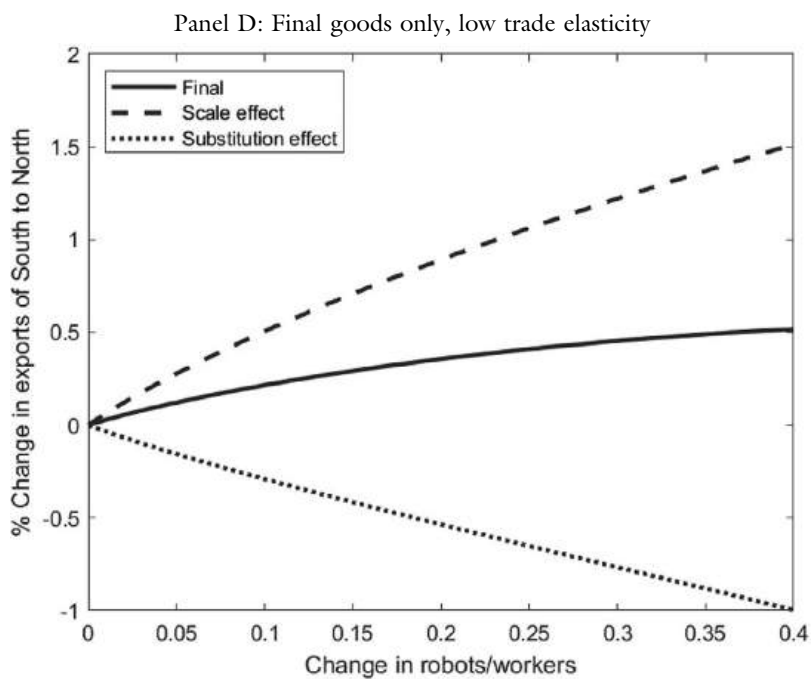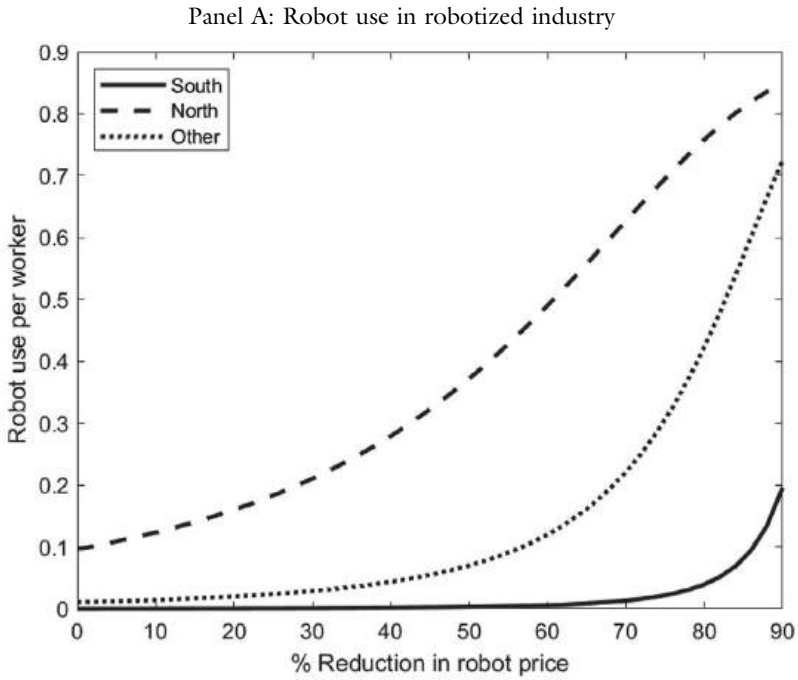


*Figure 8.A2* Low Elasticity of Substitution between Robots and Workers

Notes: This figure presents results from simulations of the effects of lower robot prices on robot use, labor allocation, wages and trade, for a case with low elasticity of substitution between robots and workers. Specifically, this elasticity is 3 in these graphs, rather than 10 in the baseline case – so robots are thus modelled as being similar to conventional capital. For full discussion, see Section 2 in the main text.

Panel B: Labor use in robotized industry
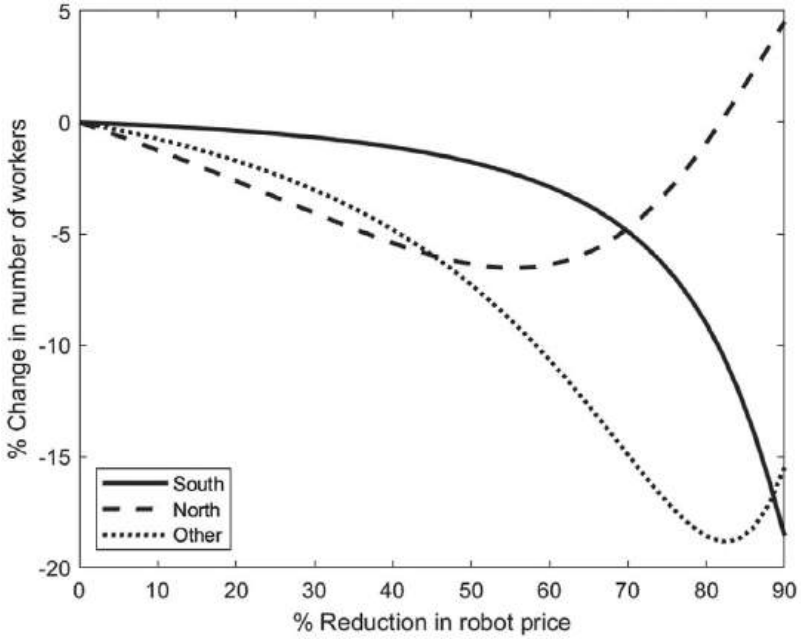


*Figure 8.A2* (*Continued*)

Panel C: Wages



*Figure 8.A2* (*Continued*)

Panel D: South's exports to North in robotized industry
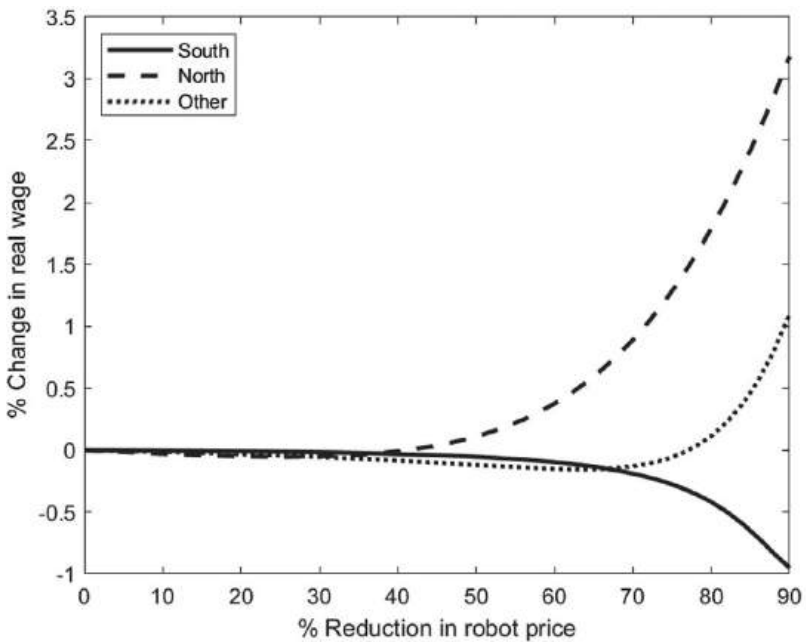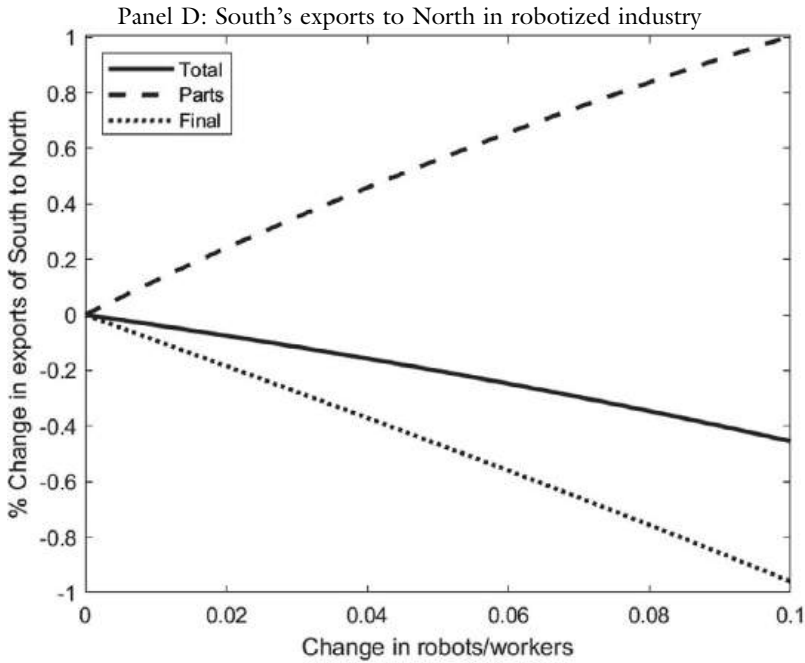


*Figure 8.A2    (Continued)*

## Notes

1  A technical outline of the model is provided in the Appendix.
2  The model combines elements from a large number of papers in the literature, including Grossman and Rossi-Hansberg (2008), Eaton and Kortum (2002), Acemoglu and Restrepo (2020), Caliendo and Parro (2015), Lee and Yi (2018), and Artuc and McLaren (2015).
3  Offshoring in the model takes place through imports of intermediate inputs, which embody tasks performed abroad. This allows us to calibrate all trade flows, production functions and labor shares using the World Input-Output Database. Given our focus on industrial robots and trade in goods, the distinction between offshored tasks and intermediate inputs is largely semantic (Grossman and Rossi-Hansberg, 2008). Future research could extend the model by allowing direct offshoring of tasks to consider cases where this distinction is more substantive (e.g. in services trade).
4  Throughout this chapter the set of tasks that can feasibly be performed by robots is fixed. Increased robotization results only from a fall in the price of existing robots, not an expansion in their functionality. Technological advances which enable robots to perform new tasks, or indeed create new human-only tasks, are a distinct issue, which we leave to other work (e.g. Acemoglu and Restrepo, 2018).
5  In the model, which assumes full employment, the displaced workers compete for the remaining non-automated tasks, bidding down wages and generating a second-order increase in hiring.
6  Following Graetz and Michaels (2018), we measure replaceability by comparing robot applications recorded by the IFR with three-digit occupation names and

descriptions in the US Census, then aggregating to the industry level using the occupation-composition of industries. See Artuc et al. (2018) for further details of the empirical strategy and variable construction.

7 When running separate regressions for intermediates vs. other goods, the respective increases in imports from the South are 6.8% and 5.6% (using the Broad Economic Categories (BEC) classification of goods) or 8.6% and 4.9% (using the classification from Schott, 2004).

8 Specifically, the net increase in imports of parts and components implies that the robotization-induced scale effect, which increases demand for imported intermediates, outweighs any robotization-based reshoring (i.e., substitution effects from increased robot use by Northern intermediates producers).

9 We use the World Input Output Database (WIOD) to calibrate international trade, production functions and labor shares. In the baseline simulation, we use WIOD data for 2005 to calibrate initial trade patterns. We group countries into three broad categories, based on their income per capita, robot density and data availability. The group of countries in the North is composed of Belgium, Germany, Denmark, Finland, France, Italy, Netherlands, Sweden and the United States. The group of countries in the South is composed of Brazil, China, India, Indonesia, Mexico, Turkey and Taiwan, China. Based on these two groupings, we construct the representative countries in the North and South. The group of other developed countries results from the aggregation of other OECD and EU countries for which data are available in WIOD. This group consists of Australia, Austria, Bulgaria, Canada, Czech Republic, Spain, the United Kingdom, Greece, Croatia, Hungary, Ireland, Portugal, the Slovak Republic, Poland, Norway and Switzerland. Various robustness checks in Artuc et al. (2018) find that results are qualitatively robust across a variety of alternative groupings.

10 This setup is suitable for illuminating the relevant dynamics without losing tractability. If we were to aggregate within groups, rather than averaging to create representative countries, the North would account for more than 50% of world GDP, and the bulk of world trade would occur within the North. This setting would underrepresent the importance of North-South trade, and trade as share of GDP would be very small. To avoid this aggregation bias, we instead construct representative countries in the North and the South. Considering a relatively large group of other developed countries is also important to allow for the possibility that competitiveness gains associated with robot adoption in the North translate into higher demand for its final-goods exports.

11 Broadly, lower robot prices initially cause displacement of human labor at the 'extensive margin', but subsequently reduce costs and increase productivity at the 'intensive margin' (Acemoglu and Restrepo, 2019). Such sequencing could help explain differing empirical findings on the impact of robots: countries in the displacement phase (e.g., the USA (Acemoglu and Restrepo, 2020)) may experience larger wage declines from additional robotization than countries further ahead in the process of adoption (e.g., Germany (Dauth et. al, 2021)).

12 However, for a sufficiently large reduction in robot prices (greater than 85% in Figure 8.2 panel A) the South in turn adopts robots, lowering Southern wages (panel C) due to the initial substitution effect of robot adoption.

13 We place particular emphasis on the trade results because they illuminate the various mechanisms behind the modelled impacts on wages and GDP, and because they relate most closely to our core regressions.

14 This effect could theoretically drive 'reshoring' of production.

15  Future research with more granular data on robot use (i.e., distinguishing between robots used in the production of final vs. intermediate goods) could also separate these mechanisms in reduced-form empirics. Here, our regressions focus on the net effect, which we can observe. In the simulations, we have experimented with a larger trade elasticity and found that, for final goods, the substitution effect could indeed outweigh the scale effect – but only for a very high trade elasticity (Figure 8.A1 panel B).

16  Specifically, Figure 8.A1 uses trade elasticities of 2 and 10, whereas the baseline model uses 4.

17  The paths of other key variables (e.g., labor use, wages, welfare) are almost unchanged across the various trade elasticity scenarios.

18  Specifically, Figure 8.A2 uses an elasticity of substitution between robots and workers of 3, rather than 10 in the baseline model. The trade elasticity is reset to 4.

19  In particular, Artuc, Bastos, and Rijkers (2018) check that the results are not driven by a select few sectors, the financial crisis, tariff patterns or correlations between robotization and other types of investment. The results are also robust to alternative specifications using the inverse hyperbolic sine, variation over longer time periods, alternative instruments, and an alternative proxy for automation.

20  Specifically, we use an unbalanced panel of value added and employment data from Russia, China, India, Cyprus, Colombia, Costa Rica, El Salvador, Honduras, Peru, and the Dominican Republic between 1980 and 2016.

21  Adding an additional country to the model, as opposed to re-calibrating South to represent China, allows us to consider the impact of subsidies on China's trade with both developed and developing countries.

22  The subsidy is financed by taxing all Chinese factors of production in proportion to income.

23  The strength of this effect depends on the level of initial robot prices. If robot prices are already low (so automation levels in the world are already high) then subsidies are more effective, as at this point even small subsidies tip robots into being the cheaper production option in China. This is the scenario shown in the graphs. Versions for a starting point of high robot prices and low automation levels are qualitatively similar, but with the impact of the subsidy only kicking in once it reaches a higher level (60%+) – effectively all the action in the graphs shifts rightwards.

24  In the very long run, new tasks can be created and/or some existing tasks can become obsolete – thus the robotization frontier can also move, which is an aspect omitted from our model. Depending on the direction of the shift of the robotization frontier, labor demand can increase or decrease.

25  How do these falls in imports from the South relate to the increasing overall imports from the South in panel D? Note that panel D shows total trade, so also includes the non-robotized tradeable sector. As China specializes in the robotized sector, it increases its imports in this other sector, generating a net increase in aggregate imports from the South.

26  Interestingly, Stapleton, and Webb (2020) illuminate a firm-level analogue of the contrasting forces in our model, finding that firm-level sequencing matters for the net impact of robotization on offshoring. For firms that had not yet offshored any production, robotization simply allowed them to expand, which caused them to begin new offshoring. In contrast, for firms that had already offshored some production, there was also a negative effect on offshoring – as robots allowed some previously-offshored production to be automated domestically. In the Spanish case they find that the effect for the former group dominates, with

robotization in the full sample having a net positive impact on imports from lower-income countries.

27  Source: The World Bank's Exporter Dynamics Database, which covers all trade transactions except those of oil and arms. We use data from importer-exporters in Bangladesh, Chile, China, Colombia, Ecuador, Egypt, Mexico, Peru, Romania and South Africa, which contain 10,312 separate robot purchases by 4646 distinct firms.

28  We also include industry-year and country-year fixed effects and cluster at the firm level.

29  Concentration is measured by a Herfindahl index of export sales, using each firm-product's share of total firm exports. Market shares are the firm's share of total sales from the home country to each given export destination, which are then averaged across all the firm's export dyads. Offshoring is the sum of imports in the same HS4 category as goods sold by the firm, following the 'narrow' measure of Hummels et al. (2014). Roundtripper is a dummy that takes value one only for firms which export and import the same HS6 product to the same partner in a given year. Relationship stickiness is a weighted average across either exports or imports of the measure of Martin et al. (2020).

30  We use a four-year window to maximise the number of automation events for which pre- and post-trends can be detected, given the short panel lengths in some of our countries. Results are qualitatively robust to using a longer window and fewer observations.

31  If we expand the sample to include never-adopters, rather than only not-now-adopters, the relative post-adoption expansion is even larger.

32  This aligns with findings from developed countries that large firms adopting robots expand at the expense of more labor-intensive competitors (Koch et al., 2019; Acemoglu et al., 2020). Smaller and less productive firms may also be more vulnerable to automation-driven business-stealing from abroad (Aghion et al., 2020).

33  Parameters $\psi$ throughout denote various constants.

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# 9 Automation in Indonesia

## Productivity, Quality, and Employment

*Lili Yan Ing and Rui Zhang*

## 1 Introduction

A significant increase in wages in developed countries since the 1980s has pushed firms to invest in and use more automation equipment. To offset high labor costs in these economies, manufacturers have been replacing workers with machines. Industrial robots and equipment that use artificial intelligence (AI) – what we call 'automation equipment' – not only helps human workers perform their tasks more efficiently, but also improves precision, accuracy, and reliability, thereby reducing overall costs while also raising product quality and overall firm productivity. The use of automation equipment has increased in emerging countries such as Singapore, Taiwan, South Korea, and Hong Kong, since the 2000s; in China, it has grown notably since 2015. Thailand, Malaysia, Indonesia, as well as other developing countries have followed suit.

While automation reduces costs, improves product quality, and increases productivity, it may also displace workers. A number of studies have examined the effects of automation on productivity, product quality, wages, and employment in developed countries, but studies of automation effects in developing countries are still rare. This is partly because relatively low levels of automation in developing countries make it difficult to measure automation and partly because firm-level data for these countries are often lacking.

With these challenges in mind, we undertook to examine 'automation in Indonesia' for two reasons. First, Indonesia has exhibited one of the highest growth rates in automation among developing countries, with annual growth in the use of automation equipment averaging 24% for more than a decade (since 2007). Second, Indonesia, with a population of 276 million people in 2021, is the fourth most populated country in the world. Almost 60% of its population is in the labor force. In this context, the displacement of workers by automation equipment can create huge social challenges. It therefore becomes important to understand how firms in a developing country such as Indonesia make decisions about automation and how these decisions are correlated with overall economic outcomes. We examine this question in three steps.

In the first step, we define automation in Indonesia. Most existing studies focus exclusively on industrial robots, an advanced type of automation equipment that is sometimes used as a proxy for automation. Yet, industrial robots accounted for less than 1% of Indonesia's total imports of automation equipment over the last two decades. The share of industrial robots increased from a mere 0.15% of all imported automation equipment in 2000 to 1.45% in 2019. An exclusive focus on industrial robots thus misses the complete story of automation in Indonesia. Instead, we use a broader definition of automation that includes regulating and control instruments, numerically controlled appliances, automatic machine tools, and other types of automation equipment, consistent with a recent study by Acemoglu and Restrepo (2021).

To obtain a comprehensive picture of automation in Indonesia, one would ideally include both domestically produced and imported equipment. Apparently, the amount and value of domestically produced automation equipment in Indonesia is still very low: most equipment of this type is only assembled in Indonesia while engines and other major parts are produced overseas. The International Federation of Robotics (IFR) maintains a database that records annual installations of industrial robots. In 2019, China, Japan, the United States, South Korea, and Germany were the top five installers of industrial robots. The IFR database also reports robot density as measured by the number of industrial robots in operation for every 10,000 workers. Using this ratio as a measure of automation intensity, the countries with the highest levels of automation intensity in 2019 were mostly developed countries such as Japan (364 robots per 10,000 workers) and Germany (346 robots per 10,000 workers). Other countries with high automation intensity by this measure were Singapore, South Korea, and China. However, IFR does not have data on domestically produced robots in Indonesia.

We therefore focus on imports and exports of automation equipment to Indonesia using UN Comtrade, an international database of trade statistics maintained by the United Nations (the classification of automation equipment is based on Harmonized System 6-digit codes). The data show that Indonesia ran a massive trade deficit in automation equipment from 2000 to 2019. Moreover, the data reveal interesting patterns. For example, imports of the type of automation equipment used in the textile and apparel industries, such as weaving and knitting machines and other textile machinery, declined as a share of all automation equipment imports. This is consistent with a slowdown in these industries, which had been darlings of the Indonesian economy in the 1990s. The data also show significant increases in imports of automation equipment that is intensively used in high-tech industries such as motor vehicles and metals. Imports of other general automation equipment, such as regulating and control equipment and automatic conveyors, also increased. Considering that most of the automation equipment used in Indonesia is imported, it is reasonable to use imports of automation equipment as a proxy for Indonesia's overall level of automation.

In the second step, we undertake an empirical analysis of the effects of automation on productivity, quality, and employment. Previous studies take either

a macro-level approach, looking at country-level or regional labor market outcomes (e.g., Graetz and Michaels (2018) for cross-country evidence; Acemoglu and Restrepo (2020) for labor markets in the United States; Adachi, Kawaguchi, and Saito (2022) for labor markets in Japan), or they rely on firm-level data to identify the effects of automation, mostly in terms of employment (e.g., Koch, Manuylov and Smolka (2021) using Spanish data; Humlum (2019) using Danish data; Acemoglu, Lelarge and Restrepo (2020) using French data). We use a firm–product level approach, employing three data sets from the most disaggregated micro-level database of Indonesian manufacturing firms. The database, which compiles results from an annual survey of about 35,000 firms, includes raw materials and product outputs at the firm level, and exports and imports at the firm level. Merging these three main data sets leaves us with a total sample of 118,570 firms for the period 2008–2012.

Merging the three data sets allows us to identify each manufacturing firm's direct imports of automation equipment. Because the firm-level import data are consistent with nationally aggregated import data, we conclude that the firm-level data are fairly representative. This consistency is illustrated by three observations: (i) Indonesian firms run large deficits of automation equipment throughout the years, (ii) both the firm-level data and the national data show the same patterns in terms of imports of automation equipment by industry (for example, a substantial reduction in shares of imports for the textile and apparel industries and an increase in shares of imports for the motor vehicle and metals industries), and (iii) we find that more industries overall have become active in importing automation equipment. During the study period, 3.07% of manufacturers in our sample imported automation equipment. In 2012, these firms accounted for 13.57% of total outputs and 12.75% of total production workers.

Using the merged data, our analysis documents cross-sectional associations between firm-level automation status and other firm-level outcomes. Our findings show that firms that imported automation equipment during the study period (henceforth, '*automators*') produced more outputs, hired more workers, and had relatively higher labor productivity and total factor productivity (TFP) than firms that never imported any automation equipment (henceforth, '*non-automators*'). In addition, automators paid relatively higher wages for both production and non-production workers, had lower labor shares, and used capital more intensively than non-automators. Automators also produced more varieties of outputs and were more actively engaged in exports and imports. Moreover, automators produced outputs of relatively higher inferred quality than non-automators.

To see how automation correlates with firm outcomes over time, we conducted estimations based on a firm-level long-difference specification. We find that automators see larger increases in outputs and productivity. Automators also experience larger increases in export shares and higher inferred product quality. We also examine its impacts on employment. While most studies to date have found that advanced automation, such as the adoption of industrial robots, tends to

substitute for production workers in developed economies, we find that Indonesian automators employ more workers compared to non-automators. In particular, we document a relative increase in the number of production workers compared to non-production workers. Thus, our results suggest that different levels of automation may result in different employment outcomes. In Indonesia and perhaps other developing countries that are at earlier stages of automation, automation can be a complement to the employment of production workers because it increases the overall scale of production, and ultimately, the level of employment in the manufacturing sector.

As a last step, we propose a theoretical framework of heterogeneous firms that incorporates firm-level automation decisions to rationalize our empirical results. Because automation offers a better option for completing some easily automated tasks that would otherwise be performed by human workers, it lowers the unit cost of production. Meanwhile, automation equipment is purchased for a fixed cost. Firms differ in productivity and decide the quality of goods they produce. The model predicts that more productive firms are more likely to automate, produce more outputs, and produce higher-quality goods than non–automators. These results are consistent with our empirical findings. The model also predicts a theoretically ambiguous correlation between employment and automation status due to two opposite effects: a positive size effect that increases labor demand of automators and a negative substitution effect that reduces their labor demand.

The rest of this chapter is organized as follows. Section 2 presents firm- and product-level data and discusses what these data tell us about automation in Indonesia. Section 3 reports empirical evidence on automation in Indonesia at the firm and product level. Section 4 offers a possible explanation for our empirical results by proposing a theoretical framework. Section 5 concludes.

## 2  Automation in Indonesia: What Do the Data Tell Us?

In this section, we identify 'automation equipment' using Harmonized System (HS) product codes, describe Indonesia's export and import patterns of automation equipment, and examine direct imports of automation equipment by Indonesian manufacturing firms. First, we collect the HS 6-digit codes used by Acemoglu and Restrepo (2021) to define industrial automation equipment. These codes include the following types of equipment: industrial robots, machinery, numerically controlled machines, automatic machine tools, automatic welding machines, weaving and knitting machines, other textile dedicated machinery, automatic conveyors, and regulating and control instruments. We refer to equipment with these product codes as 'automation equipment'. We can then identify the quantity and value of automation equipment purchased from abroad by a country or a manufacturing firm.

Using UN Comtrade data from the World Bank's World Integrated Trade Solution (WITS) database, we observe annual exports and imports of automation equipment to Indonesia, by value, for the 2000–2019 period (Figure 9.1). Since Indonesia is not a major producer of automation equipment, we can see that
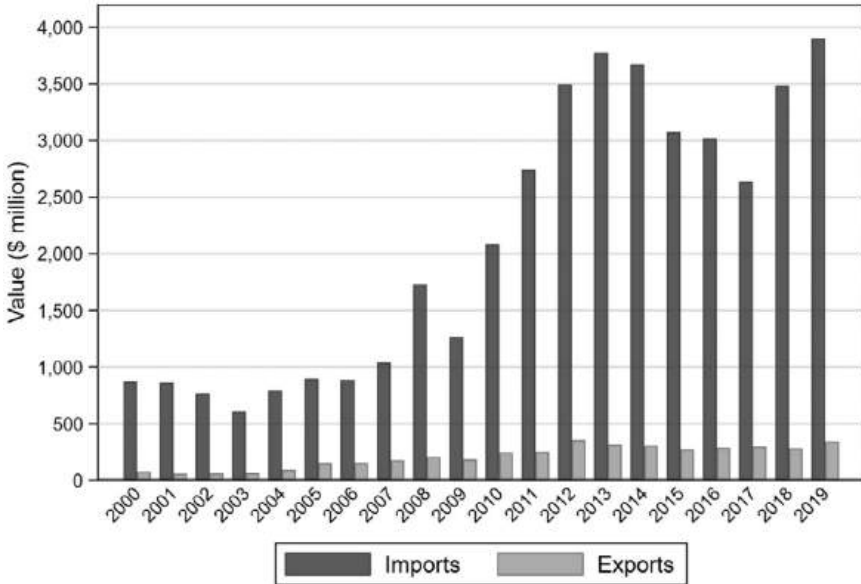
*Figure 9.1* Exports and Imports of Automation Equipment by Firms in Indonesia, 2000–2019

the value of its automation exports is much smaller than the value of its automation imports. As indicated in Figure 9.1, Indonesia ran a massive trade deficit in automation equipment, with a significant increase in import value over the last two decades, from $871 million in 2000 to $3.9 billion in 2019. Automation equipment accounted for about 2.3% of Indonesia's total imports (by value) in 2019. Imports increased over the last several decades, with noticeably higher growth since 2008: annual imports grew 24% between 2007 and 2013; imports then declined between 2014 and 2017 and subsequently increased again.

Based on the UN Comtrade data, four patterns in Indonesia's imports of automation equipment are worth noticing. First, imports of weaving and knitting machines and other textile dedicated machinery showed a persistent and significant decline as a share of total imports of automation equipment. These two types of equipment together accounted for more than 45% of total automation imports in the early 2000s; they accounted for only around 18% in 2019. This contraction is consistent with the declining shares of the textile and apparel industries in Indonesia's overall economy (where they have been referred to as 'sunset industries') and their slow growth prospects.[1] Second, regulating and control instruments have become the most important category of imported automation equipment, growing as a share of all automation imports from around 20% in 2000 to around 35% in 2019. The trend of rising imports of regulating and control instruments reflects the expansion of high-tech industries

that use this type of equipment intensively, such as in the motor vehicles and metals industries. Third, the industrial robots and dedicated machinery categories also show substantial increases as a share of overall automation imports. In 2019, these two types of equipment accounted for around 10% of automation equipment imports. Last, imports of automatic machine tools have been relatively stable during this period, accounting for around 20% of imported automation equipment in most years.[2]

We next examine firm-level production and trade data from Statistics Indonesia (BPS) to identify automators. As a first step, we combined three main micro-level data sets. The first data set is from an annual survey of large and medium-sized manufacturing firms in Indonesia. The survey includes around 35,000 firms annually and records firm-level production and financial information, including information on gross production output, value added, number of production and non-production workers, wages, capital, domestic and foreign equity shares, materials usage, and export and import shares. The second data set includes specific, additional information from the manufacturing survey, including detailed information on outputs and inputs and raw materials at the firm-product level. Specifically, the data set reports the annual value, quantity, and export value of each product that a firm produces. It also documents the annual value and quantity of each product that a firm purchases domestically or imports as an input material.[3] The third data set contains customs trade information including value, quantity, HS product code, and import country of origin, as well as export destination countries for each Indonesian firm in a given year. The customs trade data set is essential for identifying direct imports of automation equipment at the firm level. We match these three data sets using a unique firm identifier provided by BPS. The merging and cleaning steps we implemented to ensure good data quality left us with matched samples spanning from 2008 to 2012.

Our approach to identifying automation at the firm level follows Humlum (2019) and Acemoglu, Lelarge, and Restrepo (2020), who use imports of industrial robots as an indicator of firm-level robot adoption by Danish and French firms. Due to data limitations, our firm-level measure of automation only captures direct imports of automation equipment from abroad during the sample period; it does not account for purchases of automation equipment from domestic wholesalers and retailers. Therefore, the matched sample focuses on a subset of manufacturing firms that implement automation – as indicated by their direct imports of automation equipment in a particular time period (as explained in the previous section, we use imports of automation equipment as the best proxy for automation in Indonesia, at the national and firm level, for which data can be obtained at this time). Moreover, since imports of automation equipment to Indonesia began growing rapidly after 2008, we expect that most purchases and installations of automation equipment have taken place since 2008.

Table 9.1 reports the annual growth and composition of direct imports of automation equipment by Indonesian manufacturing firms using the matched

*Table 9.1* Direct Imports of Automation Equipment by Indonesian Manufacturing Firms

| | Growth (in %) | | | | |
|---|---|---|---|---|---|
| *Equipment Type* | *2008* | *2009* | *2010* | *2011* | *2012* |
| Automatic machine tools | . | −67.59 | 286.45 | 21.24 | 24.73 |
| Automatic welding machines | . | −64.11 | 29.85 | 148.51 | 21.47 |
| Industrial robots | . | −87.71 | 1953.86 | −11.21 | 88.86 |
| Numerically controlled machines | . | −45.70 | 245.17 | 59.78 | 61.80 |
| Other textile dedicated machinery | . | −14.86 | 50.98 | 83.88 | 20.98 |
| Regulating & control instruments | . | 49.13 | −6.71 | 23.38 | 29.23 |
| Weaving & knitting machines | . | −64.39 | 110.74 | 52.15 | −41.18 |
| **Total** | **.** | **−57.30** | **154.64** | **48.91** | **12.29** |
| | Shares (in %) | | | | |
| *Equipment Type* | *2008* | *2009* | *2010* | *2011* | *2012* |
| Automatic machine tools | 8.79 | 6.67 | 10.12 | 8.24 | 9.16 |
| Automatic welding machines | 4.68 | 3.94 | 2.01 | 3.35 | 3.62 |
| Industrial robots | 4.83 | 1.39 | 11.21 | 6.68 | 11.24 |
| Numerically controlled machines | 14.61 | 18.58 | 25.18 | 27.02 | 38.93 |
| Other textile dedicated machinery | 9.34 | 18.62 | 11.04 | 13.63 | 14.69 |
| Regulating & control instruments | 1.00 | 3.48 | 1.28 | 1.06 | 1.22 |
| Weaving & knitting machines | 56.75 | 47.32 | 39.16 | 40.02 | 20.96 |
| **Total** | **100.00** | **100.00** | **100.00** | **100.00** | **100.00** |

Source: Authors' calculation from BPS data.

data set. Direct imports of automation equipment fell significantly in 2009, but recovered rapidly and substantially grew in subsequent years. The global financial crisis in 2008 was likely to be responsible for the decline of imports in 2009. However, a strong rebound following the decline may suggest that financially unconstrained firms managed their resources so that they could build up their automation capacities during the crisis-induced downturn in product demand. The same pattern holds for almost all types of automation equipment and is broadly consistent with the pattern we observe in the UN Comtrade data at the national level. This suggests that the matched firm–product level data set provides a good representative sample for an overview of automation in Indonesia.[4]

Turning to the types of automation equipment included in Table 9.1, we see that weaving and knitting machines and other textile dedicated machinery together accounted for 66% of the total value of automation equipment imports in 2008, but was only 35% in 2012. This decline can be explained by the overall contraction of the textile and apparel industries in Indonesia over the same period. Whereas, import shares for both industrial robots and numerically controlled machines increased significantly from 2008 to 2012. These increases were driven by expansion in the industries that were the primary users of these types of equipment, particularly motor vehicles, transport equipment, metals, and rubber and plastics (Table 9.2). Table 9.2 also reports the

*Table 9.2* Shares of Direct Imports of Automation Equipment (in %), by Industry

| ISIC 2-digit industry | 2008 | 2009 | 2010 | 2011 | 2012 |
|---|---|---|---|---|---|
| Food | 1.34 | 0.46 | 0.19 | 0.83 | 1.12 |
| Beverage | 0.00 | 0.00 | 0.00 | 0.03 | 0.00 |
| Tobacco | 0.02 | 0.03 | 0.03 | 0.01 | 0.56 |
| Textiles | 61.21 | 55.32 | 45.43 | 41.50 | 24.91 |
| Apparel | 2.45 | 2.76 | 2.02 | 5.10 | 2.77 |
| Leather | 0.10 | 0.67 | 0.16 | 3.72 | 1.23 |
| Wood and Straw | 0.01 | 0.00 | 0.06 | 0.04 | 0.03 |
| Paper | 0.00 | 0.34 | 0.01 | 0.01 | 0.39 |
| Printing | 0.09 | 0.00 | 0.00 | 0.00 | 0.00 |
| Chemicals | 1.30 | 2.31 | 0.90 | 0.56 | 0.05 |
| Medicine | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 |
| Rubber and Plastics | 2.40 | 7.20 | 3.68 | 3.20 | 5.49 |
| Non-metallic Minerals | 0.62 | 0.04 | 0.47 | 0.22 | 0.43 |
| Basic Metals | 0.68 | 1.89 | 1.91 | 3.54 | 9.70 |
| Fabricated Metal | 1.47 | 5.01 | 2.26 | 6.67 | 4.15 |
| Computer, Electronic and Optical | 0.98 | 3.63 | 2.38 | 2.62 | 3.08 |
| Electrical Equipment | 2.23 | 4.78 | 4.47 | 1.83 | 0.94 |
| Machinery | 9.62 | 1.73 | 5.57 | 1.13 | 4.40 |
| Motor Vehicles | 7.82 | 6.89 | 24.55 | 23.57 | 32.14 |
| Other Transport Equipment | 4.50 | 5.73 | 2.71 | 4.52 | 6.02 |
| Furniture | 2.49 | 0.11 | 2.20 | 0.03 | 0.72 |
| Other Manufacturing | 0.68 | 1.10 | 0.99 | 0.82 | 1.78 |
| Repair and Installation | 0.00 | 0.00 | 0.00 | 0.04 | 0.09 |
| Total | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |

Source: Authors' calculation from BPS data.

industry composition of direct imports of automation equipment – in other words, the distribution of automation imports across industries. The textiles industry substantially declined, from 61% to 25%, in its share of the value of total direct imports of automation equipment. By contrast, other industries, such as rubber and plastics, motor vehicles, and basic metals, significantly increased their shares. Overall, it seems that Indonesian manufacturing firms have shifted from importing automation equipment that is specific to certain industries to importing equipment that is applicable to a broader range of industries.

Next, we use our matched data set to examine the distribution of direct imports of automation equipment across different types of firms. We classify an active firm in the current year as either an incumbent firm or an entering firm (a new firm) based on whether the firm is active in the previous year. If a firm that is active in 2009 is also active in 2008, it is classified as an incumbent firm in 2009. Otherwise, it is classified as an entering firm in 2009. Similarly, we can classify an active firm in the current year as an incumbent firm or an existing firm. If a firm that is active in 2009 is also active in 2010, it is classified as an incumbent firm in 2009. Otherwise, it is classified as an existing firm in 2009. The general message is that the intensive margin drives aggregate changes in firms' direct imports of automation equipment: incumbent firms accounted for more than 90% of direct imports

of automation equipment in all years; in 2010, newly entering firms accounted for about 10% of direct imports.[5] Over the years, more firms imported automation equipment. The fraction of medium-sized and large manufacturers that had ever imported automation equipment increased from 0.98% in 2008 to 3.07% in 2012. Overall, relatively few firms in Indonesia, even among medium-sized and large manufacturers, import automation equipment.

We offer some statistics to shed light on the importance of automators. In 2008, 6.43% of production workers and 4.21% of non-production workers in our sample were hired by manufacturing firms that directly import automation equipment. In 2012, these numbers were 12.75% and 9.25% respectively. Manufacturers that directly imported automation equipment at least once during the period 2008–2012 accounted for 6.69% of total outputs in our sample. This number increased to 13.57% in 2012. In short, employment and output shares for direct importers of automation equipment roughly doubled from 2008 to 2012. On average, firms that directly import automation equipment hired more workers and produced more outputs than other firms.

# 3 Automation in Indonesia: Evidence at the Firm–Product Level Evidence

This section investigates the association between firm-level automation and firm-level outcomes. Our empirical analysis does not attempt to infer causality between automation and firm-level outcomes. Instead, we aim to document correlations between automation and firm-level outcomes. The analysis consists of two parts. The first part focuses on cross-sectional comparisons between firms that directly import automation equipment and firms that do not. The second part examines correlations between automation and firm outcomes over time, using an empirical approach that follows Koch, Manuylov, and Smolka (2021) and Acemoglu, Lelarge, and Restrepo (2020) and a firm-level long-difference specification.

## 3.1 Cross-Sectional Comparisons

How do automators differ from non–automators in a given industry? We use the following empirical specification to examine these cross-sectional differences:

$$y_{ft} = \beta^a \times \mathbf{a}_{ft} + \mathbf{X}_{ft} + \delta_{it} + \delta_{rt} + \epsilon_{ft}, \tag{1}$$

where $y$ is the outcome variable, and $f$, $t$, $i$, and $r$ represent firm, year, International Standard Industrial Classification of All Economic Activities (ISIC) 2-digit industry code, and region (located on Java or not),[6] respectively. The indicator variable $\mathbf{a}_{ft}$ takes the value of 1 if firm $f$ imported automation equipment at least once during 2008–2012; otherwise it takes the value of 0.[7] The set of control variables $\mathbf{X}_{ft}$ includes firm export share, import share, and foreign ownership, which may correlate with $y_{ft}$ and $\mathbf{a}_{ft}$ at the same time.[8] Export share and

import share are values from 0 to 1, so there are exporters, importers, and firms that neither export nor import in the estimation sample. Importantly, we include industry–year fixed effects $\delta_{it}$ and region–year fixed effects $\delta_{rt}$ to control for time-varying shocks specific to an industry (e.g., technological progress) and specific to a location (e.g., costs of labor, energy, land, ICT, and other location specific variables). Therefore, $\beta^a$ is the 'automation premium' identified within an ISIC 2-digit industry in a given year. The error term is denoted by $\epsilon_{ft}$. This term may contain unobserved confounding factors that affect firm-level outcomes $y_{ft}$, such as management capability or financial constraints.[9] Standard errors are clustered at the firm level to account for potential within-firm correlation in the error term.

In the first set of results, we focus on firm-level measures of size and productivity. The variables of interest are gross output value, employment, labor productivity, and total factor productivity (TFP).[10] To visualize the cross-sectional difference between automators and non–automators, Figure 9.2 plots the distributions of log output, log employment, log labor productivity, and log TFP for these two groups of firms separately, without controlling for other firm-level attributes $X_{ft}$. The visualization shows that automators have higher output, employ more workers, and have higher labor productivity and TFP.

We estimate (1) to further control for other firm characteristics that may be correlated with $y_{ft}$ and $\mathbf{a}_{ft}$[11]. Table 9.3 reports the results. We find that automators produce more output and hire more employees than non-automators – by around 1.389 and 0.995 log points, respectively. Meanwhile, automators also
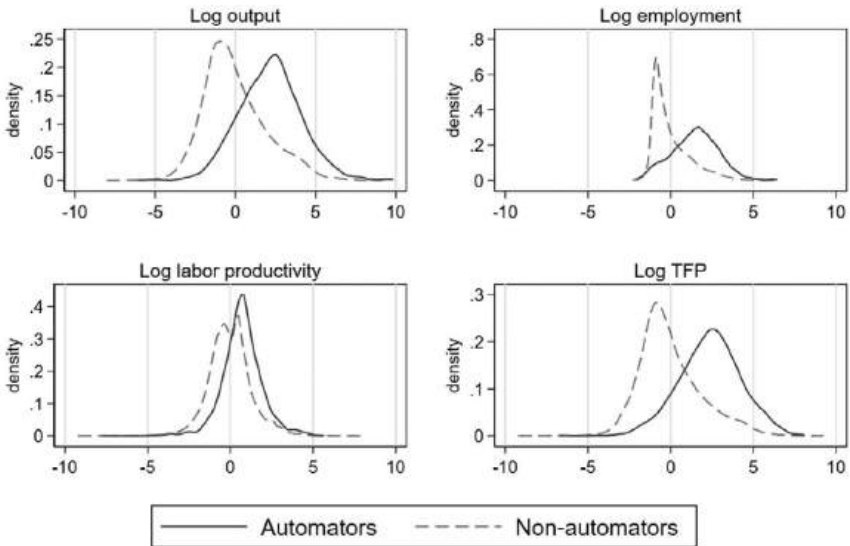


ISIC = International Standard Industrial Classification. TFP = total factor productivity.
Note: ISIC 2-digit-year fixed effects are removed.
Source: Authors' calculation from BPS data.

*Figure 9.2* Size and Productivity: Automators versus Non-automators

*Table 9.3* Automation, Size, and Productivity: Cross-Sectional Comparison

| Dependent Variable: (in Log) | (1) Output | (2) Employment | (3) Value Added per Worker | (4) TFP |
|---|---|---|---|---|
| Automation | 1.389*** | 0.995*** | 0.396*** | 1.445*** |
| | (0.085) | (0.060) | (0.048) | (0.112) |
| Export share | 0.860*** | 0.756*** | 0.031 | 1.144*** |
| | (0.038) | (0.026) | (0.021) | (0.045) |
| Import share | 1.424*** | 0.804*** | 0.641*** | 1.316*** |
| | (0.055) | (0.036) | (0.031) | (0.071) |
| Foreign-owned | 1.448*** | 0.745*** | 0.708*** | 1.425*** |
| | (0.046) | (0.031) | (0.028) | (0.059) |
| Fixed effects | industry-year, region-year | | | |
| No. of observations | 110,735 | 110,735 | 109,039 | 69,655 |

TFP = total factor productivity.
Notes: This table reports the cross-sectional comparisons of firm-level size and productivity measures between firms that import automation equipment and firms that do not. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Source: Authors' calculation from BPS data.

exhibit higher labor productivity and TFP. The labor productivity premium is about 0.396 log points, while the TFP premium is about 1.445 log points.[12] These results are consistent with empirical findings for Spanish manufacturing firms that adopt industrial robots (Koch, Manuylov, and Smolka, 2021).

We then turn to differences in factor price and factor usage between automators and non-automators. Figure 9.3 shows that automators pay higher wages for both production and non-production workers. A possible explanation is that automators hire workers with different skills and occupations than the workers hired by non-automators. At the same time, automators have lower labor shares and higher capital-labor ratios compared to non-automators.

Table 9.4 documents the cross-sectional regression results. After controlling for trade participation, foreign ownership, industry-year fixed effects, and region-year fixed effects, we find that automators pay higher wages for production and non-production workers. The wage premiums are very similar for both types of workers (0.15 log points).[13] Meanwhile, automators also have lower labor shares (–0.208 log points) and higher capital-labor ratios (0.445 log points).[14]

We next investigate outcomes related to the number of different products or outputs generated by a firm and the firm's participation in international trade. First, we focus on firms' variety of outputs and variety of inputs.[15] Figure 9.4 suggests that differences in these two variables are not as visible as differences in the variables shown in previous figures.[16] Second, we plot the distributions of export and import shares, including those observations that report zero value. Automators export more of their outputs and import more of their inputs than other firms.
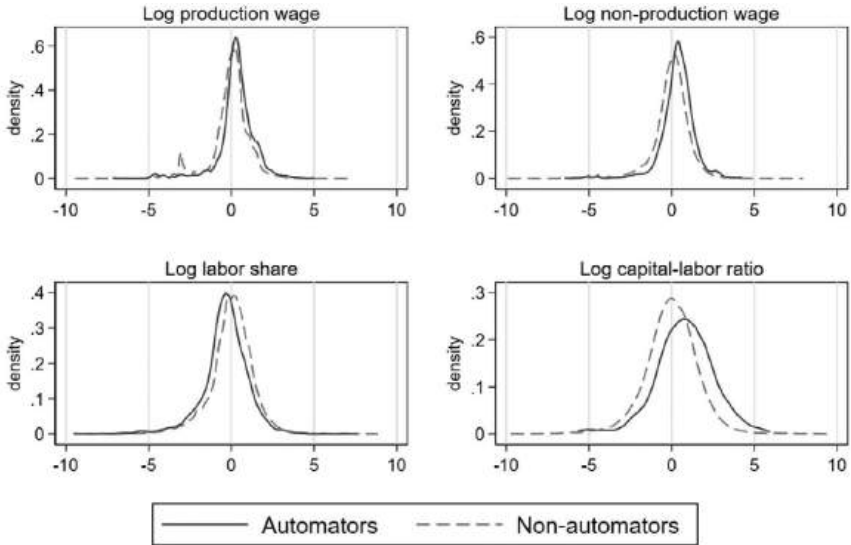
ISIC = International Standard Industrial Classification.
Note: ISIC 2-digit-year fixed effects are removed.
Source: Authors' calculation from BPS data.

*Figure 9.3* Factor Usages: Automators versus Non-automators

*Table 9.4* Automation and Factor Usages: Cross-Sectional Comparison

| Dependent Variable: (in Log) | (1) Production Wage | (2) Non-Production Wage | (3) Labor Share | (4) Capital-Labor Ratio |
|---|---|---|---|---|
| Automation | 0.150*** | 0.151*** | –0.208*** | 0.445*** |
| | (0.030) | (0.032) | (0.043) | (0.084) |
| Export share | 0.040*** | 0.147*** | 0.047** | –0.049 |
| | (0.015) | (0.018) | (0.019) | (0.037) |
| Import share | 0.383*** | 0.481*** | –0.197*** | 0.464*** |
| | (0.019) | (0.022) | (0.025) | (0.056) |
| Foreign-owned | 0.337*** | 0.361*** | –0.329*** | 0.807*** |
| | (0.016) | (0.019) | (0.025) | (0.052) |
| Fixed effects | industry-year, region-year | | | |
| No. of observations | 110,707 | 90,251 | 109,038 | 72,635 |

Notes: This table reports the cross-sectional comparisons of firm-level factor usages between firms that import automation equipment and firms that do not. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Source: Authors' calculation from BPS data.

We include the control variables and estimate (1). In Table 9.5 columns 1 and 2, we compare firms with similar export and import intensities and foreign ownership but different levels of automation. We find that automators produce a greater variety of outputs than other firms – by 0.095 log points – but do not

*Figure 9.4* Output and Input Varieties and Trade Participation: Automators versus Non–automators

*Table 9.5* Automation, Input-Product Varieties, Trade Shares: Cross-Sectional Comparison

| Dependent Variable: | (1) Log no. of Produced Varieties | (2) Log no. of Input Varieties | (3) Export Share | (4) Import Share |
|---|---|---|---|---|
| Automation | 0.095*** | −0.006 | 0.087*** | 0.150*** |
| | (0.026) | (0.027) | (0.013) | (0.014) |
| Export share | 0.034*** | 0.079*** | | 0.065*** |
| | (0.012) | (0.014) | | (0.005) |
| Import share | 0.057*** | 0.101*** | 0.093*** | |
| | (0.015) | (0.019) | (0.008) | |
| Foreign-owned | 0.032** | −0.071*** | 0.196*** | 0.234*** |
| | (0.014) | (0.017) | (0.008) | (0.008) |
| Fixed effects | industry-year, region-year | | | |
| No. of observations | 110,735 | 110,735 | 110,735 | 110,735 |

Notes: This table reports the cross-sectional comparisons of firm-level input and product varieties and trade shares between firms that import automation equipment and firms that do not. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Source: Authors' calculation from BPS data.

seem to use a greater variety of inputs. In column 3 (4), we compare the export (import) shares of firms with similar import (export) intensities and foreign ownership but different levels of automation. We find that automators are more likely to engage in international trade: these firms export 8.7 percentage points more of their outputs and import 15 percentage points more of their inputs. Therefore, firms that engage in more exporting and importing seem more likely to invest in automation equipment.

Using the product-level information for Indonesian manufacturing firms, we next examine how automation is correlated with product-level outcomes across different firms. We focus on product-level market shares, prices, and product quality (or product appeal), as inferred from sales and price information.

We define product quality as 'inferred quality' because it cannot not be directly observed in the data. We follow Khandelwal, Schott, and Wei (2013) and Fan, Li, and Yeaple (2015) to infer quality from sales and price data in a constant elasticity of substitution (CES) preference:

$$U = \left( \int_{\omega \in \Omega} [q(\omega) \cdot z(\omega)^{\eta}]^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}, \sigma > 1, \eta > 0,$$

where $q(\omega)$ is the quantity of variety $\omega$ consumed and $z(\omega)$ is the quality (or appeal) of the variety. In this equation, $\sigma$ is the elasticity of substitution between different varieties and $\eta$ governs customer's preference for quality relative to quantity. The budget constraint of the customer is:

$$\int_{\omega \in \Omega} p(\omega) \cdot q(\omega) d\omega \leq X,$$

where $X$ is the total expenditure. The demand function of each variety $\omega$ is thus:

$$q(\omega) = z(\omega)^{\eta(\sigma-1)} \cdot p(\omega)^{-\sigma} \cdot P^{\sigma-1} \cdot X.$$

Conditional on price $p(\omega)$, higher quality $z(\omega)$ increases the demand for a particular variety $\omega$. We use $P$ to denote the CES quality-adjusted price index that aggregates all varieties in the market. The sales revenue of variety $\omega$ thus follows:

$$x(\omega) = p(\omega) \cdot q(\omega) = z(\omega)^{\eta(\sigma-1)} \cdot p(\omega)^{1-\sigma} \cdot P^{\sigma-1} \cdot X.$$

Therefore, the product quality or product appeal of variety $\omega$ can be expressed as:

$$\eta \ln z(\omega) = \frac{1}{\sigma-1} \ln s(\omega) + \ln p(\omega) - \ln P,$$

where $s(\omega) = \frac{x(\omega)}{X}$ is the market share of variety $\omega$. Using information on firm–product level outputs, we construct the quality measure as follows:

$$\eta_k \ln z_{fjgt} = \frac{1}{\sigma_k - 1} \ln s_{fjgt} + \ln p_{fjgt} - \ln P_{kt}, \tag{2}$$

where $f$, $g$, $k$, and $t$ stand for firm, product, industry, and year, respectively. We assume that different products produced by different firms in the same industry $k$ are imperfect substitutes for one another. $s_{fgt} = \frac{x_{fgt}}{X_{kt}}$ is the market share of firm $f$'s product $g$ in industry $k$ in year $t$. Therefore, conditional on price, we assign higher quality to a firm/variety with a higher market share. Because we infer quality within a particular industry in a particular year, variation in price index $P_{kt}$ at the industry–year level does not affect our empirical results so long as industry–year fixed effects are included in the analysis.

We define $k$ using HS 4-digit product codes and use the estimated for Indonesia from Broda and Weinstein (2006). Figure 9.5 shows that products made by automators account for larger market shares than products made by non–automators. On the other hand, the price distributions of products made by these two types of firms do not seem to differ. Therefore, it is reasonable to expect that automators also produce high-quality goods, as indicated in the lower-left panel of Figure 9.5.

To estimate these cross-sectional differences more precisely, we use the same empirical specification in Table 9.6 as we do in Tables 9.3–9.5, including the same control variables. Instead, however, we control for HS-4-digit-year fixed effects[17] to compare the product-level outcomes of firms with similar trade intensities and foreign ownership but different levels of automation statuses. First, we find that products made by automators account for larger market shares than other products, on average. The automation premium in the market share is about 1.175 log points. Second, the price difference between products made
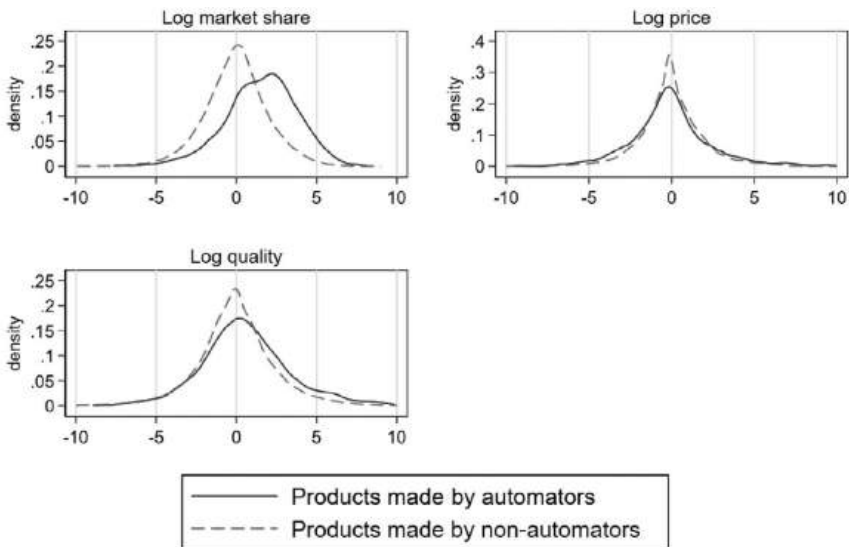


HS = Harmonized System.
Note: HS 4-digit-year fixed effects are removed.
Source: Authors' calculation from BPS data.

*Figure 9.5* Product-Level Characteristics: Automators versus Non–automators

*Table 9.6* Automation and Product Quality: Cross-Sectional Comparison

| Dependent Variable (in Log): | (1) Market Share | (2) Price | (3) Inferred Quality |
|---|---|---|---|
| Automation | 1.175*** | −0.002 | 0.441*** |
| | (0.117) | (0.122) | (0.150) |
| Export share | 0.637*** | 0.080** | 0.369*** |
| | (0.048) | (0.038) | (0.046) |
| Import share | 1.165*** | −0.193** | 0.462*** |
| | (0.081) | (0.075) | (0.102) |
| Foreign-owned | 1.057*** | −0.052 | 0.493*** |
| | (0.062) | (0.056) | (0.070) |
| Fixed effects | HS4-year, region-year | | |
| No. of observations | 118,570 | 118,570 | 118,570 |

HS = Harmonized System.
Notes: This table reports the cross-sectional comparisons of product-level character-istics between firms that import automation equipment and firms that do not. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Source: Authors' calculation from BPS data.

by automators and products made by non–automators is economically and statis-tically insignificant (point estimate of –0.002 log points with a standard error of 0.122). Third, we document a significant automation premium in the inferred product quality or product appeal. On average, the inferred quality of goods sup-plied by automators is 0.441 log points higher than the inferred quality of goods supplied by non-automators.

To summarize, cross-sectional comparisons between automators and non-automators reveal systematic differences. Automators have higher product output and employ more workers; they also have higher labor productivity and TFP. Automators pay higher wages but their wage bills are lower as a share of sales, and they use capital more intensively. Moreover, these firms produce more varieties of output and are more actively engaged in international trade. Finally, the products made by automators account for higher market shares and exhibit higher inferred quality. These empirical results indicate that automa-tion is highly selective – thus, automators tend to be exceptional.

## 3.2 Firm-Level Changes

Having examined cross–sectional correlations between automation and firm-level outcomes across firms (and products), we turn next to an analysis of whether firm-level changes in various outcomes are associated with automation status. We use a long-difference specification, similar to that used in Acemoglu, Lelarge and Restrepo (2020), as follows:

$$\Delta y_{f,2012-2008} = \beta^{\Delta a} \times \Delta \mathbf{a}_{f,2012-2008} + \mathbf{X}_{f,2008} + \delta_i + \delta_r + \epsilon_f, \tag{3}$$

where $\Delta y_{f,2012-2008}$ is the long-difference of firm $f$'s outcome variable $y$ during the sample period 2008–2012. The indicator variable $\Delta a_{f,2012-2008}$ takes the value of 1 if firm $f$ imported any automation equipment during the period 2008–2012; otherwise, it takes a value of 0. The set of lagged variables in 2008 $\mathbf{X}_{f,2008}$ controls for a firm's initial conditions, including log labor productivity, log employment, log capital–labor ratio, log ratio between non-production worker compensation and production worker compensation, foreign ownership, export share, and import share. The ISIC 2-digit fixed effect $\delta_i$ accounts for industry-specific trends in this period. The region fixed effect $\delta_r$ differs for firms that locate on Java and firms that do not. Finally, the error term $\varepsilon_f$ contains other unobserved confounding factors. In this specification, we exploit how changes in firm-level outcomes vary with the firm's automation status.

Our long-difference specification controls for unobserved time-invariant firm characteristics that affect both $\Delta y_{f,2012-2008}$ and $\Delta a_{f,2012-2008}$. The lagged variables $\mathbf{X}_{f,2008}$ also control for some firm-specific changes that may correlate with these lagged variables. However, we may still suffer from omitted variable bias because unobserved time-varying firm characteristics in $\varepsilon_f$ could still drive $\Delta y_{f,2012-2008}$ and $\Delta a_{f,2012-2008}$ at the same time. For example, suppose a firm becomes financially healthier. In that case, the firm may be more likely to import automation equipment as an investment to expand production. This would cause a positive correlation between automation decisions and gross output value. Therefore, we interpret the empirical results in the long-difference specification as reflecting associations between automation decisions and changes in firm-level outcomes, rather than causal effects of automation on firm-level outcomes.

Table 9.7 reports results from our long-difference regressions, using output, value added, and TFP as dependent variables. By construction, the long-difference specification only uses firms active in both 2008 and 2012 – most of these firms were also present for all five years of the period 2008–2012. Firm entry and exit leaves us with a sample of 17,496 firms (Table 9.7 column 1). Column 1 shows that automators during this period also see a larger increase in their gross output value – by 0.145 log points – than other firms in the same period. In column 2, we further control for the lagged log non-production share of the workforce as a measure of skill intensity and for the lagged log K/L ratio as a measure of capital intensity. Due to missing values for these two variables, the sample size in column 2 drops to 8,947 firms.[18] After controlling for initial skill and capital intensities, we still see a larger increase in output value, by 0.189 log points, for automators. Columns 3 and 4 show that automators experience a larger increase in value added – by 0.167 and 0.212 log points, respectively. Columns 5 and 6 further report the estimation results for TFP. We find that automators' TFP also grow faster than non-automators' TFP – by 0.223 and 0.204 log points. Overall, automators also see relative increases in gross output, value added, and TFP. These associations might indicate that

*Table 9.7* Automation, Size, and Productivity: Long-Difference Specification

| Dependent Variable: (Log Difference) | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Output | | Value Added | | TFP | |
| Automation | 0.145*** | 0.189*** | 0.167*** | 0.212*** | 0.223*** | 0.204*** |
| | (0.056) | (0.072) | (0.056) | (0.074) | (0.074) | (0.074) |
| Lagged log labor productivity | −0.350*** | −0.385*** | −0.446*** | −0.548*** | −0.163*** | −0.175*** |
| | (0.011) | (0.019) | (0.012) | (0.020) | (0.012) | (0.016) |
| Lagged log employment | −0.046*** | −0.013 | −0.008 | 0.035** | −0.083*** | −0.076*** |
| | (0.010) | (0.014) | (0.011) | (0.014) | (0.012) | (0.013) |
| Lagged foreign ownership | 0.157*** | 0.074 | 0.182*** | 0.065 | 0.063 | 0.058 |
| | (0.041) | (0.054) | (0.041) | (0.056) | (0.053) | (0.057) |
| Lagged export share | −0.057 | −0.116** | −0.064* | −0.098** | −0.103** | −0.115** |
| | (0.038) | (0.047) | (0.038) | (0.048) | (0.042) | (0.046) |
| Lagged import share | 0.158*** | 0.078 | 0.214*** | 0.154** | 0.114* | 0.074 |
| | (0.048) | (0.066) | (0.048) | (0.069) | (0.058) | (0.065) |
| Lagged log non-production share | | 0.045*** | | 0.081*** | | 0.011 |
| | | (0.011) | | (0.012) | | (0.011) |
| Lagged log *K/L* ratio | | 0.070*** | | 0.118*** | | 0.034*** |
| | | (0.010) | | (0.010) | | (0.009) |
| Fixed effects | industry, region | | | | | |
| No. of observations | 17,496 | 8,947 | 17,288 | 8,841 | 9,921 | 7,934 |

Note: This table reports how firm size and productivity measures vary with the imports of automation equipment over time. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Source: Authors' calculation from BPS data.

automation increases output and productivity, or firms that oversee better growth opportunities are also the ones that choose to automate.

In Table 9.8, we use the long-difference specification to examine changes in firm-level employment. In columns 1 and 2, we observe a relative increase of 0.113 and 0.204 log points in total employment associated with firms that import automation equipment. Similar findings are documented by Koch, Manuylov and Smolka (2021) and Acemoglu, Lelarge, and Restrepo (2020) in their analysis of the firm-level impacts of adopting industrial robots for Spanish and French firms, respectively. We further examine the impacts on the employment of production and non-production workers. Columns 3 and 4 show a larger increase in employment of production workers for automators compared to non-automators – by 0.115 and 0.230 log points, respectively. By contrast, columns 5 and 6 reveal no significant increase in the employment of non-production workers by automators relative to non-automators. Therefore, the relative increase in firm-level employment among automators mainly reflects a relative increase in these firms' employment of production workers.

Although we are cautious about interpreting our long-difference results as causal, it is still worthwhile to compare our findings with findings from previous studies that use data from developed economies. In these economies, automation equipment such as industrial robots tends to substitute for production workers who perform routine tasks. Therefore, one would expect production workers to be negatively affected by the adoption of advanced automation technologies. This hypothesis is supported by Humlum (2019), who finds that Danish production workers experience subsequent wage losses when their employers adopt industrial robots. In addition, Acemoglu, Lelarge, and Restrepo (2020) find that production workers' employment shares declined following the adoption of industrial robots by firms in France.

By contrast, Indonesia, as a developing economy, is still at a relatively early stage of automation.[19] At this stage, automation equipment other than industrial robots, such as numerically controlled machines and automatic machine tools, may increase production workers' efficiency and accuracy in performing specific tasks and thereby enable increased production.[20] Our conjecture, therefore, is that early-stage automation is more likely to complement production employment.

We further explore whether importing automation equipment is associated with firm-level changes in factor usage. Table 9.9 reports results for this part of the analysis. We find that changes in labor share, production wage, non-production wage, and capital–labor ratio do not seem to differ between automators and non-automators. Combined with the results in Tables 9.7 and 9.8, we see similar increases in total wage bill and output for automators, leaving the total wage bill as a share of output invariant. Finally, our results for the capital–labor ratio also suggest that capital grows at the same rate as employment for automators.

Table 9.10 examines changes in output variety and international trade participation. We see no significant difference in output and input variety between

*Table 9.8* Automation and Employment: Long-Difference Specification

| Dependent Variable: (Log Difference) | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Employment | | Production Employment | | Non-Production Employment | |
| Automation | 0.113*** | 0.204*** | 0.115*** | 0.230*** | 0.028 | 0.054 |
| | (0.038) | (0.044) | (0.039) | (0.046) | (0.051) | (0.065) |
| Lagged log labor productivity | 0.053*** | 0.027*** | 0.059*** | 0.025*** | 0.023*** | 0.035*** |
| | (0.005) | (0.007) | (0.006) | (0.008) | (0.008) | (0.011) |
| Lagged log employment | −0.177*** | −0.138*** | −0.173*** | −0.138*** | −0.158*** | −0.106*** |
| | (0.006) | (0.008) | (0.007) | (0.009) | (0.009) | (0.012) |
| Lagged foreign ownership | 0.008 | −0.011 | 0.010 | −0.015 | 0.012 | 0.015 |
| | (0.026) | (0.033) | (0.028) | (0.035) | (0.036) | (0.044) |
| Lagged export share | 0.036 | −0.012 | 0.023 | −0.039 | 0.098*** | 0.064 |
| | (0.023) | (0.028) | (0.024) | (0.029) | (0.037) | (0.043) |
| Lagged import share | 0.072** | 0.072* | 0.081*** | 0.061 | 0.036 | 0.071 |
| | (0.029) | (0.037) | (0.030) | (0.053) | (0.041) | (0.053) |
| Lagged log non-production share | | 0.008 | | 0.053*** | | −0.143*** |
| | | (0.006) | | (0.007) | | (0.010) |
| Lagged log *K/L* ratio | | 0.020*** | | 0.016*** | | 0.022*** |
| | | (0.005) | | (0.005) | | (0.008) |
| Fixed effects | industry, region | | | | | |
| No. of observations | 17,892 | 9,130 | 17,889 | 9,130 | 13,349 | 7,668 |

Notes: This table reports how firm-level employment varies with the imports of automation equipment over time. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Source: Authors' calculation from BPS data.

Table 9.9 Automation, Wages, and Capital-Labor Ratio: Long-Difference Specification

| Dependent Variable: (Log Difference) | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Labor Shares | | Production Wages | | Non-Production Wages | | K/L Ratio | |
| Automation | −0.024 | 0.048 | 0.068* | 0.073 | −0.037 | 0.054 | −0.053 | 0.066 |
| | (0.060) | (0.086) | (0.040) | (0.060) | (0.055) | (0.082) | (0.112) | (0.093) |
| Lagged log labor productivity | 0.189*** | 0.291*** | −0.303*** | −0.287*** | −0.269*** | −0.222*** | −0.081*** | 0.131*** |
| | (0.015) | (0.026) | (0.008) | (0.014) | (0.011) | (0.015) | (0.015) | (0.017) |
| Lagged log employment | −0.198*** | −0.200*** | −0.045*** | −0.050*** | −0.055*** | −0.063*** | 0.138*** | 0.100*** |
| | (0.011) | (0.016) | (0.007) | (0.010) | (0.010) | (0.014) | (0.017) | (0.017) |
| Lagged foreign ownership | −0.111*** | −0.038 | 0.091*** | 0.048 | 0.001 | −0.037 | −0.050 | 0.086 |
| | (0.041) | (0.057) | (0.027) | (0.041) | (0.039) | (0.052) | (0.079) | (0.074) |
| Lagged export share | 0.107** | 0.070 | −0.007 | −0.006 | 0.019 | 0.002 | −0.055 | −0.100 |
| | (0.042) | (0.051) | (0.029) | (0.036) | (0.044) | (0.050) | (0.062) | (0.062) |
| Lagged import share | −0.209*** | −0.153** | −0.026 | −0.032 | −0.135*** | −0.053 | −0.045 | 0.090 |
| | (0.048) | (0.073) | (0.031) | (0.048) | (0.045) | (0.061) | (0.076) | (0.078) |
| Lagged log non-production share | | −0.103*** | | 0.017* | | −0.272*** | | 0.042*** |
| | | (0.014) | | (0.009) | | (0.014) | | (0.013) |
| Lagged log K/L ratio | | −0.151*** | | −0.059*** | | −0.034*** | | −0.429*** |
| | | (0.012) | | (0.008) | | (0.010) | | (0.017) |
| Fixed effects | | | | industry, region | | | | |
| No. of observations | 17,288 | 8,841 | 17,889 | 9,130 | 12,842 | 7,668 | 10,118 | 8,083 |

Notes: This table reports how firm-level wages and capital/labor ratio vary with the imports of automation equipment over time. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Source: Authors' calculation from BPS data.

*Table 9.10* Automation and Input-Output Varieties and Trade: Long-Difference Specification

| Dependent Variable: (Difference) | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Log no. of Produced Varieties | | Log no. of Input Varieties | | Export Share | | Import Share | |
| Automation | −0.005 | 0.044 | −0.018 | −0.036 | 0.042*** | 0.059*** | 0.033*** | 0.018 |
| | (0.028) | (0.039) | (0.037) | (0.054) | (0.014) | (0.021) | (0.013) | (0.017) |
| Lagged log labor productivity | 0.001 | −0.005 | −0.017*** | −0.024*** | −0.004*** | −0.004 | 0.003*** | 0.001 |
| | (0.004) | (0.006) | (0.005) | (0.008) | (0.001) | (0.003) | (0.001) | (0.002) |
| Lagged log employment | −0.006 | −0.008 | −0.015** | −0.024*** | 0.030*** | 0.031*** | 0.010*** | 0.011*** |
| | (0.004) | (0.007) | (0.006) | (0.009) | (0.002) | (0.003) | (0.001) | (0.002) |
| Lagged foreign ownership | 0.020 | −0.031 | 0.040 | 0.028 | 0.090*** | 0.105*** | 0.071*** | 0.056*** |
| | (0.019) | (0.029) | (0.027) | (0.040) | (0.010) | (0.015) | (0.008) | (0.011) |
| Lagged export share | 0.017 | −0.003 | 0.007 | 0.040 | −0.487*** | −0.463*** | 0.013** | 0.024*** |
| | (0.018) | (0.024) | (0.025) | (0.033) | (0.013) | (0.016) | (0.006) | (0.007) |
| Lagged import share | −0.019 | 0.030 | −0.091*** | −0.200*** | 0.018* | 0.027* | −0.306*** | −0.305*** |
| | (0.022) | (0.033) | (0.031) | (0.049) | (0.009) | (0.015) | (0.012) | (0.017) |
| Lagged log non-production share | | 0.002 | | −0.003 | | 0.003 | | 0.003** |
| | | (0.005) | | (0.007) | | (0.002) | | (0.001) |
| Lagged log K/L ratio | | 0.006 | | 0.002 | | −0.006*** | | 0.002 |
| | | (0.004) | | (0.006) | | (0.002) | | (0.001) |
| Fixed effects | | | | industry, region | | | | |
| No. of observations | 17,496 | 8,947 | 17,659 | 9,017 | 17,496 | 8,947 | 17,659 | 9,017 |

Notes: This table firm-level input and output varieties and trade shares vary with the imports of automation equipment over time. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Source: Authors' calculation from BPS data.

automators and other firms. However, automators experience a relative increase in their export share of 4.2 percentage points when we do not control for skill and capital intensities and a relative increase of 5.9 percentage points when we do control for skill and capital intensities. The evidence on import shares is mixed. In column 7, automators see a larger increase in import share (3.3 percentage points) than non–automators when we do not control for skill and capital intensities. This increase is statistically significant. When we include skill and capital intensities in column 8, the estimated coefficient obtained in the smaller and more restricted sample becomes smaller and more imprecise (point estimate 0.018 with a standard error of 0.017).

Finally, we turn to outcomes at the firm–product level in Table 9.11. Due to massive entry and exit at the firm–product level during the period 2008–2012, we are left with 5,871 firm–product pairs in the long-difference specification (Table 9.11 column 1). Column 1 shows that products made by automators also exhibited a larger but statistically insignificant increase in market share. When we further control for skill and capital intensities in It, the estimation sample size falls to 2,851 firms. It shows that importing automation equipment is associated with an increase of 0.499 log points in product-level market share. We also estimate how changes in the product-level price vary with automation status. Columns 3 and 4 show that the price increase is associated with importing automation equipment, but the coefficients are not statistically significant. Columns 5 and 6 indicate that automators also see a larger increase – of 0.478 and 0.604 log points – in the inferred quality of their products.

To summarize, we identify the associations between changes in various firm-level outcomes and automation status. Consistent with the empirical findings of studies that use firm-level data from other countries, we find that importing automation equipment is associated with larger increases in output and employment. The larger increase in employment is mainly concentrated in production workers, while changes in labor share and wages are not systematically associated with automation status. Automation is also correlated with increases in export share, product-level market share, and product-level inferred quality.

We reiterate that our findings should not be interpreted as reflecting causality because we do not use exogenous shocks or policy changes that induce firms to automate (such as a reduction in the cost of automation equipment) to study how automation affects firm-level outcomes. Such exogenous variations would be needed to make causal inferences but are beyond the scope of this chapter.

## 4 Interpreting Empirical Findings: A Simple Framework

This section proposes a simple model of heterogeneous firms that make firm-level automation decisions to rationalize our empirical findings. Our model is stylized and shares many features with existing models that characterize the sorting of firms based on differences in the decisions they make (e.g., Melitz, 2003; Antras, Fort, and Tintelnot, 2017). Therefore, we highlight key elements

*Table 9.11* Automation and Product-Level Outcomes: Long-Difference Specification

| Dependent Variable: (Log Difference) | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Market Share | | Price | | Quality | |
| Automation | 0.238 | 0.499* | 0.221 | 0.294 | 0.478** | 0.604** |
| | (0.243) | (0.289) | (0.155) | (0.229) | (0.223) | (0.299) |
| Lagged log labor productivity | −0.420*** | −0.484*** | −0.226*** | −0.204*** | −0.473*** | −0.510*** |
| | (0.033) | (0.046) | (0.026) | (0.039) | (0.036) | (0.051) |
| Lagged log employment | −0.178*** | −0.143*** | 0.006 | 0.008 | −0.091** | −0.056 |
| | (0.036) | (0.052) | (0.030) | (0.044) | (0.037) | (0.054) |
| Lagged foreign ownership | 0.173 | 0.106 | 0.180 | 0.057 | 0.303 | 0.107 |
| | (0.129) | (0.185) | (0.113) | (0.219) | (0.137) | (0.244) |
| Lagged export share | −0.065 | −0.168 | 0.217** | 0.129 | 0.159 | 0.056 |
| | (0.108) | (0.130) | (0.106) | (0.123) | (0.120) | (0.140) |
| Lagged import share | 0.105 | −0.121 | 0.127 | 0.186 | 0.263 | 0.314 |
| | (0.193) | (0.276) | (0.124) | (0.249) | (0.188) | (0.351) |
| Lagged log non-production share | | −0.025 | | 0.014 | | 0.005 |
| | | (0.033) | | (0.029) | | (0.037) |
| Lagged log $K/L$ ratio | | 0.034 | | 0.070*** | | 0.089*** |
| | | (0.029) | | (0.024) | | (0.031) |
| Fixed effects | | | HS 4-digit, region | | | |
| No. of observations | 5,871 | 2,851 | 5,871 | 2,851 | 5,871 | 2,851 |

Notes: This table reports how product-level outcomes vary with the imports of automation equipment over time. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Source: Authors' calculation from BPS data.

and main predictions of the model here but leave the technical details in Appendix A for interested readers.

In our framework, automation equipment can be purchased for a fixed cost. This equipment lowers the unit cost of production by offering alternative and better technologies to complete automated tasks in the production process that were previously exclusively performed by human workers. The marginal costs and benefits of automation constitute the trade-offs that firms must consider when deciding whether to automate or not.

We assume that firms differ in productivity. Firms decide the quality of goods they produce; quality is modeled as a residual demand term in a CES preference. Higher quality entails a higher unit cost of production and a higher fixed cost of investment. However, because consumers value higher quality, a firm will consider the marginal costs and benefits of reaching a particular level of product quality so as to maximize profits. As the decision to automate features economies of scale, only firms with sufficiently high productivity find it profitable to automate.

Our model generates several predictions about cross-sectional differences in firm characteristics between automators and non-automators. First, automators have higher output and productivity than non-automators.[21] Second, because automation lowers the unit cost of production for any given level of product quality, automators produce higher-quality products.[22] The model also predicts an ambiguous correlation between firm-level employment and automation because of two opposite forces. On the one hand, a reduction in unit cost leads to a positive size effect that increases demand for labor. On the other hand, automation equipment reduces the share of tasks performed by human workers, leading to a substitution effect that depresses demand for labor. The net effects hinge on which force is dominant and depend on the values of related parameters.

## 5 Conclusions

We conduct an empirical analysis of automation in Indonesia, with a particular focus on how firm-level automation is associated with different firm-level outcomes. We measure direct imports of automation equipment by Indonesian firms and describe patterns of automation by these firms. Combining data on firm-level imports of automation equipment with other micro-level information, we find that automators produce more outputs, hire more workers, and have higher productivity. They also pay higher wages, have lower labor shares, and use capital more intensively. We find further that automators produce a larger variety of outputs, engage more actively in exports and imports, and produce higher-quality goods. Using a firm-level long-difference specification, we find that automators see larger increases in outputs, employment of production workers, export shares, and inferred product quality. Last, we propose a simple theoretical framework of heterogeneous firms that make decisions to automate to rationalize our empirical results.

We offer suggestive evidence on the correlations between automation and other firm and product-level outcomes. To further establish causality, we would need to rely on exogenous shocks or policy changes that affect the costs and benefits of automation. In addition, it would be essential to understand how automation benefits a firm and to identify barriers to automation. For example, does automation facilitate the production of high-quality goods? Do financial constraints prevent a firm from purchasing automation equipment? We plan to extend our future research along these lines.

## Notes

1  In the late 1990s, the textile and apparel industries accounted for about 16% of the manufacturing value added in Indonesia. This figure dropped to about 7% during the 2008–2012 sample period.
2  We observe Indonesia's exports and imports of automation equipment from 2000 to 2019, by type and by Harmonized System 6-digit product code, based on the UN Comtrade WITS database.
3  We define a 'product' as a unique Kode Klasifikasi Industri (KKI) 9-digit code or a unique textual product description.
4  For all firms that imported automation equipment for at least once during 2008–2012, about 42% of them have imported in at least two successive years.
5  As the matched samples consist of medium-sized and large manufacturing firms, the samples may be less subject to entry and exit. However, as we show later, automators are usually large and productive firms amongst this selective sample, so we expect that the inclusion of small firms in future studies (if data are available) would not significantly change the results.
6  Java is one of Indonesia's main islands. It is home to 56% of Indonesia's population as well as some of the country's main businesses and a large number of manufacturing firms. Java accounted for 57% of Indonesia's GDP in 2012.
7  Ideally, the automation indicator should also capture firms' purchases of automation equipment before 2008. Unfortunately, this information is not provided in our data sets.
8  For example, firms that use imported inputs may have lower production costs and larger sales and may find it easier to import automation equipment because they already know how to find suitable suppliers in other countries.
9  Since the decision to automate is endogenous, there is a possibility that $\epsilon_{ft}$ correlates with $\mathbf{a}_{ft}$ due to omitted variables. Therefore, we view our empirical results as descriptive rather than causal.
10  To obtain a simple measure of TFP, we run the following regression:

$$\ln Y_{ft} = \beta^K \ln K_{ft} + \beta^L \ln L_{ft} + \beta^M \ln M_{ft} + \delta_f + \delta_t + \epsilon_{ft},$$

where $Y_{ft}$, $K_{ft}$, $L_{ft}$ and $M_{ft}$ are the gross output value, capital stock, employment, and material cost of firm $f$ in year $t$, respectively. The terms $\delta_f$ and $\delta_t$ are firm-specific and year-specific fixed effects; $\epsilon_{ft}$ is the error term. Measured TFP in log is thus $\ln T\hat{F}P_{ft} = \ln Y_{ft} - \hat{\beta}^K \ln K_{ft} - \hat{\beta}^L \ln L_{ft} - \hat{\beta}^M \ln M_{ft}$.
11  For example, access to export markets may generate larger sales and raise incentives to automate.
12  The number of observations in Table 9.3 column 4 drops significantly because around 35% of the observations in the firm–year sample report zero capital stocks.

13  The number of observations in Table 9.4 column 2 is fewer than in column 1 because some firms in the sample do not report wages or compensation for non-production workers.

14  Again, the number of observations in Table 9.4 column 4 drops because of reported zero values in the capital stock variables.

15  For the purposes of this analysis, we define a 'variety' (or a distinct product) based on whether it has a unique KKI 9-digit code or a unique textual description.

16  Because we subtract industry–year averages when plotting the distributions, observations with negative values appear in the figures.

17  The numbers of observations are close to those reported in the previous firm-level regressions for two reasons. First, around 60% of firms in the sample are single-product firms. Second, not all the products in the sample can be mapped to an HS code.

18  This is mainly because many firms in the sample report a zero value of their capital stocks.

19  According to Aswicahyono and Rafitrandi (2020), the stock of operational industrial robots relative to the number of workers is still low in Indonesia compared to other countries in the Association of Southeast Asian Nations (ASEAN), such as Singapore, Malaysia, Thailand, and the Philippines.

20  For example, regulating and control instruments can help production workers become more efficient in identifying and correcting flaws and defects in the production process.

21  One can extend along the argument of selection to incorporate other cross-sectional features in the data. For example, more productive firms pay higher wages, export more outputs, import more inputs from abroad, and are more likely to automate.

22  The model also explains why the prices of goods produced by automators do not differ from those of goods produced by non-automators. On the one hand, automation directly decreases marginal cost given output quality. On the other hand, by lowering unit cost, automation is also associated with higher quality that increases marginal cost. The magnitudes of these two opposite effects depend on the values of model parameters.

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# A Model Details

Motivated by the empirical evidence, we develop a theoretical framework to understand firm-level automation decisions. The model features cost-minimizing allocation of tasks between labor and automation equipment, heterogeneous firm productivity, endogenous quality choice, and automation decisions subject to variable benefit and fixed cost. We use this model to derive predictions about the cross-sectional features of automators.

## A.1 Allocation of Tasks between Labor and Automation Equipment

We first describe a framework of task allocation to illustrate how a firm decides to allocate its production tasks between labor and automation equipment. Following Acemoglu and Restrepo (2018) and Koch, Manuylov, and Smolka (2021), we assume that each firm produces a final good $y$ by combining a continuum of tasks, $m(v)$, with a constant elasticity of substitution (CES) technology:

$$y(\varphi) = \varphi \times \left( \int_0^1 m(v)^{\frac{\rho-1}{\rho}} dv \right)^{\frac{\rho}{\rho-1}}, \tag{A.1}$$

where $\rho$ is the elasticity of substitution between tasks and $\varphi$ is the Hicks-neutral productivity, which varies across firms. For an automator, every task can be completed by labor or automation equipment. For a non-automator, tasks are completed by labor.

For a given firm $\varphi$, the unit cost of completing $v$ using labor is:

$$c_l(v) = \frac{w}{z_l(v)},$$

and the unit cost of completing $v$ using automation equipment is:

$$c_a(v) = \frac{r}{z_a(v)},$$

where $w$ and $r$ are the cost shifters of using labor and automation equipment to complete tasks, respectively. The terms $z_l(v)$ and $z_a(v)$ denote idiosyncratic efficiency shocks of completing task $v$ using labor and automation equipment, respectively. These idiosyncratic shocks reflect the idea that it may still be

efficient to complete certain tasks using labor because not all tasks are equally 'automatable'.[1] An automator minimizes the cost of completing v by choosing between labor and automation equipment:

$$c(v) = \min\left\{\frac{w}{z_l(v)}, \frac{r}{z_a(v)}\right\}. \tag{A.2}$$

For a non-automator, its unit cost of performing v is simply $\frac{w}{z_l(v)}$.

Following Eaton and Kortum (2002), we assume that $z_l(v)$ for each task is independently drawn from a Fréchet distribution:

$$Pr[z_l(v) \le z] = F_l(z) = \exp\left[-T_l \cdot z^{-\theta}\right], \tag{A.3}$$

where $T_l$ determines the mean of the efficiency draws and $\theta$ governs the dispersion of the efficiency draws when labor is used to perform tasks. $z_a(v)$ for each task is also independently drawn from a Fréchet distribution:

$$Pr[z_a(v) \le z] = F_a(z) = \exp\left[-T_a \cdot z^{-\theta}\right], \tag{A.4}$$

with $T_a$ determining the mean of the efficiency draws when automation equipment is used to perform tasks. The distribution of $c_l(v)$ and $c_a(v)$ are thus:

$$G_l(c) = 1 - F_l\left(\frac{w}{c}\right) = 1 - \exp[-(T_l \cdot w^{-\theta})c^{\theta}]$$

$$G_a(c) = 1 - F_a\left(\frac{r}{c}\right) = 1 - \exp[-(T_a \cdot r^{-\theta})c^{\theta}].$$

For an automator, the distribution of $c(v)$ is

$$G(c) = 1 - \Pi_{s=l,a}[1 - G_s(c)] = 1 - \exp\left[-\left(T_l \cdot w^{-\theta} + T_a \cdot r^{-\theta}\right)c^{\theta}\right]. \tag{A.5}$$

The probability that the firm uses automation equipment to perform a particular task v thus follows:

$$\lambda_a = Pr[c_a(v) \le c_l(v)] = \int_0^{\infty} [1 - G_l(c)]dG_a(c) = \frac{T_a \cdot r^{-\theta}}{T_a \cdot r^{-\theta} + T_l \cdot w^{-\theta}}. \tag{A.6}$$

$\lambda_a$ is also the fraction of tasks that an automator allocates to automation equipment. Therefore, an increase in the overall efficiency of automation equipment, $T_a$, leads to an expansion of the share of automated tasks and, therefore, a decline in the share of tasks performed by labor.

We can also show that, for an automator, the cost distribution of tasks performed by automation equipment and the cost distribution of tasks performed by labor are both $G(c)$ in the equilibrium. Such a no-arbitrage condition is a result from the cost minimization of an automator seeking the lowest cost for each task v across different options (labor and automation equipment).

Therefore, the unit cost of an automator $\varphi$ is:

$$c(\varphi, \mathbf{a}(\varphi) = 1) = \frac{E\left[c(v)^{1-\rho} \mid \mathbf{a}(\varphi) = 1\right]^{\frac{1}{1-\rho}}}{\varphi} = \gamma_0 \cdot \frac{\left(T_a \cdot r^{-\theta} + T_l \cdot w^{-\theta}\right)^{-\frac{1}{\theta}}}{\varphi},$$

(A.7)

where $\gamma_0 = \Gamma\left(1 - \frac{\rho-1}{\theta}\right)^{\frac{1}{1-\rho}}$ is a constant that depends on the value of $\frac{\rho-1}{\theta}$.[2] $\mathbf{a}(\varphi)$ is an indicator function of whether the firm automates or not. Similarly, the unit cost of a non-automator $\varphi$ is:

$$c(\varphi, \mathbf{a}(\varphi) = 0) = \frac{E\left[c(v)^{1-\rho} \mid \mathbf{a}(\varphi) = 0\right]^{\frac{1}{1-\rho}}}{\varphi} = \gamma_0 \cdot \frac{\left(T_l \cdot w^{-\theta}\right)^{-\frac{1}{\theta}}}{\varphi}.$$

(A.8)

Hence, the purchase of automation equipment allows a firm to source tasks from a broader choice set, either from automation equipment or labor, depending on the associated costs. The firm uses automation equipment to complete easily automated tasks and uses labor to complete less automatable tasks. As a result, automation decreases a firm's effective production cost.

While automation lowers production costs for a particular firm, it is also costly because of related purchase, installation, and maintenance costs. We model these costs of automation as a fixed cost $f_a$. The introduction of the automation-related fixed cost follows the assumption in Koch, Manuylov and Smolka (2021). More broadly, our theoretical treatment of the benefits and costs of automation also resembles Antras, Fort, and Tintelnot (2017), who assume that a fixed cost is incurred when a firm chooses to include additional supplying countries in its sourcing strategy. In our setup, automation adoption effectively allows a firm to expand its sourcing of tasks from only *{l}* to *{l, a}*, at the expense of incurring the additional fixed cost $f_a$.

## A.2 Costly Quality Upgrading

A firm $\varphi$ also decides the quality of its output, $z(\varphi, \mathbf{a}(\varphi))$. Increasing product quality is also costly, and we allow for two types of quality upgrading costs. First, the variable cost of producing one unit of goods with quality $z(\varphi, \mathbf{a}(\varphi))$ is:

$$c(\varphi, \mathbf{a}(\varphi)) \times z(\varphi, \mathbf{a}(\varphi))^{\alpha}, \quad \alpha > 0.$$

(A.9)

Higher quality output requires a higher marginal cost of production. Parameter $\alpha$ governs the rate at which the marginal cost of production increases with output quality. This is a standard assumption used in studies about product quality, e.g., Khandelwal (2010); Kugler and Verhoogen (2012).

Second, there is another fixed cost associated with quality investment:

$$z(\varphi, \mathbf{a}(\varphi))^{\xi}, \quad \xi > 1.$$

(A.10)

The fixed cost of quality investment is assumed to be increasing in quality. We

use $\xi > 1$ to capture the diminishing returns to quality investment. A similar assumption about the fixed cost of quality upgrading is also used by Fan, Li, and Yeaple (2015). As will become evident later, the fixed cost of quality investments gives rise to economies of scale related to quality upgrading, so the firm-level quality choice will also interact with the decision to automate.

## A.3 Firm-level Pricing, Sales, and Profit

Next, we discuss how firms make decisions about automation and product quality. Firms produce and supply differentiated goods to their customers. The preference of a representative customer follows a CES form:

$$u = \left( \int_{\omega \in \Omega} [q(\omega) \cdot z(\omega)^\eta]^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}, \sigma > 1, \eta > 0. \tag{A.11}$$

where $q(\omega)$ is the quantity of variety $\omega$ consumed, $z(\omega)$ is the quality of the variety, $\sigma$ is the elasticity of substitution between different varieties, and $\eta$ governs customer's preference for quality relative to quantity. The budget constraint of the customer is:

$$\int_{\omega \in \Omega} p(\omega) \cdot q(\omega) d\omega \leq X,$$

where $X$ is the total expenditure. The demand function of each variety $\omega$ is thus:

$$q(\omega) = z(\omega)^{\eta(\sigma-1)} \cdot p(\omega)^{-\sigma} \cdot P^{\sigma-1} \cdot X. \tag{A.12}$$

The CES quality-adjusted price index $P$ aggregates all active varieties in the market. Conditional on price $p(\omega)$, higher quality $z(\omega)$ increases the demand for a particular variety $\omega$.

Each firm produces one variety, so we index variety $\omega$ using productivity $\varphi$. The market is monopolistically competitive. Given quality $z$ and market-level aggregates $P$ and $X$, a firm's optimal price is

$$p(\varphi, \mathbf{a}(\varphi)) = \frac{\sigma}{\sigma - 1} \cdot c(\varphi, \mathbf{a}(\varphi)) \cdot z(\varphi, \mathbf{a}(\varphi))^\alpha$$

It follows that firm-level sales $x(\varphi, \mathbf{a}(\varphi))$ and profit $\pi(\varphi, \mathbf{a}(\varphi))$ are:

$$x(\varphi, \mathbf{a}(\varphi)) = \left( \frac{\sigma}{\sigma - 1} \cdot c(\varphi, \mathbf{a}(\varphi)) \cdot z(\varphi, \mathbf{a}(\varphi))^{\alpha-\eta} \right)^{1-\sigma} P^{\sigma-1} X$$

$$\pi(\varphi, \mathbf{a}(\varphi)) = \frac{x(\varphi, \mathbf{a}(\varphi))}{\sigma} - z(\varphi, \mathbf{a}(\varphi))^\xi. \tag{A.13}$$

Next, we solve for the optimal quality level $z(\varphi, \mathbf{a}(\varphi))$ given a firm's productivity

$\varphi$ and automation adoption decision $\mathbf{a}(\varphi)$. The maximization problem is

$$\max_{z(\varphi, \mathbf{a}(\varphi))} \frac{1}{\sigma} \left( \frac{\sigma}{\sigma - 1} c(\varphi, \mathbf{a}(\varphi)) z(\varphi, \mathbf{a}(\varphi))^{\alpha - \eta} \right)^{1 - \sigma} P^{\sigma - 1} X - z(\varphi, \mathbf{a}(\varphi))^{\xi}.$$

The optimal quality choice is therefore:

$$z(\varphi, \mathbf{a}(\varphi)) = \gamma_1 \left[ \frac{P^{\sigma - 1} X}{c(\varphi, \mathbf{a}(\varphi))^{\sigma - 1}} \right]^{\frac{1}{\xi - (\eta - \alpha)(\sigma - 1)}}, \tag{A.14}$$

where $\gamma_1 = \left[ \frac{\eta - \alpha}{\xi} \left( \frac{\sigma - 1}{\sigma} \right)^{\sigma} \right]^{\frac{1}{\xi - (\eta - \alpha)(\sigma - 1)}}$. We can further calculate the price of $\varphi$ given its automation decision $\mathbf{a}(\varphi)$:

$$p(\varphi, \mathbf{a}(\varphi)) = \gamma_1^{\alpha} \cdot \frac{\sigma}{\sigma - 1} \cdot c(\varphi, \mathbf{a}(\varphi))^{\frac{\xi \xi - \eta(\sigma - 1)}{\xi - \alpha)(\sigma - 1)}} \cdot (P^{\sigma - 1} X)^{\frac{\alpha}{\xi - (\eta - \alpha)(\sigma - 1)}}. \tag{A.15}$$

Sales and profit for firm $\varphi$ given its automation decision $\mathbf{a}(\varphi)$, are:

$$x(\varphi, \mathbf{a}(\varphi)) = \frac{\zeta^{\tau} \sigma}{(\eta - \alpha)(\sigma - 1)} z(\varphi, \mathbf{a}(\varphi))^{\xi} \pi(\varphi, \mathbf{a}(\varphi))$$

$$= \left[ \frac{\zeta^{\xi}}{(\eta - \alpha)(\sigma - 1)} - 1 \right] z(\varphi, \mathbf{a}(\varphi))^{\xi}. \tag{A.16}$$

We impose $\xi > (\eta - \alpha)(\sigma - 1)$ to ensure that firms earn non-negative profits. Under this parameter assumption, lower production cost, higher price index, and higher demand all lead a firm to choose higher quality, resulting in higher sales and profits.

## A.4 Automation Decisions and Firm-Level Outcomes

We now discuss the automation decision. It entails solving the cut–off productivity, $\varphi_a^*$, at which a firm is indifferent between automation and no automation:

$$\pi\big(\varphi_a^*, \mathbf{a}\big(\varphi_a^*\big) = 0\big) = \pi\big(\varphi_a^*, \mathbf{a}\big(\varphi_a^*\big) = 1\big) - f_a.$$

We can therefore solve $\varphi_a^*$:

$$\varphi_a^* = \frac{\gamma_2 \cdot f_a^{\frac{\xi - (\eta - \alpha)(\sigma - 1)}{(\sigma - 1)\xi}}}{\big(P \cdot X^{\frac{1}{\sigma - 1}}\big) \big[ (T_a \cdot r^{-\theta} + T_l \cdot w^{-\theta})^{\frac{(\sigma - 1)\xi}{\theta[\xi - (\eta - \alpha)(\sigma - 1)]}} - (T_l \cdot w^{-\theta})^{\frac{(\sigma - 1)\xi}{\theta[\xi - (\eta - \alpha)(\sigma - 1)]}} \big]^{\frac{\xi - (\eta - \alpha)(\sigma - 1)}{(\sigma - 1)\xi}}} \cdot \tag{A.17}$$

where $\gamma_2 = \gamma_0 \gamma_1^{\frac{(\eta - \alpha)(\sigma - 1) - \xi}{\sigma - 1}} \left[ \frac{\xi}{(\eta - \alpha)(\sigma - 1)} - 1 \right]^{\frac{(\eta - \alpha)(\sigma - 1) - \xi}{(\sigma - 1)\xi}}$ is a constant term. The numerator of the right-hand side of (A.17) represents the incremental cost of purchasing automation equipment for a given firm $\varphi$, while the denominator multiplied by $\varphi$ is the incremental profit of purchasing automation equipment for that firm. Thus, only firms with $\varphi > \varphi_a^*$ have higher incremental profit than the cost of

automation, and will therefore choose $\mathbf{a}(\varphi) = 1$. The automation decision rule is described in Proposition 1.

**Proposition 1.** *Firms with $\varphi > \varphi_a^*$ purchase automation equipment. Firms with $\varphi < \varphi_a^*$ do not purchase automation equipment. The term $\varphi_a^*$ is defined by (A.17).*

As long as automation features economies of scale, there is selection or sorting into automation. Only firms with sufficiently high productivity will find it sensible to purchase automation equipment because they can take advantage of the resulting reduction in production cost to spread their fixed costs $f_a$ across a greater volume of output. Meanwhile, firms that automate also exhibit higher product quality, larger sales, and higher profit. These 'automation premiums' reflect two factors. First, automators are more productive than non-automators, as shown by Proposition 1. Second, automation leads to a lower production cost $(c(\varphi, \mathbf{a}(\varphi) = 1) < c(\varphi, \mathbf{a}(\varphi) = 0))$.

Intuitively, a higher fixed cost of automation $f_a$ increases the cut–off $\varphi_a^*$. A larger market size $X$ increases aggregate demand and therefore lowers barriers to automation. Finally, a better automation technology (higher $T_a$ or lower $r$) leads to a higher marginal benefit of automation and, therefore, increased automation.

Proposition 2 describes the differences between automators and non-automators in various firm-level outcomes.

**Proposition 2.** *Compare an automator $(\mathbf{a}(\varphi) = 1)$ to a non–automator $(\mathbf{a}(\varphi') = 0)$ where both face the same P and X. The differences in production cost, quality, price, and sales are (note that $\varphi \geq \varphi'$ according to Proposition 1):*

$$
\begin{aligned}
\frac{c(\varphi, \mathbf{a}(\varphi) = 1)}{c(\varphi', \mathbf{a}(\varphi') = 0)} &= \frac{\varphi'}{\varphi} \cdot \frac{(T_a \cdot r^{-\theta} + T_l \cdot w^{-\theta})^{-\frac{1}{\theta}}}{(T_l \cdot w^{-\theta})^{-\frac{1}{\theta}}} = \frac{\varphi'}{\varphi} (1 - \lambda_a)^{\frac{1}{\theta}} < 1 \\
\frac{z(\varphi, \mathbf{a}(\varphi) = 1)}{z(\varphi', \mathbf{a}(\varphi') = 0)} &= \left( \frac{c(\varphi, \mathbf{a}(\varphi) = 1)}{c(\varphi', \mathbf{a}(\varphi') = 0)} \right)^{\frac{1-\sigma}{\xi - (\eta - a)(\sigma - 1)}} > 1 \\
\frac{p(\varphi, \mathbf{a}(\varphi) = 1)}{p(\varphi', \mathbf{a}(\varphi') = 0)} &= \left( \frac{c(\varphi, \mathbf{a}(\varphi) = 1)}{c(\varphi', \mathbf{a}(\varphi') = 0)} \right)^{\frac{\xi - \eta(\sigma - 1)}{\xi - (\eta - a)(\sigma - 1)}} \\
\frac{x(\varphi, \mathbf{a}(\varphi) = 1)}{x(\varphi, \mathbf{a}(\varphi) = 0)} &= \left( \frac{z(\varphi, \mathbf{a}(\varphi) = 1)}{z(\varphi, \mathbf{a}(\varphi) = 0)} \right)^{\xi} > 1.
\end{aligned}
\tag{A.18}
$$

*The difference in total labor compensation is*

$$
\begin{aligned}
\frac{W(\varphi, \mathbf{a}(\varphi) = 1)}{W(\varphi', \mathbf{a}(\varphi') = 0)} &= \frac{x(\varphi, \mathbf{a}(\varphi) = 1)}{x(\varphi', \mathbf{a}(\varphi') = 0)} \cdot (1 - \lambda_a) \\
&= \left( \frac{\varphi'}{\varphi} \right)^{\frac{\xi(1-\sigma)}{\xi - (\eta - a)(\sigma - 1)}} (1 - \lambda_a)^{\frac{1-\sigma}{\theta} \frac{\xi}{\xi - (\eta - a)(\sigma - 1)} + 1}.
\end{aligned}
\tag{A.19}
$$

Recall that $\lambda_a = \frac{T_a \cdot r^{-\theta}}{T_a \cdot r^{-\theta} + T_l \cdot w^{-\theta}}$ is the fraction of tasks performed by automation equipment in an automator. Proposition 2 shows that automation is associated

with decreased unit production costs, increased product quality, and increased sales. The correlations between automation and total labor compensation, however, are ambiguous: while size effect $\frac{x(\varphi, \mathbf{a}(\varphi)=1)}{x(\varphi', \mathbf{a}(\varphi')=0)}$ tends to raise payments to labor by increasing sales; substitution effect $1 - \lambda_a$ tends to depress the share of revenue allocated to labor. Thus, the net effects depend on the parameter values. Likewise, the correlations between automation and product prices are also ambiguous. On the one hand, automation decreases marginal production costs, given a certain level of output quality. On the other hand, by lowering the unit production cost, automation is also associated with quality upgrading that increases the marginal cost. The net effects depend on whether $\xi > \eta(\sigma - 1)$.

## Notes

1 For example, it may be easier to automate the process of assembling parts and components to make a product, but not the design process used to create the product.

2 $\Gamma(\cdot)$ is the Gamma function. Specifically, $\Gamma(z) = \int_0^\infty x^{z-1} \exp(-x) dx$, in which $z$ is a constant.

# 10 AI, Trade, and Creative Destruction: A First Look

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The transformative potential of artificial intelligence (AI) is apparent from our daily use of smartphones. We log in using AI-enabled facial recognition, issue commands with AI-enabled speech recognition, conduct AI-enabled internet searches, buy from stores pushing AI-enabled recommendations, and receive goods shipped with AI-enabled logistics systems. Not only has AI enabled the creation of new services, it has improved on existing services and disrupted older services in a familiar process of creative destruction (Schumpeter, 1942). All of these changes can be seen in the palm of our hand and are meticulously tracked by corporations. This chapter uses big data on international App downloads and AI patents to track how AI is changing the pattern of trade in services, the variety of services available in each country, and the process of creative destruction.

The early hype about AI has given way to more sober analysis showing that to date AI has had limited effects on tasks (Brynjolfsson, Mitchell, and Rock, 2018), employment, and wages (Acemoglu, Autor, Hazell, and Restrepo, 2020). Less is known about AI's impact on international trade either theoretically or empirically. In this chapter we explore that impact on (*a*) bilateral trade flows, (*b*) the variety of goods imported, and (*c*) the creation and destruction of varieties. The impact of AI on trade flows is of great interest, but ultimately we care about welfare. We thus also calculate the welfare effects due to AI-induced changes in the availability of varieties to consumers.

There is good reason to expect all three of the previous impacts. (*a*) For bilateral trade flows, McKinsey Global Institute (2019) predicts that AI will reduce outsourced business process and IT services. It will also reduce goods trade by facilitating additive manufacturing that moves production to the point of consumption. McKinsey predicts that together these developments will reduce trade by a trillion dollars. Of course, this reduction in trade tells us nothing about AI's impact on welfare. Indeed, in McKinsey's scenario, trade volumes and welfare likely move in opposite directions. (*b*) For product variety, AI leads both to new services (horizontal differentiation) and to improvements on existing services (vertical differentiation). These are known to affect the pattern of trade and the welfare gains from trade, usually in positive ways. See Krugman (1979), Helpman (1981), Feenstra (1994, 2010), Melitz (2003),

Broda and Weinstein (2006), and Hsieh, Li, Ossa, and Yang (2020) for analysis of horizontal differentiation. (*c*) For creative destruction, AI's impact on vertical differentiation disrupts and displaces existing services. On this process of creative destruction through endogenous innovation see Aghion and Howitt (1992) and Akcigit and Kerr (2018) for closed-economy models and Grossman and Helpman (1991*a,b*) for both closed- and open-economy models.

Despite intense public interest in AI, research on the impacts of AI on trade, product variety and creative destruction is almost nonexistent. Goldfarb and Trefler (2019a) review the theoretical issues for international trade raised by AI. They argue that key features of AI are scale, local knowledge diffusion, and the degree of international knowledge diffusion. Scale and local knowledge diffusion/externalities have implications for trade flows that have long been understood in the economic geography literature. As well, the degree of local versus international diffusion is central to the endogenous growth literature e.g., Rivera-Batiz and Romer (1991), Grossman and Helpman (1991b) and Irwin and Klenow (1994). Goldfarb and Trefler (2019a,b) also argue that AI affects trade costs in complex ways. For example, privacy concerns create additional trade costs not usually considered by international trade economists. Further, interstate competition can create national regulatory responses best characterized as a privacy race to the bottom. Royal Society-National Academy of Sciences (2019) summarizes the proceedings of a Washington D.C. symposium on international harmonization of AI regulations, including a summary of Goldfarb's and Trefler's views.

The only empirical paper directly on AI and trade is by Brynjolfsson, Hui, and Liu (2019). They show that eBay's introduction of a machine translation system increased its exports by 17.5%. This is the opposite of McKinsey Global Institute's (2019) speculations. Our work is closely related to Brynjolfsson et al. The advantage of their approach is that it carefully identifies the exact AI (machine translation) and the exact mechanism for eBay. In contrast, we will work with a wide set of AIs, companies, and services. This allows us to employ the standard gravity equation for examining impacts on trade as well as product variety and creative destruction.

There are other more distantly related papers. Beraja, Yang, and Yuchtman (2020) show how Chinese government security contracts for facial recognition software provided confidential security data to Chinese firms, data that improved these firms' products. By implication, the paper shows how government subsidies in the AI sphere can improve competitiveness. More tangential to our interests here, Bailey, Gupta, Hillenbrand, Kuchler, Richmond, and Stroebel (2020) use Facebook data to construct bilateral social connections between countries and show that these are a more powerful determinant of bilateral trade flows in *goods* than are traditional determinants such as distance and borders. Though tangential to our main results, we include their bilateral social connections measure and find that it impacts App-based service trade as well.[1]

This review, even if missing some citations from the rapidly growing AI literature, clearly demonstrates that the literature on AI and trade is very small. This is

in part because trade in AI-enabled services is hard to document. At the core of this chapter is the observation that there is actually a vast amount of data available.

Motivated by the tremendous amount of AI that underlies our smartphone Apps, this chapter is about international trade in mobile App services as well as its implication for product variety and creative destruction. The core of our analysis is based on two types of data. The first is data from a private data provider (SensorTower) on the number of mobile App downloads by App, by producer country, and by user country for the period 2014–2020. The second data source is Bureau van Dijk's Orbis Intellectual Property patent database. We adopt the methodology behind the WIPO PATENTSCOPE Artificial Intelligence Index to determine whether or not a patent in Orbis is an AI patent. We review this complex methodology in Section 2.3. A difficult part of building our database is merging the App and patent databases. Each app in the SensorTower data is identified with an ultimate owner. For example, Alphabet owns Google Chrome, Nest Home, YouTube, Waze, and Fitbit. We then match ultimate owners with those in Orbis. We do the match by hand for the 834 ultimate owners with the most downloads globally. We show in the following that the Apps and ultimate owners excluded from our analysis are mostly small and obscure.

We use information about each ultimate owner's Apps, AI patents, and assets to develop a measure of 'App-deployment' by year, exporter, and App category. App categories are defined as follows. The Apple App Store places Apps into 19 App groups (e.g., social networking, productivity). We further refine each group by 19 2-digit NACE industries (e.g., mining, finance). We refer to this cross of groups × industries as 'App categories'. There are 292 categories. Aggregating up from Apps and ultimate owners, we compute AI patent counts by category × exporter × year bins. This is our novel measure of AI deployment by category × exporter × year bins. (We scale this measure by the value of assets held by firms in the bin; however, our results are not sensitive to this scaling.)

We can summarize our database handily by comparing it to COMTRADE, the standard international trade database used for gravity estimation. We have 53 exporters, 84 importers, seven years (2014–2020), and 292 App categories (App categories are like HS2 or HS4 codes in COMTRADE). Further, many studies of creative destruction and changes in the number of traded varieties (e.g., Broda and Weinstein, 2006) define varieties as US HS10 product lines. There are roughly 20,000 HS10 codes/varieties. In contrast, we have 82,850 Apps/varieties.

Our main results flow from regressions of various outcomes on our AI deployment measure. An obvious concern is the endogeneity of AI deployment. We therefore need an instrument that captures exogenous shocks to the cost of deployment. Heckscher-Ohlin theory provides one. A country with deep AI expertise will have cheap and ready access to the inputs used in deploying AI, which in turn provides a cost advantage that is especially pronounced in App categories that use these inputs intensively. We therefore instrument App deployment with the interaction of (1) a country's *AI expertise* as measured by its AI

research output and (2) an App category's *AI intensity*. This serves as an exogenous shifter of the costs of AI deployment.[2]

We have three main IV findings. All of them exploit within-App-category variation.

1. *Bilateral Trade*: We estimate a gravity model of App downloads whose dimensions are importer-exporter dyads, App categories, and years. Using IV, we find that AI deployment causes a sixfold increase in App downloads.

Beyond the Brynjolfsson et al. study of eBay's use of machine translation, this is the first and most systematic evidence of the impact of AI on trade.

2. *Varieties*: AI deployment doubles the number of bilaterally traded Apps/varieties.
3. *Creative Destruction and Welfare*:
    (a) *Entry and Exit*: AI deployment causes high levels of entry into and exit out of the Apps/varieties available in the importer country. That is, it causes creative destruction.
    (b) *Welfare*: We calculate the welfare implications of entry and exit using Feenstra's (1994, 2010) technique. We find that in 2020, welfare from Apps was 2.5% higher than it would have been under the counterfactual of no AI deployment. Both are large numbers and the range depends on whether the elasticity of substitution between Apps is high (5) or low (2). An important caveat is that in the Feenstra formula we use download shares rather than expenditure shares.

These three results demonstrate that AI deployment in the mobile App space has already had tangible effects on trade, product variety, creative destruction, and welfare.

One might wonder whether our conclusions are the result of a spurious correlation between AI patenting and other unobservables. To examine this, we consider non-AI patents and find that their effects are modest and their inclusion in the analysis does not affect our results.

Section 1 provides background on mobile Apps and AI. Section 2 describes the database. Section 3 uses bilateral gravity equations to estimate the impact of AI deployment on trade. Section 4 estimates the impact of AI deployment on the extensive margin, that is, on the number of Apps/varieties. Section 5 examines the impact of AI deployment on entry, exit, creative destruction and welfare.

## 1  A Brief Overview of Apps and AI

As wireless internet technology and personal portable devices have come down in cost and risen in accessibility, mobile applications have become a fixture of daily life. In 2020, the number of mobile internet users hit 4.3 billion globally or 92%

of all internet users.[3] Each and every day we use mobile applications to read our mail, browse the internet, post to our social network, shop, bank, take photos, play games, watch videos, and more. The mobile application industry has been fast-growing and will continue to expand at a significant pace. It currently generates upwards of $700 billion in revenues and is growing rapidly.[4]

The biggest two application marketplaces, App Store (for iOS) and Google Play (for Android), launched in 2008 alongside the release of the first smartphones (iPhone 3G and T-mobile G1). At the time, these two application marketplaces had about 500 Apps. Today the App Store has 1.82 billion Apps and Google Play has 2.8 billion Apps.

Turning from Apps to AI, Agrawal, Gans, and Goldfarb (2018) define AI as a collection of complementary technologies involving algorithms, data, and computing power that allow predictive programs to automatically improve their performance through experience. The authors date the commercial introduction of AI to 2012. Since then, some of the companies that have pushed the frontiers of AI have grown to be among the biggest in the world. Table 10.1 lists the eight largest companies in the world by market capitalization. Column 2 is 2020 market capitalization in millions USD. Every one of these companies uses AI to improve its services and expand its service offerings. One, albeit limited, indication of this is the number of AI patents held by these companies. These companies have a large number of such patents. (We do not have data for Tesla, which is not in our dataset.)

*Table 10.1* The World's Largest Companies: AI, Growth, Location, and Internationalization

| Company | Market Cap ($B) | AI Patents | 2011 Rank | Nationality | Total Downloads Worldwide (millions) | Foreign Share |
|---|---|---|---|---|---|---|
| (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| 1. Apple | $2,254 | 1,071 | 3 | USA | 151 | 76% |
| 2. Microsoft | $1,682 | 7,088 | 10 | USA | 4,023 | 81% |
| 3. Amazon | $1,634 | 509 | 77 | USA | 3,015 | 69% |
| 4. Alphabet | $1,185 | 5,675 | 28 | USA | 16,155 | 81% |
| 5. Facebook | $777 | 1,243 | <500 | USA | 21,913 | 91% |
| 6. Tencent | $683 | 2,930 | 178 | China | 7,160 | 22% |
| 7. Tesla | $668 | - | <500 | USA | - | - |
| 8. Alibaba | $629 | 1,767 | <500 | China | 5,065 | 52% |

Notes: Data for 2011 and 2020 are as of December 31. See https://en.wikipedia.org/wiki/List_of_public_corporations_by_market_capitalization#2020. Market capitalization is in millions USD. 2011 ranks are from the *Financial Times* FT500 as of March 31, 2011 (http://media.ft.com/cms/33558890-98d4-11e0-bd66-00144feab49a.pdf). AI patents are computed by the authors as described in the following. '<500' means the company is not on the list. Data on Tesla's AI patents are not part of our database, but the company is at the frontier of AI algorithms for autonomous vehicles. Google Play is not available in China, so Android App downloads in China are imputed in this table. We estimate China's total downloads as China's iOS downloads divided by the market share of Apple devices in China (21.8% in 2020).

Two things stand out in the table. For one, with the exception of Apple and Microsoft, these companies had relatively little presence in the 2011 list of the largest companies in the world. Indeed, Facebook, Tesla and Alibaba were not even in the top 500. This illustrates just how dynamic these companies are and, by implication, how dynamic are the effects of AI likely to be. For another, all of these companies are based either in the United States or China. This has led Kai-Fu (2018), former CEO of Google China, to argue that in the future these two countries will produce all AI-enabled services, and the rest of the world will be stuck paying hefty royalties. This potentially has dramatic implications for the pattern of international service trade flows.

Table 10.1 makes two other points about these companies. Column 6 shows that these firms all have heavily downloaded Apps, an average of 8 billion per firm. Column 7 shows that these Apps are heavily downloaded internationally. On average, 61% of these firms' downloads are done outside of the firms' home countries. This fact is not unique to our top-tier companies: The median value of foreign download shares is 64% in our sample of 834 firms. This is quite remarkable compared to the goods economy where all but a few of the largest multinationals earn most of their revenue in their home markets. Thus, App services are much more internationalized than say manufacturing. Interestingly, the Chinese companies in one table are much less internationalized than their US counterparts.

## 2 The Data

### 2.1 Mobile Application Data

Our primary database is the App download data purchased from SensorTower. SensorTower is the largest and most reliable company providing App-level metadata. The data track App-level downloads by user country from 2014 to 2020 for the Apps available in the Apple App Store and Google Play, which are the biggest application marketplaces for the iOS and Android operating systems.[5] Each App in the Apple App Store and Google Play has a unique, time-invariant product ID and is accompanied by the name of the developer, the name of the selling publisher (App terminology for 'firm'), and the selling publisher's website. Sensor-Tower consolidates App IDs to deal with the fact that an App may have different IDs in different countries, e.g., TikTok in the US and Douyin in China. We use consolidated IDs to avoid overstating the number of Apps. SensorTower also creates a 'unified' firm name that keeps track of the fact that publishers often have different names in different countries and sometimes have different names across wholly owned subsidiaries. We use the unified firm name to link with patent and financial data.

The App Store and Google Play place Apps into groups.[6] These are displayed in Table 10.2 along with the top-3 Apps in the group. For each App, the table also shows the company and its headquarters country. Most of the top Apps are owned by large digital platforms located in the US and China.

*Table 10.2* App Categories

| Group | AI Patents | Single-category AI Patents | Top 3 Apps by Download in 2020 |
|---|---|---|---|
| Games | 5,560 | 1,270 | Garena Free Fire (Garena, Singapore), PUBG MOBILE (PUBG, Singapore), Subway Surfers (Sybo Game, Denmark) |
| Photo and Video | 4,357 | 295 | Instagram (Facebook, US), Snapchat (Snap, US), Likee (Bigo, US) |
| Utilities | 14,193 | 632 | UC-broswer (Alibaba, China), Truecaller (True Software, Sweden), Chrome (Google, US) |
| Social Networking | 1,448 | 16 | Whatsapp (Facebook, US), Facebook (Facebook, US), Messenger (Facebook, US) |
| Entertainment | 6,417 | 307 | TikTok (ByteDance, China), Netflix (Netflix, US), Youtube (Google, US) |
| Shopping | 3,442 | 412 | Amazon (Amazon, US), Wish (ContextLogic, US), Shopee (Shopee, Singapore) |
| Music | 1,601 | 528 | Spotify (Spotify, Sweden), Youtube Music (Google, US), Shazam (Apple, US) |
| Finance | 11,791 | 2,608 | Google Pay (Google, US), Paypal (Paypal, US), Caixa Tern (Caixa Economica Federal, Brazil) |
| Education | 13 | 12 | Google Classroom (Google, US), YouTube Kids (Google, US), Duolingo (Duolingo, US) |
| Productivity | 7,621 | 59 | Shareit (SHAREit, China), Gmail (Google, US), Microsoft Word (Microsoft), Word (Microsoft, US) |
| Business | 3,225 | 2,861 | Zoom (Zoom, US), Google Meet (Google, US), Microsoft Team (Microsoft, US) |
| Lifestyle | 20,133 | 2,871 | Pinterest (Pinterest, US), Tinder (IAC, US), Airtel Thanks (Bharti Airtel, Indian) |
| Sports, Health, and Fitness | 1,608 | 1,569 | Aarogya Setu (NIC, India), Home Workout (ABISHKKING, Singapore), Mi Fit (Xiaomi, China) |
| Books, News, and References | 183 | 175 | Wattpad (Wattpad, Canada), Amazon Kindle (Amazon, US), Audible (Audible, US) |
| Travel | 1,892 | 160 | Uber (Uber, US), Google Earth (Google, US), Booking.com (Booking.com, Netherlands) |
| Food and Drink | 52 | 22 | |

*(Continued)*

*Table 10.2*  (Continued )

| Group | AI Patents | Single-category AI Patents | Top 3 Apps by Download in 2020 |
|---|---|---|---|
| Navigation | 6,991 | 4,041 | McDonald's (McDonald's, US), Uber Eat (Uber, US), Domino's Pizza (Domino's Pizza, US) Google Map (Google, US), Waze (Google, US), Gaode Map (Alibaba, China) |
| Weather | 12,280 | 10,747 | Whether&Radio (WetterOnline, German), The Weather Channel (IBM, US), Whether Forcast (Smart-Pro, Indian) |
| Medical | 303 | 251 | NHS COVID-19(GOV, UK), COCOA(GOV, Japan), Pregnancy + (Health&Parenting, UK) |
| **Total** | **103,110** | **28,836** | |

Notes: Groups are ordered by downloads with the most downloaded group on top. Some firms have patents in multiple categories. Since we cannot assign all patents to groups (see Table 10.3) and since we want to avoid double counting patents in the "AI Patents" column, we assign all of a firm's patents to its largest (most downloaded) group. We do this for this table only.

*Table 10.3* Summary Statistics of Downloads: Full Sample and Subsample

| | | | | Percentiles | | |
|---|---|---|---|---|---|---|
| Sample | N | Mean | Std. Dev. | 10th | 50th | 90th |
| Full Sample | 78,042,301 | 7,819 | 231,443 | 2 | 35 | 3,514 |
| Subsample | 4,733,652 | 47,204 | 841,535 | 2 | 107 | 22,496 |

This table reports statistics on the number of Apps and their downloads. An observation refers to a unique App × importer × year triplet where importer is the country downloading the App. *N* is the number of observations. The columns report moments of the distribution of downloads across App-importer-year observations.

One obvious issue with groups is that they are not fine enough to be useful. For example, the 'Utilities' group includes Google's Chrome and Toyota's DV, an application for real-time video display. To deal with this we interact the 19 App groups with the 19 2-digit NACE industries to define 292 *App categories* at the level of App group × NACE industry.[7]

There are billions of Apps in the App Store and Google Play, many of which have no downloads or just one or two. It is not computationally feasible to deal with terabytes of such data. We therefore initially restrict the sample by selecting the 1,000 most downloaded unified firms. Over our 2014–2020 sample period these unified firms had 223 billion downloads of 82,850 Apps.

We are using download data whereas revenue data would be better. To show that the two are correlated, we divide our Table 10.3 subsample into two bins,
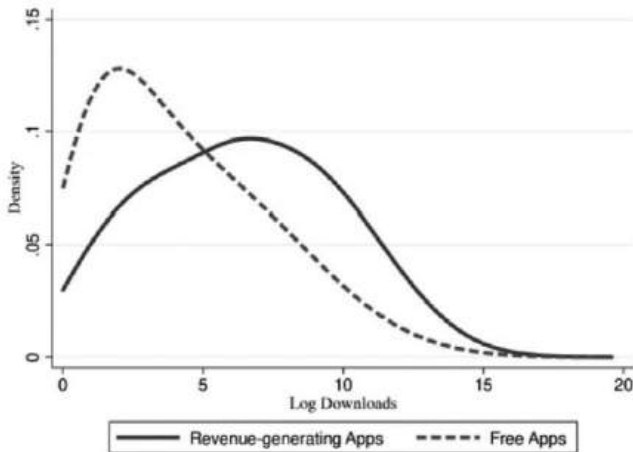
*Figure 10.1* Distributions of log Downloads: Free vs. For-Pay Apps

one for Apps with revenues and one for Apps without revenues. In Figure 10.1 we plot the kernels of log downloads separately for the two bins. The kernel for revenue-generating App downloads is substantially right-shifted relative to the kernel for free App downloads. This illustrates that more-downloaded Apps tend to be revenue-generating Apps.

## 2.2 Linkage to Patent and Financial Data

Our core analysis is about the impact of AI on a variety of trade and welfare outcomes. We will be measuring AI using patent data. We use SensorTower's unified firm names to link with the Bureau Van Dijk Orbis Intellectual Property database. This provides us with patent and financial data. We were unable to reliably match firm names across the two data sets using machine learning tools. We therefore select the largest 1,000 unified firms in the world (as measured by global downloads) and then find by hand their global ultimate owners in the Orbis database. We match 834 of the 1,000 firms. Unlike many studies, there is no linkage error here.[8]

To investigate the representativeness of our sample we also looked at the 100,000 unified firms with the most downloads—these are not matched to patent and financial data—and call this the 'full sample'. Table 10.3 displays summary statistics for the full sample and our subsample.[9] Two things stand out. First, our sample is skewed towards unified firms with large downloads (see the 90th percentile column). Second, both samples have 10th percentile downloads that equal 2 so that our sample differs from the full sample primarily in dropping Apps with extremely small download numbers.

This vividly illustrates that our sample selection criteria do not drop any major apps or firms. One would be hard pressed to recognize any of the Apps excluded from our analysis. The highest-ranked App excluded from our data is slither.io,

an obscure action game from Kooapps. The highest-ranked firm not in our data is SayGames, an obscure game startup from Belarus whose most popular App is Twist Hit!. In short, we do not think that our subsample excludes any important Apps or that conclusions drawn from it are biased for our set of questions.

## 2.3  AI Patent Data

To estimate the impact of AI on trade and welfare we need to be precise about what we mean by AI and how we measure it. We use AI-related patents as the basis of our measure. From the Orbis data we know the 10,144,089 patents assigned to our 834 firms. We categorize each of these patents as AI or non-AI patents following the WIPO (2018, 2019) methodology. For each patent we check if it meets one of three criteria.

1. The main and/or minor CPC codes are on a list of CPC codes that WIPO uses to identify specific AI technologies. For example, CPC subclass G10L-015 is speech recognition.
2. The title and/or abstract contains a phrase that is on a keyword list that WIPO uses to identify specific AI technologies. The list includes phrases such as 'machine learning' and 'neural network' along with extensions of these phrases such as 'neural networks' and 'neural-network'.
3. Some patents are about AI, but not about a specific AI technology. Here WIPO combines a CPC code with a keyword to identify an AI patent. For example, GTL-013is speech synthesis (text to speech), which may or may not involve AI. However, if a patent in CPC subclass GTL-013 has a title or abstract with keywords such as 'backpropagation' or 'self learning' then WIPO identifies it as an AI patent.

Table 10.4 gives examples of AI patents identified through each of the previous three methods. We have duplicated the WIPO methodology with one exception. Their keyword search is over the English title, English abstract, English claims, and English object of invention. Our keyword search is over the English title and English abstract.

Our procedure identifies 103,110 patents as AI patents and the remaining 10,038,168 patents as non-AI patents. Column 2 of Table 10.2 displays the number of AI patents by App group. Among the 834 firms, 309 firms own at least one AI patent. Finally, our AI patents grow rapidly from 1990 to 2020.

When we speak of a firm's AI patents in year $t$ we will mean its cumulative AI patent applications from 1990 to year $t$. That is, our AI patents are a *stock* of patent applications. Using applications rather than grants avoids the worst of the right-truncation problem associated with delays in granting patents.

## 2.4  AI Deployment in Apps

We require a measure of the AI deployed in each App category. If each firm's Apps were in a single App category this would be an easy matter of counting

*Table 10.4* Examples for AI Patents

| Current Onwner | Patent Number | CPC Classification Criterion | Specific AI Technology | Keywords | Portion of Abstract |
|---|---|---|---|---|---|
| **Method 1: Patent Class** | | | | | |
| Facebook | US20190012697A1 | G06Q30/0242 | G06Q - Data processing sustems; 30 - Commerce; 0242 - Determination of advertisement effectiveness | N/A | A client relationship management (CRM) application can generate a ranked list of client engagement tools by computing a rank score for available client engagement tools and determining an order among the available client engagement tools based on the rank scores. The CRM application can use one or more trained prediction models and business rules to compute a prediction for success for client engagement tools. |
| **Method 2: Keywords** | | | | | |
| Microsoft | EP3424044A1 | **N/A** | N/A | deep learning | The technology described herein uses a modular model to process speech. A **deep learning** based acoustic model comprises a stack of different types of neural network layers. |

(*Continued*)

*Table 10.4* (Continued )

| Current Onwner | Patent Number | CPC Classification Criterion | Specific AI Technology | Keywords | Portion of Abstract |
|---|---|---|---|---|---|
| **Method 3: Patent Class phis Keywords** | | | | | |
| Microsoft | KR1020130110565A | G06Q10/109 | G06N - Computer sustems based on specific computational models; 10 - Administration; Management; 109 - Time management | predictive models | The present invention relates to a system and methodology to facilitate collaboration and communications between entities such as between automated applications, parties to a communication and/or combinations thereof. The systems and methods of the present invention include a service that supports collaboration and communication by learning **predictive models** that provide forecasts of one or more aspects of a users' presence and availability. |

the AI patents of all firms producing Apps in the category. Unfortunately, a large number of firms (ultimate owners) have Apps in multiple categories. For example, the ultimate owner Alphabet controls Google, Nest, YouTube, Waze, and Fitbit, all of which operate in different App categories. We therefore purify our measure of the AI deployed in App categories by adapting to our setting the approach of De Loecker, Goldberg, Khandelwal, and Pavcnik (2016). In estimating production-function parameters they only include single-product firms. We define a single-category firm as a firm whose primary category accounts for over 85% of its total downloads.[10] Column 3 of Table 10.2 shows the AI patents owned by single-category firms. There are 28,836 such patents and they account for a substantial 28% of all AI patents in our sample. There are 549 single-category firms (including some with zero patents) among the 834 firms in our sample. Together they account for 42% of all downloads in our sample.

We construct our measure of the AI deployment of an App category only from the patents of single-category firms. Let $Patent_{cxt}$ and $K_{cxt}$ be AI patent application stocks and total assets summed across all single-category firms in country $x$ in year $t$ that produce Apps only in category $c$. $AI_{cxt} = Patent_{cxt}/K_{cxt}$ will be our key measure of AI deployment.[11]

It is of independent interest to know about the AI patents of multi-category firms. In every specification reported later we have also examined the same specification but with the addition of a variable that captures the AI deployment of multi-category firms. To this end, we define $multipleAI_{cxt}$ as the total AI patent application stocks over total assets for multi-category firms from country $x$ with Apps in category $c$ in year $t$.[12] To control for the general effects of patenting, we also construct $nonAI_{cxt}$ as the total non-AI patent application stocks over total assets for all firms in category $c$, country $x$ and year $t$. In our regressions, adding these two variables *never* affects the magnitude or statistical significance of the coefficients on our AI deployment variable $AI_{cxt}$.

## 2.5 Summary Statistics

Table 10.5 reports summary statistics of our data. Each observation is uniquely identified by an App category (292), an exporter (53), an importer (84) and a year (2014–2020). We have 469,879 observations with positive levels of downloads. There are several points to note about the sample size. First, we do not work at the firm level and this requires an explanation. We do not know whether any given App uses AI so we cannot work at the level of a firm's Apps. What we do know is the extent to which AI is deployed in an App category in an exporter country. So we must aggregate up from firms to App-categories and exporters. Second, we exclude zero downloads, but return to this later using PPML. Third, Google Play is banned in China, so we only have Apple App Store data for Chinese downloads. We thus exclude observations for which China is the importer. Note however that we keep China as an exporter and that including China as an importer makes no difference to our results.

*Table 10.5* Summary Statistics

|  | N | Mean | sd |
|---|---|---|---|
| ***App Downloads:*** | | | |
| Total downloads: $\ln(y_{cmxt})$ | 469,879 | 6.45 | 3.95 |
| Number of Apps: $\ln(N_{cmxt})$ | 469,879 | 1.05 | 1.19 |
| Average downloads: $\ln(\bar{y}_{cmxt})$ | 469,879 | 5.40 | |
| ***Patent Variables:*** | | | |
| AI Patents: $\ln(1+AI_{cxt})$ | 469,879 | 0.13 | 0.60 |
| AI Multiple: $\ln(1+multipleAI_{cxt})$ | 469,879 | 0.60 | 0.90 |
| Non-AI patents: $\ln(1+nonAI_{cxt})$ | 469,879 | 2.96 | 2.78 |

Notes: The table presents summary statistics of variables used in the gravity equations of Section 3. Each of the 469,879 observations is uniquely identified by an App category $c$, a downloading user country or importer $m$, a producing country or exporter $x$, and a year $t = 2014,...,2020$. To be included, the *cmxt* observation must have strictly positive downloads.

Table 10.5 reports the dimensions of each variable. These are App category $c$, importer $m$, exporter $x$, and year $t$. We winsorize the top 1% of observations for the download and patent variables. From the first line of the table, the mean downloads of a *cmxt* observation is 633 ( $= e^{6.45}$), the mean number of Apps is 2.85 ( $= e^{1.05}$), and the mean downloads per App is 221 ( $= e^{5.40}$). The latter illustrates that when we report results *within* App category, the analysis is at a very fine level.

## 3 AI and Trade: Bilateral Gravity

We estimate the following gravity equation:

$$\ln(y_{cmxt}) = \beta \ln(1 + AI_{cxt}) + \theta X_{cmxt} + \alpha_{mxt} + \alpha_{cm} + \varepsilon_{cmxt}; . \tag{1}$$

In this regression $y_{cmxt}$ is downloads by consumers in country $m$ of Apps in category $c$ produced by firms headquartered in country $x$. We are interested in international trade in this section so we exclude domestic observations, i.e., observations for which the importer is the exporter. Including these observations does not affect our conclusions. Since we only include non-zero trade flows, $y_{cmxt} \geq 1$. Our key independent variable is $\ln(1+AI_{cxt})$ and our hypothesis is that AI deployment increases trade ($\beta > 0$). $X_{cmxt}$ is a set of gravity variables. $\alpha_{mxt}$ and $\alpha_{cm}$ are the fixed effects. The only other fixed effect that we can add while still identifying $\beta$ is $\alpha_{cx}$. Adding these weakens our results because $\ln(1+AI_{cxt})$ has relatively limited variation across time. Aside from this, our results are not at all sensitive to the choice of fixed effects.

Table 10.6 reports the OLS results. In column 1, we examine whether standard gravity covariates from CEPII behave the same way for App trade as they do for goods trade.[13] To this end we consider the full sample, that is, before restricting it by linking to Orbis data. (See Section 2.2.) We include an importer fixed effect, an exporter fixed effect, a year fixed effect and a category fixed effect. Log distance between $m$ and $x$ matters but is much smaller than the median

*Table 10.6* Gravity Equation: Independent Variable is ln($y_{cmxt}$)

| | OLS | | | | | | |
|---|---|---|---|---|---|---|---|
| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* | *(7)* |
| ln($1 + AI_{cxt}$) | | 1.21*** | 1.33*** | 1.20*** | 1.13*** | 1.04*** | 1.04*** |
| | | (0.194) | (0.225) | (0.203) | (0.210) | (0.200) | (0.197) |
| ln($1 + multipleAI_{cxt}$) | | | | | 1.02*** | 0.80*** | 0.80*** |
| | | | | | (0.239) | (0.252) | (0.246) |
| ln($1 + nonAI_{cxt}$) | | | | | | 0.14*** | 0.14*** |
| | | | | | | (0.042) | (0.041) |
| ln(Distance$_{mx}$) | –0.39*** | –0.37*** | –0.23*** | | | | |
| | (0.036) | (0.058) | (0.038) | | | | |
| Contiguous$_{mx}$ | 0.38*** | 0.35*** | 0.31*** | | | | |
| | (0.073) | (0.105) | (0.106) | | | | |
| Common Language$_{mx}$ | 0.76*** | 0.53*** | 0.39*** | | | | |
| | (0.106) | (0.097) | (0.105) | | | | |
| Colonial Dependence$_{mx}$ | 0.08 | 0.39*** | 0.31*** | | | | |
| | (0.138) | (0.122) | (0.115) | | | | |
| Regional Trade Agreement$_{mxt}$ | 0.11** | 0.03 | –0.10 | | | | |
| | (0.054) | (0.067) | (0.066) | | | | |
| ln($GDP_{xt}$) | 0.04 | 0.18 | –0.01 | | | | |
| | (0.336) | (0.335) | (0.302) | | | | |
| ln($GDP_{mt}$) | –0.11 | –0.01 | –0.06 | | | | |
| | (0.630) | (0.321) | (0.340) | | | | |
| Social Connectedness Index$_{mx}$ | | | 0.18*** | | | | |
| | | | (0.055) | | | | |
| Constant | 12.43 | 5.53 | 8.29 | 6.29*** | 5.69*** | 5.42*** | 5.43*** |
| | (13.964) | (9.253) | (9.021) | (0.022) | (0.144) | (0.168) | (0.168) |
| Observations | 774,414 | 468,679 | 399,873 | 465,955 | 465,955 | 465,955 | 464,567 |
| Fixed effects | *t, m, x, c* | *t, m, x, c* | *t, m, x, c* | *t-m-x, c* | *t-m-x, c* | *t-m-x, c* | *t-m-x, m-c* |

(*Continued*)

*Table 10.6* (Continued )

| | OLS | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- |
| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* | *(7)* |
| $R^2$ | 0.559 | 0.386 | 0.396 | 0.429 | 0.448 | 0.451 | 0.486 |
| Within $R^2$ | 0.033 | 0.040 | 0.044 | 0.027 | 0.059 | 0.063 | 0.065 |

Notes: Each observation is an App category ($c$), a downloading country or importer ($m$), an App producing country or exporter ($x$) and a year ($t$ = 2014, ..., 2020). The dependent variable is the log of the number of downloads, $\ln(y_{cmxt})$. In column 1 we use the full sample covering all Apps (we do not restrict the sample to firms that can be linked to Orbis). In columns 2–7, we use our subsample of 834 firms to construct a panel of 292 App categories, 53 exporters, 84 importers, and 7 years. In the fixed effect rows, *t-m-x* and *m-c* refer to year-importer-exporter and importer-category fixed effects, respectively. The number of observations is degrees-of-freedom corrected as calculated by Stata's reghdfe command and so declines as more fixed effects are added. Standard errors are based on two-way clustering by importer and by exporter. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

estimate of -0.85 reported in Head and Mayer's (2014) meta-analysis of gravity studies. That distance plays less of a role in digital trade will come as no surprise. The coefficient on contiguity is a little smaller than in Head, and the coefficient on common language is just a little larger. We also include dummies for whether $m$ and $x$ were ever in a colonial relationship and whether they are in the same regional trade agreement. These covariates are less significant and much smaller than in Head and Mayer. The importer GDP and exporter GDP coefficients are very small, but this is not surprising given that they do not vary much over our period 2014–2020 and so are largely soaked up by the fixed effects. We do not include the populations of either $m$ or $x$ because these are also largely soaked up by fixed effects.

In column 2, we use our subsample matched with patent and financial data to estimate equation 1. The coefficients on the gravity covariates do not change, which provides evidence that our sample is representative in dimensions familiar to trade economists. Crucially, the estimate of $\beta$ is positive and significant. In OLS, AI deployment is correlated with downloading.

In column 3 we include the Bailey *et al.* (2020) index of pairwise social connectedness. Their index is based on an anonymized snapshot of all friendship links on Facebook. It is the log of the relative probability of a friendship link between a Facebook user in $m$ and a Facebook user in $x$. The coefficient on social connectedness of 0.18 is significant at the 1% level though smaller than in Bailey *et al.*. However, when we use the full sample of column 1 the coefficient rises to 0.25, which is close to what they report. More importantly, the introduction of social connectedness does not affect the estimated coefficient on our key $AI_{cxt}$ variable and indicates that what we are finding is very different from the channel identified by Bailey *et al.*[14]

In column 4, we introduce year-importer-exporter and category fixed effects. It makes little difference to our estimates of the coefficient on $\ln(1+ AI_{cxt})$.

In columns 5–7 of Table 10.6 we add two additional covariates, $\ln(1+ multipleAI_{cxt})$ and $\ln(1+ nonAI_{cxt})$. In column 5, AI deployment for multiple category firms is significant. More importantly, its inclusion does not affect the coefficient on our key AI variable $\ln(1+ AI_{cxt})$. In column 6, non-AI patents $\ln(1+ nonAI_{cxt})$ is significant, but as we shall see its economic magnitude is half that of $\ln(1+ AI_{cxt})$. If these patents are correlated with AI patents then it is possible that our AI results are just proxying for the effects of patenting in general; however, inclusion of $\ln(1+ nonAI_{cxt})$ has little effect on the coefficient on our key AI deployment variable.

In column 7, we introduce importer-category fixed effects. The coefficient on $\ln(1+ AI_{cxt})$ does not change.

## 3.1 IV

Our OLS results potentially suffer from the endogeneity of AI deployment. There are two obvious sources of bias. The first is reverse causality and/or omitted variables: firms with high levels of downloads may have other

characteristics such as size that justify investing in AI. See Lileeva and Trefler (2010) for a discussion. In this case we expect IV to be smaller than OLS. The second is heterogeneous impacts of the type addressed by Imbens and Angrist's (1994) LATE estimator. We expect that the returns to AI are higher for firms that invest then for firms that do not. If so, IV will overestimate the mean impact of AI deployment (Card, 2001, eq. 1) and, by implication, IV may be larger than OLS.

An ideal instrument is an exogenous cost shock to the deployment of AI, i.e., a shock that exogenously drives AI deployment. The comparative advantage logic of Heckscher-Ohlin (HO) provides such a shock. The cost of AI deployment by producers of product $c$ in country $x$ is low if (1) the *country* is abundant in AI and (2) the *product* is AI intensive. We measure a country's AI abundance using the number of AI conference papers presented by scholars from exporter country $x$ in year $t$. Denote this by *ConfPaper*$_{xt}$. This is a commonly used measure of a country's AI capacity. See for example Goldfarb and Trefler (2019a). Data are from Zhang *et al.* (2021). We measure the AI intensity of a product or App category as the sum of all single-category-firm AI patents for firms in category $c$ divided by the sum of all single-category-firm assets for firms in category $c$. This is calculated at the global level, meaning we sum across firms in *all* countries. Further, it is calculated separately for each year. Denote this by $AI_{ct}$, and note that as in the HO literature, it is a global variable rather than an exporter-level variable. Our instrument for $\ln(1+ AI_{cxt})$ is then $\ln(1+ AI_{ct})\cdot(ConfPaper_{xt})$. Note the interaction of country ($x$) and product ($c$) characteristics, which is the fundamental core of all comparative advantage theories. More specifically, our first stage will look a lot like the test of HO comparative advantage in Romalis (2004).

Table 10.7 reports our IV estimates. Panel B reports the first-stage, that is, a regression of our endogenous variable $\ln(1+ AI_{cxt})$ on our instrument $\ln(1+ AI_{ct})\cdot\ln(ConfPaper_{xt})$. Only the coefficients on the instrument are reported. These coefficients are all positive and statistically significant. Further, the Kleibergen-Paap weak-instruments $F$-statistic hovers around the Stock-Yogo significance threshold of 20.

The IV estimates of the coefficient on AI deployment appear in Panel A of Table 10.7. Columns 1–6 correspond to columns 2–7 of table 6, respectively. The remaining regressors are included but not reported. The IV results are somewhat bigger than the OLS results, which suggests that heterogenous impacts are more important than reverse causality and/or omitted variables. While the IV results are larger than OLS, the difference is small relative to the IV standard error.

## 3.2 Economic Magnitudes when Patents are Right-Skewed

In this section we explore an alternative specification that makes it easier to interpret the size of the impact of AI deployment on exports of Apps. The specification also addresses a major concern that arises in the patent literature. A small number of firms hold a large fraction of all patents and of all patent citations, leading to a concern that the impacts of AI deployment are significant

*Table 10.7* Gravity Equation: Instrumental Variables

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Panel A. IV* | | | | | |
| | 1.75*** | 1.47*** | 1.70*** | 1.46*** | 1.54*** | 1.56*** |
| | (0.415) | (0.332) | (0.427) | (0.433) | (0.460) | (0.474) |
| $\ln(1 + multipleAI_{cxt})$ | | | | 1.01*** | 0.82*** | 0.82*** |
| | | | | (0.244) | (0.235) | (0.230) |
| $\ln(1 + nonAI_{cxt})$ | | | | | 0.11*** | 0.11*** |
| | | | | | (0.040) | (0.040) |
| Observations | 468,679 | 399,873 | 465,955 | 465,955 | 465,955 | 464,567 |
| Gravity covariates | yes | yes | no | no | no | no |
| Social Connectedness | no | yes | no | no | no | no |
| Fixed effects | t, m, x, c | t, m, x, c | t-m-x, c | t-m-x, c | t-m-x, c | t-m-x, m-c |
| | *Panel B. First Stage* | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Instrument | 0.613*** | 0.720*** | 0.602*** | 0.598*** | 0.622*** | 0.612*** |
| | (0.138) | (0.0835) | (0.143) | (0.142) | (0.135) | (0.133) |
| K-P *F*-value | 19.78 | 74.45 | 17.65 | 17.71 | 21.16 | 21.33 |
| Fixed effects | t, m, x, c | t, m, x, c | t-m-x, c | t-m-x, c | t-m-x, c | t-m-x, m-c |

Notes: This table reports the IV counterparts to the OLS results of Table 10.6. Columns 1–6 correspond respectively to columns 2–7 of Table 10.6. We suppress the estimates of the gravity and social connectedness coefficients. Panel A displays the IV estimates and panel B displays the first stage. In the first stage the dependent variable is $\ln(1 + AI_{cxt})$ and the independent variable is the Heckscher-Ohlin instrument $\ln(1 + AI_{ct}) \cdot ConfPaper_{xt}$. All other first-stage coefficients are suppressed. Standard errors are based on two-way clustering by importer and by exporter. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. See the notes to Table 10.6 for details.

only for a small number of large firms and insignificant for all other firms. See Aghion, Bergeaud, Lequien, and Melitz (2018) for a discussion. In this section we investigate an alternative specification that is more robust to the right skew of the patent distribution and that yields easily interpreted coefficient magnitudes.

We divide $AI_{cxt}$ into four groups. The first is all observations with $AI_{cxt} = 0$. We then take the remaining observations and divide them into terciles of the distribution of strictly positive $AI_{cxt}$. Table 10.8 reports the results. Consider column 1 of Panel A which reports our OLS results for each of the three tercile dummies of $AI_{cxt}$. The omitted category is observations with $AI_{cxt} = 0$. There is no evidence that impacts vary across terciles: The $F$-statistic for the test of equality of the three tercile coefficients is tiny across all specifications ($F \approx 1.2$, $p \approx 0.30$). This is useful because it shows that our results are not driven by the upper end of the distribution of patents; rather, our estimates are homogeneous across the distribution of patents.

Turning to coefficient magnitudes, consider two exporters of category-$c$ Apps, one exporter having $AI_{cxt} = 0$ and the other having $AI_{cxt}$ in the first tercile. From column 1, the latter has downloads that are 2.12 log points higher or 8.3 times higher ($8.3 = e^{2.12}$).

Adding additional covariates, as in columns 3–5, does not alter this conclusion. In columns 3–4 we add terciles of multiple-category AI and non-AI patents. For non-AI patents we see that the results are driven entirely by the high-patenting observations, as we have come to expect from the patent literature. It is reassuring to see this for non-AI patents where we expect them, but not for our AI deployment measure. Also note that the three non-AI tercile coefficients are jointly insignificant at the 1% level in columns 4–5 ($F \approx 4$, $p \approx 0.012$). In columns 2 and 5 we add finer fixed effects and this has no impact.

IV results appear in panel B of Table 10.8. There are now three endogenous variables (the terciles of $\ln(1 + AI_{cxt})$ so that we must be very cautious in lending too much weight to the results. We create three instruments by interacting our single instrument $\ln(1 + AI_{ct}) \cdot ConfPaper_{xt}$ with tercile dummies. The first-stage results are reported in table A1 and are very strong. This is apparent from the K-P weak instruments $F$-statistic of approximately 40 reported at the bottom of panel B. It is well above the threshold of 20. What is remarkable about the IV results is that they are almost identical to the OLS results. This raises our confidence in the causal interpretation of our results.

Looking at the IV coefficients on the tercile dummies for $\ln(1 + AI_{cxt})$, the smallest value is 1.71. We use this as a conservative guide to our headline number: *AI deployment leads to a sixfold increase in downloads ($5.52 = e^{1.71}$). This is a very large effect.*

## 4 Product Variety: The Extensive Margin of Trade

We now examine the number of varieties traded in a bilateral relationship. This is called the extensive margin of trade. Let $N_{cmxt}$ be the number of category-$c$ Apps

*Table 10.8* Gravity Equation: Non-parametrics and Magnitudes

| | *Panel A. OLS* | | | | |
|---|---|---|---|---|---|
| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* |
| $\ln(1 + AI_{cxt})$ | | | | | |
| First positive tercile | 2.12*** | 2.14*** | 2.14*** | 1.98*** | 1.97*** |
| | (0.289) | (0.299) | (0.306) | (0.271) | (0.275) |
| Second positive tercile | 1.81*** | 1.81*** | 1.94*** | 1.69*** | 1.67*** |
| | (0.237) | (0.237) | (0.255) | (0.259) | (0.253) |
| Third positive tercile | 1.63*** | 1.61*** | 1.70*** | 1.37*** | 1.37*** |
| | (0.335) | (0.346) | (0.301) | (0.304) | (0.303) |
| $\ln(1 + multipleAI_{cxt})$ | | | | | |
| First positive tercile | | | 0.37 | 0.19 | 0.20 |
| | | | (0.331) | (0.345) | (0.334) |
| Second positive tercile | | | 0.97*** | 0.62** | 0.63** |
| | | | (0.296) | (0.301) | (0.288) |
| Third positive tercile | | | 1.99*** | 1.39*** | 1.40*** |
| | | | (0.436) | (0.457) | (0.441) |
| $\ln(1 + nonAI_{cxt})$ | | | | | |
| First positive tercile | | | | –0.14 | –0.14 |
| | | | | (0.309) | (0.310) |
| Second positive tercile | | | | 0.16 | 0.15 |
| | | | | (0.212) | (0.218) |
| Third positive tercile | | | | 0.84*** | 0.83*** |
| | | | | (0.288) | (0.283) |
| Observations | 468,679 | 465,955 | 465,955 | 465,955 | 464,567 |
| Fixed effects | t, m, x, c | t-m-x, c | t-m-x, c | t-m-x, c | t-m-x, m-c |
| $R^2$ | 0.384 | 0.428 | 0.442 | 0.446 | 0.482 |
| Within $R^2$ | 0.037 | 0.025 | 0.048 | 0.054 | 0.057 |
| | *Panel B. IV* | | | | |
| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* |
| $\ln(1 + AI_{cxt})$ | | | | | |
| First positive tercile | 2.13*** | 2.09*** | 1.97*** | 1.86*** | 1.87*** |
| | (0.301) | (0.312) | (0.299) | (0.267) | (0.274) |
| Second positive tercile | 2.27*** | 2.21*** | 2.15*** | 2.05*** | 2.08*** |
| | (0.352) | (0.350) | (0.374) | (0.357) | (0.362) |
| Third positive tercile | 1.91*** | 1.84*** | 1.87*** | 1.71*** | 1.75*** |
| | (0.197) | (0.198) | (0.185) | (0.162) | (0.171) |
| K-P $F$-value | 40.91 | 39.20 | 39.57 | 42.49 | 40.99 |

Notes: The dependent variable is the log number of downloads ($\ln(y_{cmxt})$). An observation is uniquely identified by the App category ($c$), the exporter ($x$), the importer ($m$), and the year ($t$). We break AI deployment $AI_{cxt}$ into four dummies. The omitted dummy is for observations with $AI_{cxt} = 0$. The remaining three dummies are for the terciles of the distribution of $AI_{cxt}$ conditional on $AI_{cxt} > 0$. Likewise for $\ln(1 + multipleAI_{cxt})$ and $\ln(1 + nonAI_{cxt})$. Note that the specification in column 1 includes all the same gravity equation regressors as appear in column 1 of table 6, but these are not reported. The first-stage results appear in table A1. See the notes to Table 10.6 for details.

from country $x$ available to consumers in country $m$ in year $t$. We view each App within an App category as a variety. For example, Chrome (Google), Baidu (Baidu), Internet Explorer (Microsoft), and Safari (Apple) are varieties of browsers. Following Eaton, Kortum, and Kramarz (2011) we decompose total downloads into average downloads per App times the number of Apps. Mathematically,

$$\ln y_{cmxt} = \ln \bar{y}_{cmxt} + \ln N_{cmxt} \text{where;} \bar{y}_{cmxt} \equiv y_{cmxt}/N_{cmxt}. \tag{2}$$

$\ln \bar{y}_{cmxt}$ corresponds to the intensive margin and $\ln N_{cmxt}$ corresponds to the extensive margin or number of varieties. We estimate

$$\ln (N_{cmxt}) = \beta \ln (1 + AI_{cxt}) + \alpha_{mxt} + \alpha_{cm} + \varepsilon_{cmxt}.$$

That is, we estimate the same equations as before, but with a different dependent variable.

Table 10.9 reports the results. From panel A, AI deployment is associated with greater numbers of bilaterally traded Apps and this result is robust across specifications. The coefficient is about half the size of the coefficient when then dependent variable is total downloads. Panel B reports IV results. These are larger than the OLS results, but not statistically so.

When looking at the extensive margin, the issue of zero trade flows looms large. To investigate, instead of omitting observations with zero downloads, we change the dependent variable from $\ln N_{cmxt}$ to $N_{cmxt}$ and keep zero-download observations ($N_{cmxt} = 0$). This doubles the number of observations. We then use PPML estimation. The results appear in panel C of table 9 and are very similar to the OLS results, indeed identical in columns 4–5.

To get a clearer sense of magnitudes and to ensure that our specifications are robust to firms with very large numbers of patents, we return to our analysis of terciles. In Table 10.10 we repeat 1 with just a single change: the dependent variable is now the log of the number of varieties $\ln N_{cmxt}$. There is evidence of modest coefficient heterogeneity across terciles, but otherwise the conclusions here about the impact of AI deployment on varieties are very similar to those about impacts on downloads. Since the IV and OLS results are very similar, we do not report the former. Averaging across the tercile coefficients in column 5 we get 0.81, which drives our headline number that *AI deployment doubles the number of imported varieties* ($2.25 = e^{0.81}$).[15]

## 5 Creative Destruction

We start by reviewing the literature on estimating the welfare gains from new products and product churning. This will motivate the empirics. We then turn to a brief review of the literature on creative destruction.

*Table 10.9* Product Variety and the Extensive Margin

| | Panel A. OLS $\ln(N_{cmxt})$ | | | | |
|---|---|---|---|---|---|
| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* |
| $\ln(1 + AI_{cxt})$ | 0.49*** | 0.50*** | 0.47*** | 0.47*** | 0.47*** |
| | (0.064) | (0.065) | (0.067) | (0.069) | (0.069) |
| $\ln(1 + multipleAI_{cxt})$ | | | 0.37*** | 0.35*** | 0.35*** |
| | | | (0.090) | (0.098) | (0.097) |
| $\ln(1 + nonAIcxt)$ | | | | 0.01 | 0.01 |
| | | | | (0.019) | (0.019) |
| Observations | 468,679 | 465,955 | 465,955 | 465,955 | 464,567 |
| Fixed effects | t, m, x, c | t-m-x, c | t-m-x, c | t-m-x, c | t-m-x, m-c |
| $R^2$ | 0.461 | 0.478 | 0.504 | 0.504 | 0.525 |
| Within $R^2$ | 0.056 | 0.053 | 0.100 | 0.100 | 0.103 |

| | Panel B. IV $\ln(N_{cmxt})$ | | | | |
|---|---|---|---|---|---|
| | *(1)* | *(3)* | *(4)* | *(5)* | *(6)* |
| $\ln(1 + AI_{cxt})$ | 0.69*** | 0.70*** | 0.62*** | 0.62*** | 0.63*** |
| | (0.108) | (0.119) | (0.111) | (0.108) | (0.113) |
| $\ln(1 + multipleAI_{cxt})$ | | | 0.36*** | 0.35*** | 0.36*** |
| | | | (0.089) | (0.093) | (0.091) |
| $\ln(1 + nonAI_{cxt})$ | | | | 0.00 | 0.00 |
| | | | | (0.018) | (0.018) |
| Observations | 468,679 | 465,955 | 465,955 | 465,955 | 464,567 |
| Fixed effects | t, m, x, c | t-m-x, c | t-m-x, c | t-m-x, c | t-m-x, m-c |

| | Panel C. PPML $N_{cmxt}$ | | | | |
|---|---|---|---|---|---|
| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* |
| $\ln(1 + AI_{cxt})$ | 0.53*** | 0.55*** | 0.51*** | 0.47*** | 0.47*** |
| | (0.132) | (0.137) | (0.103) | (0.095) | (0.095) |
| $\ln(1 + multipleAI_{cxt})$ | | | 0.77*** | 0.59*** | 0.59*** |
| | | | (0.173) | (0.173) | (0.173) |
| $\ln(1 + nonAI_{cxt})$ | | | | 0.13* | 0.13* |
| | | | | (0.070) | (0.069) |
| Observations | 958,974 | 944,599 | 944,599 | 944,599 | 914,186 |
| Fixed effects | t, m, x, c | t-m-x, c | t-m-x, c | t-m-x, c | t-m-x, m-c |

Notes: Each observation is an App category ($c$), a downloading country or importer ($m$), an App-producing country or exporter ($x$) and a year ($t = 2014, \ldots, 2020$). We use a panel of 292 App categories, 53 exporters, 84 importers, and 7 years. The dependent variable is the number of imported Apps in category $c$: $\ln(N_{cmxt})$ in panel A (OLS), $\ln(N_{cmxt})$ in panel B (IV), and $N_{cmxt}$ in panel C (PPML). For PPML we keep observations with $N_{cmxt} = 0$. For IV, the first stage already appears in panel B of Table 10.7 and so is not repeated here. The specification in column 1 includes the same gravity regressors as in column 1 of Table 10.6, but these are not reported. In the fixed-effect rows, $t$-$m$-$x$ and $m$-$c$ refer to year-importer-exporter and importer-category fixed effects, respectively. Standard errors are based on two-way clustering by importer and by exporter. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% levels, respectively.

*Table 10.10* Extensive Margin $\ln(N_{cmxt})$: Non-parametric and Magnitudes

| | OLS | | | | |
|---|---|---|---|---|---|
| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* |
| $\ln(1 + AI_{cxt})$ | | | | | |
| First positive tercile | 0.95*** | 0.96*** | 0.95*** | 0.91*** | 0.91*** |
| | (0.082) | (0.081) | (0.073) | (0.074) | (0.074) |
| Second positive tercile | 0.94*** | 0.95*** | 1.00*** | 0.95*** | 0.95*** |
| | (0.129) | (0.131) | (0.142) | (0.151) | (0.149) |
| Third positive tercile | 0.60*** | 0.61*** | 0.64*** | 0.56*** | 0.58*** |
| | (0.116) | (0.122) | (0.109) | (0.123) | (0.121) |
| $\ln(1 + multipleAI_{cxt})$ | | | | | |
| First positive tercile | | | 0.10 | 0.06 | 0.07 |
| | | | (0.115) | (0.128) | (0.126) |
| Second positive tercile | | | 0.31*** | 0.23** | 0.24** |
| | | | (0.099) | (0.107) | (0.104) |
| Third positive tercile | | | 0.81*** | 0.67*** | 0.68*** |
| | | | (0.151) | (0.169) | (0.163) |
| $\ln(1 + nonAI_{cxt})$ | | | | | |
| First positive tercile | | | | 0.02 | 0.02 |
| | | | | (0.118) | (0.121) |
| Second positive tercile | | | | 0.04 | 0.03 |
| | | | | (0.116) | (0.118) |
| Third positive tercile | | | | 0.22* | 0.22* |
| | | | | (0.124) | (0.124) |
| Observations | 468,679 | 465,955 | 465,955 | 465,955 | 464,567 |
| Fixed effects | *t, m, x, c* | *t-m-x, c* | *t-m-x, c* | *t-m-x, c* | *t-m-x, m-c* |
| $R^2$ | 0.465 | 0.482 | 0.508 | 0.510 | 0.531 |
| Within $R^2$ | 0.063 | 0.061 | 0.107 | 0.111 | 0.115 |

Notes: This table is identical to Panel A of Table 10.9. The only difference is in the treatment of the patent variables. We break $AI_{cxt}$ into four dummies. The omitted dummy is for observations with $AI_{cxt} = 0$. The remaining three dummies are for the terciles of the distribution of $AI_{cxt}$ conditional on $AI_{cxt} > 0$. Likewise for the multi-category patents and the non-AI patents. The specification in column 1 includes all the same gravity equation regressors as in column 1 of Table 10.6, but these are not reported. See the notes to Table 10.6 for details.

## 5.1 The Welfare Gains from New Products

Feenstra (1994) considers a consumer having CES preferences with an elasticity of substitution $\sigma$. He explains how to construct expenditure functions and how to do welfare analysis in the presence of a changing set of varieties induced by an arbitrary shock such as the introduction of AI or a trade-liberalizing event. Let $E_{t-1}$ and $E_t$ be the expenditure functions pre- and post-shock. His now-famous formulation is that the impact of changing sets of varieties on welfare is captured by an extra multiplicative term in the expression for $E_t/E_{t-1}$. This extra term is constructed as follows. Define

$$\lambda_t = 1 - \frac{\text{year } t \text{ expenditures on new varieties (varieties available in } t \text{ but not } t-1)}{\text{year } t \text{ expenditures on all varieties that are available in } t}. \quad (3)$$

Then the extra multiplicative term is

$$\left(\frac{\lambda_t}{\lambda_{t-1}}\right)^{-1/(\sigma-1)}. \tag{4}$$

Feenstra (2010, ch. 2) offers a nice review of this result.

In this formula one can also interpret $\lambda_t$ and $\lambda_{t-1}$ as actual data and counterfactual data, respectively. For example, equation (4) can be related to a familiar result in Arkolakis, Costinot, and Rodriguez-Clare (2012). Reinterpreting new varieties as imported goods, $\lambda_t$ is the share of expenditures on domestic varieties using actual data. Letting $\lambda_{t-1} = 1$ be expenditure shares on domestic data in the counterfactual of autarky, equation (4) reduces to $(\lambda_t)^{-1/(\sigma-1)}$. This is the familiar Arkolakis et al. (2012) formula for the gains from trade when moving from autarky to the existing level of period-$t$ trade restrictions. In similar fashion, we will interpret $\lambda_t$ as actual data in a world with AI and $\lambda_{t-1}$ as a counterfactual in a world in which there is no AI.

Broda and Weinstein (2006) is an important empirical application of equation (4) to international trade. They find that the number of new varieties made available to US consumers through imports tripled between 1972 and 2001 and this resulted in welfare gains valued at 2.6% of GDP. Feenstra (2010, Table 2.1) finds that if all countries in the world moved from autarky to their 1996 levels of trade, welfare gains would be valued at 12.5% of world GDP. See Melitz and Trefler (2012) for further discussion. The Melitz (2003) model adds firm-level selection to the discussion of why varieties are created and destroyed by international trade. Trade reduces the number of domestic varieties and increases the number of foreign varieties. The net effect is ambiguous. Hsieh et al. (2020) revisits the Broda and Weinstein (2006) analysis and the Trefler (2004) analysis of the Canada-US Free Trade Agreement and shows that the net effect of changes in varieties was negative.

## 5.2 The Welfare Gains from Creative Destruction

The previous subsection dealt with CES-based models. Because CES goods are complements, more varieties are preferred to fewer varieties. An alternative approach emphasizes vertically differentiated goods, that is, goods differentiated by quality. Vertical differentiation underpins models of growth through creative destruction. By innovating, a firm can generate a profit by displacing an existing lower-quality good with its own higher-quality good. This process has come to be known as *creative destruction*. See Aghion and Howitt (1992) and Akcigit and Kerr (2018) for closed-economy models and Grossman and Helpman (1991*a,b*) for both closed- and open-economy models. Aghion, Bergeaud, Boppart, Klenow, and Li (2019) explore the role of creative destruction for measuring US growth. While their primarily empirical paper treats innovation as exogenous, they provide formulas related to equation (4). We now turn to estimating the

impact of AI on creative destruction and plug the estimates into equation (4) to generate welfare calculations.

## 5.3 AI and Creative Destruction in the Global Economy: A First Look

In this subsection we look at the raw data on AI and creative destruction, that is, on how the download shares of new and exiting Apps are impacted by AI. Consider an App in App category $c$ that is downloaded by country $m$. The App is 'new' in year $t$ if it was downloaded in $t$, but not $t - 1$. The App is 'exiting' in year $t$ if it was downloaded in $t - 1$ and $t$, but not $t + 1$. The App is 'continuing' in year $t$ if it was downloaded in $t - 1$, $t$ and $t + 1$. For each *cmt* triplet, let $\Omega_{cmt}^{n}$, $\Omega_{cmt}^{e}$, and $\Omega_{cmt}^{c}$ be the sets of *n*ew, *e*xiting and *c*ontinuing Apps, respectively.

Let $\omega$ index Apps and let $y_{cmt}(\omega)$ be downloads of App $\omega$ in category $c$ by country $m$ in year $t$. For each *cmt* triplet let $y_{cmt}^{k} \equiv \sum_{\omega \in \Omega_{m}^{k}} y_{cmt}(\omega)$ be type-$k$ downloads where $k$ indexes new Apps ($k = n$), exiting Apps ($k = e$), or continuing Apps ($k = c$). All Apps fall into one and only one of these three types. The share of type-$k$ App downloads is

$$\theta_{cmt}^{k} = \frac{y_{cmt}^{k}}{\sum_{k'} y_{cmt}^{k'}} = \frac{\text{country } m's \text{ downloads of type}-k \text{ Apps in category } c \text{ and year } t}{\text{country } m's \text{ downloads of all Apps in category } c \text{ and year } t}. \quad (5)$$

The denominator is total downloads for *cmt* (including downloads of domestically produced Apps). Since these shares are calculated using data for $t - 1$ and/or $t + 1$ we drop the $\theta_{cmt}^{k}$ for the first and last years and work with $t = 2015, \ldots, 2019$.

We are interested in how AI impacts the entry of Apps ($\theta_{cmt}^{n}$) and the exit of Apps ($\theta_{cmt}^{e}$). While our interest is in what is consumed at the *cmt* level, our AI deployment measure is about what is produced at the *cxt* level. Therefore, for each importer $m$ and App category $c$ we take the average of the $AI_{cxt}$ across exporters $x$ that export to $m$. We use a weighted average with weights proportional to importer $m$'s downloads of $c$. As is common in international trade regressions we will be exploiting how the composition of exporters of $c$ Apps varies across importers $m$ e.g., Vietnam imports social networking from China (WeChat) while Canada imports it from the US (Facebook). Mathematically, let $w_{cmxt} \equiv y_{cmxt}/\sum_{x'} y_{cmx't}$ be the share of $m$'s downloads originating from producer country $x$. (Again, we include domestic downloads $m = x$.) Then our key importer-level independent variable is

$$AI_{cmt} = \sum_{x} w_{cmxt} \cdot AI_{cxt}. \quad (6)$$

Table 10.11 reports some basic sample statistics on creative destruction. There are 78,741 category-importer-year (*cmt*) observations in our data, which includes zero-download observations. The left panel of Table 10.11 reports cross-tabulations for whether there was entry ($\theta_{cmt}^{n} > 0$) and whether there was AI deployment ($AI_{cmt} > 0$). Among observations with positive AI deployment, 91% have some entry. In contrast, among observations with no AI deployment, only 66% have some entry. Thus, AI is (non-causally) correlated with the entry of

*Table 10.11* Creative Destruction

| | *Number of Category-Importer-Year Pairs by AI-Deployment Status and* | | | | |
|---|---|---|---|---|---|
| | *ENTRY Status* | | | *EXIT Status* | |
| | *AI Deploy > 0* | *AI Deploy = 0* | | *AI Deploy > 0* | *AI Deploy = 0* |
| No entry | 1,644 | 20,467 | No exit | 3,072 | 30,887 |
| | (9%) | (34%) | | (17%) | (51%) |
| Entry | 16,973 | 39,657 | Exit | 15,545 | 29,237 |
| | (91%) | (66%) | | (83%) | (49%) |

Notes: Each observation is an App category ($c$), a downloading country or importer ($m$), and a year ($t = 2015, \ldots, 2019$). We use a panel of 292 App categories, 84 importers, and 5 years and have 78,741 observations. The numbers are counts of observations. Numbers in parentheses are counts as a percentage of the total observations in the table (78,741).

new varieties. The right panel of Table 10.11 repeats the exercise using exits. Among observations with positive AI deployment, 83% have some exit. In contrast, among observations with no AI deployment, only 49% have some exit. AI is correlated with the exit of varieties. *Taken together, these two results point to the role of AI deployment for entry and exit i.e., for creative destruction.*

## 5.4 The Welfare Gains from AI: New Empirics

We saw in equation (4) that the welfare gains from AI deployment can be expressed as

$$\Delta W_t = (\lambda_t / \lambda_t^{\text{no AI}})^{-1/(\sigma-1)}$$

where $\lambda_t$ equals one minus the share of new Apps in total downloads and $\lambda_t^{\text{no AI}}$ is its counterfactual value in a world with no AI deployment. Before explaining how we estimates $\Delta W_t$ we make two observations. The first is the major caveat that we are using download data whereas the welfare calculation should be based on expenditure data. Second, this is a welfare calculation for the mobile App category. It ignores all other goods.

To estimate $\Delta W_t$, we first need an empirical counterpart to $\lambda_t$. From equations (3) and (5), it is natural to equate $\lambda_t$ with $1 - \theta_{cmt}^n$, that is, with one minus the new downloads share for category-$c$ Apps downloaded by users in country $m$ in year $t$. Since we do not want to get bogged down in reporting welfare for each App category and importer, we take $\lambda_t$ to be the download-weighted average of the $1 - \theta_{cmt}^n$.[16] This is the obvious empirical counterpart to $\lambda_t$.

Our next challenge is to calculate the counterfactual $\lambda_t^{\text{no AI}}$. To this end, we regress $1 - \theta_{cmt}^n$ on AI deployment $\ln(1+ AI_{cmt})$. We interact this with year dummies so that we can do counterfactuals separately by year. $\theta_{cmt}^n$ is not defined for 2014 so we omit the year. Table 10.12 reports the regressions. The first three columns are OLS. The negative coefficients mean that high AI deployment is associated with low $1 - \theta_{cmt}^n$ and hence with high new-App

*Table 10.12* (1 – New Product Share) Regressed on AI Deployment

| | OLS | | | IV | | |
|---|---|---|---|---|---|---|
| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* |
| $\ln(1 + AI_{cmt})$ • Year 2020 | –2.56*** | –2.53*** | –2.51*** | –2 91*** | –2.88*** | –2.89*** |
| | (0.115) | (0.111) | (0.111) | (0.191) | (0.187) | (0.188) |
| $\ln( + AI_{cmt})$ • Year 2019 | –1.76*** | –1.78*** | –1.72*** | –2.03*** | –2.06*** | –2.04*** |
| | (0.097) | (0.096) | (0.095) | (0.182) | (0.181) | (0.182) |
| $\ln(1 + AI_{cmt})$ • Year 2018 | –1.60*** | –1.54*** | –1.48*** | –1.88*** | –1.83*** | –1.81*** |
| | (0.105) | (0.106) | (0.105) | (0.177) | (0.177) | (0.177) |
| $\ln(1 + AI_{cmt})$ • Year 2017 | –0.83*** | –0.77*** | –0.70*** | –0.94*** | –0.88*** | –0.83*** |
| | (0.109) | (0.101) | (0.099) | (0.179) | (0.167) | (0.167) |
| $\ln(1 + AI_{cmt})$ • Year 2016 | 0.17 | 0.09 | 0.17 | –0.04 | –0.11 | –0.05 |
| | (0.121) | (0.120) | (0.119) | (0.201) | (0.197) | (0.197) |
| $\ln(1 + AI_{cmt})$ • Year 2015 | 0.88*** | 0.87*** | 0.95*** | –0.95*** | –0.93*** | –0.90*** |
| | (0.135) | (0.133) | (0.133) | (0.309) | (0.302) | (0.302) |
| $\ln(1 + \text{Multiple } AI_{cmt})$ | | –1.00* | –0.17 | | –0.97* | –0.15 |
| | | (0.581) | (0.448) | | (0.577) | (0.445) |
| $\ln(1 + \text{non} AI_{cmt})$ | | | –51.43*** | | | –51.29*** |
| | | | (14.812) | | | (14.783) |
| Observations | 78,614 | 74,606 | 74,606 | 78,614 | 74,606 | 74,606 |
| Fixed effects | *t-m, c* | *t-m, c* | *t-m, c* | *t-m, c* | *t-m, c* | *t-m, c* |
| K-P *F*-value | | | | 215.1 | 214.9 | 214.4 |
| $R^2$ | 0.335 | 0.333 | 0.333 | | | |

Notes: The dependent variable is $(1 − \theta^n_{cmt}) \cdot 100$. Each observation is indexed by an App category $c$, a downloading country or importer $m$, and a year $t$. We use a panel of 292 App categories, 84 importers, and 6 years. The independent variable is $\ln(1 + AI_{cmt})$ where $AI_{cmt}$ is defined in equation (6). Columns 1–3 are OLS and columns 4–6 are IV. The first-stage results appear in Table 10.A2 in the appendix. 'K-P' *F*-value is the Kleibergen-Paap weak-instruments test statistic. We include fixed effects for year-importer and for App category. Standard errors are clustered by importer. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% levels, respectively.

download shares. This is sensible and expected. Also as expected, the AI deployment coefficient becomes more negative with time: As AI has become more sophisticated, its positive impact on new-App downloads has grown.

In columns 2 and 3 we add our covariates for non-AI patents and multiple-category AI patents.[17] Adding them does not alter the coefficients on our AI-deployment variables.

IV estimates are reported in columns 4–6. We use the same instrument as before, but with one alteration. That instrument was at the *cxt* level: $\ln(1+ AI_{ct})\cdot(ConfPaper_{xt})$. As in equation (6), we aggregate this to the *cmt* level using importer download weights, that is, $\sum_x w_{cmxt}\cdot\ln(1+ AI_{ct})\cdot(ConfPaper_{xt})$. We then interact this with year dummies to create six instruments for our six endogenous variables. The first stages appear in Appendix Table 10.A2 where it is shown that the instruments are highly significant and the first-stage coefficients are sensible. With five instruments we must be especially mindful of the weak-instruments problem; however, our Kleibergen-Paap *F*-statistics of over 200 are well above the Stock-Yogo threshold of 20. See the second-to-last row of Table 10.12. With instruments in place, columns 4–6 show that the IV estimates are similar to OLS, are statistically significant, are negative in 2020, and decline over time. The exception is 2015.

We can now quantify how AI has influenced the welfare gains from creative destruction. We are interested in $\Delta W_t = (\lambda_t/\lambda_t^{no\ AI})^{-1/(\sigma-1)}$. We set $\sigma$ to 5.03, which is the Head and Mayer (2014) median estimate of $\sigma$ from their meta-study. However, it seems reasonable given network effects that the elasticity relevant to Apps is closer to unity. If this is the case, we are understating the welfare gains. Table 10.13 reports calculations of $\Delta W_t$ for 2020 and 2015. Consider the first column of numbers. From row 1, one minus the new-App share is 0.878 in 2020. From row 2, we estimate that AI induces $\lambda_t$ to change by 0.082. This is calculated as follows. From column 1 of Table 10.12, the impact of AI deployment on $\lambda_{2020}$ is $-2.56/100$. (We divide by 100 because the dependent variable in the table was multiplied by 100.) The weighted average of $\ln(1+ AI_{cm,\ 2020})$

*Table 10.13* Quantifying Welfare Gains from AI's Creative Destruction

|  | 2020 | | 2015 | |
| --- | --- | --- | --- | --- |
|  | *OLS* | *IV* | *OLS* | *IV* |
| 1. $\lambda_t$ | 0.878 | 0.878 | 0.867 | 0.867 |
| 2. $\Delta\lambda_t$ | 0.082 | 0.093 | -0.023 | 0.025 |
| 3. $\lambda_t^{no\ AI} = \lambda_t + \Delta\lambda_t$ | 0.960 | 0.971 | 0.844 | 0.892 |
| 4. Gains from AI ($\sigma = 5.03$) | 1.022 | 1.025 | 0.993 | 1.007 |
| 5. Percentage Gains from AI ($\sigma = 5.03$) | 2.2% | 2.5% | -0.7% | 0.7% |
| 6. Gains from AI ($\sigma = 2.00$) | 1.093 | 1.106 | 0.973 | 1.029 |
| 7. Percentage Gains from AI ($\sigma = 2.00$) | 9.3% | 10.6% | -2.7% | -2.9% |

Notes: Row 1 uses observed data. Row 2 is based on estimates from Table 10.12. See the text for an explanation. Row 3 is the sum of rows 1 plus 2. Row 4 is $\Delta W_t = (\lambda_t/\lambda_t^{no\ AI})^{-1/(5.03-1)}$. Row 5 is $100\cdot(\Delta W_t-1)$. Row 6 is $\Delta W_t = (\lambda_t/\lambda_t^{no\ AI})^{-1/(2.00-1)}$. Row 7 is $100\cdot(\Delta W_t-1)$.

conditional on $AI_{cm,\,2020} > 0$ is 3.19. Hence the estimated change in $\lambda_{2020}$ from shutting down AI is $\Delta\lambda_t = (\text{-}2.56/100) \cdot (\text{-}3.19) = 0.082$. We compute the counterfactual $\lambda_t$ as $\lambda_t^{\text{no AI}} = \lambda_t + \Delta\lambda_t$, and this appears in row 3. Row 4 reports $\Delta W_t = (\lambda_t/\lambda_t^{\text{no AI}})^{-1/(5.03-1)}$. Row 5 expresses this as the percent $100\cdot(\Delta W_t - 1)$. Using OLS, we estimate that AI led to welfare gains of 2.2% in 2020. *Our headline number, based on IV, is that AI led to welfare gains of 2.5%.* There is limited evidence on elasticities of substitution between Apps. We therefore also consider a common alternative estimate of $\sigma$, namely, $\sigma = 2$. From rows 6–7, this implies that *AI led to welfare gains of 10.6%, a very large number.*

The commercialization of AI is usually dated to 2012 (Agrawal *et al.*, 2018) so that in 2015, the use of AI in mobile Apps was in its early days. We should therefore expect smaller welfare benefits of AI in 2015. This is a bit like a placebo test. In Table 10.13 we repeat the analysis for 2015. The calculations are similar except that now we use the 2015 coefficients from Table 10.12 (0.88 for OLS and -0.95 for IV) and we use the weighted average of $\ln(1+AI_{cm,\,2015})$ conditional on $AI_{cm,\,2015} > 0$, which is 2.64. From Table 10.13 (IV), in 2015 AI led to welfare gains of 0.7%. This is for $\sigma = 5.03$. It is 2.9% for $\sigma = 2.00$. As expected, these are much smaller than the corresponding gains in 2020.

*Summarizing, in 2020, AI deployment raised welfare from creative destruction by between 2.5% and 10.6%. Further, in 2015, when AI deployment in mobile Apps was still in its infancy, AI deployment raised welfare from creative destruction by only between 0.7% and 2.9%.*

## 6 Conclusions

Artificial Intelligence is a powerful new technology, yet almost nothing is known empirically about this process, partly because impacts on goods trade have likely been minimal and partly because researchers have failed to look where the action is most obvious — in the palms of our hands. We observed that mobile Apps provide a large and growing collection of services that billions of people use daily and whose international dimension is captured by mobile App downloads. We developed a new database of App downloads and the AI deployed in those Apps. Using an IV strategy to estimate the impacts of AI deployment we presented three results:

1. *Bilateral Trade*: AI deployment increased App downloads by a factor of six. This is the first systematic evidence of the impact of AI on trade.
2. *Variety Effects*: AI deployment doubled the number of bilaterally traded App varieties.
3. *Entry, Exit, and Creative Destruction*: AI deployment caused high levels of entry into and exit out of Apps/varieties available in the importer country. This has important welfare implications. Comparing the actual evolution of mobile App downloads to a counterfactual world in which no AI is deployed, AI deployment in 2020 raised welfare from App downloads by between 2.5%

(when Apps are highly substitutable) and 10.6% (when Apps are less substitutable).[18]

With regards to international App markets, AI deployment has already had tangible impacts on trade, product variety, creative destruction, and welfare.

## Notes

1  AI is part of a larger process of automation and is thus part of a larger literature on the impact of trade and technology on employment, wages, and inequality. A recent contribution to this literature with an international dimension is Stapleton and Webb (2020) who consider the impact of robots on Spanish multinationals during 1990–2016.
2  More specifically, AI intensity is measured as total global AI patents associated with the App category. AI expertise is measured as the number of papers presented at AI conferences by researchers affiliated with the country's universities and other research institutions. Data on AI expertise are from Zhang, Mishra, Brynjolfsson, Etchemendy, Ganguli, Grosz, Lyons, Manyika, Niebles, Sellitto et al. (2021).
3  https://www.statista.com/statistics/617136/digital-population-worldwide.
4  https://www.statista.com/statistics/269025/worldwide-mobile-app-revenue-forecast.
5  This database does not cover downloads from the remaining application market-places. The largest of these are Huawei App Gallery, Xiaomi App Store, Amazon App Store, and Samsung Galaxy Store. Nor do we track downloads done directly from web pages.
6  The two marketplaces define groups slightly differently, but it is easy to convert the Google Play groups into Apple Store groups.
7  Some of the $19 \times 19$ potential App categories have no Apps, leaving us with 292 App categories.
8  We initially used the Python-based FuzzyWuzzy matching algorithm. However, even after extensive pre-cleaning of firm names, a visual inspection of the match-ing results showed that it was of insufficient accuracy for our comfort. We there-fore verify each match by hand. This verification is what constrains us to working with 834 ultimate owners.
9  Apps that have zero downloads are excluded from this table and from all of our analysis. We re-introduce zeros whenever we do PPML.
10  Using 95%, 90%, or 80% as the threshold does not affect our main results.
11  We are grateful to an anonymous referee for suggesting that we scale patents to control for the size of firms in the *cxt* bin. We choose assets because, relative to other variables in Orbis that we could use for scaling such as employment, assets have few missing values. An earlier version of this chapter that did not scale reported similar results.
12  In constructing *multipleAI*$_{cxt}$, a multi-category firm's AI patents are given to each of its categories, e.g., if a firm has 10 patents and operates in two categories

we do not know which patent applies to which category (indeed, some AI patents may apply to both) so we assume that the firm has 10 patents in *each* category.

13  See Head and Mayer (2014) and Head, Mayer, and Ries (2010). Since the CEPII data end in 2019 we linearly extrapolate the time-varying variables by one year to 2020.

14  The coefficient is 1.21 in column 2 and 1.33 in column 3. However, this difference is entirely due to the difference in samples rather than to the inclusion of social connectedness. If we redo column 2 with the smaller sample of column 3, the coefficient in column 2 rises to exactly 1.33.

15  For the intensive margin ($\ln \bar{y}_{cmxt}$), these results are very similar to the results for $\ln(N_{cmt})$ that we reported in Table 10.9. Restated, the intensive-margin effects are very significant and half the size of the total effects. This is true for OLS, IV and PPML. We do not report these results.

16  For each $t$, the $cm$ download weights are the denominator of $\theta^n_{cmt}$, that is, the downloads of all varieties of category-$c$ Apps available to users in country $m$ in year $t$.

17  These are the download-weighted average of non-AI patents and the download-weighted average of the AI patents of multi-category firms. See equation (6) for weights.

18  An important caveat is that our welfare calculations use download shares rather than expenditure shares.

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# APPENDIX TABLES

*Table 10.A1* First Stage for Table 10.8

|  | $\ln(1 + AI_{cxt})$ • *First Positive Tercile* | $\ln(1 + AI_{cxt})$ • *Second Positive Tercile* | $\ln(1 + AI_{cxt})$ • *Third Positive Tercile* |
|---|---|---|---|
| Instrument • First positive tercile | 0.810*** (0.0506) | –0.036*** (0.00964) | –0.023*** (0.00624) |
| Instrument • Second positive tercile | –0.053*** (0.0155) | 0.911*** (0.101) | –0.030*** (0.00426) |
| Instrument • Third positive tercile | –0.067*** (0.0249) | –0.049*** (0.0175) | 0.898*** (0.0466) |
| *F-value* | 807 | 385 | 596 |
| Fixed effects | *t-m-x, c* | *t-m-x, c* | *t-m-x, c* |

Notes: This table displays the first stage for our preferred specification in Table 10.8 (column 2). The dependent variable in the first stage is $\ln(1 + AI_{cxt})$. Its instrument is $\ln(1 + AI_{ct}) \cdot (Conf\ Paper_{xt})$. Both are interacted with terciles dummies of the distribution of $AI_{cxt}$ conditional on $AI_{cxt} > 0$. There are thus three independent variables and hence three first stages or columns. We include fixed effects for year-importer-exporter and category. Standard errors are clustered by importer. ***, **, and * indicates statistical significance at the 1%, 5% and 10% levels, respectively.

*Table 10.A2* First Stage for Table 10.12

| | ln(1 + $AI_{cmt}$) • *Year 2020* | ln(1 + $AI_{cmt}$) • *Year 2019* | ln(1 + $AI_{cmt}$) • *Year 2018* | ln(1 + $AI_{cmt}$) • *Year 2017* | ln(1 + $AI_{cmt}$) • *Year 2016* | ln(1 + $AI_{cmt}$) • *Year 2015* |
|---|---|---|---|---|---|---|
| Instrument • Year 2020 | 10.25*** | –1.040*** | –0.818*** | –1.066*** | –1.162*** | –1.468*** |
| | (0.289) | (0.0561) | (0.0477) | (0.0344) | (0.0399) | (0.0593) |
| Instrument • Year 2019 | –1.461*** | 10.37*** | –0.700*** | –0.993*** | –0.990*** | –1.296*** |
| | (0.0666) | (0.312) | (0.0471) | (0.0360) | (0.0416) | (0.0495) |
| Instrument • Year 2018 | –2.204*** | –1.417*** | 14.93*** | –1.431*** | –1.424*** | –1.905*** |
| | (0.0896) | (0.0776) | (0.351) | (0.0510) | (0.0581) | (0.0608) |
| Instrument • Year 2017 | –2.207*** | –1.468*** | –1.082*** | 16.39*** | –1.670*** | –2.048*** |
| | (0.0955) | (0.0846) | (0.0741) | (0.377) | (0.0652) | (0.0729) |
| Instrument • Year 2016 | –2.634*** | –1.550*** | –1.111*** | –1.737*** | 15.80*** | –2.451*** |
| | (0.120) | (0.0919) | (0.0869) | (0.0681) | (0.543) | (0.106) |
| Instrument • Year 2015 | –3.136*** | –1.785*** | –1.642*** | –2.831*** | –2.831*** | 19.95*** |
| | (0.154) | (0.103) | (0.101) | (0.140) | (0.159) | (0.778) |
| *F-value* | 403 | 387 | 783 | 785 | 630 | 535 |
| Fixed effects | *t-m, c* | *t-m, c* | *t-m, c* | *t-m, c* | *t-m, c* | *t-m, c* |

Notes: This table displays the first stages for our preferred specification in Table 10.12 (column 4). The dependent variable in the first stage is ln(1 + $AI_{cmt}$) defined in equation (6). Its instrument is $\sum_x w_{cmxt} \cdot \ln(1 + AI_{ct}) \cdot (\text{Conf Paper}_{xt})$. Both are interacted with year dummies. With six years there are six dependent variables and hence six first stages or columns. We include fixed effects for year-importer and category. Standard errors are clustered by importer. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% levels, respectively.

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