

# Long Time Out: Unemployment and Joblessness in Canada and the United States

Kory Kroft, Fabian Lange, Matthew J. Notowidigdo, and Matthew Tudball\*

## PRELIMINARY AND INCOMPLETE

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### **Abstract**

We compare patterns of long-term unemployment and duration dependence between the U.S. and Canada. First, we estimate the incidence of long-term unemployment by demographic group, occupation, industry, region, and reason for unemployment, extending past research in the U.S. to the most recent years available and producing new results for Canada covering the same sample period. Second, we extend the matching model in Kroft et al. [2016], which allows for duration dependence in the exit rate from unemployment and transitions between employment (E), unemployment (U), and non-participation (N), to allow for duration dependence in the exit rate from non-participation. We calibrate the model using restricted-access data from the Canadian Labor Force Survey and a new historical vacancy series based on a proxy variable derived from time series employment trends in “recruiting” industries. The main goals of this analysis are to decompose the sources of differences in the incidence of long-term unemployment between the two countries in recent years, and also to assess the role of duration dependence in non-participation in accounting for trends in long-term unemployment and movements in the Beveridge curve in Canada.

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\*Kory Kroft, University of Toronto, Department of Economics and NBER (kory.kroft@utoronto.edu); Fabian Lange, McGill University, Department of Economics, Leacock Building, 855 Sherbrooke Street West, Montreal Quebec H3A2T7, Canada (fabolange@gmail.com); Matthew J. Notowidigdo, Northwestern University, Department of Economics and NBER (noto@northwestern.edu); Matthew Tudball, University of Toronto (matthew.tudball@utoronto.edu).

# 1 Introduction

The textbook model of the labor market features a matching function mapping unmet search demand and supply into new employment relationships (Mortensen and Pissarides [1994]; Pissarides [1985]). The Great Recession, which featured a dramatic rise in long-term unemployment and an outward shift of the Beveridge curve, provides a valuable opportunity to learn whether and to what extent this framework can capture labor market dynamics. In previous work, we examined the performance of this framework over the Great Recession in the United States (Kroft et al. [2016]). In particular, we enriched a standard matching model along two dimensions. First, we allowed for duration dependence in the job-finding rate of the unemployed, consistent with empirical evidence in Kroft et al. [2013]. Second, we allowed for flows between employment (E), unemployment (U), and non-participation (N), instead of focusing exclusively on flows between E and U, as in a standard matching model. We calibrated our enriched matching model on monthly data in the years before the onset of the Great Recession and studied how well the calibrated model fit the data during the Great Recession, holding fixed the parameters. We treated vacancies, transitions from E to U and N and transitions between N and U as the exogenous “forcing variables” of our model and allowed job-finding rates for both the unemployed and non-participants to evolve endogenously. This exercise demonstrated that our model could account for most the rise in long-term unemployment and about half of the shift in the Beveridge curve

In this paper, we compare the labor market dynamics in the U.S. and Canada during the Great Recession, using the model in Kroft et al. [2016]. This comparison is of interest because the dynamics of the Great Recession in Canada and the U.S. were quite different, as we discuss below. By focusing on Canada, we thus subject our matching model to a new “out-of-sample” test. In the process, we also expand and build on our prior analysis in several ways. First, we exploit the recent data that has become available to document how the U.S. labor market has evolved since March 2013 (where our prior analysis left off). Second, we exploit restricted-use Canadian labor force data which has several unique features which allow us to augment and improve the matching model that we analyzed previously. In particular, the Canadian Labor Force Survey (LFS) – the counterpart the U.S. Current Population Survey (CPS) – surveys respondents about their (ongoing) length of unemployment as well as their (ongoing) length of joblessness. The latter question in the LFS is posed both to the unemployed and to non-participants and thus allows us to estimate how job-finding rates among *non-participants* changes with the duration of time since their most recent job. This information is not available in the CPS, and likely at least partly explains why most work in the U.S. has focused on duration dependence among unemployed individuals. By contrast, the LFS data will allow us to study duration dependence among the unemployed as well

as among non-participants. This allows us to make a straightforward – but potentially important – extension in our model to model duration dependence in the job-finding rates of both the unemployed and among non-participants. This could potentially improve the fit of our calibrated model which in our earlier work could not account for the increase in non-participation during the Great Recession.

Both the U.S. and Canada experienced a rapid, sharp increase in the unemployment rate during the Great Recession, but the magnitude, persistence, and onset of the Great Recession differed between the two countries. The NBER has determined the U.S. to be in recession from December 2007 to June 2009, while the recession in Canada has been determined to last from November 2008 to May 2009.<sup>1</sup> The recession thus lasted 18 months in the U.S. compared to only 7 in Canada. The recessions differed not just in length but also in their severity. The movements in labor shares, illustrated in figures 1 and 2, were about twice as large in the U.S. as in Canada. Figure 1 shows that for the U.S., the unemployment rate among 25-55 year olds increased from about 4 percent to about 9 percent and the employment-to-population ratio declined by about 4 percentage points. On the other hand, Figure 2 shows that for Canada, the unemployment rate rose from 4 percent to about 6 percent during 2008 and 2009 and the employment-to-population ratio declined by only about 2 percentage points.<sup>2</sup> The figures also show that labor force rates in Canada recovered more rapidly from the increase in unemployment than in the U.S.. By mid-2010, the unemployment rate had dropped back by about half of its increase in 2009, whereas for the U.S., the unemployment rate was still at levels similar to those in late 2009. Since then, both the U.S. and Canada slowly returned to unemployment rates comparable to the pre-period. The U.S. has however only managed to claw back about half of the decrease in the employment-to-population ratio. The U.S. also experienced an extremely severe recession as measured by vacancies, as shown in Figure 3 (which compares the Great Recession to the early 1980s recession).

Our model is useful for understanding the dynamics of long-term unemployment. Figure 4 shows the share of the unemployed with durations exceeding 6 months (for the U.S.) and the share with durations exceeding 26 weeks (for Canada). In both countries, the LTU share increased, but the rise was much more pronounced in Canada (see Figure 4). In the U.S., the LTU share increased from about 20 percent to a peak of more than 50 percent. In Canada, the share increased from 15 percent to roughly 25 percent. Additionally, the decline in the LTU share in both countries has been very slow. By October 2015, the LTU share in the U.S. was about 30 percent and in Canada was about 20 percent.

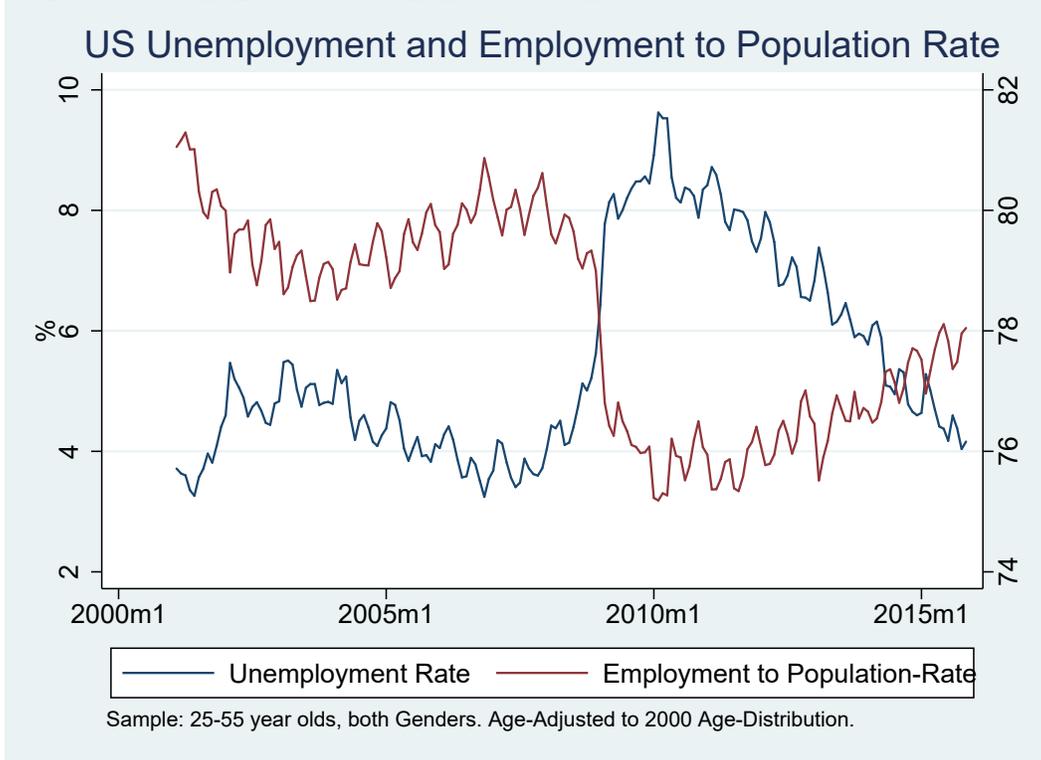
Another use of our model is to try to account for outward shifts in the Beveridge curve. To do this, we

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<sup>1</sup>See <http://www.nber.org/cycles/cyclesmain.html> for the U.S. and <https://www.cdhowe.org/cpc-communicue/cd-howe-institute-business-cycle-council-issues-authoritative-dates-20082009-recession> for Canada.

<sup>2</sup>In this paper, all statistics are constructed using prime age populations (25-55) and are age adjusted to the 2000 age distributions in the two countries.

Figure 1: Unemployment and Employment-to-Population Rate in the U.S. and Canada



need to construct the Beveridge curve in Canada. To our knowledge, there is no widely-accepted vacancy series in Canada covering the years before, during, and after the Great Recession. The “before” period is crucial because we would like to use data before the Great Recession to calibrate the model parameters. As we described in more detail below, we use employment in “recruiting” industries to construct a proxy for vacancies, following the methodology in Landais et al. [2016]. This method has been shown to be a useful proxy for the U.S., and we make the assumption that it is an equally suitable proxy in Canada. This allows us to construct vacancy proxy that we can use to calibrate our matching model.

The remainder of the paper proceeds as follows. In Section 2 we describe the data sources used in the analysis. Section 3 revisits the analysis in KLNK using U.S. data, replicating the main results and extending the results to the most recent data available. Section 4 describes composition analysis of LTU and long-term non-participation using LFS data, to learn about the incidence of LTU. Section 5 describes the construction of our vacancy proxy using “recruiting” industries. Section 6 describes the extended model and discusses the model calibration and counterfactual results using the restricted-use LFS data. Section 7 concludes.

Figure 2: Unemployment and Employment-to-Population Rate in the U.S. and Canada

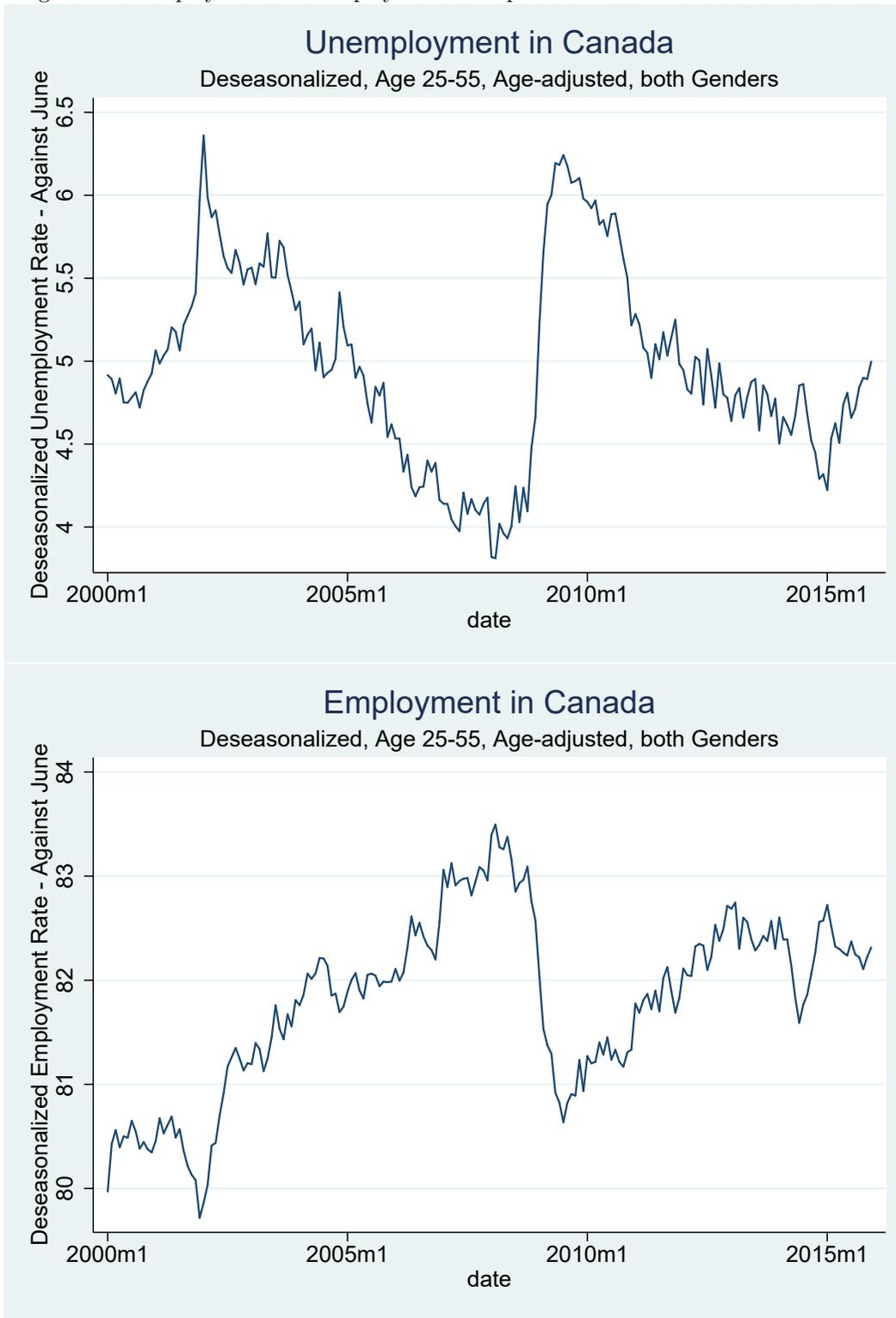
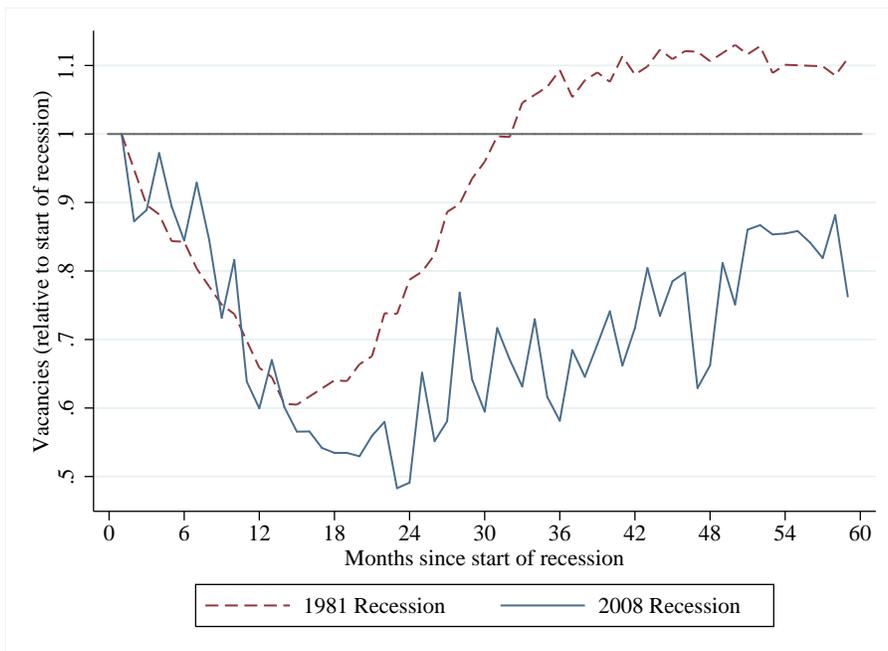


Figure 3: Dynamics of Vacancies in Great Recession and 1982 Recession (U.S.)



## 2 Data

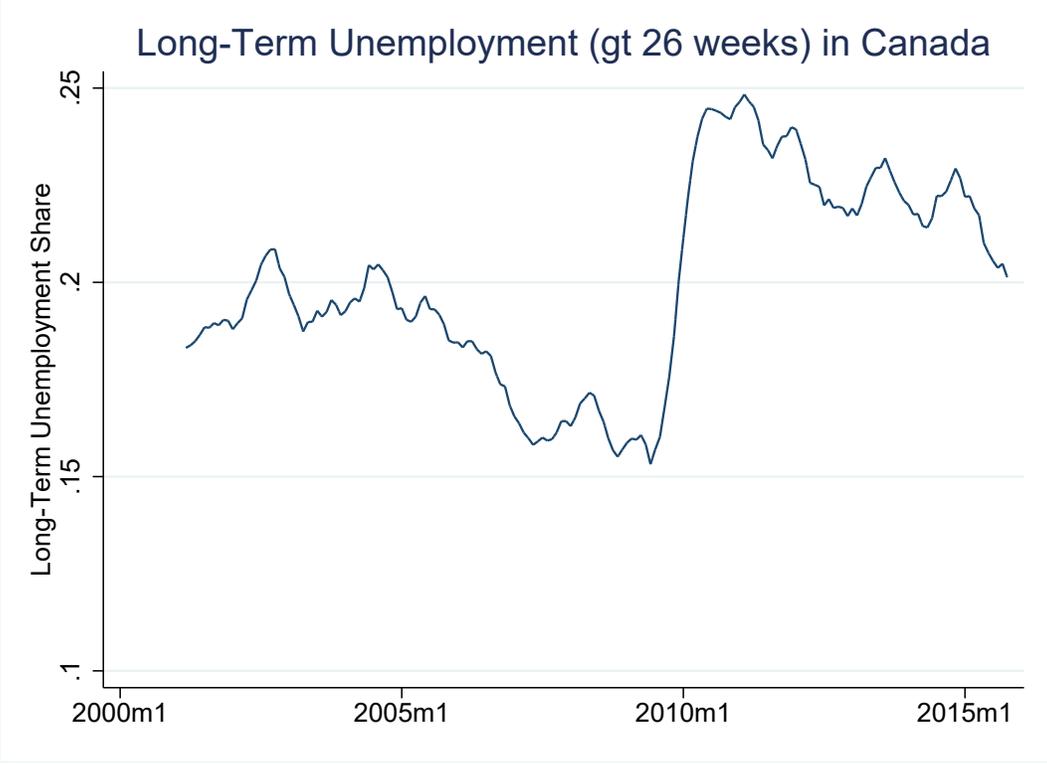
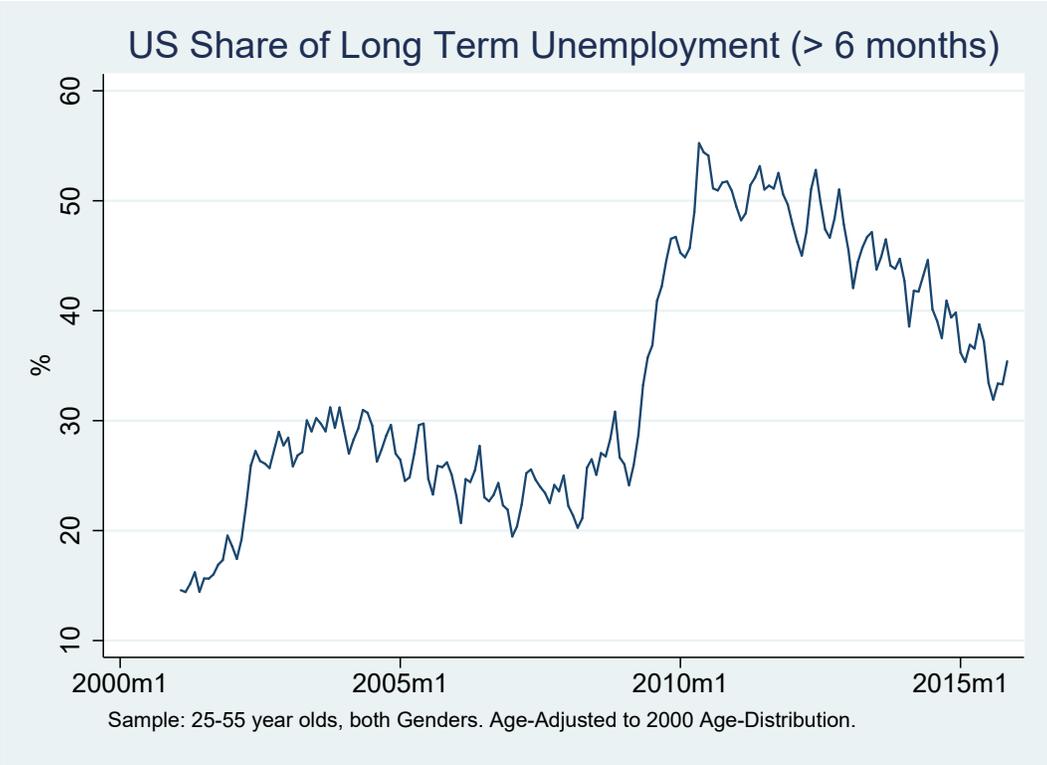
### 2.1 United States

This section briefly describes our data sources. See Kroft et al. [2013] for more details on the U.S. data.

#### Current Population Survey (CPS)

We use monthly CPS data between 2002 and 2013 (ending in April 2013), limiting the sample to individuals between the ages of 25 to 55. We focus on this prime-age sample to enable us to ignore issues of delayed labor force entry of younger workers and changes in retirement patterns of older workers. We use these CPS data in several ways. First, we use repeated cross-sectional data when investigating the role of composition, limiting the sample to unemployed workers. Second, we use both cross-section and panel data (merging individuals across months to build panel data) to investigate the role of duration dependence and non-participation. For this exercise, we use data on all employed, unemployed, and non-participants. In the cross-section, we keep track of the total population of each category to estimate the "stocks." To create panel data, we match observations across successive months, matching on household identifier, line number, age, gender, and race. We use the matched panel data in addition to the CPS cross-sectional estimates of the unemployed, the employed, and non-participants to estimate the transition rates between

Figure 4: LTU Share in the U.S. and Canada



unemployment, employment, and non-participation in each month. We also compute overall (pre-2008) transition rates by unemployment duration (into both employment and non-participation). Finally, we compute transition rates from employment and non-participation into unemployment by unemployment duration.

### **Job Openings and Labor Turnover Survey (JOLTS)**

We use monthly JOLTS data between 2002 and 2013 to compute the total number of vacancies. We use these vacancy data to calibrate the matching model below during the pre-2008 period. We then use the post-2008 vacancy data as one of the exogenous "forcing variables" for our counterfactual scenarios.

## **2.2 Canada**

1. Canadian data from restricted-access Canadian Labor Force Survey (LFS)
2. Data on labor force states is made to be comparable between CPS and LFS.
3. Age adjusted to 2000 age distributions in both countries and analysis is always limited to ages 25-55.
4. Labor Force transition rates made consistent with cross-sectional labor force statuses using procedure outlined in Kroft et al. [2013].

### **Duration Dependence and Long-Term Joblessness**

One of the advantages of the Canadian data is that respondents were asked not just about the duration of unemployment, but also about the duration of joblessness. As Elsbey et al. [2013a] and Kroft et al. [2016] both report, reported unemployment durations in the CPS are frequently inconsistent with the observed panel of labor force states when observations in the CPS are linked to construct a panel. In the CPS, respondents are asked to report how long they have been unemployed. If respondents interpreted their labor force states as labor statisticians do, they should report durations of less than a month when surveyed in the month after transition from either employment or out of the labor force to unemployment. However, respondents often report substantially longer durations of unemployment during these months, suggesting recall bias and differences in how respondents interpret unemployment compared to the classification procedures in the CPS. Durations of joblessness do not require interpreting search behavior over time as required to determine unemployment durations. This suggests that responses to the duration of joblessness are more likely to align with the concept in question. In addition, the duration of joblessness question is asked both of the unemployed and of those out of the Labor Force.

### 3 Replication and Extension of Kroft et al. [2016] Analysis

Here we briefly review the methodology employed by Kroft et al. [2016].<sup>3</sup> Our treatment here is sparse and we refer the reader to Kroft et al. [2016] for details.

#### The Matching Function

At the core of this analysis is a matching function which determines the number of meetings between job openings and both unemployed and non-participants.

$$M(U_t + sN_t, V_t) = m_0 (U_t + sN_t)^\alpha V_t^{1-\alpha}$$

Here  $(U_t, N_t)$  are the unemployed and those officially “Out of the Labor Force” (OLF);  $V_t$  are vacancies and  $(m_0, s, \alpha)$  are parameters. One can interpret  $(U_t + sN_t)$  as the total units of search effort on the labor supply side where each unit of search effort delivers an identical probability of a meeting with a vacancy. Then  $s$  represents the relative search effort of those OLF. The probability of a meeting per unit of search effort is  $\frac{M(U_t + sN_t, V_t)}{U_t + sN_t} = m_0 x_t^{1-\alpha}$  where  $x_t = \frac{V_t}{U_t + sN_t}$  is a measure of market tightness that accounts for the non-participants.<sup>4</sup>

The function  $A(d)$  is defined as the relative job finding rate of unemployed of different durations of unemployment  $d$ . This function captures “true” duration dependence, that is a causal effect of longer durations on the exit rate of unemployment. As described in Kroft et al. [2016], this modelling assumption is motivated partly by recent field experimental evidence on duration dependence in “callbacks” for interviews (Ghayad [2013], Kroft et al. [2013]). The job finding rates of unemployed of duration  $d$  and the non-participants are then given by

$$\lambda^{UE}(x_t; d) = A(d)m_0 x_t^{1-\alpha} \tag{1}$$

$$\lambda^{NE}(x_t) = sm_0 x_t^{1-\alpha} \tag{2}$$

We normalize  $A(0) = 1$  and assume as that  $A(d)$  follows a double-exponential decay function. We estimate the parameters of  $A(d)$  and the parameter  $s$  using data on job finding rates by duration and non-participation from the period 2002-2007 preceding the Great Recession.

Table 1 in Kroft et al. [2016] and replicated here reports the parameter estimates governing the

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<sup>3</sup>Some of the formulations in this Section are lifted directly from that paper and edited for brevity.

<sup>4</sup>See Kudlyak and Lange [2014] for an index of labor search that accumulates various different groups among the non-employed including the marginally attached, the discouraged and those with diverse labor search histories in a similar manner.

transitions into employment. These parameters are estimated using the data from the pre-period 2002-2007.

**Table 1**  
**Model-Based Estimates**

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Duration Dependence Parameters	
$a_1$ (intercept parameter 1)	0.314
$a_2$ (intercept parameter 2)	0.393
$b_1$ (slope parameter 1)	1.085
$b_2$ (slope parameter 2)	0.055
$A(d) = (1 - a_1 - a_2) + a_1 \exp(-b_1 \times d) + a_2 \exp(-b_2 \times d)$	
Matching Model Parameters	
$\alpha$	0.753
$m_0$ (scale parameter)	0.435
$s$ (relative search intensity of inactive)	0.218
$M(U + sI, V) = m_0(U + sI)^\alpha V^{1-\alpha}$	

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Notes: This table reports the model-based estimates using monthly CPS data and JOLTS data from 2002-2007. See main text for more details. These parameter estimates are used to create the counterfactual predictions reported in the figures.

The functional form and parameters of the functions  $M(U + sN, V)$  and  $A(d)$  and  $s$  are constant over time. Thus, when we examine the performance of our model over the Great Recession, we ask whether the search environment accounting for duration dependence is stable over the Great Recession except for the demand for labor.

## Simulating labor flows

To simulate the labor market, we require flows between all three labor force states ( $E, U, N$ ) and we need to model the duration distribution of the flows into unemployment.<sup>5</sup> Above we showed how to model the endogenous flows into employment:  $\lambda_t^{UE}(d)$  and  $\lambda_t^{NE}$ . The remaining flows in the labor market are exogenous driving variables in our analysis. As stated in Kroft et al. [2016], to construct these flows we assume that if “non-participants move to unemployment, they draw an unemployment duration from the (empirical) distribution of unemployment durations estimated from observed N-to-U transitions ... when employed workers move into unemployment, they draw an unemployment duration from the empirical distribution of unemployment durations. ... . These two empirical distributions are  $\theta_t^{NU}(d)$  and  $\theta_t^{EU}(d)$ , respectively.” (page #)

The dynamic equations governing changes in the stocks are then

$$N_{t+1} = N_t \left( 1 - \lambda_t^{NU} - \hat{\lambda}_t^{NE} \right) + E_t \lambda_t^{EN} + U_t \lambda_t^{UN} \quad (3)$$

$$U_{t+1}(0) = E_t \theta_t^{EU}(0) \lambda_t^{EU} + N_t \theta_t^{NU}(0) \lambda_t^{NU} \quad (4)$$

$$U_{t+1}(d) = U_t(d) \left( 1 - \hat{\lambda}_t^{UE}(d) - \hat{\lambda}_t^{UN}(d) \right) + E_t \theta_t^{EU}(d) \lambda_t^{EU} + N_t \theta_t^{NU}(d) \lambda_t^{NU} \quad (5)$$

$$E_t = P_t - N_t - U_t \quad (6)$$

where  $P_t$  denotes the total population aged 25-55. We placed “ $\hat{\phantom{x}}$ ” above the endogenous flow variables where as the other flow variables are exogenous driving variables (together with the vacancies) in our analysis.

### 3.1 Updating KLNK to Oct. 2015

The analysis in Kroft et al. [2016] exploit data up until April 2013. In this Section, we explore the implications and performance of the model up since then. Before we turn to that analysis, we however have to face an uncomfortable task.

#### Discrepancy from Kroft et al. [2016]

Some of the results shown here for the period up to April 2013 differ slightly from those reported in Kroft et al. [2016]. In preparation for this paper, we revisited the code used for KLNK and discovered a slight

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<sup>5</sup>The latter is necessary because there is ample evidence Elsby et al. [2013a,b] (@I think those are the correct cites. Check) that both new unemployed coming from both employment or non-participation often report durations greater than 0. Thus, to match the duration data we need to account for these distribution of these flows.

coding error in the dynamic equations used in constructing the flows. In particular, the calculation of the flows did not exactly match the equations above (which were correct in paper but not in the computer code). Upon rerunning the analysis, we found that this mistake did not affect our basic conclusions but it did have a some effect on a few of the quantitative results.

In Figure 5, we compare the predicted and observed shares in LTU in Panel A and B. Panel A shows the results updated to October 2015 using our original code. By contrast, Panel B shows results using the updated code. Panel B shows that we underestimate the actual share of long-term unemployed in the population of unemployed by about 5 - 10 percentage points.

This implied that we reported a higher average duration of unemployment in our counterfactual series than warranted. By implication, our reported counterfactual job finding rate was too low. Consequently, while our prior simulations from Kroft et al. [2016] fit the job finding rates conditional on unemployment very closely, we now tend to find a counterfactual job finding rate conditional on unemployment that exceeds the actual job finding rate by about 2 percentage points in the period following the Great Recession (see 6). This tends to narrow as the discrepancy in the LTU share declines towards the later years.

The consequence of this coding discrepancy is fairly minor relative to the observed job finding rates that typically vary between 20 and 30 percent. Given these large rates of finding jobs conditional on unemployment, a deviation of around 2 percentage points in the rate of finding jobs will not substantively affect the ability of the model to fit the simulated stocks in the labor market and thus leaves our conclusions largely unchanged.

### **KLNK since April 2013**

How did the model fare in the two-and-a-half years since we completed the previous analysis? We find that the model does quite well when considering the share of LTU (4) and the job finding rates conditional on unemployment 6. Indeed, on both dimensions the model does better later in the latter period than in the period up to April 2013. Figure (4) shows that the stock of LTU declines rather slowly even if steadily. By the end of 2015, the observed and counterfactual share of LTU has declined to 35 and 30% respectively from about 50 and 40% respectively right after the Great Recession.

The model however fits the data much less well when we consider job finding rates among the non-participants. Those rates are consistently overestimated after 2008 (see 6, Panel B). The persistent feature of the U.S. labor market that is most difficult to explain is not unemployment or long-term unemployment, but non-participation since 2008.

Consider next the Beveridge curve shown in 7. Since April 2013, labor demand as measured by

Figure 5: LTU Old and Fixed

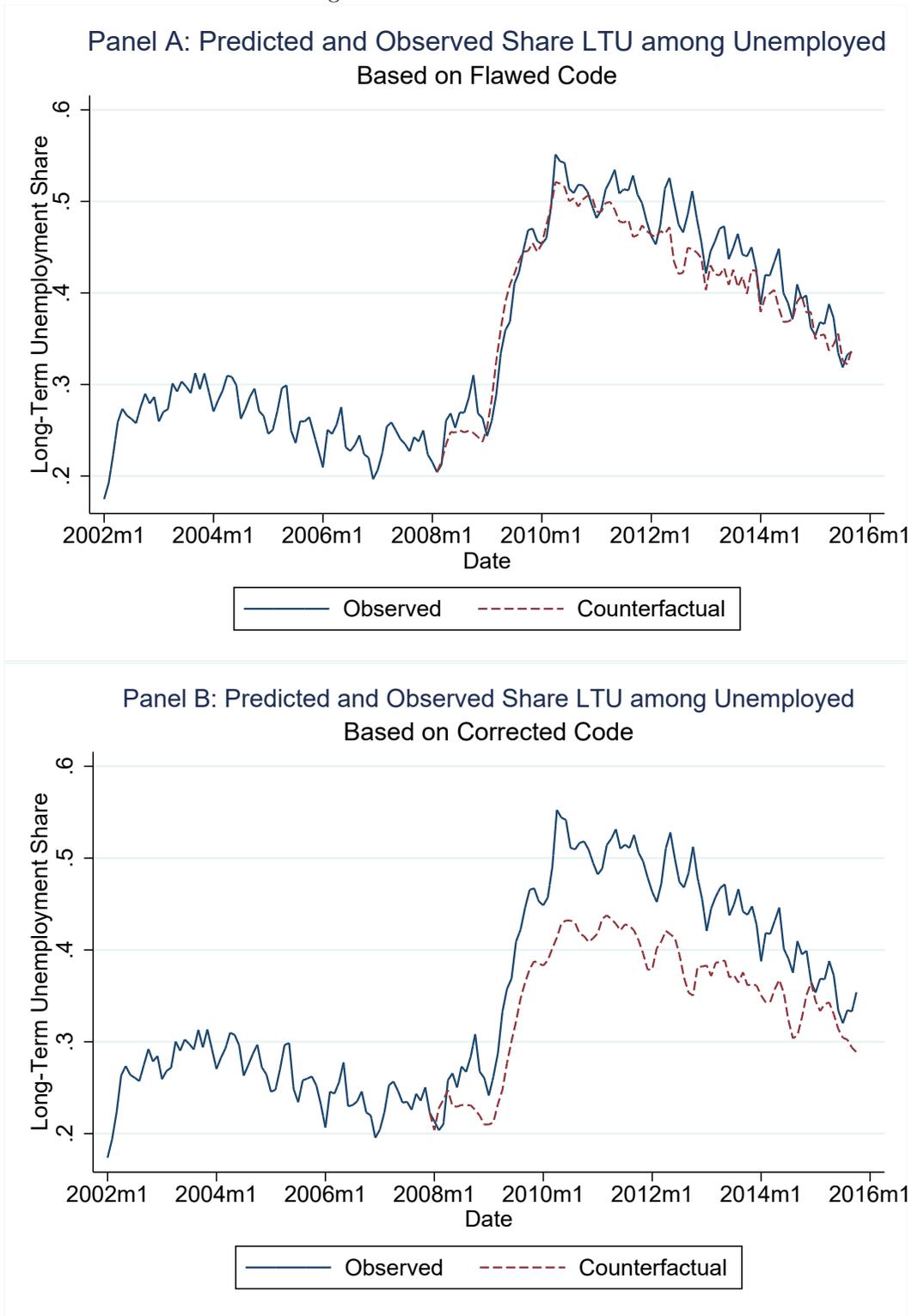


Figure 6: Job finding rates conditional on unemployment

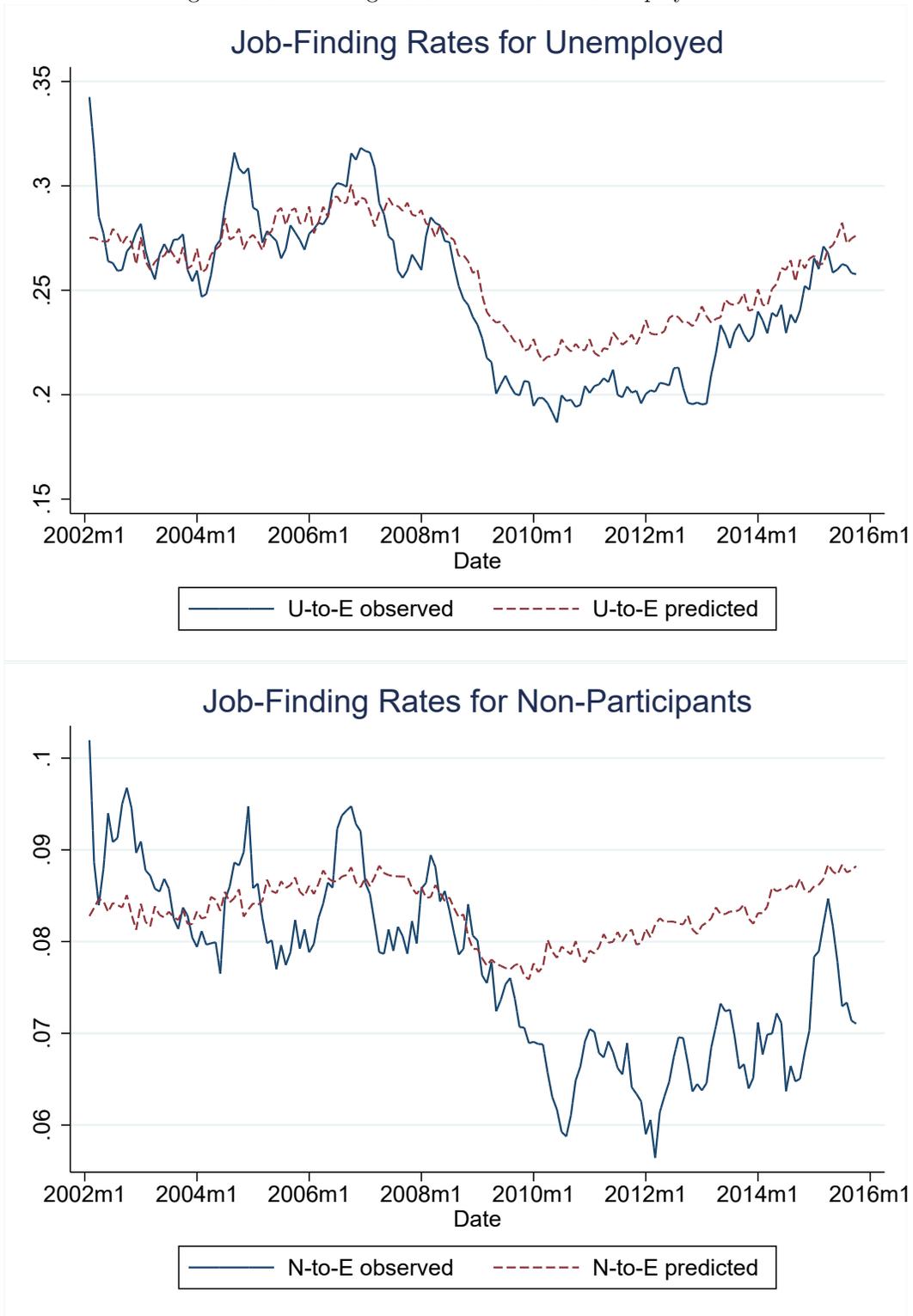
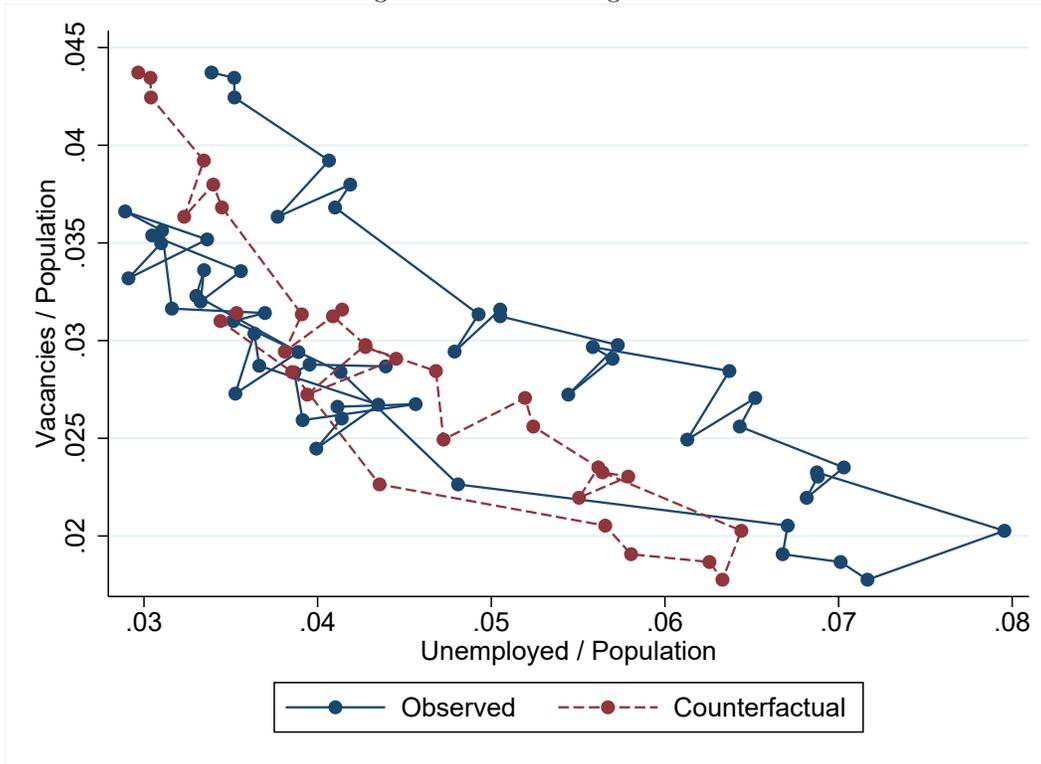


Figure 7: The Beveridge Curve

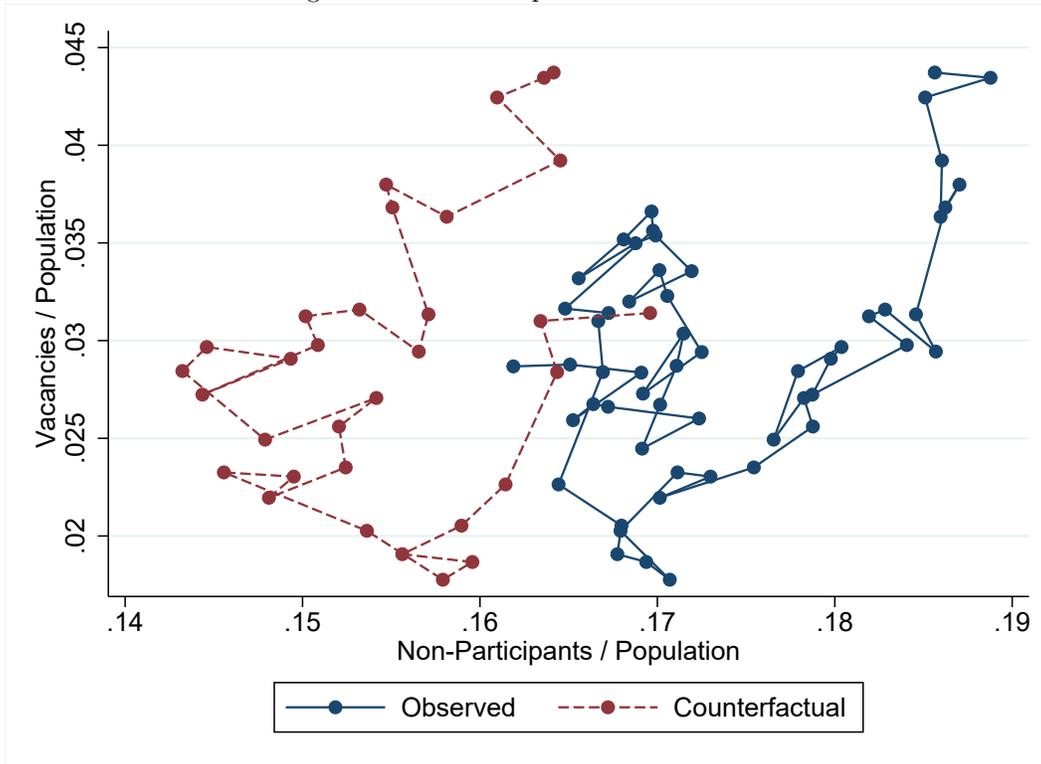


vacancies has continued to increase and unemployment continued to decline. However, even though vacancies exceed the rates observed at any time between 2002 and 2007, unemployment however has not declined to those levels seen in that period - indicating that the Beveridge curve has indeed shifted.

With regards to the performance of our model, we note that in Kroft et al. [2016] we reported that up until April 2013 we could explain about half of the shift in the Beveridge curve using the changing duration structure. A gap of about 1 percentage point however remained to be explained outside of our model and maybe due to changes in the structure of the matching relationship. Since then, we have seen the gap between the observed and the counterfactual Beveridge curve close from about 1 percentage point to about half a percentage point. Overall, the model does a fairly good job of accounting for these additional 30 month of data on unemployment and vacancies.

As noted in Kroft et al. [2016], the model fails to explain the shift along the non-participation margin over the period up until April 2013 and it continues to do so until Oct. 2015 (see Figure 8). It should be noted however that the failure comes entirely from predicting a sharp decline in non-participation rather than the observed increase during the first half of the period up until about April 2013. Besides this shift early in the Great Recession, the model has tracked how the stock of non-participants evolved quite well.

Figure 8: Non-Participation and Vacancies



## 4 LTU and LTN in Canada: Assessing the Role of Composition

[To be completed]

## 5 Constructing Vacancy Series in Canada

In Kroft et al. [2016], we used the Job Openings and Labor Turnover Survey (JOLTS) to compute the total number of vacancies each month. Unfortunately, in Canada, there is no counterpart data series that allows us to directly compute vacancies for the relevant time period. The vacancy measure from the Job Vacancy Statistics (JVS) series is only available since 2011 and the measure from the Job Vacancy and Wage Survey (JVWS) is only available since 2015.<sup>6</sup> While other data sources exist, none is adequate for our purposes.<sup>7</sup>

<sup>6</sup>The JVS is reported monthly and the data is collected at the establishment level, whereas the JVWS is reported quarterly and the data is collected at the business location level. The JVWS also has a larger sample, and includes vacancies from businesses primarily involved in agriculture, which the JVS does not. For more information on these two vacancy series, see the publication <http://www.statcan.gc.ca/pub/75-514-g/75-514-g2015002-eng.htm>.

<sup>7</sup>The Canadian Federation of Independent Businesses (CFIB) produces a survey of vacancies. However, it suffers from a number of limitations. First, it excludes the public and utilities sector. Second, it allows for passive job search and doesn't require an open position to exist, just for the business to have an unmet need. Third, it comes from registered CFIB members who voluntarily take the "Your Business Outlook Survey". Non-responses to the vacancy question are coded as zero vacancies. The other source of vacancy data comes from the Conference Board which uses online data from roughly 80 job-posting websites collected by WANTED Technologies. However, this vacancy series also suffer from serious limitations

Recently, Landais et al. [2016] have developed a proxy for vacancies in the U.S. This proxy called the "recruiting-producer ratio" is defined theoretically as the ratio of the number of recruiters in a firm to the number of workers engaged in production in a firm. Empirically, this is defined as

$$\tau = \frac{\xi \times rec}{l - \xi \times rec}$$

where  $rec$  is the seasonally-adjusted monthly number of workers in the recruiting industry, with North American Industry Classification System (NAICS) code 56131 and  $l$  is the seasonally-adjusted monthly number of workers in all private industries.<sup>8</sup> The parameter  $\xi$  is a scaling factor used to adjust for labor devoted to recruiting by firms not belonging to the recruiting industry. In the U.S., Landais, et al (2016) set  $\xi = 8.4$  based on survey evidence from 1997. Why should this measure be correlated with vacancies? The basic idea is that when firms are posting relatively more jobs, there are more resources tied up in recruiting. Thus,  $\tau$  should be procyclical. This is indeed what Landais et al. [2016] find.

We adopt this same methodology to impute a vacancy series for Canada over the relevant time horizon. Unfortunately, employment counts by 5-digit NAICS codes are not available in Canada. Thus, we used the Survey of Employment, Payrolls and Hours to construct employment levels for the industry 5613. To measure total private employment, we use the industrial aggregate, excluding unclassified businesses.<sup>9</sup> We estimated the adjustment factor as one of the parameters to be estimated below and found  $\xi = 6$ .

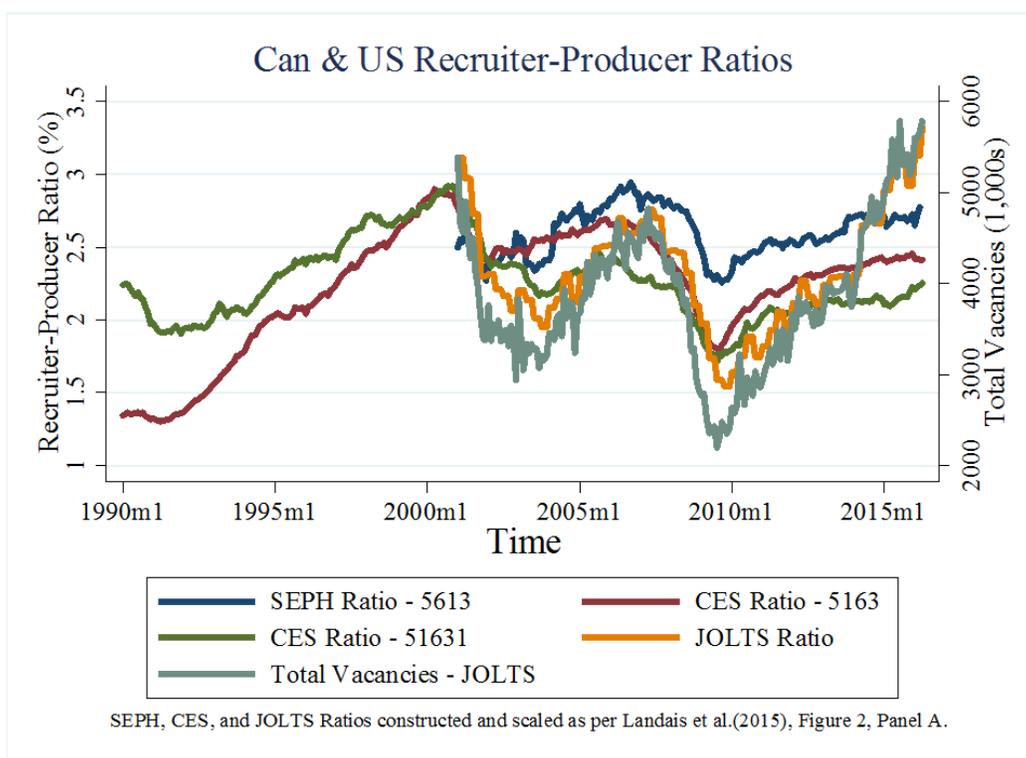
The next figure compares the recruiter-producer ratio in the U.S. with the vacancy measure taken from JOLTS and also shows the recruiter-producer ratio for Canada. Note that in the U.S., the recruiter producer ratios based on NAICS code 56131 and 5613 behave very similarly over time. Further, over time, the recruiter-producer ratio and JOLTS show the same behavior - rapid declines at the on-set of the 2001 and 2008 recession with recovery in between and comparable relative movements during the recovery and the recessions. The recruiter-producer ratio for Canada taken from SEPH show similar behavior except that the magnitude of the decline during the Great Recession is about comparable with the increase between 2001 and 2007. This lines up with the general observation that the recession was less severe in Canada than in the U.S. In calibrations with Canadian data, we use scaling parameter of 6.0. When calibrating the matching model in the pre-recession period, we replace the  $V$  stock that was used in KLNK with the Landais et al. [2016] recruiter-producer ratio. We then calibrate the scaling parameter  $p$  in the recruiter-producer ratio along with the other matching model parameters  $m_0$ ,  $\alpha$  and  $s$ .

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and was infact discontinued because of reliability issues.

<sup>8</sup>This official name for this industry is "employment placement agencies and executive search services".

<sup>9</sup>The seasonally-adjusted employment counts were available from CANSIM table 281-0047.



## 6 Long-Term Unemployment and the Great Recession in Canada

### Transition Rates in Canada

**Unemployment-to-Employment transitions (U-to-E):** Turning to transitions from unemployment in Canada, we see that the monthly job-finding rate from unemployment to employment was around 30 percent in the pre-recession period, dropped sharply to 24 percent at the end of 2009, and then rebounded somewhat to around 26-27 percent. By contrast, the monthly job-finding rate for the U.S. was around 25 percent in the pre-recession period and dropped to around 18 percent during the recession. The decline appears rather smoother in the U.S. than it is for Canada. Additionally, while the job-finding rate remained at low levels in the U.S., it tended to rebound more quickly in Canada, reflecting the fact that the recession was more persistent in the U.S.

**Non-participation-to-Employment transitions (N-to-E):** Focusing on flows from non-participation, we see that the monthly transition rate from non-participation to employment is about 12 percent in the pre-recession period and drops to 10 percent during the recession. The magnitudes for the U.S. are very

similar; the transition rate is roughly 8 percent and drops to about 5-6 percent during the recession. As we saw above, the low monthly job-finding rate for non-participants implies that the bulk of them have very long non-employment spells.

### **LTU Shares in Canada**

The share of long-term unemployed (LTU) for Canada, defined as being unemployed for more than 26 weeks, increased sharply starting at the end of 2009 from roughly 12 percent to 20 percent. This increase occurred very rapidly. While this share has recovered somewhat, it still remains elevated around 16 percent. Thus, half of the increase in long-term unemployment still remains.

Turning to the U.S., we found that the share of long-term unemployed increased from around 20 percent in the pre-recession period to a staggering 45 percent. This increase in long-term unemployment began earlier than the corresponding increase in Canada, reflecting the fact that the recession hit the U.S. earlier, and also appears to have been more smooth than the increase in Canada. Thus, the overall severity of the recession, as reflected in the the LTU share, was much deeper in the U.S. than it was in Canada.

A neat feature of the Canadian data is that we can observe spell length for non-participants, something that the CPS does not keep track of. Thus, we can document trends in joblessness for this group. Similar to the unemployed, see that the share of long-term joblessness for non-participants was on somewhat of a downward trend in the pre-recession period and increased slightly from around 77 percent to about 79-80 percent during the recession. Thus, rates of long-term joblessness are much higher for non-participants than they are for the unemployed and this increased only slightly during the recession. This reflects the fact that this group is not on the margin of the labor market.

### **Duration Dependence in Canada**

Next, we examine duration dependence among the unemployed. In particular, we plot the job-finding rate at duration  $d$  relative to the job-finding rate at duration 0 during the pre-recession period. This is the function  $A(d)$  reported in Kroft et al. [2016]. By construction, this series is 1 for the newly unemployed. Here, we do not control for observables. Interestingly, the pattern of duration dependence for Canada is very similar to the pattern for the U.S. In particular, we see that in Canada after 3 months, this ratio is 60 percent and then levels off to around 40 percent after 15-20 months although the data are noisy for the last few months. For the U.S., we find the exact same pattern.

One thing we were unable to evaluate for the U.S. is duration dependence among non-participants. This is because the CPS does not record the spell length and thus, we cannot fully observe transitions

from N-to-E for each  $d$ . However, the Canadian data allows us to gauge this. In the next figure, we repeat the same exercise but instead focus on transitions from non-participation. Similar to our figures for the unemployed, we find that the relative job-finding rate falls to about 60 percent after several months. However, the job-finding rate falls off to about 20 percent after 15 months, more than double what we find for the unemployed.

We next examine how the job-finding rate changes over time based solely on changes to the distribution of unemployment. This is the average of the  $A(d)$  function. Intuitively, in a recession, longer spells receive more weight and so pull down the mean  $A(d)$ . For Canada, the mean is roughly 90 percent in the pre-recession period and drops to about 85 percent during the recession. For the U.S., the predicted job-finding rate is about 75 percent and falls to about 65 percent during the recession. Again, this is consistent with the trends in LTU for both countries, showing that the recession was much deeper in the U.S.

Since we can estimate the  $A(d)$  function for non-participants in Canada, we also report the predicted job-finding probability for this group based solely on the distribution of durations. The average  $A(d)$  is much lower for non-participants than it is for the unemployed, starting around 23 percent in the pre-recession period and falling to about 21-22 percent during the recession. This reflects the fact that most of the jobless among the non-participants have very long spells and long-term joblessness increased only slightly for this group.

The Canadian data has a significant advantage over the U.S. data in that it allows us to track duration of joblessness, not just duration of unemployment. Joblessness is a less difficult concept to understand for survey respondents than unemployment. As conceived by labor economists, unemployment is defined as a period of non-employment during which individuals actively search for employment. Unemployment duration refers to the duration of continuous active search for employment. Responses to the duration question in the CPS are however not consistent with this definition. In many instances, individuals report long durations of unemployment even though they were just observed to transition from OLF to unemployment. It is plausible to us that such respondents might report on the length of time they have been out of a job as opposed to reporting on the duration of active search. Since joblessness does not require understanding the concept of active search, survey responses related to joblessness are likely to align more closely with how labor economists interpret this concept.

A second and maybe more important advantage of the data on joblessness duration is that it is available for both the unemployed and for those Out of the Labor Force. We can thus examine the duration structure and its impact on the job finding rate among both those OLF and unemployed. The next figures show the trends in long-term joblessness (LTN) overall as well as in long-term joblessness

condition on unemployment and OLF.

As figures 9 reveal, long-term joblessness increased among both the unemployed and those OLF since 2009. However, while most of this increase in long-term joblessness concentrated in the first few months of the Great Recession among the unemployed, the increase in LTN among the OLF has been much more gradual. It is indeed not clear whether this increase in LTN has run its course by October 2015, when our data ends. Overall, the relative increase in LTN is much more pronounced among the unemployed since the share of LTN is of course much lower among the unemployed. OLF includes many individuals permanently separated from the labor market, maybe because of disabilities or for other reasons. Nevertheless, since so many more individuals are OLF as compared to unemployed, an increase in 4 percentage points from trough to peak in LTN among the OLF is an important empirical pattern.

How do job-finding rates vary with LTN? The panel structure of our data allows us to answer this question as well. The next figures show the job finding rates among both U and OLF conditional on LTN. These empirical relations between joblessness duration and job finding rates are taken from the period prior to the Great Recession and we will use them to augment the model described above.

The pattern in duration dependence with joblessness are similar to those found among the unemployed when we consider duration of unemployment as the independent variable. Job-finding rates decline rapidly over the first few months and then less quickly as durations accumulate. Job-finding rates among the long-term jobless conditional on OLF are very low and amount to just 10% of those exiting to OLF from employment.

The equations above described the job finding rate conditional on unemployment duration for the unemployed and unconditionally for those out of the labor force. In this section, we now model the job finding rate of those OLF analogously to the job finding rate of the unemployed using as our duration measure the time-period that an agent has been jobless. Thus, we replace equation for job-finding rate for unemployed with the following

$$\lambda^{NE}(x_t) = sB(d)m_0x_t^{1-\alpha} \tag{7}$$

where  $B(d)$  captures the duration dependence in the job finding rate among those OLF analogously to  $A(d)$  in equation 1. Besides this change, the model remains unchanged.

### **Calibrating the model with Canadian data**

[To be completed]

Figure 9: Long Term Joblessness

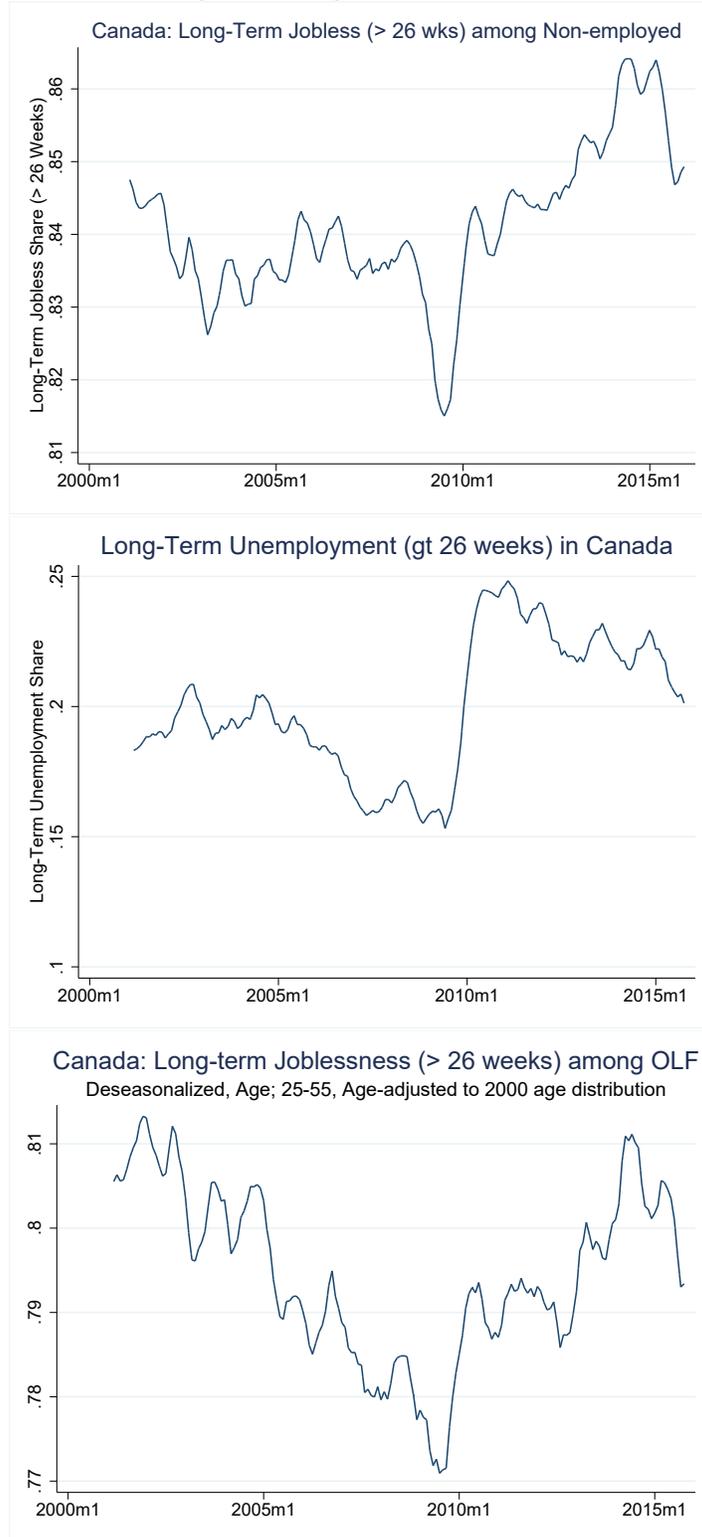
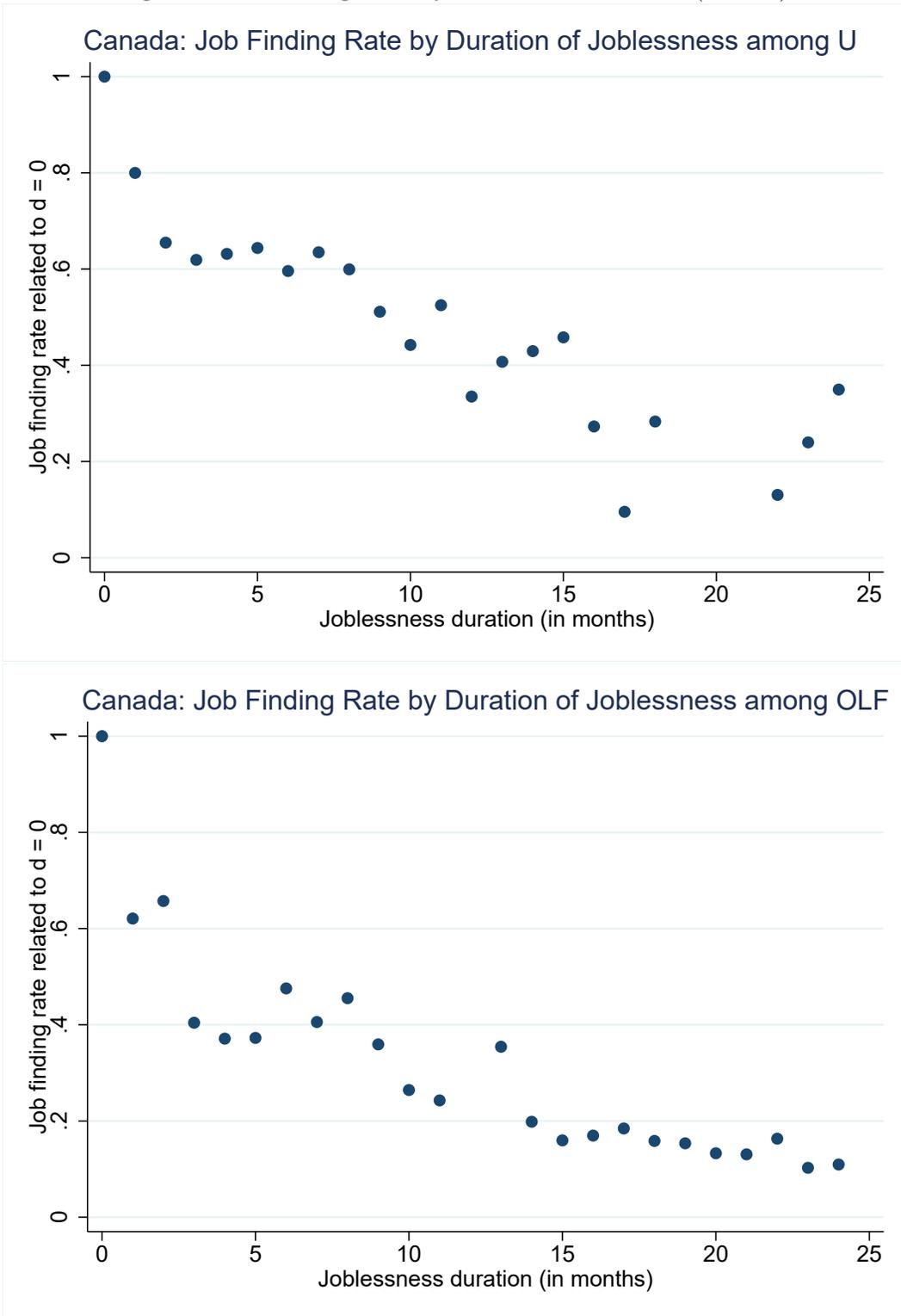


Figure 10: Job Finding Rates by Duration of Joblessness (Canada)



## Counterfactual Results

To obtain counterfactual predictions, we implement the estimation procedure in Kroft et al. [2016] for Canada. Our estimates of the matching function are contained in Table [To be completed]. We begin by plotting our model predictions of the job-finding rates for the unemployed and non-participants. For the unemployed, we do a fairly decent job of matching job-finding rates in the pre-period although there is a bit of a gap between the predicted and observed series. Qualitatively, our model predicts a drop in the job-finding rate in 2010, similar to the patterns in the observed job-finding rate. However, we see that the drop-off is less pronounced than what is observed in practice. This stands in contrast to our results for the U.S. where we can also quantitatively match the magnitude of the decline in the unemployed job-finding rate with our model. Turning to job-finding rates for non-participants, we see that incorporating duration dependence into the job-finding rate does not appear to considerably improve the fit of the model.

Next, we perform counterfactuals for long-term unemployment ( $>26$  weeks and  $>52$  weeks). For Canada, we see qualitatively that the model can match the predicted increase in LTU shares although because we over-predict job-finding rates during the recession, we slightly under-predict LTU shares. In the U.S., we also slightly under-predicted LTU shares although the model fit was better.

Turning to our results for the Beveridge curve, our results for Canada show a decent fit of the model, with a slight under-prediction of unemployment again due to the inflated job-finding rates for the unemployed. Similar to our results for the U.S., the fit of the N-V curve is worse for Canada.

## 7 Conclusion

[To be completed]

Figure 11: Vacancy Rate Proxy and Job-Finding Rate for Unemployed (Canada)

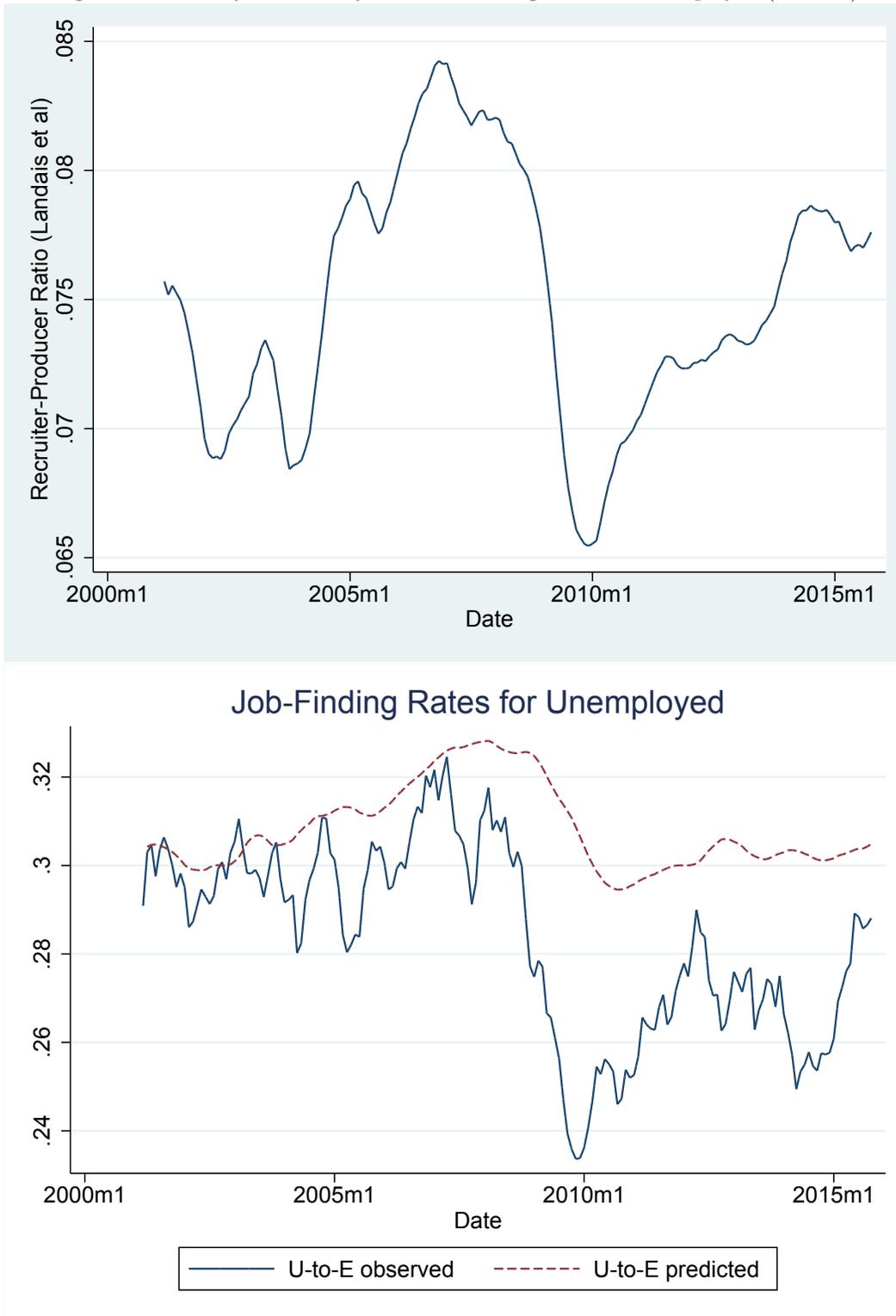


Figure 12: Counterfactual Long-Term Unemployment Share (Canada)

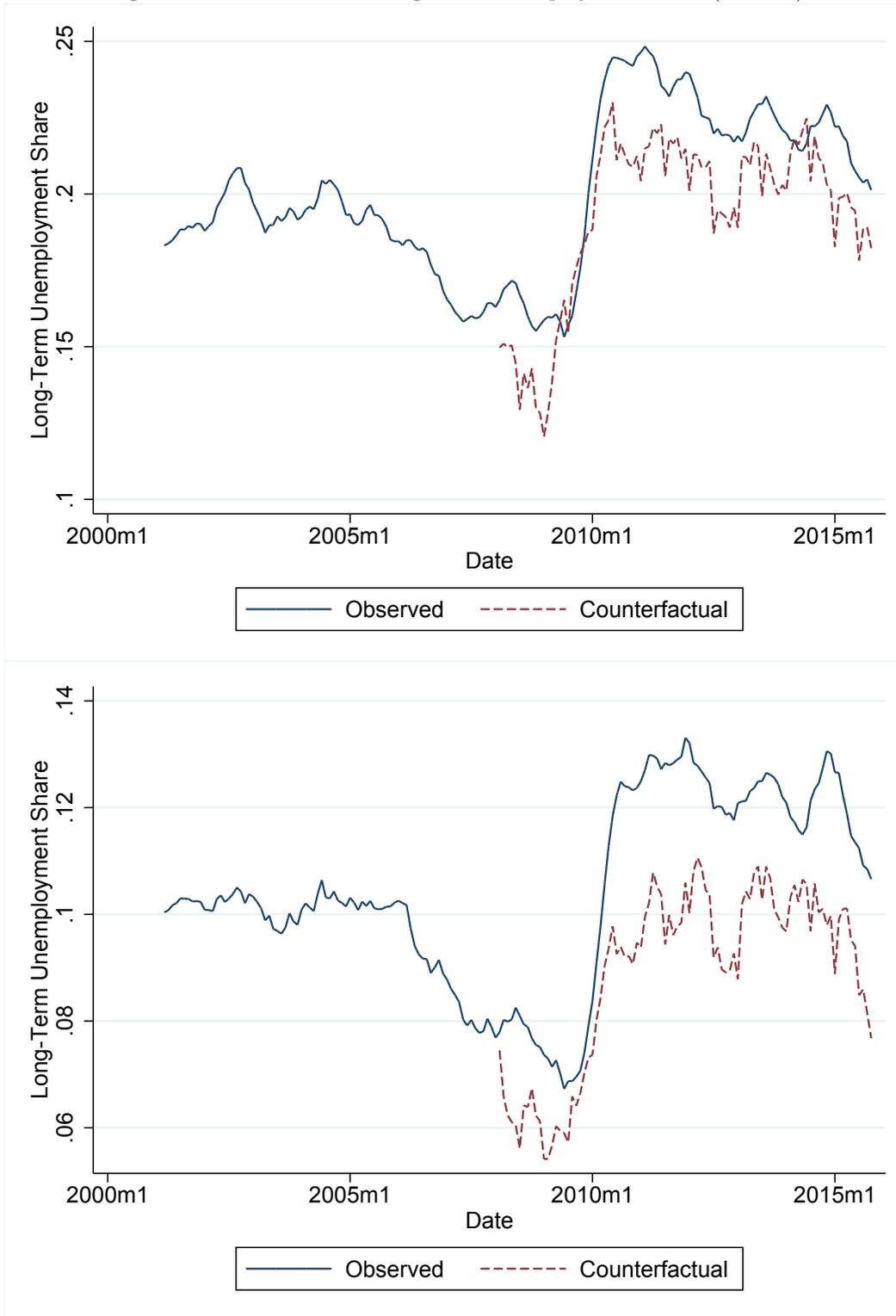
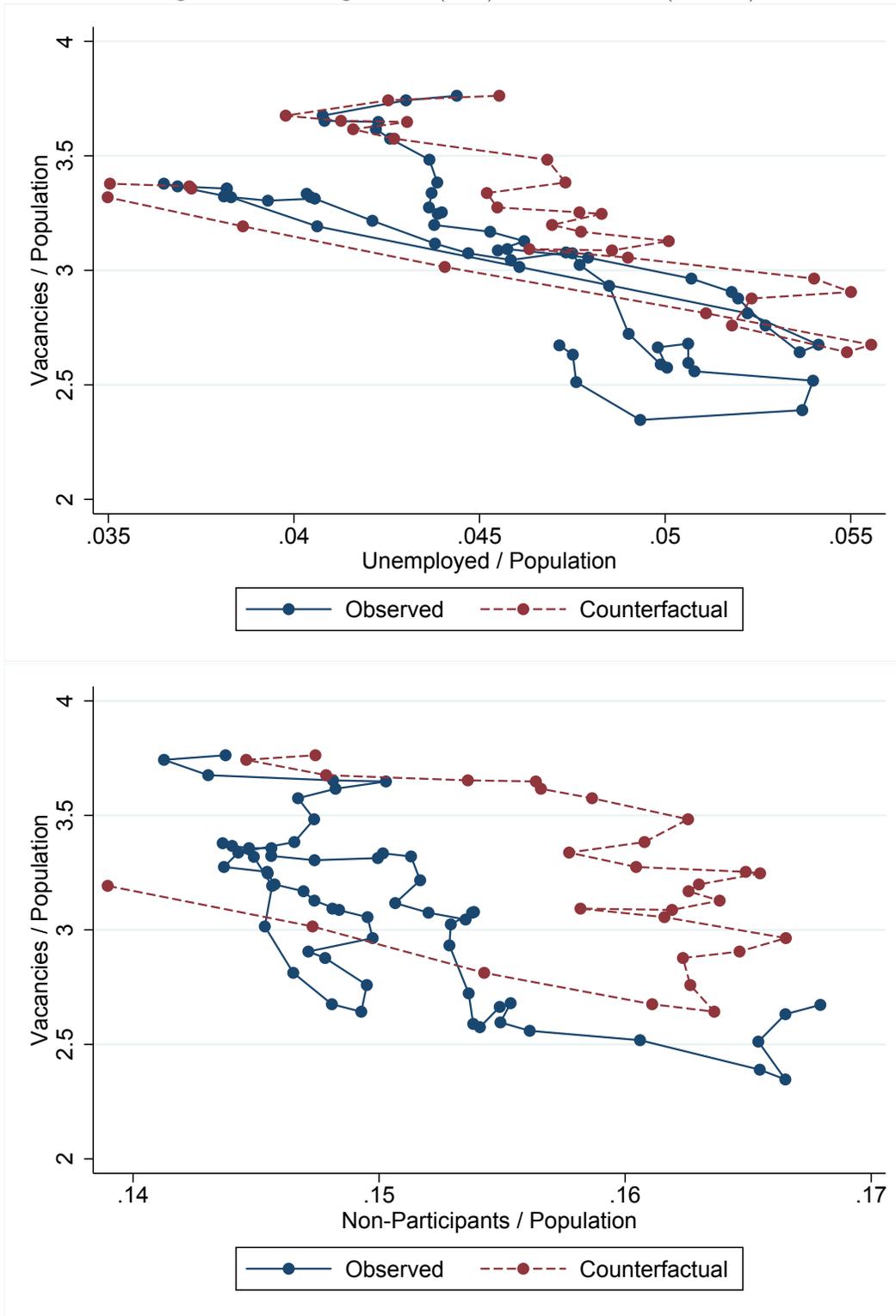


Figure 13: Beveridge Curve (V-U) and V-N Curve (Canada)



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