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INFORMATION FRICTIONS IN TRADE

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INFORMATION FRICTIONS IN TRADE

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It is costly to learn about market conditions elsewhere, especially in developing countries. This paper examines how such information frictions affect trade. Using data on regional agricultural trade in the Philippines, I first document a number of observed patterns in trade flows and prices that suggest the presence of information frictions. I then incorporate information frictions into a perfect competition trade model by embedding a process whereby heterogeneous producers engage in a costly sequential search process to determine where to sell their produce. I show that introducing information frictions reconciles the theory with the observed patterns in the data. Structural estimation of the model finds that information frictions are quantitatively important: roughly half the observed regional price dispersion is due to information frictions. Furthermore, incorporating information frictions improves the out-of-sample predictive power of the model.

KEYWORDS: Trade, information, trade costs, agriculture, Philippines, search.

1. INTRODUCTION

IT IS COSTLY FOR PRODUCERS TO LEARN ABOUT market conditions elsewhere, especially in developing countries. While the effect of search costs on spatial price dispersion has been well documented (e.g., Jensen (2007), Aker (2010), and Goyal (2010)), little is known about how these "information frictions" affect trade flows.[2] Understanding the role of information frictions is particularly important to policy makers, as policies that reduce information frictions differ substantially from policies that reduce traditional trade costs.

In this paper, I use a new data set on regional agricultural trade flows in the Philippines to document several patterns in the observed prices and trade flows that suggest the presence of information frictions. I then incorporate information frictions into a perfect competition trade model by assuming that producers undergo a costly search process to acquire information about market conditions elsewhere. I derive a structural equation relating bilateral trade flows to prices, transportation costs, information frictions, and producer heterogeneity. The equation implies a relaxation of the standard no-arbitrage condition and

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[2]Trade models that incorporate incomplete information include the firm learning models of Albornoz, Pardo, Corcos, and Ornelas (2010) and Eaton, Eslava, Krizan, Kugler, and Tybout (2011), the advertising model of Arkolakis (2010), the network models of Rauch (1999), Rauch and Trindade (2002, 2003), Rauch and Casella (2003), and Chaney (2014). None of these models incorporates the search costs incurred by producers attempting to find the best price.

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is able to explain the observed patterns in the data. I then structurally estimate the model to quantify the importance of information frictions. I find that approximately half the observed price dispersion across regions is due to information frictions rather than transportation costs. This implies that the transportation costs necessary to match the observed price dispersion are half the size of those estimated using a standard no-arbitrage equation, bringing the estimates more in line with observed freight costs. Finally, I show that incorporating information frictions improves the ability of a trade model to predict out-of-sample trade flows given the observed distribution of prices.

Agriculture is an important part of the Philippines economy. Staple agricultural commodities—primarily rice and corn—are grown by farmers of various sizes throughout the country. Partly because of idiosyncratic weather shocks, there exists substantial variation over time in the market prices for these commodities, providing incentives for inter-island trade to take advantage of price differentials. Using a comprehensive data set detailing the monthly regional price of each commodity and the universe of over-water domestic shipments of agricultural commodities from 1995 to 2009, I document five patterns in the observed prices and trade flows: first, observed freight costs cannot fully explain why trade flows decline with distance; second, while it is commonplace for a region to simultaneously import and export the same commodity, the incidence declines with access to mobile phones; third, the pass-through of price shocks between provinces, while incomplete, is stronger when both provinces have access to mobile phones; fourth, while larger farmers are more likely to trade, the introduction of mobile phones induces smaller farmers to begin trading; fifth, trade flows are more elastic to destination prices the greater is the heterogeneity of producers in the origin.

I next show that while these patterns are difficult to resolve with a simple complete information trade model, they can be explained by the presence of information frictions. To introduce information frictions, I embed a sequential search process based on the seminal job-search models of McCall (1970) and Mortensen (1970) into a many-region trade model with heterogeneous producers. Producers are endowed with heterogeneous quantities of a homogeneous commodity and sell it in perfectly competitive regional markets. After production, producers can either sell locally or search for a better price elsewhere. If a producer decides to search, she pays a fixed cost and observes the price (net of transportation costs) in another market. The producer can then sell in that market or pay the fixed cost and search again. A producer finds it optimal to sell in the first market where she discovers a price greater than her reservation price. If information is complete (i.e., search is costless), equilibrium prices are determined by a standard no-arbitrage equation, where the origin to destination price ratio of any pair of trading regions is equal to the transportation cost. When search is costly, because the fixed cost of search comprises a smaller proportion of total revenue the greater is the quantity produced, larger producers have higher reservation prices. The heterogeneity in reservation prices results in a threshold producer size that determines the range of producers willing to sell to any given destination. Bilateral trade flows can be calculated by aggregating across the range of willing producers who search a particular destination.

With information frictions, trade flows can decline with distance either because transportation costs increase or because the probability of searching a destination decreases, thereby providing an explanation as to why observed freight costs are unable to fully explain the decline of trade with distance. Because it is costly to learn about prices elsewhere, the model with information frictions implies that price arbitrage opportunities exist in equilibrium: as the fixed costs of search fall, producers search more intensively, reducing the extent of equilibrium arbitrage opportunities. As a result, information frictions can explain why regions import and export the same commodity, why price shocks are imperfectly transmitted to trading partners, and why these two phenomena are mitigated by the introduction of mobile phones. Finally, because larger producers search more intensively and, on average, sell to destinations with higher prices than smaller producers, information frictions can also explain why the elasticity of trade flows to destination prices increases with the heterogeneity of producers.

I proceed by structurally estimating the model to quantify the importance of information frictions. To disentangle the information frictions from transportation costs, I rely on comparisons of the extensive and intensive margins of trade. According to the model, transportation costs alone affect whether or not a region exports any of a commodity to another region, while both transportation costs and information frictions affect the quantity exported. The intuition is straightforward: because producers only export when it is profitable to do so, bilateral trade occurs only when the price gap between destination and origin exceeds the trade cost. In contrast, total trade flows depend on the number of producers who have discovered the arbitrage opportunity as well as the cost of transporting the good. I estimate the average ad valorem transportation cost to be 47%, which is roughly half the size of traditional estimates and more consistent with observed freight costs and detailed marketing cost surveys. I then show that a model with information frictions does better than a model without in predicting out-of-sample trade flows given observed prices.

The paper is organized as follows. In the next section, I describe the empirical context, discuss the data, and present several patterns observed in the trade flows and prices. In Section 3, I present the model and discuss how information frictions can explain the observed patterns in the data. In Section 4, I structurally estimate the model, quantify the importance of information frictions, and assess the predictive power of the model. Section 5 concludes. Appendices and replication files are provided in the Supplemental Material (Allen (2014)).

2. AGRICULTURAL TRADE IN THE PHILIPPINES

In this section, I provide a brief description of agricultural trade in the Philippines, describe the data, and present several patterns observed in the data that are consistent with the presence of information frictions.

2.1. *Empirical Context*

Agriculture is an important component of the Philippines economy: in 2010, one-third of workers were employed in agriculture and the sector comprised 17% of the Philippines gross domestic product (GDP) (Bureau of Agricultural Statistics (BAS) (2011)). The three major crops produced in the Philippines are rice, corn, and coconuts: in 2010, 81% of arable land was devoted to their production and they are responsible for 57% of the value of agricultural output (BAS (2011)). While coconuts are primarily processed into coconut oil and exported, both rice and corn are produced entirely for domestic consumption.[3] The empirical analysis that follows considers the trade of 10 agricultural commodities; however, because of the importance of rice and corn, the following discussion focuses on these two crops, which are produced nearly everywhere in the Philippines.

There are typically two growing seasons each year: the dry season (roughly December–April) and the wet season (roughly June–October): about 60% of the annual production is produced during the wet season (BAS (2011)). After production, farmers typically consume a portion of their produce and sell the rest to traders. Because unprocessed rice and corn degrades in quality quickly, most farmers sell their produce to traders shortly after harvest; for example, Hayami and Kikuchi (2000) find that between 60 and 90% of the production in their village of study was sold during the two months of peak harvest.

Surprisingly little is known about traders. Part of the reason appears to be due to the importance of private information: "Information is one source of success in the trading business, so traders are understandably hesitant to disclose details of their businesses" (Hayami and Kikuchi (2000, p. 185)). That said, there are several patterns in common across the interviews of traders and farmers conducted by Hayami and Kikuchi (2000) and BAS (2002), as well as informal interviews I conducted in Camarines Sur province in January 2011.[4] First, there are a large number of traders: Hayami and Kikuchi (2000) find that the 45 farmers they surveyed living in the same village sold their produce to 37 different buyers. Second, most traders are small: BAS (2002) find that 85% of the traders interviewed worked alone and were self-financed. Third, there is intense competition among traders: given the large number of traders and their

[3]The exportation of rice and corn is strictly regulated and de facto prohibited by the Philippines government. Because domestic prices almost always exceed world prices, this constraint is almost never binding.

[4]See Table XII in the Supplemental Material for details on their responses.

small size, the price at which rice and corn is transacted does not deviate much from the prevailing market price. This is evident in the farmer and wholesaler survey data used by the Philippines government to construct market prices: the average standard deviation of log prices across farmers for rice and corn within a given market is 0.04; the same figure for wholesalers is 0.03.

While there exists little variation in prices within a given market, there is substantial variation in prices across markets and over time. The average standard deviation of log prices of rice and corn across markets in a given month is 0.15. Within a given province, the average standard deviation of log (real) prices of rice and corn across time is 0.16. As a result, the ranking of a commodity price in one province relative to prices elsewhere changed substantially over time: Figure 1 depicts the correlation over time in the rankings of rice and corn prices (measured as the empirical cumulative distribution function of the price across all provinces in a given month). While the correlation is reasonably high (0.6–0.8) from one month to the next, the correlation decays quickly with time, so that there is very little correlation in price rankings after a few years. One important reason for the variation of prices is variation in weather; a Shapley–Shorrocks decomposition (see Shorrocks (2013)) implies that 35% of the variation in log (real) prices is due to time-invariant province fixed ef-

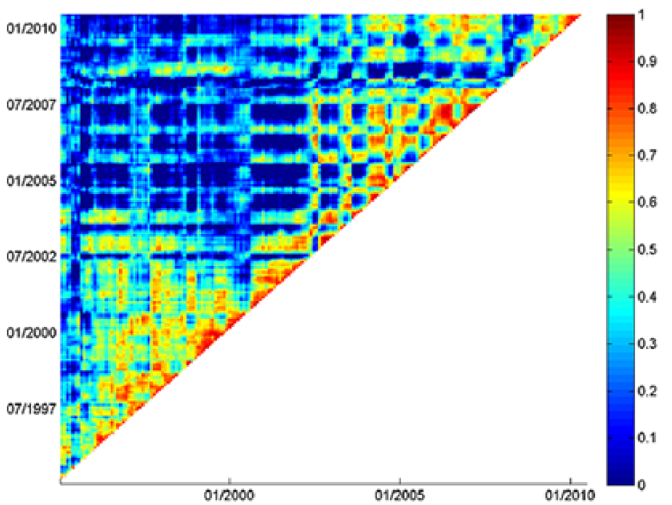

FIGURE 1.—Correlation of relative prices over time. This figure shows the correlation of the relative ranking of the price within a given province across time. The unit of observation is a province–commodity–month. The relative ranking is measured as the empirical cumulative distribution function of the price of a particular commodity in a particular province (i.e., the fraction of prices in other provinces below that province's price in a particular month). Lighter indicates a high correlation and darker indicates a low correlation (negative correlations are also darker). The sample includes all available rice and corn prices for all provinces from January 1995 to December 2010.

fects, 42% is due to location-invariant aggregate time shocks, 12% is due to differences in monthly rainfall across provinces, and 11% is unexplained.

Because of the substantial variation of prices across markets, there exist incentives for traders to ship rice and corn between provinces to take advantage of arbitrage opportunities. However, because the rankings of prices across provinces change substantially over time, this requires an investment in keeping up to date about prices elsewhere. In the four qualitative interviews I conducted with farmers and in three of the five interviews I conducted with traders, the interviewee had little knowledge of prices in nearby cities, let alone in other provinces. The two traders I spoke with who had knowledge of prices elsewhere (who were both among the largest traders in the province) emphasized the substantial effort required to keep their information up to date. Both did so by directly contacting traders in other markets on a frequent basis, and a substantial portion of their produce was sold to retailers and traders elsewhere in the Philippines.

2.2. *Data*

Data on the flow of goods within a country is rare, especially in the developing world.[5] Because of its island geography, I have been able to assemble data detailing the universe of commodities shipped by water throughout the Philippines.[6] I summarize the data I have collected here; see Appendix B (in the Supplemental Material) for a detailed description. The data provide the quantity and value of every commodity (at the Standard International Trade Classification (SITC) five-digit level) shipped each year from every port to every other port in the Philippines from 1995 to 2009. For a subset of trade flows, I also observe the direct freight cost incurred on the shipment; however, because these freight costs do not capture expenses such as local distribution costs, I use them only as a reference in assessing the realism of the magnitudes of the estimated transportation costs (see Section 4.4).

The core data set used in the subsequent sections consists of 4,332 observations of annual bilateral trade flows between provinces of 10 major agricultural commodities. The data set is summarized in Table I. Rice and corn are responsible for 3,769 of the observed bilateral trade flows and comprise 97.8% of the total value of trade, reflecting their importance as staple crops. Figure 2 illustrates the network of rice trade flows; as is evident, each province trades with many other provinces.

I combine the trade data with a number of other data sources, giving me information on (i) province–month–commodity wholesale prices; (ii) province–quarter–commodity production and yields; (iii) a census of farms producing

[5]The collection of trade flows within colonial India in Donaldson (2014) is a notable exception.

[6]Similar data for trade via air are unavailable. As trade via air constitutes less than 1% of total trade flows in terms of both quantity and value (National Statistics Office (NSO) (2001)), its exclusion from the following analysis is unlikely to substantially affect the results.

TABLE I

AGRICULTURAL COMMODITIES IN THE TRADE DATA[a]

Commodity	(1) Land Area (%)	(2) Output (%)	(3) Provinces Producing	(4) Province Markets	(5) Percentage of Trade Value	(6) Annual Trade Observations	(7) Monthly Price Observations
Banana	3.4	13.8	75	22	0.5	170	1,923
Cabbage	0.1	0.2	58	22	0.0	34	367
Corn	20.2	11.3	75	71	48.0	1,354	14,571
Garlic	0.0	0.1	27	16	0.0	70	715
Mung bean	0.3	0.2	73	10	0.0	7	65
Onion	0.1	0.6	39	17	0.1	92	1,091
Pineapple	0.5	1.7	71	17	0.0	44	371
Rice	34.5	35.8	75	77	49.8	2,415	27,776
Sweet potato	0.9	0.8	75	19	0.0	37	442
Tomato	0.1	0.4	74	25	1.5	109	1,262
Total	60.1	64.9	82	82	100	4,332	48,583

[a]Columns 1 and 2 are the average share of total land area and total agricultural output value from 2008 to 2010 taken from BAS (2011). Columns 3 and 4 report the number of provinces reporting any production or market price, respectively, in any year between 1990 and 2009. Column 5 reports the percentage of value of each commodity in the trade data set. Column 6 reports the number of annual bilateral trade flows observed in the trade set. Column 7 reports the number of observations in which the monthly price of the crop is observed in both the origin and the destination provinces, and trade flows are observed in the year. The trade data set includes all bilateral trade flows where (i) the market price in at least one month in the origin and destination are observed and (ii) the amount produced in the origin is observed.

each commodity in each province; (iv) daily rainfall data from 47 rainfall stations spread throughout the Philippines; and (v) the location and the month of construction of all cell phone towers in the Philippines. The price data allow me to observe the market price that producers would receive (excluding transportation costs) should they choose to sell to a particular destination.[7] The production data allow me to determine the fraction of produce exported of each commodity. The agricultural census allows me to estimate the shape parameter of the land distribution for each commodity in each province (see Appendix B.6 for details). The rainfall data provide a measure of exogenous productivity shocks. The cell phone tower data allow me to examine how the introduction of mobile phones affected the observed patterns of trade and prices. Mobile phone access expanded rapidly over the period of study: in 1996, there was one mobile phone subscriber for every 100 people in the Philippines; by 2007, there was one mobile phone subscriber for every 1.5 people (National Telecommunications Commission (NTC) (2008)).

[7]As a result, I do not have to rely on the unit prices reported in the trade data, which are unobserved when trade flows do not occur. The correlation between log (monthly) wholesale prices and log (annual) unit values when trade flows are observed is 0.2839.

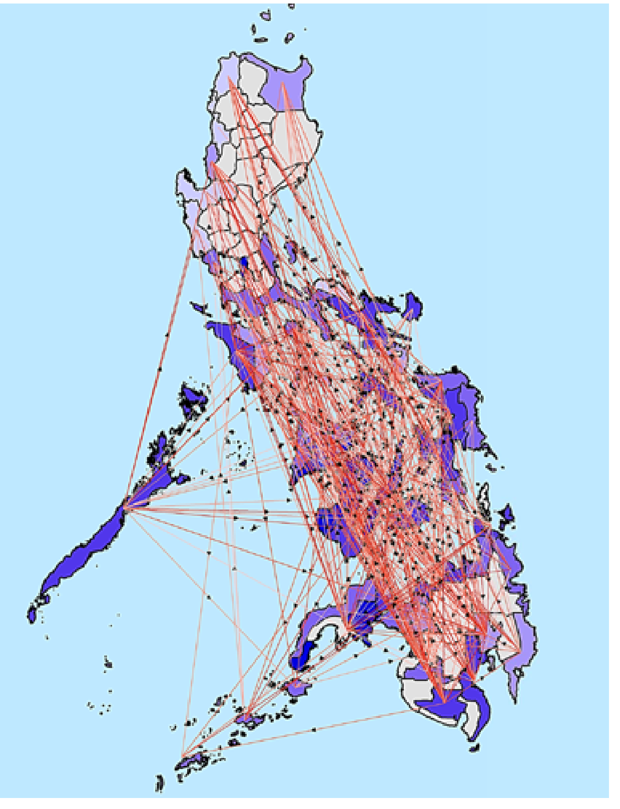

FIGURE 2.—Rice trade network in the Philippines. This figure shows the rice trade network in the Philippines. The shading of the provinces indicates the total observed rice trade flows (imports plus exports) from 1995 to 2009, where a darker shading indicates greater trade flows and gray indicates no observed trade flows. The lines indicate that trade in rice flows occurred between the two provinces in at least one year, with the arrow indicating the direction and the darker lines indicating a greater amount of trade.

2.3. *Empirical Patterns*

In this section, I document five patterns observed in the data. In the following section, I show that these patterns can be explained by the presence of information frictions.

Pattern 1: Transportation Costs Alone Cannot Explain Why Trade Flows Decline With Distance

Table II depicts the results of a gravity regression, where the (log) bilateral trade flows are regressed on the log over-water shipping distance, conditional on origin–commodity–year and destination–commodity–year fixed effects (FE). Columns 1 and 3 report the results of such a regression using trade

TABLE II

TRADE FLOWS, FREIGHT COSTS, AND SHIPPING DISTANCE[a]

	Log Quantity Shipped (kg)		Log Value Shipped (PHP)		Log Freight Costs (% of value)
Dependent Variable	(1)	(2)	(3)	(4)	(5)
Log shipping distance	−0.42***	−0.390***	−0.420***	−0.376***	0.130***
	(0.052)	(0.052)	(0.053)	(0.052)	(0.034)
Log freight costs (% of value)		−0.251***		−0.333***	
		(0.044)		(0.044)	
Origin–commodity–year FE	Yes	Yes	Yes	Yes	Yes
Destination–commodity–year FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.806	0.811	0.805	0.814	0.773
Observations	2,723	2,723	2,723	2,723	2,723

[a] Ordinary least squares. Each observation is an origin–destination–commodity–year quadruplet in which trade occurred and freight costs were recorded. Standard errors are reported in parentheses. Asterisks indicate statistical significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

flows measured in quantities and value, respectively. In both cases, a 10% increase in shipping distance is associated with a 4.2% decline in bilateral trade flows. However, column 5 of Table II reports that a 10% increase in shipping distance increases log freight costs (measured as a fraction of the value shipped) by only 1.3%, suggesting that transportation costs alone cannot explain the entirety of why trade flows decline in distance. Indeed, as columns 2 and 4 show, conditioning on freight costs results in only a slight decline in the effect of distance on trade flows. Hence, there appear to exist other frictions contributing to the gravity relationship between trade flows and distance.

Pattern 2a: Regions Often Simultaneously Import and Export the Same Commodity…

The top panel of Figure 3 indicates that half of provinces engaging in trade (30% overall) both import and export the same commodity in the same year. For import crops like rice, the figure is even higher: approximately 80% of provinces import and export rice in the same year. The bottom panel indicates that, on average, 28% of ports engaged in trade (5% of all ports) both imported and exported the same commodity within a 3 month period, suggesting that spatial and temporal aggregation cannot be the sole driver of this phenomenon.

Pattern 2b: … but Are Less Likely to Do so When There Is Access to Mobile Phones

Table III depicts how the prevalence of regions simultaneously importing and exporting is affected by mobile phone access. The incidence of regions simultaneously importing and exporting the same commodity, while remaining

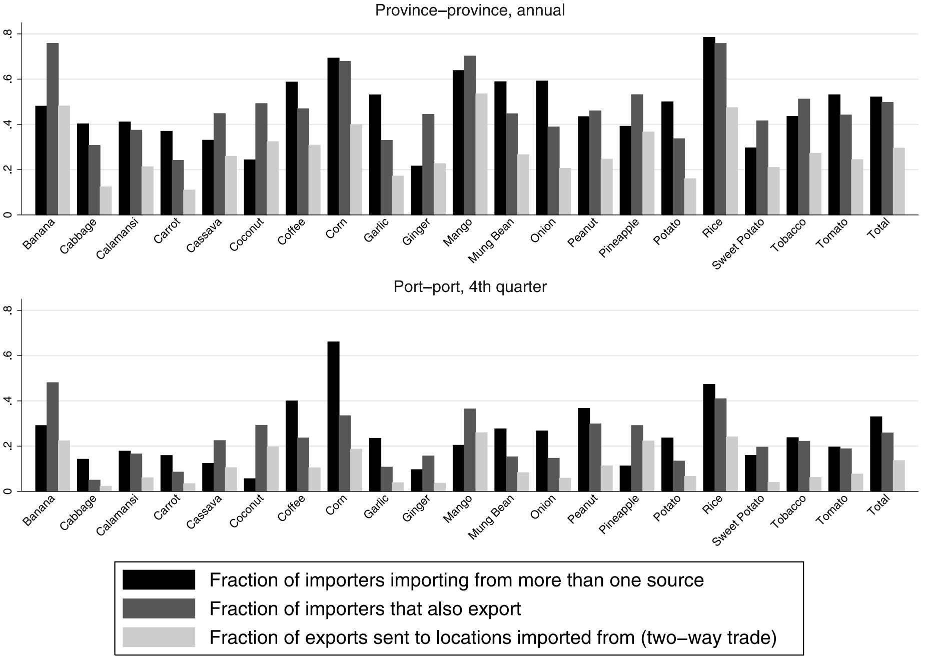

FIGURE 3.—Agricultural trade patterns in the Philippines by commodity. This figure shows the fraction of importers who import the same commodity from multiple sources, the fraction of importers who also export the same commodity, and the fraction of importers who export to destinations from which they import. Cebu and Manila are excluded to avoid instances of *entrepôt*. The sample for the top chart includes all annual bilateral agricultural trade flows between provinces. The sample for the bottom chart includes all bilateral trade flows occurring in the fourth quarter of each year disaggregated to port-to-port level. In both cases, all agricultural commodities are included, rather than just those with observed market prices.

common, is lower when regions have access to mobile phones. Controlling for variation across provinces and commodities,[8] a simple regression of whether or not a province simultaneously imported and exported a commodity in a given year on whether or not the province had access to a mobile phone indicates that the incidence of simultaneously importing and exporting was 11 percentage points (36%) lower overall for provinces with mobile phone access and 15 percentage points (30%) lower conditional on engaging in trade. A similar pattern is also evident at the more disaggregated level between ports within the fourth quarter of the year.

[8]I purposely do not include year fixed effects because I want to retain the identifying variation arising from the general equilibrium effect of mobile phones on the distribution of prices across regions. Indeed, the model with information frictions presented below implies that, conditional on prices in all regions, mobile phones will not affect whether a region simultaneously imports and exports (see equation (7) below).

TABLE III

SIMULTANEOUSLY IMPORTING/EXPORTING AND MOBILE PHONE ACCESS[a]

Dep. Var.: Simultaneously Imported & Exported	Province–Province, Annual		Port–Port, Fourth Quarter	
	(1)	(2)	(3)	(4)
Mobile phone access	−0.106***	−0.152***	−0.021***	−0.080***
	(0.007)	(0.010)	(0.002)	(0.009)
Commodity FE	Yes	Yes	Yes	Yes
Province/port FE	Yes	Yes	Yes	Yes
Sample	All provinces	Trading provinces	All ports	Trading ports
Mean of dep. variable	0.297	0.499	0.053	0.280
R-squared	0.502	0.398	0.408	0.400
Observations	14,025	8,359	52,605	9,914

[a] Ordinary least squares. Each observation is a province–commodity–year (columns 1–2) or port–commodity–fourth quarter (columns 3–4) triplet. The dependent variable is an indicator variable equal to 1 if a province/port both imported and exported a given commodity in a given year/4th quarter. Mobile phone access is an indicator variable equal to 1 if a province/port has a civilian cell phone tower in operation in a given year. Standard errors are reported in parentheses. Asterisks indicate statistical significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Pattern 3a: The Pass-Through of Price Shocks Is Incomplete...

Suppose region i exports both commodities c (corn) and d (rice) to region j in periods t and $t-1$. Then we can assess how price shocks in the origin affect prices in the destination by regressing changes in the log price ratio of c and d in the origin on the change in the log price ratio in the destination region,

$$\Delta \ln\left(\frac{p_{jct}}{p_{jdt}}\right) = \beta \Delta \ln\left(\frac{p_{ict}}{p_{idt}}\right) + \upsilon_{ijt}, \tag{1}$$

where υ_{ijt} is an idiosyncratic error term (which captures, for example, the change in the log of the relative transportation costs of corn and rice), Δ denotes the difference between t and $t-1$, and β captures how responsive the destination prices are to origin price shocks.[9] Because I observe bilateral trade flows at an annual frequency and observe prices at a monthly frequency, I consider origin–destination pairs that trade both rice and corn in each of two consecutive years, and measure the price ratio as the maximum monthly price ratio

[9]Equation (1) resembles the "pass-through test" of how the relative price of a commodity in two countries responds to shocks in the exchange rate between those countries (e.g., Goldberg and Verboven (2001)). In that literature, arbitrage may fail because of firms using market power to vary their mark-ups across destinations, which is unlikely in the context of agricultural commodity prices with many producers. In Table XIV in the Supplemental Material, I extend equation (1) to include many commodities and allow the estimated coefficient to vary by the degree of homogeneity of the commodity pair using the Rauch (1999) classification. I find that the price arbitrage equation actually does worse for more homogeneous goods (i.e., β is lower), suggesting that the results are not due to imperfect competition.

TABLE IV

PRICE PASS-THROUGH AND MOBILE PHONE ACCESS[a]

Dep. Var.: Change in Log Destination Price Ratio	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
Change in log origin price ratio	0.586*** (0.027)	0.390*** (0.093)	0.480*** (0.046)	0.251*** (0.079)
Change in log origin price ratio $*$ Mobile phone access			0.160*** (0.056)	0.307** (0.126)
Year fixed effects	Yes	Yes	Yes	Yes
R-squared	0.548	0.518	0.552	0.535
Observations	808	808	808	808
Test for complete pass-through (p-value)	0.000	0.000		
Test for complete pass-through without mobile phones (p-value)			0.000	0.000
Test for complete pass-through with mobile phones (p-value)			0.000	0.000

[a]First differences. The dependent variable is the change in the log wholesale price ratio of corn to rice in the destination province. Each observation is an exporter–importer–year triplet. The prices used in the price ratio are the monthly prices in which the ratio of importer to exporter price is largest. The change in the origin price ratio of corn to rice is instrumented with the change in the mean and standard deviation of monthly rainfall. The p-value of the test whether the estimated coefficient is 1 (as is implied by price arbitrage) is reported for all columns. Mobile phone access is an indicator variable equal to 1 if a civilian cell phone tower exists in both the exporting and importing province. Standard errors are reported in parentheses. Asterisks indicate statistical significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

observed in each of the two years. I then use a two-stage least squares (2SLS) estimation strategy to estimate β by instrumenting $\Delta \ln(\frac{p_{ict}}{p_{idt}})$ with a vector of changes in province-level rainfall and include year fixed effects to control for Philippines-wide weather and price shocks. As long as the weather shocks are uncorrelated with the change in the relative transportation costs of corn and rice, the estimated β will be unbiased.[10] Table IV presents the estimation results of equation (1). Columns 1 and 2 present the ordinary least squares (OLS) and 2SLS results, respectively, for the relative price of corn to rice in the Philippines. The estimated elasticities (0.59 for OLS and 0.39 for 2SLS) are precisely estimated and substantially below 1, allowing me to strongly reject ($p < 0.001$) that origin price shocks completely pass through to the destination.

Pattern 3b: . . . but Is More Complete When Trading Partners Both Have Access to Mobile Phones

It is also possible to compare the extent of price pass-through with and without mobile phone access. To do so, I allow the price pass-through coefficient β

[10]This procedure has the added benefit of correcting for any bias due to (classical) measurement error. Furthermore, since spatially correlated weather shocks would bias the 2SLS estimates upward, the estimates indicate an upper bound for the extent of pass-through.

in equation (1) to differ depending on whether both the origin and the destination province had at least one operating cellular tower. Columns 3 and 4 of Table IV present the OLS and 2SLS results, respectively. Province pairs with mobile phone access had substantially (and statistically significantly) greater price pass-through than those without: the 2SLS estimates report a pass-through rate of 25% without mobile phone access compared to a pass-through rate of 56% with mobile phone access.

Pattern 4a: Larger Farmers Are More Likely to Trade...

In addition to the trade and price data mentioned in Section 2.2, I have assembled more than two million observations of farmer sales for more than 200 agricultural crops within the period 2000–2009 (see Appendix B.7 for details). For each farmer who sold her produce in a particular month, data are collected on the price the farmer received, the quantity the farmer sold, and how much (if any) freight costs the farmer incurred.

Column 1 of Table V presents the results of a regression of whether or not a farmer incurred freight costs on the (log) quantity of produce the farmer sells and a province–commodity–month–year fixed effect so that identification arises only from within-market variation. A 10% increase in the quantity sold is associated with a 0.29 percentage point (1.6%) increase in the probability of incurring freight costs, indicating that larger farmers are more likely to sell to nonlocal destinations (i.e., to trade).

TABLE V

FARMER TRADE AND THE IMPACT OF MOBILE PHONES[a]

Dep. Var.: Farmer Incurred Freight Costs	(1) OLS	(2) OLS	(3) OLS
Log quantity sold	0.029***	0.041***	0.047***
	(0.001)	(0.001)	(0.004)
Mobile phone access		0.057***	
		(0.005)	
Mobile phone access ∗ log quantity sold		−0.014***	−0.018***
		(0.001)	(0.004)
Province–commodity–year FE	Yes	Yes	Yes
Commodity–year–month FE	Yes	Yes	Yes
Province–commodity–year–month FE	Yes	No	Yes
Mean of dep. var.	0.178	0.178	0.178
R-squared (within)	0.007	0.007	0.008
Observations	2,357,257	2,357,257	2,357,257

[a]The dependent variable is an indicator variable equal to 1 if the farmer incurred freight costs. The unit of observation is a farmer sale in a province–commodity–year–month. Mobile phone access is an indicator variable equal to 1 if there existed a cell tower in the province in that particular month. Standard errors clustered at the province–commodity–year–month are reported in parentheses. Asterisks indicate statistical significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Pattern 4b: … but Access to Mobile Phones Disproportionately Increases the Probability That Small Farmers Trade

Column 2 of Table V examines how access to mobile phones affects the probability that large and small farmers incur freight costs ("trade") using the regression

$$\text{trade}_{ficmt} = \beta_1 \ln q_{ficmt} + \beta_2 \,\text{phone}_{imt} + \gamma \ln q_{ficmt} \times \text{phone}_{imt} + \delta_{ict} + \delta_{cmt} + \varepsilon_{ficmt},$$

where trade_{ficmt} is an indicator function equal to 1 if farmer f incurred freight costs, phone_{imt} is an indicator function equal to 1 if there exists a cell phone tower in province i in month m in year t, δ_{ict} is a province–commodity–year fixed effect, and δ_{cmt} is a commodity–month–year fixed effect. The inclusion of δ_{ict} ensures that the effect of the introduction of mobile phones is identified only by comparing months prior to the construction of the first cell phone tower to the months after the construction of the tower within the same year, limiting the concern of the endogeneity of tower placement.[11] The inclusion of δ_{cmt} controls for aggregate variation in market conditions of commodity c within a given month, for example, seasonality of production. In the months after the construction of the first cell phone tower, the fraction of farmers incurring freight costs increased by 5.7 percentage points relative to the months prior to the construction of the first cell phone tower within a given year. Furthermore, after the construction of a tower, the relationship between trader search and log quantity sold falls by 0.014, a decline of 30%. Column 3 includes a province–commodity–month–year fixed effect so as to control for any concern about the endogeneity of the month a tower was constructed. While the fixed effect does not allow for the identification of β_2, the interaction γ remains negative and statistically significant. Hence, while larger farmers are more likely to incur freight costs, the introduction of mobile phones disproportionately increased the probability that smaller farmers incur freight costs.

Pattern 5: The Elasticity of Trade to Destination Prices Increases With the Heterogeneity of Producers in the Origin

The fifth pattern examines how the elasticity of trade to (exogenous) differences in destination prices is affected by the heterogeneity of producers in the origin. To measure producer heterogeneity, I apply a maximum likelihood routine to the microdata from the 1991 Philippines Agricultural Census so as to estimate a Pareto shape parameter of the distribution of land used in the production of each commodity in each province, θ_{ic} (see Appendix B.6 for details). I then regress the log quantity traded from province i to province j

[11] An alternative specification comparing the six months prior to cell phone tower construction to the six months after yields similar results.

of commodity c in year t, $\ln Q_{ijct}$, on the observed log price in month m in both the destination and the origin provinces, $\ln p_{jctm}$ and $\ln p_{ictm}$, as well as an interaction term of θ_{ic} and the log destination price (note that the origin–destination–commodity fixed effect controls for the direct effect of θ_{ic} on trade flows):

$$\ln Q_{ijct} = \beta_1 \ln p_{jctm} + \beta_2 \ln p_{ictm} + \gamma\theta_{ic} \times \ln p_{jctm} + \delta_{ijc} + \delta_{ctm} + \varepsilon_{ijctm}. \tag{2}$$

I include origin–destination–commodity fixed effects to control for all commodity-specific bilateral variables (such as transportation costs), so the identification arises only from variation across time in the prices and the trade flows within bilateral pairs for a particular commodity pair. To control for aggregate price and trade shocks, I also include commodity–year–month fixed effects. Because trade flows and prices are jointly determined, OLS estimation is subject to simultaneity bias. To circumvent this problem, I use a 2SLS estimation technique to isolate changes in the origin and destination prices due solely to local weather shocks by instrumenting for $\ln p_{jctm}$ and $\ln p_{ictm}$ with the mean and standard deviation of the monthly rainfall in their respectful locations.[12] Finally, because prices are observed at the monthly level while trade flows are only available at the annual level, I include a separate observation for each month, but allow for an arbitrary correlation across months (and years) by clustering the standard errors at the origin–destination–commodity level.

Columns 1 and 2 of Table VI present the OLS and 2SLS results, respectively, without the interaction term. In both specifications, I find that trade flows increase as the destination price increases or the origin price decreases (although the latter result is statistically significant only for the 2SLS specification). Consistent with simultaneity bias, the 2SLS results are approximately an order of magnitude larger than the OLS results, suggesting that a 10% increase (decrease) in the destination (origin) price is associated with a 45% (28%) increase in bilateral trade flows.

Columns 3 and 4 of Table VI present the OLS and 2SLS results, respectively, with the interaction term. In both columns, an decrease in θ_{ic}—corresponding to greater heterogeneity in landholdings—is associated with a greater responsiveness of trade flows to changes in the destination price. While the effect is statistically significant only for the 2SLS specification, the magnitude of the effect is large: the 2SLS estimate indicates that a 1 standard deviation (1.92) increase in θ_{ic} from the mean (3.16) causes the elasticity of bilateral trade flows to destination prices to decrease from 4.89 to 4.01, a fall of 18%. Hence, exports

[12]I allow idiosyncratic rainfall shocks to have different effects on the prices of each commodity by interacting the rainfall shock with a commodity fixed effect.

TABLE VI

TRADE FLOWS, PRICES, AND PRODUCER HETEROGENEITY[a]

Dep. Var.: Log Quantity Exported	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
Log destination price	0.460***	4.529***	0.730***	6.331***
(2000 PHP)	(0.170)	(1.703)	(0.266)	(2.165)
Log origin price	−0.192	−2.847*	−0.176	−2.812*
(2000 PHP)	(0.183)	(1.638)	(0.181)	(1.593)
Log destination price ∗ origin			−0.057	−0.457**
producer heterogeneity			(0.037)	(0.192)
Origin–destination–commodity FE	Yes	Yes	Yes	Yes
Commodity–month FE	Yes	Yes	Yes	Yes
R-squared (within)	0.002	−0.107	0.002	−0.110
Observations	48,583	48,583	48,583	48,583

[a]The dependent variable is the log quantity exported. Each observation is an origin–destination–year–month–commodity quintuplet. Because the quantity traded is observed annually while prices are observed monthly, standard errors are clustered at the origin–destination–commodity level. In the 2SLS columns, the origin and destination prices are instrumented with the mean and standard deviation of monthly rainfall in their respective locations. The origin producer heterogeneity is a province–crop specific Pareto shape parameter estimated from the 1990 Agricultural Census microdata; lower values indicate greater heterogeneity across farmers in land allocated to a particular crop. Clustered standard errors are reported in parentheses. Asterisks indicate statistical significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

from provinces are more responsive to destination price shocks the greater is the heterogeneity of producers.

That the trade flows become more responsive as the heterogeneity of landholdings in the origin increases suggests that larger farmers are more responsive to differences in destination prices than smaller farmers. As I show in the next section, one explanation for such a pattern is that there is a fixed cost associated with learning prices in other locations—a cost larger farmers are more willing to incur. It is important to note, however, that there may exist alternative explanations for this pattern (and the other patterns) that do not rely on information frictions. One possible alternative explanation is that producers are capacity constrained and there are fixed costs to exporting to other markets, so that only larger producers end up exporting. Another alternative is that producers within a location face different trade costs, leading only some to take advantage of price differentials.[13] The fact that the introduction of mobile phones affected prices and trade flows, however, suggests that it is plausible that information frictions exist. With this in mind, in the next section, I present a simple model of trade that incorporates information frictions and then show that the model is consistent with each of the patterns presented in this section.

[13]I examine both these alternative explanations in detail in Appendix D.

3. A TRADE MODEL WITH INFORMATION FRICTIONS

In this section, I present a trade model with information frictions. I assume that each producer has to undergo a search process to learn what prices are in other destinations. While the model yields a standard no-arbitrage condition when the search process is costless, when search is costly, larger producers will search more intensively and, on average, sell to destinations with higher prices. I use this result to analytically characterize bilateral trade flows as a function of prices, information frictions, and the distribution of producer's endowments, and show that the simple model is consistent with the empirical patterns presented in the previous section.

3.1. *Setup*

There are a large number of regions in the world, each inhabited by consumers and an exogenous mass of farmers.[14] In what follows, I use i to refer to the origin region and j to refer to the destination region. Each farmer produces a single commodity c and maximizes profits; let the mass of farmers producing commodity c in region i be denoted by M_{ic}. Each commodity is produced and consumed in all regions.

Demand

Consumers in region j are endowed with exogenous wealth and have preferences that induce an inverse demand function $D_{jc}:\mathbb{R}_+ \to \mathbb{R}_+$. The inverse demand function (which may differ across regions) gives the market clearing price p_{jc} as a function of the quantity of commodity c sold r_{jc}, that is, $p_{jc} = D_{jc}(r_{jc})$. (This assumption implicitly assumes that preferences are quasi-linear in commodity c.) I assume that D_{jc} is nonnegative, continuous, and strictly decreasing for all j. Farmers producing commodity c in region i and selling it to consumers in region j incur iceberg transportation costs $\tau_{ijc} \geq 1$, where $\tau_{iic} = 1$ for all i and c.[15] This implies that the price a farmer from region i selling to region j receives for commodity c net of transportation costs is $p_{ijc} \equiv p_{jc}/\tau_{ijc}$.[16] These transportation costs are meant to capture all costs associated with transporting a good from one location to another, including freight costs, the time spent in transit, policy barriers (e.g., tariffs), risk of damage, insurance costs, and local distribution costs.

[14] I follow Lucas and Prescott (1974) in defining "large" as a continuum or a countable infinity of regions. The large number of regions is necessary to ensure that the distribution of prices faced by producers is invariant to the particular realization of productivity shocks.

[15] In Appendix E.2, I extend the model to incorporate fixed costs of export in addition to variable transportation costs. The insights of the model remain qualitatively unchanged.

[16] In Appendix E.4, I extend the model to allow for farmers selling greater quantities to receive higher prices because of economies of scale (e.g., because the fixed costs of making a transaction are spread across greater volumes). The results that follow remain qualitatively unchanged.

Production

Each commodity in each region is subject to idiosyncratic productivity shocks $A_{ic} \in (0, 1]$, where A_{ic} indicates the fraction of farmers growing commodity c who are successfully able to produce. If a farmer produces, she produces an amount equal to her landholdings φ.[17] Landholdings $\varphi \in [1, \infty)$ are heterogeneous across farmers and distributed according to the cumulative distribution function F_φ^{ic}, which is assumed to be a Pareto distribution with shape parameter $\theta_{ic} > 1$, that is, $F_\varphi^{ic}(\varphi) = 1 - \varphi^{-\theta_{ic}}$.[18]

Search

Farmers know their local price and the true distribution of prices (net of transportation costs), but must engage in a search process to learn the prices elsewhere. I model the search process as an undirected sequential search process.[19] After production, a farmer can either sell at home or search for another destination to which to sell her produce.[20] Define the *fixed cost of search* f_{ic} to be the cost of each search. If a farmer decides to search, she (randomly) draws the name of a single region, for which she learns the price (net of transportation costs). The farmer can then sell to that destination or search again, in which case she again incurs the fixed cost of search f_{ic} and draws (with replacement) the name of a new region. The process continues until the farmer finds a destination to which she is willing to sell her produce. Define the *search probability* $s_{ijc} > 0$ to be the probability that a farmer producing commodity c from region i draws the name of region j conditional on searching.[21] I assume that the set of search probabilities $\{s_{ijc}\}_j$ is the same for all farmers from a particular region producing the same commodity and is constant throughout the search process.

[17]I assume that the landholdings of farmers are determined exogenously, which is a realistic assumption in a context like the Philippines where most land is acquired by inheritance and land markets are largely missing (cf. Estudillo, Quisumbing, and Otsuka (2001)).

[18]The Pareto distribution is a reasonable approximation of the observed land distribution in the Philippines; see Appendix B.6 for details.

[19]In Appendix C, I consider a number of alternative frameworks for modeling the search process, including several variants of a directed search process, a bilateral search process where both farmers and consumers engage in a costly search process to secure a match, and a framework where farmers establish network connections prior to the realization of prices. Of the many ways to model the search process, I find that the undirected sequential search process does the best job of matching the empirical patterns of trade and prices while remaining tractable.

[20]For simplicity, I abstract from the role of intermediary traders by assuming that farmers sell directly to consumers. In Appendix E.1, I extend the model to include such traders and show that the central predictions of the model remain unchanged.

[21]With a discrete number of regions, the search probabilities must sum to 1, that is, $\sum_{j \neq i} s_{ij} = 1$. With a continuum of regions, the search probability becomes a search density $s_i(j)$ such that $\int_J s_i(j)\,dj = 1$, where J is the set of destinations. For simplicity, in what follows I use the notation for a discrete number of regions.

The model has two types of information frictions: the fixed cost of search f_{ic} and the search probability s_{ijc}. The fixed cost of search f_{ic} captures all costs associated with gathering sufficient information about a market so as to sell there. Since a farmer pays the fixed cost prior to searching a particular destination, the fixed cost is destination invariant. The search probability s_{ijc} captures the many reasons that farmers search certain destinations more often than others.

A (weighted) random search process is less of a simplification than it may at first appear. One might think that farmers ought to first search the destination with the highest expected price net of transportation costs. However, since prices are equilibrium objects that depend in part on the search probabilities themselves, any initial arbitrage opportunity from such a strategy would be eroded by other farmers' exports. As long as there is a sufficient mass of farmers exporting, any individual farmer could profit by instead first searching the second-most attractive destination. This implies that the only symmetric equilibrium search strategy is a mixed strategy.[22]

3.2. *Equilibrium With Complete Information*

To highlight the effect of information frictions, I first derive the equilibrium with complete information. Suppose that the search process is costless, that is, the fixed cost of search is zero. Because farmers know the true distribution of prices net of transportation costs, farmers will choose to search if and only if the maximum price net of transportation costs is at least as great as the local price. Conditional on searching, farmers will continue to search until they find the destination with that maximum price. Hence, for any producer to be willing to sell locally, the equilibrium local price must be at least as high as any destination price net of transportation costs, that is, for all i, j, and c, $p_{ic} \geq \frac{p_{jc}}{\tau_{ijc}}$. Furthermore, if positive trade flows of commodity c are observed from location i to location j, then it must be the case that traders are indifferent between exporting and selling locally, so that the price net of transportation cost must be equal in both destinations, that is,

$$Q_{ijc} > 0 \implies p_{ic} = \frac{p_{jc}}{\tau_{ijc}}, \tag{3}$$

where Q_{ijc} is the quantity of commodity c shipped from location i to location j. In what follows, I refer to this simple model as a *complete information trade model* and refer to equation (3) as the *complete information no-arbitrage equation*. I show below that the presence of information frictions will cause the

[22]In particular, the mass of exporting farmers in a particular region i must be sufficiently large so that the expected price net of transportation costs in the most attractive destination conditional on all exporting farmers from i selling there is less than the expected price net of transportation costs in the second-most attractive destination conditional on no farmers selling there.

complete information no-arbitrage equation to fail; however, it is important to keep in mind that there are many other possible reasons that it may fail, for example, market power, heterogeneity in trade costs, fixed costs of export with capacity constraints, and so forth.

3.3. *Optimal Search Behavior*

Suppose now that search is costly, that is, the fixed cost of search f_{ic} is strictly positive. In this subsection, I determine the optimal search behavior of a farmer given a distribution of prices (equilibrium prices are determined below in Section 3.5). Consider a farmer with landholdings φ from region i who has positive production. Suppose she has learned of a price (net of transportation costs) of p and is deciding whether to sell at that price or search again. Define $F_p^{ic}(p)$ to be the cumulative distribution function of prices net of transportation costs that the farmer believes she will draw from if she chooses to search.[23] The value function of the farmer is

$$V_{ic}(p;\varphi) = \max\Bigg\{\underbrace{\varphi p}_{\text{sell}}\underbrace{\int_{p_{ic}^{\min}}^{p_{ic}^{\max}} V_{ic}(p';\varphi)\,dF_p^{ic}(p') - f_{ic}}_{\text{search again}}\Bigg\},$$

where $p_{ic}^{\min} \equiv \min_{j\neq i} p_{ijc}$ and $p_{ic}^{\max} \equiv \max_{j\neq i} p_{ijc}$ are the worst and best prices net of transportation costs that a farmer can encounter.

It is straightforward to show that the farmer's optimal strategy is to sell if and only if the discovered price exceeds her reservation price, that is, $p \geq \bar{p}_{ic}(\varphi)$, where the equilibrium condition governing the reservation price is

$$f_{ic} = \varphi \int_{\bar{p}_{ic}(\varphi)}^{p_{ic}^{\max}} \big(p' - \bar{p}_{ic}(\varphi)\big)\,dF_p^{ic}(p'). \tag{4}$$

Equation (4) states that at the optimal reservation price, the cost of continuing to search is equal to the marginal benefit of continuing to search. As long as the fixed cost of search f_{ic} is positive, equation (4) implies that the reservation price $\bar{p}_{ic}(\varphi)$ is strictly increasing in φ, that is, larger farmers have higher reservation prices. Intuitively, larger farmers have more to sell, so their returns from discovering a better price are greater. As a result, they search more intensively than smaller farmers.[24] Since $\bar{p}$ is strictly increasing in φ, I can invert

[23]For what follows, $F_p^{ic}(p)$ need not be everywhere differentiable. For ease of notation in what follows, however, I use $\int g(p)\,dF_{p/\tau}^{ic}(p)$ to refer to the Lebesgue integral, that is, for any function $g(\cdot)$, $\int g(p)\,dF_{p/\tau}^{ic}(p) = \sum_{j\neq i} s_{ijc}\, g(\frac{p_{jc}}{\tau_{ijc}})$.

[24]I show in Appendix F.1 that the expected per-unit revenue that a farmer receives from searching is her reservation price $\bar{p}(\varphi)$, which implies that the expected per-unit revenue is also increasing in quantity produced.

equation (4) to yield the threshold landholding size $\varphi^*_{ic}(p)$ such that all farmers with landholdings larger than the threshold will continue to search, while all farmers below the threshold will choose to sell at price p:

$$\varphi^*_{ic}(p) \equiv \frac{f_{ic}}{K_{ic}(p)}, \tag{5}$$

where

$$K_{ic}(p) \equiv \int_p^{p^{\max}_{ic}} (p' - p)\, dF^{ic}_p(p'). \tag{6}$$

I define $K_{ic}(p)$ as the *value of search* since it measures the per-unit benefit of continuing to search as a function of the current price p. Note that $K_{ic}(p)$ is strictly decreasing: the greater is the offer in hand, the lower is the value of continuing to search. As a result, $\varphi^*_{ic}(p)$ is strictly increasing: as the price in hand increases, larger farmers become willing to sell at that price.

Unlike in Melitz (2003), the threshold landholding size $\varphi^*_{ic}(p)$ indicates the *maximum* land size such that a farmer would be willing to sell to a particular destination rather than the *minimum* productivity required to enter a market. The difference arises because in this model, farmers have a fixed amount of produce to sell, so the decision to sell to one destination comes at the cost of selling elsewhere, whereas in Melitz (2003) firms have constant marginal costs, allowing them to decide how much to produce in each market independently of all other markets. Hence, the model developed here is more realistic in settings where production cannot easily be scaled to respond to changes in market demand (e.g., agriculture).

3.4. *Bilateral Trade*

Given the optimal search behavior of each farmer, it is possible to characterize total bilateral trade flows by aggregating across all farmers within a region.

Consider first whether or not any trade from i to j occurs. Only farmers with reservation price $\bar{p}_{ic}(\varphi) \geq p_{iic}$ will decide to search rather than sell to their own region. As a result, if $p_{ijc} < p_{iic}$, then no farmer searching region j will choose to sell there, since all farmers who choose to search are unsatisfied with prices lower than their local price. Conversely, if $p_{ijc} \geq p_{iic}$, then any farmer with reservation price $\bar{p}_{ic}(\varphi) \in [p_{iic}, p_{ijc}]$ (or, equivalently, landholdings $\varphi \in [\varphi^*_{ic}(p_{iic}), \varphi^*_{ic}(p_{ijc})]$) who searches region j will choose to sell there. Since the distribution of landholdings is continuous, such a farmer will search region j with a probability of 1. As a result,

$$Q_{ijc} > 0 \iff \frac{p_{jc}}{\tau_{ijc}} \geq p_{ic}, \tag{7}$$

where Q_{ijc} denotes the total quantity exported from i to j of commodity c. Unlike the complete information no-arbitrage equation (3) presented in Section 3.2, when there are information frictions, positive trade flows imply that the destination price net of transportation costs is at least as great as the origin price, that is, arbitrage opportunities remain in equilibrium. This occurs because there is an insufficient mass of producers who are aware of any particular arbitrage opportunity to cause that opportunity to fully erode.

Now consider the quantity of commodity c exported from i to j. Suppose that $p_{ijc} \geq p_{iic}$ so that some trade occurs. In general, determining total trade Q_{ijc} requires aggregating over all possible search histories for each farmer and then aggregating across all farmers. This process is simplified considerably by two results of the individual farmer search process: first, the reservation price of each farmer remains constant throughout the search process; second, the reservation price is monotonically increasing in the farmer's landholdings.

Because the reservation price remains constant throughout the search process, the probability that a farmer from region i of size φ has yet to find a destination to which she is willing to sell after k searches is simply the probability that every price she has learned of so far is less than her reservation price, that is, $F_p^{ic}(\bar{p}_{ic}(\varphi))^k$. The unconditional probability a farmer from region i of size φ producing commodity c searches region j after k searches is thus

$$\pi_{ijck}(\varphi) = s_{ijc} F_p^{ic}\big(\bar{p}_{ic}(\varphi)\big)^k.$$

By the law of large numbers, the total quantity of commodity c arriving from region i to region j after k searches from farmers of size φ, $Q_{ijck}(\varphi)$, is equal to the product of the quantity each farmer produces (i.e., φ), the density of producing farmers of size φ (i.e., $A_{ic} M_{ic}\, dF_\varphi^{ic}(\varphi)$), and the probability each farmer searches region j after k searches (i.e., $\pi_{ijck}(\varphi)$):

$$\begin{aligned} Q_{ijck}(\varphi) &= \varphi A_{ic} M_{ic}\, dF_\varphi^{ic}(\varphi) \pi_{ijck}(\varphi) \\ &= s_{ijc} A_{ic} M_{ic} \theta_{ic} \varphi^{-\theta_{ic}} F_p^{ic}\big(\bar{p}_{ic}(\varphi)\big)^k, \end{aligned}$$

where the second equality comes from the assumption that landholdings are Pareto distributed.

Upon searching destination j, all farmers with reservation prices no greater than p_{ijc} will choose to sell there. Because the reservation price is monotonically increasing in the farmer's landholdings, this implies that all farmers of size $\varphi \in [\varphi_{ic}^*(p_{iic}), \varphi_{ic}^*(p_{ijc})]$ will be both unwilling to sell locally and willing to sell to destination j. As a result, the total quantity traded of commodity c from i to j after k searches can be found by integrating over these willing farmers:

$$Q_{ijck} = \int_{\varphi_i^*(p_{iic})}^{\varphi^*(p_{ijc})} Q_{ijck}(\varphi)\,d\varphi$$
$$= s_{ijc}A_{ic}M_{ic}\theta_{ic}\int_{\varphi_i^*(p_{iic})}^{\varphi^*(p_{ijc})} \varphi^{-\theta_{ic}}F_p^{ic}\big(\bar{p}_{ic}(\varphi)\big)^k\,d\varphi.$$

Because there is a positive probability that a farmer could sell to j after conducting any number of previous searches, total trade flows from i to j can be determined by summing over all possible numbers of searches that have previously occurred:

$$Q_{ijc} = \sum_{k=0}^{\infty} Q_{ijck} = \sum_{k=0}^{\infty} s_{ijc}A_{ic}M_{ic}\theta_{ic}\int_{\varphi_i^*(p_{iic})}^{\varphi^*(p_{ijc})} \varphi^{-\theta_{ic}}F_p^{ic}\big(\bar{p}_{ic}(\varphi)\big)^k\,d\varphi. \tag{8}$$

It turns out that equation (8) can be simplified substantially. Integration by substitution yields

$$Q_{ijc} = \sum_{k=0}^{\infty} s_{ijc}A_{ic}M_{ic}\theta_{ic}\int_{p_{iic}}^{p_{ijc}} \big(\varphi_{ic}^*(p)\big)^{-\theta_{ic}}\left(\frac{\partial}{\partial p}\varphi_{ic}^*(p)\right)F_p^{ic}(p)^k\,dp.$$

Differentiating equation (5) implies $\frac{\partial}{\partial p}\varphi_{ic}^*(p) = -\frac{f_{ic}}{K_{ic}(p)^2}\frac{\partial}{\partial p}K_{ic}(p)$. Applying Leibniz's rule to the definition of $K_{ic}(p)$ in equation (6) yields $\frac{\partial}{\partial p}K_{ic}(p) = -(1-F_{p/\tau}^{ic}(p))$, so that we can rewrite bilateral trade flows as

$$Q_{ijc} = \sum_{k=0}^{\infty} s_{ijc}A_{ic}M_{ic}\theta_{ic}f_{ic}^{1-\theta_{ic}}\int_{p_{iic}}^{p_{ijc}} K_{ic}(p)^{\theta_{ic}-2}F_p^{ic}(p)^k\big(1-F_p^{ic}(p)\big)\,dp.$$

Finally, by interchanging the infinite sum and the integral (which is justified by Tonelli's theorem since the integrand is nonnegative), and using the familiar solution for the infinite sum of a geometric series, we have

$$Q_{ijc} = A_{ic}M_{ic}\theta_{ic}f_{ic}^{1-\theta_{ic}}s_{ijc}\int_{p_{iic}}^{p_{ijc}} K_{ic}(p)^{\theta_{ic}-2}\,dp. \tag{9}$$

Equation (9) shows that bilateral exports are increasing in the total quantity produced ($\theta_{ic}A_{ic}M_{ic}$), decreasing in the fixed cost of search f_{ic}, and increasing in the probability of search s_{ijc}. The integral captures how attractive a particular destination price is relative to all other destination prices. Trade flows are greater the larger is the gap between the origin price and the destination price; how that gap affects trade flows, however, depends on prices in other regions through the value of search. Because smaller producers search less intensively than larger producers, regions with many small farmers (i.e., high θ_{ic}) will concentrate exports to destinations with low relative prices (i.e., high $K_{ic}(p_{ijc})$), whereas regions with many large farmers will concentrate exports to destinations with high relative prices.

To provide some intuition for the estimation of trade costs in the following section, it is helpful to decompose bilateral trade flows into the total amount traded and the share that is exported to each destination. Define $\lambda_{ijc} \equiv \frac{Q_{ijc}}{\sum_{j\neq i} Q_{ijc}}$ as the share of exports from region i destined for region j of commodity c and define $\Lambda_{ic} \equiv \frac{\sum_{j\neq i} Q_{ijc}}{\sum_j Q_{ijc}}$ to be the fraction of production that is exported. From equations (5) and (9), we have

$$\lambda_{ijc} = s_{ijc} K_{ic}(p_{iic})^{1-\theta_i} \int_{p_{iic}}^{p_{ijc}} K_{ic}(p)^{\theta_{ic}-2}\, dp, \tag{10}$$

$$\Lambda_{ic} = \left(\frac{K_{ic}(p_{iic})}{f_{ic}}\right)^{\theta_{ic}-1}. \tag{11}$$

The share of exports sent to a destination depends on both the probability that it is searched and its predicted trade share (normalized by the value of search at the home price). In contrast, the fraction of production exported (the "openness" of a region) depends only on the fixed cost of search, the value of search at the local price, and its distribution of landholdings.

3.5. *Equilibrium*

Thus far, I have taken prices in each region as given; in equilibrium, prices will ensure supply equals demand in all regions. In particular, I define equilibrium as a set of prices $\{p_{ic}\}$ and trade flows $\{Q_{ijc}\}$ such that the following three conditions hold:

(i) Given prices and beliefs, farmers search optimally, that is, trade flows are determined by equations (7) and (9).

(ii) Farmers have the correct beliefs concerning the distribution of prices, that is, $F_p^{ic}(p) = \sum_{j\neq i} s_{ijc} \mathbf{1}\{p_{ijc} \leq p\}$ for all i and c.

(iii) The supply of each commodity in each region is consistent with the demand of that commodity at that price, that is, $p_{jc} = D_{jc}(\sum_i Q_{ijc})$ for all j and c.

Note that equilibrium condition (ii) assumes that the only uncertainty producers face regarding prices arises from not knowing which destination they will search. If producers also face uncertainty regarding the actual price realization in a particular destination, this additional uncertainty will result in a mean-preserving increase in spread of this distribution. This increased uncertainty will (weakly) increase the value of search; see Appendix G.1 for details.

In Appendix A, I show that for any nonnegative and strictly decreasing inverse demand function, there exists a set of prices and trade flows that satisfy equilibrium conditions (i)–(iii). Furthermore, there exists a $t > 0$ such that if $\tau_{ijc} < 1 + t$ for all i, j, and c, then the equilibrium set of prices and trade flows is unique (up to scale). Intuitively, differences in domestic production and demand result in differences in autarkic prices across regions. Farmers engage in price arbitrage by exporting to destinations with high prices, causing prices to converge. The set of equilibrium prices yields just enough price dispersion to generate arbitrage opportunities that incite trade flows that ensure there is no excess supply or demand in any region. The extent of the arbitrage opportunities depends on the size of the information frictions; when the fixed cost of search is arbitrarily high, there is no trade and the equilibrium prices are the autarkic prices, whereas as the fixed costs of search approach zero, all arbitrage opportunities are eroded and the model converges to the complete information trade model.

3.6. *Explaining the Empirical Patterns*

In this subsection, I discuss how the empirical patterns presented in Section 2.3 are inconsistent with the complete information trade model but can be explained by the presence of information frictions.

Pattern 1

In the complete information trade model, trade flows are only determined by the origin price, the destination price, and the bilateral transportation costs, which implies that, conditional on origin and destination prices, the distance between two locations will only affect trade through transportation costs, which is inconsistent with Pattern 1.

With information frictions, equation (9) implies that bilateral trade flows can be decomposed into the search probability s_{ijc}, the predicted trade share $\int_{p_{iic}}^{p_{ijc}} K_{ic}(p)^{\theta_{ic}-2}\,dp$, and an origin fixed effect $A_{ic}M_{ic}\theta_{ic}f_{ic}^{1-\theta_{ic}}$. This implies that trade flows will decline in distance conditional on transportation costs as long as farmers are more likely to search nearby destinations.

Patterns 2a and 3a

If transportation costs satisfy the triangle inequality (i.e., for all $i \neq j \neq k \in S$ and all $c \in S$, $\tau_{ikc} < \tau_{ijc}\tau_{jkc}$), the complete information no-arbitrage equation (3) implies that the same region never simultaneously imports and exports the same commodity, which is inconsistent with Pattern 2a. Similarly, the complete information no-arbitrage condition immediately implies that price shocks in the origin should pass through completely to destination prices, which is inconsistent with Pattern 3a.

With information frictions, from equation (7), arbitrage opportunities remain in equilibrium. This implies that region i will simultaneously import and export commodity c anytime there exist regions j and k such that $p_{kc}\tau_{kic} \leq$

$p_{ic} \leq \frac{p_{jc}}{\tau_{ikc}}$ (Pattern 2a). Intuitively, the large farmers from region i will be willing to incur the search costs to find a better price elsewhere, while smaller farmers from region k, upon searching region i, will be willing to sell there. Similarly, since there is not a no-arbitrage equation that requires the ratio of origin and destination prices to be constant, origin price shocks need not completely pass through to destination price shocks (Pattern 3a).

Patterns 2b and 3b

In the complete information trade model, the no-arbitrage equation (3) is invariant to the presence of mobile phones, which is (trivially) inconsistent with Patterns 2b and 3b.

With information frictions, it can be shown (see Appendix F.3) that as long as locations are not too different, the fixed cost of search falls in a particular location and its price will tend to rise toward the maximum price net of transportation costs of any destination, that is, $-\frac{\partial}{\partial f_{ic}}(p_{ic}^{\max} - p_{iic}) < 0$. If access to mobile phones reduces the fixed cost of search, this implies that the performance of the no-arbitrage condition (3) will improve with mobile phone access, which is broadly consistent with Patterns 2b and 3b. It should be noted, however, that if the fixed cost of search falls only in some locations, the incidence of simultaneously importing and exporting may be unchanged: while those locations where the fixed cost of search fell will export to destinations with higher prices, the export behavior of other locations—where the fixed costs of search have not fallen—will not be directly affected. Hence, strictly speaking, Pattern 2b is consistent with the model of information frictions only if the fixed costs of search fall in all regions.

Patterns 4a and 4b

In the complete information model, all producers are equally likely to trade and mobile phones have no effect on trade patterns.

With information frictions, equation (5) implies that only farmers larger than a certain threshold will sell their produce elsewhere (Pattern 4a) and that the threshold is increasing with the fixed cost of search. Hence, if mobile phones reduce the fixed cost of search, the threshold will decline, inducing smaller farmers to search other destinations (Pattern 4b).

Pattern 5

In the complete information model, the producer endowment does not affect the destination to which she sells, which is (trivially) inconsistent with Pattern 5. It should be noted that this empirical finding is also contrary to the predictions of other heterogeneous-producer trade models; for example, Eaton and Kortum (2002) and Melitz (2003)–Chaney (2008) predict that the elasticity of trade to the variable trade cost is decreasing in the heterogeneity of producers.[25] Intuitively, in these models as producer heterogeneity increases, the density of producers who are indifferent between exporting and not exporting declines, so that the extensive margin responds less to changes in trade costs.

With information frictions, larger producers search more intensively, so that they (on average) sell to destinations with higher prices than smaller producers. As a result, exports from regions with a greater relative share of large producers (i.e., lower θ_{ic}) are more responsive to changes in the destination price. By applying Leibniz's rule to equation (9), we can derive the following expression for the trade elasticity to destination prices (see Appendix F.2 for a formal proof):

$$\frac{\partial \ln Q_{ijc}}{\partial \ln p_{ijc}} = p_{ijc}\left(\int_{p_{iic}}^{p_{ijc}} \left(\frac{K_{ic}(p)}{K_{ic}(p_{ijc})}\right)^{\theta_{ic}-2} dp\right)^{-1}.$$

Since $K_{ic}(p) > K_{ic}(p_{ijc})$ for all $p \in [p_{iic}, p_{ijc}]$, $\frac{\partial \ln Q_{ij}}{\partial \ln p_{ijc}}$ is strictly decreasing in θ_{ic}, that is, increasing in producer heterogeneity.[26]

Hence, a trade model with information frictions is able to qualitatively explain a number of patterns observed in trade, price, and farmer level data from the Philippines. The following section structurally estimates model parameters so as to quantify the importance of information frictions.

4. ESTIMATION

I now structurally estimate the model to quantify the importance of information frictions. In what follows, let i denote the origin province, j denote the destination province, c denote the commodity, t denote the year, and m denote the month.

The goal of the estimation strategy is to estimate the iceberg transportation costs τ_{ij}, the search probabilities s_{ij}, and the fixed costs of search f_i using data on prices p_{icmt}, trade flows Q_{ijct}, land distribution θ_{ic}, and the number of farmers M_{ic} and productivity shocks A_{icmt} calibrated to match observed crop

[25] It is not immediately clear how to think about how bilateral trade flows respond to exogenous changes in the destination prices in either of these models, as both models derive predictions for aggregate trade flows by integrating across many different products (with different associated destination prices). However, because the variable trade cost are assumed to take an iceberg form, changes to the variable bilateral trade cost can be interpreted as exogenous changes to the price a producer receives for selling to a particular destination. Hence, the elasticity of trade flows to the variable trade cost is the relevant comparison.

[26] It is straightforward to show that the magnitude of the elasticity of bilateral trade flows to transportation costs is decreasing as the difference between the destination price net of transportation costs and the origin price increases. This is consistent with the finding of Novy (2013) that bilateral trade flows respond less to changes in transportation costs the greater is the size of trade flows.

production.[27] To do so, I pursue a two-step estimation procedure. In the first stage, I estimate the transportation costs using variation over time in origin and destination prices, and whether or not trade occurs. From equation (7), there are positive trade flows from i to j if and only if the relative price $\frac{p_j}{p_i}$ exceeds the transportation cost τ_{ij}. Hence, it is possible to identify the transportation cost τ_{ij} by determining the threshold relative price $\frac{p_j}{p_i}$ at which trade begins to occur. In the second stage, I estimate the search probabilities and the fixed cost of search using variation in prices (net of transportation costs) and the quantity of trade flows. The search probabilities can be identified from export shares: intuitively, if two destinations have the same price (net of transportation costs), but a region exports twice as much to the first as to the second, then the first destination must be searched twice as often. The fixed costs of search, on the other hand, can be identified from the openness of a region: intuitively, if two regions are otherwise identical but the first exports a greater fraction of its production, then it must have a lower fixed cost of search.[28]

In the estimation procedure, I use monthly variation in prices to identify trade frictions, even though trade flows are only observed at the annual level.[29] The advantage of using monthly price data is that I am able to account for the within-year variation in relative prices due to differences in growing seasons and within-year production shocks. This is important, as the within-year variation in prices can be substantial: for example, the median within-year variance in relative prices across origin–destination–commodity triples, measured as the percentage difference between the maximum and minimum price ratio, was 21%. The disadvantage of using monthly prices is that production data are available only at the quarterly level (for rice and corn) or annual level (for all other crops). In what follows, I construct the month-specific production shock by evenly dividing the production across months. This not only introduces measurement error, it also abstracts from the possibility that producers endogenously determine when to sell their produce. Such dynamic considerations are unlikely to be important in this context, as most producers in the Philippines do not have access to storage facilities and, as a result, sell their produce soon after harvest (see above).

[27]While equilibrium prices could be determined within the model, this would require specifying a particular demand function and source of income for consumers; I instead opt to treat the observed prices as data.

[28]Since the observed trade tends to be of commodities after they have been processed (e.g., after the rice has been milled), the quantity shipped (measured in preprocessed units) may actually be higher. While I have accounted for the typical efficiency of milling of rice (according to the Philippines Bureau of Agricultural Statistics, the typical milling recovery of dry *palay* is 65%), to the extent that this remains an issue, the true fraction of production exported will be higher than what is observed, thereby biasing the estimated fixed costs of search upward.

[29]In previous working paper versions of this paper, I estimated trade frictions using average annual prices. Because prices averaged across the year tended to exhibit less price dispersion across regions, the estimated trade frictions were smaller, although the relative importance of information frictions and transportation costs was similar.

4.1. *First Stage: Estimating Transportation Costs From Whether or Not Trade Flows Occur*

Suppose that transportation costs from i to j of commodity c in year t can be written as

$$\ln \tau_{ijct} = \ln \tau_{ijc} + \varepsilon_{ijct}, \tag{12}$$

where the idiosyncratic component is assumed to be $\varepsilon_{ijct} \sim N(0, \sigma^2)$ and is independent and identically distributed (i.i.d.).[30] This assumption allows me to use a maximum likelihood (ML) estimation procedure to identify $\ln \tau_{ij}$ based on variation in observed trade patterns and prices within an origin–destination pair over time and across crops. Consider a particular origin–destination pair ij. For each commodity in each year, I observe whether or not trade occurs (i.e., whether $Q_{ijct} = 0$ or $Q_{ijct} > 0$). In addition, for every month m within the year, I observe the price of the commodity in both the origin and the destination (i.e., p_{icmt} and p_{jcmt}, respectively). From equation (7), positive annual trade flows from i to j will occur if and only if the ratio of the destination price to the origin price exceeded the transportation costs in at least one month of the year. Let $p_{ijct}^{\max} \equiv \max_m \frac{p_{jcmt}}{p_{icmt}}$ denote the maximum price ratio observed across months within a given origin–destination–commodity–year quadruplet. The ML estimator of the bilateral transportation cost $\ln \hat{\tau}_{ij}$ maximizes the log likelihood function

$$\begin{aligned} l_{ij}(\tau) = \sum_{t=1}^{T} \sum_{c=1}^{C} & \mathbf{1}\{Q_{ijct} = 0\} \ln\left(1 - \Phi\left(\frac{1}{\sigma} \ln p_{ijct}^{\max} - \frac{1}{\sigma} \ln \tau_{ij}\right)\right) \\ & + \mathbf{1}\{Q_{ijct} > 0\} \ln\left(\Phi\left(\frac{1}{\sigma} \ln p_{ijct}^{\max} - \frac{1}{\sigma} \ln \tau_{ij}\right)\right), \end{aligned} \tag{13}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution. Equation (13) is identical to the log likelihood function of the following probit regression of an indicator for whether or not trade flows occur on the log maximum price ratio $\ln p_{ijct}^{\max}$ and an origin–destination fixed effect δ_{ij}:

$$\mathbf{1}\{Q_{ijct} > 0\} = \beta \ln p_{ijct}^{\max} + \delta_{ij} + \varepsilon_{ijct},$$

where $\hat{\sigma} = \frac{1}{\hat{\beta}}$ and $\hat{\tau}_{ij} = \exp(-\frac{\hat{\delta}_{ij}}{\hat{\beta}})$. However, there are two concerns with inferring transportation costs from such a regression. First, because prices and trade flows are jointly determined in the model, the estimation of β is likely

[30]In Table XV in the Supplemental Material, I provide evidence that there is little systematic variation in the observed freight costs over time.

subject to simultaneity bias. As in Section 2.3, I overcome this problem by using an instrumental variables probit estimator (see Newey (1987)), instrumenting for $\ln p_{ijct}^{\max}$ using rainfall variation in both the origin and the destination provinces.[31] Second, because the transportation costs are monotonic transforms of the estimated fixed effects in a probit regression, they are subject to an incidental parameter problem (see Neyman and Scott (1948)). In Appendix G.2, I perform Monte Carlo simulations of the estimation strategy to assess the extent to which this problem exists. Given that there are 13.5 observations to identify each fixed effect (652 transportation costs to identify using 8,847 total observations), I find that the bias due to the incidental parameter problem is small.

It is informative to compare this estimation strategy to the standard procedure of inferring transportation costs from price dispersion. With information frictions, positive trade flows imply that the ratio of the destination to origin price *exceeds* the transportation cost; in contrast, with complete information, positive trade implies that the ratio *equals* the transportation cost. As a result, the equivalent equation for estimating the transportation costs under complete information replaces the standard normal cumulative density function in the second term of equation (13) with the standard normal probability density function divided by the standard deviation. It is straightforward to show that this will lead to higher estimates of trade costs, that is, traditional inference overestimates the true transportation costs in the presence of information frictions. This is intuitive: while the complete information no-arbitrage condition attributes all price dispersion to transportation costs, the model above implies that information frictions also contribute to price dispersion, so that the estimated transportation costs need not be as large to be consistent with the data.

4.2. *Second Stage: Estimating Information Frictions From Total Quantity of Trade Flows*

Given estimates of transportation costs, search probabilities and the fixed costs of search can be identified from the quantity of trade flows. From equation (9), total annual trade flows from i to j of commodity c in year t can be written as the sum of total trade flows in each month m throughout the year:

$$Q_{ijct} = M_{ic}\theta_{ic}f_{ic}^{1-\theta_i}s_{ijct}\sum_{m=1}^{12}A_{icmt}\int_{p_{icmt}}^{p_{jcmt}/\tau_{ijct}}K_{icmt}(p)^{\theta_{ic}-2}\,dp. \tag{14}$$

[31] I include the mean monthly rainfall, the standard deviation of monthly rainfall, and the square of the mean monthly rainfall as instruments.

Equation (14) provides the basis for the estimation of the search probabilities and fixed costs of search. Suppose that search probabilities and fixed costs of search are constant over time except for idiosyncratic error terms[32]

$$\ln s_{ijct} = \ln s_{ijc} + v_{ijct},$$
$$\ln f_{ict} = \ln f_{ic} + w_{ict},$$

where $E[v_{ijct}] = E[w_{ict}] = 0$, and v_{ijct}, w_{ict}, and ε_{ijct} are independent from each other and over time. Because the measure of the fixed cost of search f_{ic} is destination and month invariant, dividing equation (14) by the total quantity of trade flows exported to all destinations, taking logs, and applying the law of iterated expectations yields the equation that depends only on observed covariates and the set of search probabilities,

$$E_t\left[\ln \frac{Q_{ijct}}{\sum_{j\neq i} Q_{ijct}}\right] = E_v\left[\ln s_{ijc} + E_\varepsilon\left[G_s(\mathbf{s}_{ic}, \varepsilon_{ict})\right] + v_{ijct}\right], \tag{15}$$

where

$$G_s(\mathbf{s}_{ic}, \mathbf{e}_{ict}) \equiv \frac{\sum_{m=1}^{12} A_{icmt} \int_{p_{icmt}}^{p_{jcmt}/(\hat{\tau}_{ijc}\exp(\varepsilon_{ijct}))} K_{icmt}(p; \mathbf{e}_{ict}, \mathbf{s}_{ic})^{\theta_{ic}-2}\, dp}{\sum_k s_{ikc} \sum_{m=1}^{12} A_{icmt} \int_{p_{icmt}}^{p_{kcmt}/(\hat{\tau}_{ikc}\exp(\varepsilon_{ikct}))} K_{icmt}(p; \mathbf{e}_{ict}, \mathbf{s}_{ic})^{\theta_{ic}-2}\, dp},$$

$\mathbf{s}_{ic} \equiv \{s_{ijc}\}_j$ is the vector of search probabilities, $\mathbf{e}_{ict} \equiv \{\varepsilon_{ijct}\}_j$ is the vector of idiosyncratic components of the transportation costs, and $K_{icmt}(p; \mathbf{e}_{ict}, \mathbf{s}_{ic}) \equiv \sum_{j\neq i} s_{ijc} \max\{\frac{p_{jcmt}}{\hat{\tau}_{ijc}\exp(\varepsilon_{ijct})} - p, 0\}$ is the value of search.[33] Similarly, summing equation (14) across all destinations and dividing by the total quantity produced, taking logs, and applying the law of iterated expectations yields the equation

[32]In additional results not reported, I allow there to be a secular time trend in the search probabilities. In 84% of the origin–destination–commodity triplets, the time trend is statistically insignificant; however, the mean (median) search probabilities change from 0.048 (0.015) to 0.085 (0.009).

[33]It is straightforward to show that this corresponds to equation (6) governing the value of search when there are a finite number of locations.

relating the fraction of production exported to the fixed cost of search, the set of search probabilities, and observed covariates,[34]

$$E_t\left[\ln \frac{\sum_{j\neq i} Q_{ijct}}{\sum_{j} Q_{ijct}}\right] = E_w\big[(1-\theta_{ic})\ln f_{ic} + E_\varepsilon\big[G_f(\mathbf{s}_{ij}, \varepsilon_{ijct})\big] + w_{ict}\big], \tag{16}$$

where

$$\begin{aligned} &G_f(\mathbf{s}_{ic}, \mathbf{e}_{ict}) \\ &\quad \equiv \frac{\sum_{j\neq i} s_{ijc} \sum_{m=1}^{12} A_{icmt} \int_{p_{icmt}}^{p_{jcmt}/(\hat{\tau}_{ijc}\exp(\varepsilon_{ijct}))} K_{icmt}(p; \mathbf{e}_{ict}, \mathbf{s}_{ic})^{\theta_{ic}-2}\, dp}{\sum_{m=1}^{12} A_{icmt}} \\ &\qquad + \ln(\theta_{ic} - 1). \end{aligned}$$

I use a method of simulated moments procedure (see McFadden (1989)) to estimate search probabilities and the fixed cost of search using equations (15) and (16). To summarize the procedure, for each year, I find the set of probabilities such that the sample analog of equation (15) holds with equality; given these search probabilities, I then find a year-specific fixed cost of search such that the sample analog of equation (16) holds with equality. For both equations, the inner expectation of the right hand side is approximated by taking its average over a large number of draws of the idiosyncratic bilateral transportation cost vector $\mathbf{e}_{ict}$. Then, to account for the idiosyncratic variation arising from v_{ijct} and w_{ict}, I average across years to determine the estimated search probability and fixed cost of search. Formally, the estimated search probabilities $\hat{\mathbf{s}}_{ic}$ and fixed cost of search $\hat{f}_{ic}$ minimize the objective functions

$$\hat{\mathbf{s}}_{ic} \equiv \arg\min_{\tilde{\mathbf{s}}\in\Delta^{N-1}} \sum_{j\neq i} \frac{1}{T_{ijc}} \sum_{t=1}^{T_{ijc}} \left(\ln \frac{Q_{ijct}}{\sum_{j\neq i} Q_{ijct}} - \frac{1}{Z}\sum_{z=1}^{Z} G_s\big(\mathbf{s}, \mathbf{e}_{ict}^z\big) - \ln \tilde{s}_j\right)^2, \tag{17}$$

[34]It should be noted that by treating prices as data, this estimation procedure does not account for the effect of the particular realization of the idiosyncratic component of transportation costs $\mathbf{e}_{ict}$ on prices through general equilibrium effects.

$$\hat{f}_{ic} \equiv \arg\min_{\tilde{f}\in\mathbb{R}_+} \frac{1}{T_{ijc}} \sum_{t=1}^{T_{ijc}} \Bigg((\theta_{ic}-1)\ln\tilde{f} + \ln\frac{Q_{ijct}}{\sum_{j\neq i} Q_{ijct}} - \frac{1}{Z}\sum_{z=1}^{Z} G_f\big(\hat{\mathbf{s}}_{ic}, \tilde{f}, \mathbf{e}^z_{ict}\big)\Bigg)^2, \tag{18}$$

where $\mathbf{e}^z_{ict}$ indicates the zth simulated draw of the unobserved components of $\{\hat{\tau}_{ijct}\}_j$ and T_{ijc} is the number of time periods where positive trade flows from i to j of commodity c occur. In the results that follow, $Z = 100$.

There are several things to note about equations (17) and (18). First, since the value of search depends on the entire set of search probabilities, equation (17) must be solved simultaneously for all destinations of a particular origin–commodity–year. Second, since the identification of search probabilities relies on the intensive margin of trade flows, it can only be identified for origin–destination–commodity triplets where trade flows occur.[35] Third, the model requires that i exports to j if and only if $p_{ict} \leq \frac{p_{jct}}{\tau_{ijct}}$. As a result, the random draws used in the simulation must ensure that this equation is satisfied. In particular, if trade is (is not) observed, then ε^z_{ijct} is drawn from a normal distribution truncated above (below) by $\max_m \ln\frac{p_{jcmt}}{p_{icmt}} - \ln\hat{\tau}_{ijc}$. Fourth, because the transportation costs are measured with error, the estimated variance of the price distribution net of transportation costs will be biased. Monte Carlo simulations in Appendix G.2 find that this biases the estimated fixed costs of search downward, suggesting that, if anything, information frictions are larger than the estimates suggest.[36]

4.3. *Results*

Table VII summarizes the estimated trade frictions. Estimated transportation costs are substantial, averaging 47% (in ad valorem terms). Estimated search probabilities are small, with a mean of 4.8%. Since the sum of the search probabilities across all searched destinations is equal to 1, this implies that producers search approximately 21 destinations on average. While the estimated fixed cost of search is highly variable across different origin–commodity–year

[35]This does not affect the estimation, as $K^{\nu}_{ict}(\cdot)$ can be calculated without knowing the search probabilities of destinations where $\frac{p_{jct}}{\tau_{ijct}} < p_{ict}$ using the constraint that the entire search probabilities sum to 1. However, the variance of estimates of $\hat{s}_{ijc}$ will be lower for origin–destination–commodity triplets with more years of trade; I account for this in the regressions that follow.

[36]Correcting for this bias by imposing a constant transportation cost to all destinations results in the median estimated fixed cost of search increasing from 4,173 Philippine Peso (PHP) to 7,672 PHP; see Appendix G.3 for details.

TABLE VII

SUMMARY STATISTICS OF STRUCTURAL ESTIMATES[a]

	(1) Transportation Cost $\hat{\tau}_{ijc}$	(2) Search Probability $\hat{s}_{ijct}$	(3) Fixed Cost of Search $\hat{f}_{ic}$ (PHP/kg)	Fixed Cost of Search $\hat{f}_{ic}$ (PHP/ha)
Mean	1.47	0.048	7.37	27,897
Std. Dev.	0.40	0.104	19.98	70,396
Median	1.44	0.013	1.32	4,406
Minimum	1.00	0.000	0.06	91
Maximum	4.62	0.871	129.52	368,318
Number of estimated parameters	646	803	102	102
Unit of identification	Origin–destination–commodity	Origin–destination–commodity	Origin–commodity	Origin–commodity

[a]Transportation costs are reported only for origin–destination–commodity triplets that traded in some but not all years. Search probabilities are identified only for origin–destination–commodity triplets in which trade has ever occured. Fixed costs are reported in year 2000 Philippines pesos (1 US dollar is approximately equal to 45 PHP).

triplets, the median fixed cost of 4,406 pesos ($98) is modest.[37,38] While this amount is certainly more than the cost of a phone call, it seems realistic for the entire cost of determining the market conditions in a potential destination, which includes the time and the expense incurred from discussions and negotiations with possibly multiple wholesale purchasers and shipping companies. However, the fixed costs are substantial relative to farmer income (crop income averaged 12,150 pesos in 2000), preventing a substantial portion of farmers from selling in other markets. Under alternative assumptions where farmers face additional uncertainty from not knowing the realization of prices in a particular destination, the estimated fixed costs of search are slightly larger; see Appendix G.3.

What determines why certain destinations are searched more often? Table VIII projects the estimated search probabilities on observable bilateral characteristics, conditional on origin–commodity and destination–commodity fixed effects. While estimated search probabilities unconditionally decline with shipping distance (a 10% increase in shipping distance is associated with a 1.2% decline in the search probability), this correlation halves in size (and loses

[37]To convert from the price per kilogram observed in the data to the price per hectare (which is what the model implies is the correct unit for searching an additional market), I use observed commodity–province average yields. Table VII reports estimated fixed costs of search in both units.

[38]It is common in both trade and search literature to estimate large fixed costs: Das, Roberts, and Tybout (2007) estimate that it costs a Colombian firm approximately $400,000 to begin exporting, while Brynjolfsson, Dick, and Smith (2010) estimate the search cost of clicking to the next page while shopping online is $6.55.

TABLE VIII

EXPLAINING TRADE FRICTIONS[a]

	$\ln \hat{s}_{ijc}$		$\ln \hat{\tau}_{ijc}$		Log Freight Costs (% of value)	
Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)
Log shipping distance	−0.125**	−0.065	0.022***	0.013**	0.123***	0.145***
	(0.051)	(0.056)	(0.006)	(0.006)	(0.034)	(0.038)
Same ethnicity		0.126**		−0.020***		0.065*
		(0.056)		(0.006)		(0.039)
Same religion		0.204		−0.015		0.246
		(0.151)		(0.016)		(0.215)
Mobile phone access		0.010*		−0.001**		0.056
		(0.006)		(0.001)		(0.080)
Origin–commodity FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination–commodity FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.563	0.568	0.645	0.654	0.446	0.447
Observations	10,579	10,579	8,782	8,782	2,687	2,687
Clusters	803	803	646	646	519	519

[a] Ordinary least squares. The dependent variable is indicated above the columns. Each observation is an origin–destination–commodity–year quadruplet. Standard errors are clustered at the origin–destination–commodity level to account for the fact that the estimated search probabilities and transportation costs are time invariant (each year is included separately in the regression to allow the mobile phone access variable to differ by year). Same ethnicity and same religion are equal to the (log) probability that a randomly selected individual in the origin province has the same ethnicity or religion, respectively, of a randomly selected individual in the destination province. Mobile phone access is an indicator variable equal to 1 if a civilian cell phone tower exists in both the origin and the destination provinces in a given year. Standard errors clustered at the origin–destination–commodity level are reported in parentheses. Asterisks indicate statistical significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

its statistical significance) when demographic controls are included. Since estimated search probabilities are higher between regions with similar ethnicities and religions, this suggests that one reason producers are more likely to search nearby provinces is that people nearby are more similar. Estimated search probabilities are also higher when both origin and destination provinces have access to mobile phones. Estimated transportation costs display similar patterns: transportation costs increase with shipping distance and decrease with demographic similarity and mobile phone access; unlike search probabilities, however, estimated transportation costs are statistically significantly positively correlated with shipping distance even after conditioning on demographic similarity. In contrast, observed freight costs are, if anything, greater between provinces with similar demographics and regions with mobile phone access.

4.4. *The Magnitude of Transportation Costs*

How do these estimated trade frictions compare to standard estimates? Figure 4 compares the distribution of the estimated transportation costs with information frictions to those made using observed prices and the complete in-

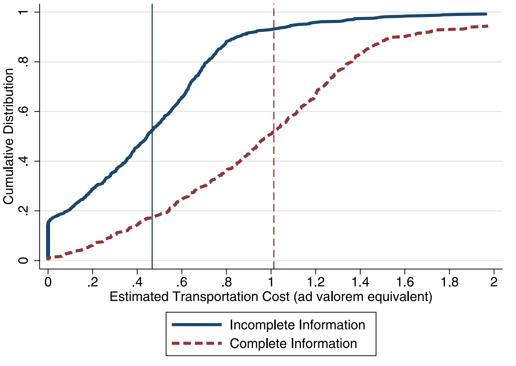

FIGURE 4.—Distribution of estimated transportation costs. This figure depicts the cumulative distribution function of estimated transportation costs across origin–destination–commodities for complete information and incomplete information. The sample includes all origin–destination–commodity triplets with wholesale markets in which trade was observed in some but not all years.

formation no-arbitrage equation.[39] Recall that the standard no-arbitrage condition implies that price dispersion arises only from transportation costs, so imposing complete information causes the distribution of estimates to shift to the right, increasing the average estimated transportation cost from 47% to 101% (in ad valorem terms). Hence, the structural estimates imply that more than half of the observed price dispersion normally ascribed to transportation costs is actually due to information frictions. Figure 5 shows how the complete and incomplete information transportation costs are affected by shipping distance. While both estimates of transportation costs increase with distance (left panel), the difference between the two estimates also increases with distance (right panel). Since the difference between the two reflects the contribution of information frictions to the observed price dispersion, this suggests that information frictions increase with shipping distance.

Which transportation cost estimates are more realistic? To answer this question, I compare the estimated transportation costs to observed freight costs. Detailed analysis of the market structure of several commodities conducted by the Philippines Bureau of Agricultural Statistics (see Appendix B.9 for details) finds that direct transportation costs comprise roughly one-fifth to one-half of the total cost of bringing a good to market, suggesting that realistic transportation costs should be between 2 and 5 times the size of observed freight costs. Figure 6 reports the median ratio of estimated transportation costs to observed freight costs for each commodity. Across all crops, the median ratio of the estimated incomplete information transportation costs to observed freight costs is 13.2 (with a 95% confidence interval of [7.4, 19.0]), whereas the median ratio

[39]For comparability, I constrain the estimate of $\hat{\sigma}$ in the complete information case to be the same as was estimated with information frictions (0.37).

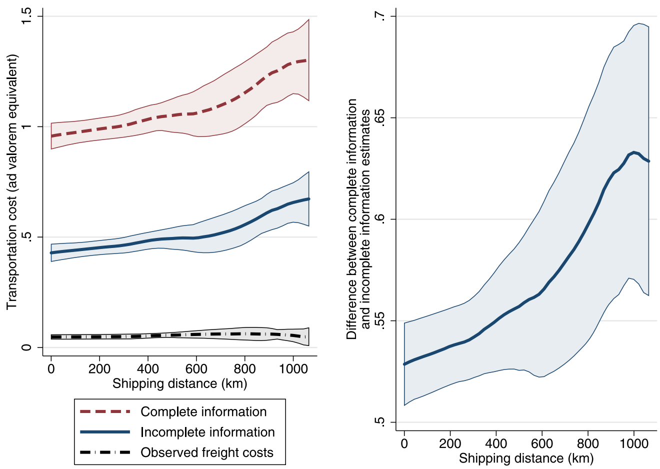

FIGURE 5.—Estimated transportation costs and shipping distance. This figure shows how the estimated transportation costs are correlated with shipping distance. The left panel depicts the estimated transportation costs across origin–destination–commodities for complete information and incomplete information by shipping distance. The right panel depicts the difference between the complete information estimate and the incomplete information estimate by shipping distance. Both panels use a nonparametric regression with an Epanechnikov kernel and 150 km bandwidth. The shaded regions indicate the 95% confidence interval. The sample includes all origin–destination–commodity triplets with wholesale markets in which trade was observed in some but not all years. Freight costs are only observed for a subset (59%) of these origin–destination–commodity triplets.

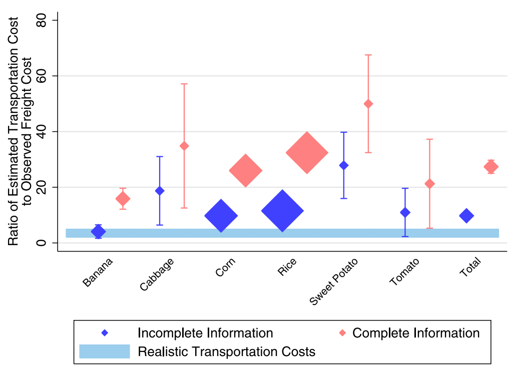

FIGURE 6.—Estimated transportation costs by commodity. Diamonds report the median ratio of the estimated transportation cost to the observed freight cost under the assumptions of incomplete and complete information. The size of each diamond (except for the total column) is proportional to the number of estimated transportation costs. Error bars report the 95% nonparametric bootstrap confidence interval. Realistic transportation costs are defined as those between two to five times the magnitude of the observed freight cost. The sample includes all origin–destination–commodity triplets with wholesale markets in which trade was observed in some but not all years and for which freight costs are observed. Commodities with five or fewer origin–destination pairs are not reported in the figure (garlic, mung bean, and pineapple).

of the estimated complete information transportation costs to observed freight costs is 29.7 (with a 95% confidence interval of [19.6, 39.8]). Hence, by incorporating information frictions, the magnitude of estimated transportation costs accords better with observed freight costs. However, while incorporating information frictions substantially bridges the gap between the trade costs implied by observed price dispersion and observed freight costs, it should be noted that information frictions alone are unable to explain why price dispersion is so much greater than observed freight costs would imply.

4.5. *The Predictive Power of the Model*

In this section, I assess how well the above trade model with information frictions is able to predict out-of-sample trade flows.[40] To do so, I divide the sample into two periods: 1995–2001 and 2002–2009. Using observed trade flows, prices, and production from the earlier period, I reestimate the trade frictions above. Given these estimated trade frictions, I then calculate the (monthly) predicted trade flows for the latter period given the observed prices and production. I then sum across months to assess how close the predicted trade flows are to the observed (annual) trade flows in the latter period using two metrics: first, I measure the predictive power on the extensive margin as the correlation between whether or not the model predicts trade flows to occur and whether or not trade flows actually occurred (oftentimes known as the *phi coefficient*); second, I measure the predictive power on the intensive measure as the correlation between (log) observed trade flows and (log) predicted trade flows, conditional on trade flows occurring and the model predicting trade flows to occur.

Recall that there are three different types of trade frictions in the model presented above: fixed costs of search, search probabilities, and transportation costs. To determine the relative importance of each type of friction, I assess the predictive power of six variants of the model. I first assume that the fixed costs of search are equal to zero, which, as discussed above, simplifies the model to a standard complete information trade model. I consider a complete information model both without transportation costs (variant 1) and with transportation costs (variant 2), where in the latter case, the transportation costs are estimated using the complete information no-arbitrage equation. The remaining four variants of the model allow for positive fixed costs of search but consider all permutations of whether or not there are transportation costs and whether

[40]The advantage of assessing the ability of the model to predict out-of-sample trade flows (given observed prices) rather than out-of-sample equilibrium prices is that it is unnecessary to specify a set of inverse demand functions $\{D_i(q)\}_i$. Nevertheless, a previous working paper version of this paper showed that a trade model with information frictions better predicted equilibrium prices than a standard complete information trade model when the inverse demand function was generated by constant elasticity of substitution (CES) preferences.

TABLE IX

PREDICTING TRADE FLOWS[a]

	Complete Information		Incomplete Information			
	(1)	(2)	(3)	(4)	(5)	(6)
Extensive margin	0.011	0.078	0.074	0.454	0.562	0.557
Intensive margin	0.415	0.232	0.066	0.105	0.295	0.407
Estimated transportation costs?	No	Yes	No	No	Yes	Yes
Estimated search probabilities?	N/A	N/A	No	Yes	No	Yes

[a]This table compares the ability of different trade models to predict trade flows for years 2002–2009 given observed production and prices after using trade cost parameters estimated using 1995–2001 data. Each column is a different trade model. The extensive margin row reports the correlation between whether or not trade flows occurred in the data and whether or not the model predicts that trade flows occur (oftentimes called the phi coefficient). The intensive margin row reports the correlation between observed and predicted log trade flows, conditional on the model predicting positive trade flows and positive trade flows being observed in the data. Transportation costs are set equal to 0 ($\tau_{ij} = 1$) in models without estimated transportation costs. Search probabilities are made equal in models without estimated search probabilities.

or not different destinations are searched with different search probabilities: variant 3 considers a model with information frictions without transportation costs where all destinations are searched with equal probability; variant 4 allows for varying search probabilities without transportation costs; variant 5 allows for transportation costs but restricts all destinations to be searched with equal probability; variant 6 allows for all types of information frictions. I redo the estimation of the existing frictions for each variant of the model separately, as the different restrictions generally affect the estimation results (e.g., without information frictions, the estimated transportation costs will be larger).

Table IX reports the predictive power of each of the model variants. In model variant 1 without information frictions or transportation costs, there is an almost zero correlation between whether trade flows occur and whether the complete information model without transportation costs predicts trade flows will occur (with a phi coefficient 0.01), although the model does do a good job predicting the total volume of trade conditional on it correctly predicting the existence of trade flows (with a correlation of 0.415); adding transportation costs substantially improves the predictive power on the intensive margin (phi coefficient of 0.078), but at a cost of reduced correlation on the intensive margin (correlation of 0.232).

In general, allowing for information frictions improves the predictive power of the model. For example, the incomplete information model with transportation costs (variant 5) does substantially better than the complete model with transportation costs (variant 2) on predicting whether or not trade flows will occur (a phi coefficient of 0.562 versus 0.078) and, conditional on successfully predicting whether trade flows occur, does a better job predicting the total volume of trade (correlation of 0.295 versus 0.232). Among variants of the incomplete information models, allowing for transportation costs but not differential search probabilities (variant 5) is a better predictor of both the extensive and intensive margins than allowing for differential search probabilities but not transportation costs (variant 4). Introducing differential search probabilities into an incomplete information model with transportation costs (variant 6) does not affect the predictive power of the extensive margin, but substantially improves the predictive power along the intensive margin. This is to be expected, as search probabilities (conditional on being positive) affect total quantity of trade flows without affecting whether or not trade flows occur.[41]

Figure 7 illustrates the relationship between predicted and observed trade flows for the complete information trade model with transportation costs (variant 2) to the model with all three trade frictions (variant 6). Two patterns are evident: first, there were many more instances in which the model with information frictions predicted positive trade flows and positive trade flows actually occurred (dots) than instances where the model without information frictions predicted positive trade flows and trade flows actually occurred (di-

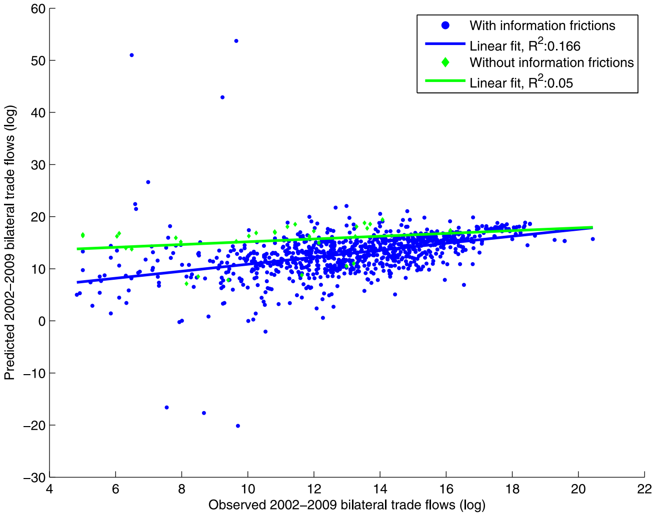

FIGURE 7.—Predicting trade flows from prices. This figure compares how well a models with and without information frictions are able to predict observed trade flows. Trade costs are estimated using data from 1995–2001; bilateral trade flows for years 2002–2009 are then calculated using each model given observed prices and production, and compared to the observed bilateral trade flows. The model without information frictions has many fewer observations because it fails to predict positive trade flows in many cases when they are observed to occur (see Table IX).

[41] Allowing for differential search probabilities improves the predictive power of a model on the extensive margin only inasmuch as certain search probabilities are estimated to be 0. A search probability is estimated to be 0 only when (a) a bilateral pair never trades in the 1995–2001 period and (b) the sum of the estimated search probabilities across all other destinations is bound by the constraint that search probabilities sum to 1.

amonds). Second, the correlation between actual and predicted volumes of bilateral trade flows is much stronger for the model with information frictions than the model without information frictions.

Hence, incorporating information frictions yields substantial improvements in the ability of trade models to accurately predict trade flows from observed prices.

5. CONCLUSION

The goal of this paper has been to show that information frictions have important implications for trade. This paper first documents a number of empirical patterns that are difficult to reconcile with standard trade models using a new data set on the trade of agricultural commodities in the Philippines. The paper then presents a trade model that incorporates the costly search process producers undergo to learn about market conditions elsewhere. The model yields tractable equations governing trade flows and provides simple explanations for the documented patterns based on the existence of information frictions.

Given the structure of the model, the paper then disentangles information frictions from transportation costs using observed trade flows and prices. The resulting estimates suggest that information frictions are important and improve the out-of-sample predictive power of the trade model.

This paper contributes to the growing literature examining the role of information frictions in trade. While the focus has been on agriculture, information frictions are likely to be important in other settings as well. A fruitful direction for future research would be to examine how information frictions affect trade flows in contexts such as manufacturing, where products are differentiated and firms have market power.

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