

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

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

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Abstract

We compare patterns of unemployment between Canada and the U.S. during the Great Recession. Similar to findings in Kroft et al. [2016], we document a rise in long-term unemployment in Canada. We consider an extended matching model using the restricted-access data from the Canadian Labor Force Survey which contains information on time since last job for both unemployed and non-participants. We create a new historical vacancy series for Canada based on relative employment in “recruiting industries” to construct a monthly Beveridge curve for Canada. Allowing for duration dependence in flows between unemployment and non-participation is crucial for explaining long-term joblessness.

*Kory Kroft, University of Toronto, Department of Economics and NBER (kory.kroft@utoronto.ca); 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.ca). The authors would like to thank Robert French, Anran Li, and Susan Ou for excellent research assistance and Andrew Berger-Gross, Samuel Bentolila, and participants at the Ottawa, October 2016 “Small Differences” conference and the Bristol Workshop on Economic Policy Interventions and Economic Behavior for helpful comments. Fabian Lange acknowledges financial support by the Social Sciences and Humanities Research Council of Canada. Much of the analysis for the paper was conducted at the Toronto Region Statistics Canada Research Data Centre, which is part of the Canadian Research Data Centre Network (CRDCN). The services and activities provided by the CRDCN are made possible by the financial or in-kind support of the SSHRC, the CIHR, the CFI, Statistics Canada and participating universities whose support is gratefully acknowledged. The views expressed in this paper do not necessarily represent the funders, the CRDCN, or any of its partners.

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]). In previous work, we examined how this framework performed over the Great Recession in the United States in accounting for the dramatic rise in long-term unemployment and the outward shift in the Beveridge curve (Kroft et al. [2016]). Our main result was that a standard matching model with unemployment (U) and vacancies (V) and a constant job finding rate did a poor job reproducing these stylized facts. We thus enriched this matching model along two dimensions. First, we allowed for duration dependence in the job finding rate of the unemployed, consistent with a range of empirical evidence (e.g., experimental work such as Kroft et al. [2013] and recent structural econometric work such as Bentolila et al. [2017]). Second, we allowed for flows between the labor market states employment (E), unemployment (U), and non-participation (N), instead of focusing exclusively on flows between employment and unemployment, as in the standard matching model.¹ We calibrated our enriched matching model and found that it accounted for most the rise in long-term unemployment and about half of the outward shift in the Beveridge curve.

In this paper, we compare the labor market dynamics in Canada and the U.S. before, during, and after the Great Recession, building on the model in Kroft et al. [2016] and using restricted-use panel from the Canadian Labor Force Survey (LFS) – the counterpart to the U.S. Current Population Survey (CPS). This comparison is of interest because, as we demonstrate, the dynamics of the Great Recession in Canada and the U.S. were quite different. 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 to make five additional contributions.

First, we document how the U.S. labor market has evolved since March 2013 (where our prior analysis left off). Our results indicate that the model continues to track long-term unemployment share fairly well and accounts for some of the outward shift of the Beveridge curve. However, the model continues to over-estimate the job finding rate among non-participants and thus under-estimate the stock of non-participants. This remains one of the enduring puzzles of the Great Recession in the U.S.

Second, we present new evidence on unemployment dynamics in Canada during the Great Recession and compare Canada to the U.S. We document a rise in long-term unemployment in Canada that was less pronounced than the rise in the U.S. Similar to what Kroft et al. [2016] found for the U.S., we find that observables cannot explain the rise in long-term unemployment; rather, the increase was widespread

¹Throughout the paper, we will use non-participation (N) and out-of-labor force (OLF) interchangeably.

across demographic groups. We also find that at the onset of the recession in Canada, job finding rates among the unemployed declined by similar amounts in the U.S. and in Canada; however, the decline in the job finding rate in the U.S. persisted for much longer. Our results indicate that Canada did not experience a decline in the rate at which non-participants transitioned into employment, which also contrasts with our findings for the U.S.

Third, we exploit a unique feature in the LFS data to study the dynamics of flows between labor force states. Similar to the CPS, the LFS records the length of ongoing unemployment spells for the unemployed. In addition to this, the LFS (but not the CPS) reports time elapsed since last employed for both non-participants and the unemployed.² We refer to this measure as “joblessness duration” and we explore how labor market flows involving non-participants vary with it. We find that the job finding rates for non-participants decline with the duration of joblessness and this decline is of the same magnitude as the one observed among the unemployed. Furthermore, we find that the unemployed become more likely to transition to non-participation and non-participants become less likely to transition to unemployment as the duration of joblessness increases.

Fourth, our finding that flows involving non-participants vary with the duration of joblessness motivates us to augment and improve the matching model in Kroft et al. [2016] in a straightforward yet important direction. We calibrate our extended matching model using a similar approach to that in Kroft et al. [2016] and find that allowing for duration dependence in joblessness for all flows involving non-participants helps account for the observed levels in long-term joblessness and their changes during the 2008-2009 recession. By contrast, allowing for duration dependence in all flows helps – but is not central to – understanding the aggregate rates of employment, unemployment, and non-participation observed over the same time-period. The observed behavior of these stocks is dominated by average flows between the three labor force states, which can be adequately captured without modeling long-term joblessness.

Our fifth contribution is to construct a new vacancy series for Canada, which we use to develop a Beveridge curve for Canada. This is necessary because (to our knowledge) there is no widely-accepted

²There are a priori reasons why one might want to use measures of joblessness duration as opposed to unemployment duration. As noted by Clark and Summers [1979], joblessness duration is a much more useful measure than unemployment duration in order to understand the costs of unemployment. Joblessness duration, as opposed to unemployment duration, is also conceptually easier for survey respondents to understand since it does not require actively tracking time spent searching for a job. Kudlyak and Lange [2017] document that the duration data based on the survey responses in the CPS is inconsistent with the observed patterns of unemployment, non-participation, and employment observed in the CPS. In many instances, individuals report long durations of unemployment even though they were just observed to transition from non-participation or employment to unemployment. In part, these responses are in fact consistent with the questions asked by the CPS. The duration question in the CPS refers to time spent searching for employment. Respondents may report long durations even though they just transitioned from employment into non-employed because they continued searching while holding stop-gap jobs. That is, the CPS-respondents might often give logically consistent answers to the questions they are asked, while labor market researchers make a logical leap in interpreting these data as representing unemployment durations. Kudlyak and Lange [2017] also present evidence from the 4-month CPS panels in the U.S. that suggests the same patterns of how joblessness affects transitions that we observe in Canada are also present in the U.S. In particular, they show that job finding rates conditional on non-participation decline rapidly in the duration since last employment.

vacancy series in Canada that spans the years before, during, and after the Great Recession. Our vacancy measure is based on relative employment in “recruiting industries” and is inspired by Landais et al. [2018]. Landais et al. [2018] use employment in recruiting industries to create a reliable proxy for the U.S., where vacancy data are more widely-available and so the proxy can be validated. We follow the same approach to create a proxy for vacancies in Canada. We use this proxy to calibrate the Canadian matching model and to construct a Beveridge curve for Canada. We demonstrate that the Beveridge curves in Canada and the U.S. have a broadly similar shape. However, unlike the U.S., the Beveridge curve in Canada did not shift outward significantly during the Great Recession.

The remainder of the paper proceeds as follows. In Section 2 we describe the data sources used in the analysis and the construction of our vacancy proxy using “recruiting industries”. In Section 3, we compare and contrast the recessions in Canada and the U.S. Section 4 analyzes the composition of the long-term unemployed and the “long-term jobless” out of the labor force. Section 5 revisits the analysis in Kroft et al. [2016] using U.S. data, replicating the main results and extending the results to the most recent data available. Section 6, focuses on the Canadian experience during the Great Recession. It describes the incidence of long-term joblessness among the unemployed in Canada, reports results from the composition analysis of long-term joblessness, describes the extension of the model to account for joblessness duration, and discusses the model calibration and counterfactual results using the restricted-use LFS data. Section 7 concludes.

2 Data

This section briefly describes our data sources. See Kroft et al. [2016] for more details on the U.S. data.

2.1 United States

Current Population Survey (CPS)

We use monthly CPS data between January 2002 and October 2015 (extending beyond the April 2013 end date in Kroft et al. [2016]). Our sample comprises all employed, unemployed, and non-participants aged 25-55. The data is age-adjusted to the 2000 age distribution.³ In the cross-section, we keep track

³Specifically, we adjust the sum of the weights for each age (in years) to be equal to the sum of the weights for the same age in the base year 2000. In the U.S., this age adjustment has a negligible effect on trends in the employment rate. This comes from the fact that we have limited the sample to ages 25-55. If we had instead used a 25-65 age range, then the trend in the employment rate would be more sensitive to whether or not we had adjusted for changes in age composition. This is because most of the changes in age distribution from 2000 until 2016 is concentrated above age 55. These results are shown in Appendix Figures 29 through 31. Thus, the main age restriction (which we carry throughout the paper) makes our main results likely insensitive to whether or not we age-adjust the sample.

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 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 to compute the total number of vacancies. We use these vacancy data to calibrate the matching model 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

Labor Force Survey (LFS)

We use restricted-access Canadian Labor Force Survey (LFS) data. The definition of unemployment varies somewhat between Canada and the U.S.. To be able to compare the data from the two countries, we went back to the survey responses to the LFS and recoded labor force states in the LFS to be comparable to those from the CPS (see Bernard and Usalca [2014] and references contain therein). Similar to the U.S., we limit ourselves to the age range 25-55 and re-weight the data to match the 2000 age distribution in Canada. We also force the transition rates to be consistent with the cross-sectional data on stocks using the methodology described in Kroft et al. [2016].

An important advantage of the Canadian data is that respondents are asked about the duration of joblessness in addition to the duration of unemployment. As Elsby et al. [2015] and Kroft et al. [2016] both report, unemployment durations as usually constructed based on the CPS are frequently inconsistent with the observed panel of labor force states when observations in the CPS are linked to construct an individual-level panel data set. In the CPS, unemployed respondents are asked to report how long they have been actively looking for a job. It has become standard practice to use reported durations in response to this question as indicating unemployment durations. If respondents interpreted this question as labor statisticians would like them to, they should report durations of less than a month when surveyed in the month after a transition from either employment or out of the labor force to unemployment. However, respondents often report substantially longer durations of unemployment during these months. Kudlyak

and Lange [2017] present evidence that respondents might include short jobs (stop-gap jobs) during which they continued to search for more permanent employment when they answered this question. By contrast, the question on the duration of joblessness in the LFS is relatively simple to interpret. 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 non-participants. We therefore focus on joblessness duration for the bulk of our empirical analysis, both for conceptual reasons and to have same duration concept for both unemployed individuals and non-participants.

2.3 A New Vacancy Series for 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 in the U.S.. Unfortunately, to our knowledge there is no counterpart data series in Canada 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 2015.⁴ While other data sources exist, none are adequate for our purposes.⁵

Recently, Landais et al. [2018] developed a proxy for vacancies in the U.S. This proxy is called the “recruiting-producer ratio” and is defined theoretically as the ratio of the number of recruiters relative to the numbers of workers engaged in production. Empirically, Landais et al. [2018] define this ratio as:

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

where *rec* is the seasonally-adjusted monthly number of workers in “recruiting industries”, defined as employment in North American Industry Classification System (NAICS) code 56131, and *l* is the seasonally-adjusted monthly number of workers in all private industries.⁶ The parameter ρ is a scaling factor used to adjust for labor devoted to recruiting by firms not belonging to the recruiting industry and therefore not captured by *rec*. In the U.S., Landais et al. [2018] set $\rho = 8.4$ based on survey evidence from 1997. Why should this measure be correlated with vacancies? The basic idea is that when firms are posting

⁴The 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>.

⁵The 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 suffers from serious limitations and was in fact discontinued because of reliability issues.

⁶The official name for this industry is “Employment placement agencies and executive search services”.

relatively more jobs, there are more resources allocated to recruiting. Thus, τ should be procyclical, and this is indeed what Landais et al. [2018] find.

In our analysis, we follow Landais et al. [2018] and use employment in recruiting industries in Canada as a proxy for the ratio of vacancies to the population. Unfortunately, employment counts by 5-digit NAICS codes are not available in Canada. Thus, we instead use employment in the 4-digit NAICS industry code 5613 measured in the Survey of Employment, Payrolls and Hours (SEPH) to measure the number of employees employed in the recruiting industries.

To construct τ , we also need an estimate of ρ , the proportionality factor meant to capture the ratio of workers outside the recruiting industry that are engaged in recruiting. We expect our estimate ρ to be smaller than the estimate from Landais et al. [2018] since we define the recruiting industry to be broader.⁷ Below, we estimate the adjustment factor ρ as one of the parameters entering the matching function. The estimate will depend on the model specification and in particular on whether we allow for duration dependence in the job finding rates of the unemployed and/or non-participants. Our preferred specification allows for both duration dependence among the unemployed and non-participants. ρ for our preferred specification is 2.6 and we will use this value when we describe the vacancy series. Fortunately, the measure τ and its cyclical properties are robust to variation in ρ ; the time series of τ varies little even when we employ substantially different values for ρ .

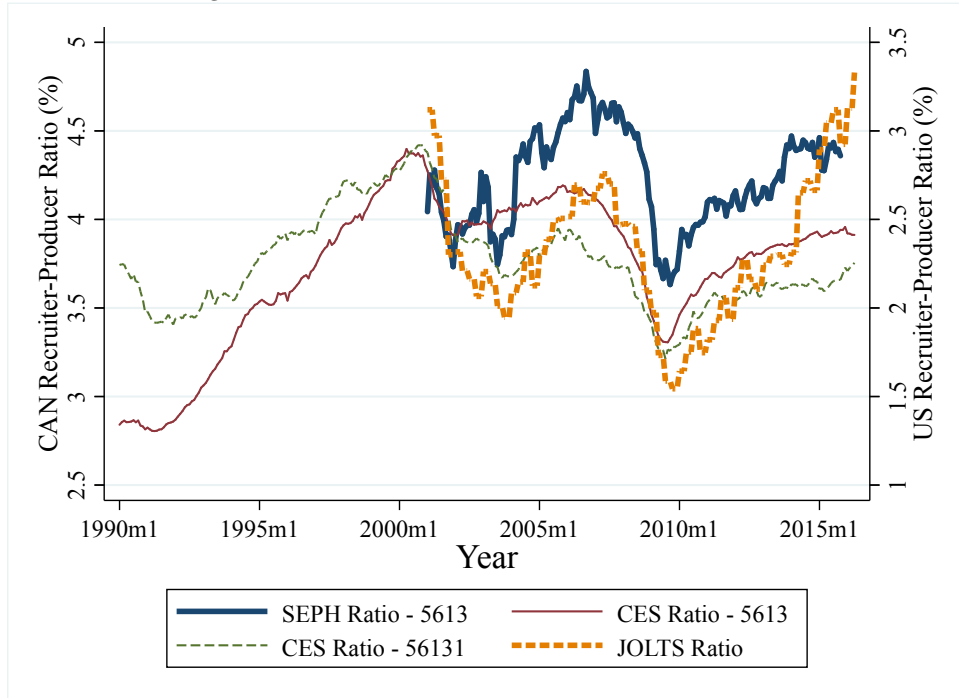
Figure 1 compares the recruiter-producer ratio in the U.S. with the vacancy measure taken from JOLTS and also shows the recruiter-producer ratio for Canada, calculated using the SEPH data. Note that in the U.S., the recruiter-producer ratios based on NAICS code 56131 and 5613 behave very similarly over time, suggesting that basing our vacancy series on the 4-digit NAICS code in Canada will not be a major problem for our analysis. Moreover, it suggests that we should not be surprised to recover a similar scaling factor, even though we are using a broader employment category.

Furthermore, the recruiter-producer ratio and JOLTS evolve similarly over time in the U.S. – the decline by similar amounts at the onset of the 2001 and 2008 recessions and likewise recover by comparable relative amounts subsequent to these recessions. To provide another way of validating the vacancy proxy in the U.S., in the Appendix we report predicted job finding rates (for both unemployed and non-participants) in the U.S. using both the JOLTS measure as well as the recruiter-producer ratio proxy. The predicted job finding rates are very similar across the two measures, bolstering the case that the proxy based on the recruiter-producer ratio in Canada may be an adequate substitute for a JOLTS-like vacancy series which does not exist for a sufficiently long period in Canada for our analysis.

Overall, comparing the U.S. and the Canadian time series patterns in vacancies as measured by the

⁷The seasonally-adjusted employment counts l stem from CANSIM table 281-0047.

Figure 1: Canada & U.S. Recruiter-Producer Ratios



Notes: The line labeled “SEPH Ratio - 5613” represents the recruiter-producer ratio in Canada constructed following the methodology by Landais et al. [2018] based on NAICS code 5613. The other four lines show vacancy rates for the U.S. The two lines referring to the CES ratio show the recruiter-producer ratios following Landais et al. [2018] using CES data and the NAICS codes 5613 or 56131 respectively. The other two are based on JOLTS data.

recruiter-producer ratio, we find that over the last recession, the recruiter-producer ratio declined less in Canada than in the U.S. This finding lines up with the general observation that the recession was less severe in Canada than the Great Recession in the U.S. – Canada instead experienced a “Not-Quite-Great Recession”.

3 The 2008-2009 Recessions in Canada and the U.S.: A Brief Overview

3.1 Unemployment and Employment-to-Population Rates

Both Canada and the U.S. 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 determined that the U.S. was in a recession for 18 months from December 2007 to June 2009, while the recession in Canada lasted only 7 months from November 2008 to May 2009.⁸ The recessions differed not just in length but also in their severity. The movements in key labor market outcomes, illustrated in Figures 2 and 3, were about twice as large in the U.S. as in Canada. Figure 2 shows that for the U.S., the unemployment rate among 25-55 year olds increased by about 5 percentage points over the Great Recession, compared to a 2.5 percentage point in the unemployment rate in Canada. In the U.S., the employment-to-population ratio (Figure 3) declined by about 4 percentage points compared to a 2 percentage point decline in Canada.⁹

The figures also show that Canada recovered more rapidly than the U.S. By mid-2010, the unemployment rate in Canada had dropped back by about half of its increase in 2009, while in the U.S. the unemployment rate remained at levels similar to those in late 2009. Since then, both Canada and the U.S. slowly returned to unemployment rates comparable to the pre-recession period. However, the U.S. has only managed to claw back about half of the decrease in the employment-to-population ratio, while Canada returned to the pre-recession levels of the employment-to-population ratio by the end of 2012.

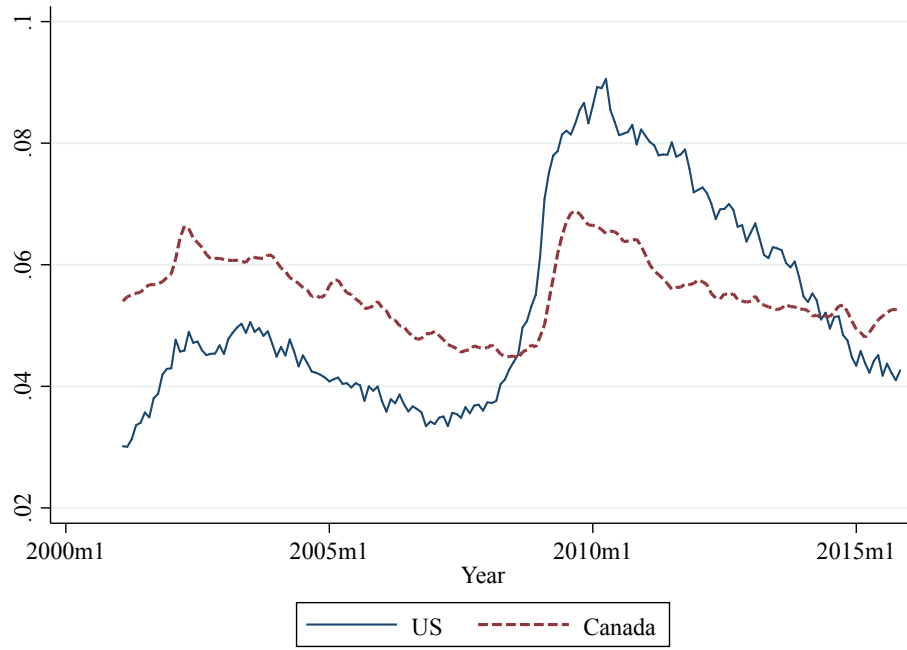
3.2 Long-Term Unemployment and Joblessness

In addition to the overall increase in unemployment, the Great Recession also increased unemployment at long durations. Figure 4 shows the share of the unemployed with unemployment durations exceeding

⁸See <http://www.nber.org/cycles/cyclesmain.html> for the U.S. and <https://www.cdhowe.org/cpc-communique/cd-howe-institute-business-cycle-council-issues-authoritative-dates-20082009-recession> for Canada.

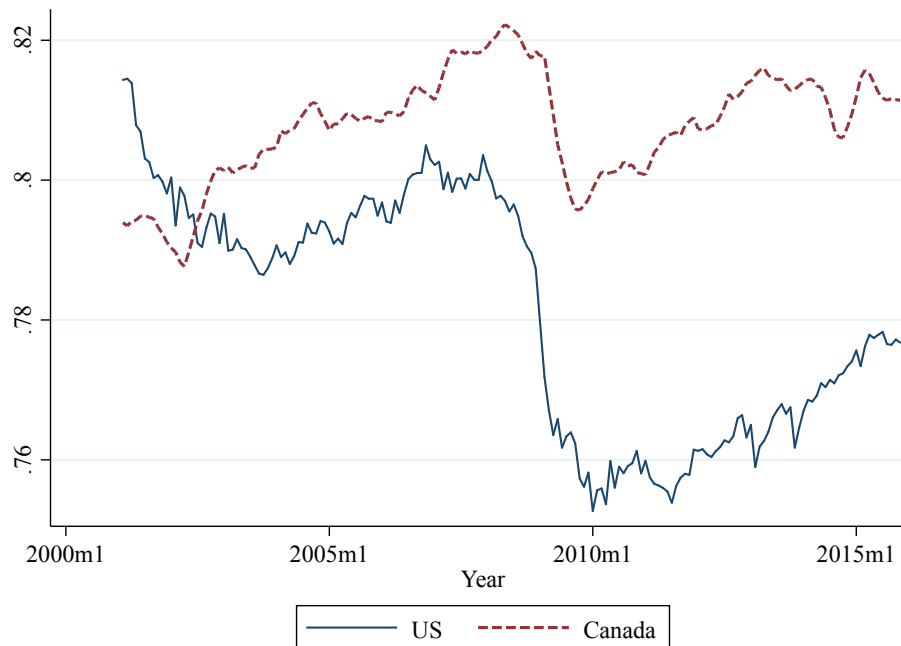
⁹In this paper, all statistics are constructed using prime age populations (25-55) and are age adjusted to the 2000 age distributions in the two countries.

Figure 2: Unemployment rates in Canada and the U.S., 1/2001-10/2015



Notes: Both data series combine men and women, restrict to ages 25-55, have been age-adjusted to hold age distribution constant at the initial year age distribution, and have been deseasonalized by regressing the series on month fixed effects and taking the residuals. Note that this figure reports the unemployment rate by dividing the number of unemployed individuals by the total labor force, while in counterfactuals we will instead normalize unemployed by total population (including non-participants).

Figure 3: Employment-to-Population Ratio in Canada and the U.S., 1/2001 - 10/2015



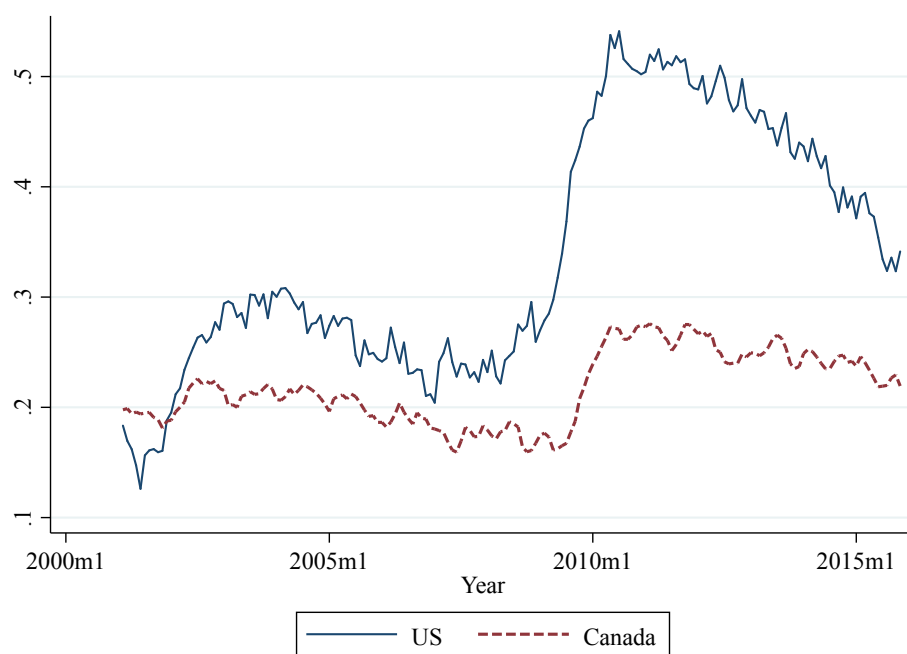
Notes: Both data series combine men and women, restrict to ages 25-55, have been age-adjusted to hold age distribution constant at the initial year age distribution, and have been deseasonalized by regressing the series on month fixed effects and taking the residuals.

6 months for the U.S. and the share of the unemployed with unemployment (not joblessness) durations exceeding 26 weeks for Canada. In both countries, the long-term unemployment (LTU) share increased significantly, but the rise was much more pronounced in the U.S. In the U.S., the LTU share increased by about 25 percentage points, while in Canada it rose by only about 10 percentage points. Additionally, the decline in the LTU shares in both countries has been very slow. By October 2015, the LTU share in the U.S. was about 30 percent and in Canada it was about 20 percent.

As described above, a useful feature of the Canadian data is that we can observe *joblessness* durations for both the unemployed and non-participants, which is something that the CPS does not keep track of. Figure 5 shows the share of long-term joblessness (LTJ) for the unemployed. We see that it fluctuates in the pre-recession period around 45 percent and increases to roughly 55 percent in the post-recession period. Among the unemployed, the increase in percentage points in long-term joblessness is of the same magnitude as the increase in long-term unemployment. In percent, it is much smaller since the base incidence of long-term joblessness is substantially larger.

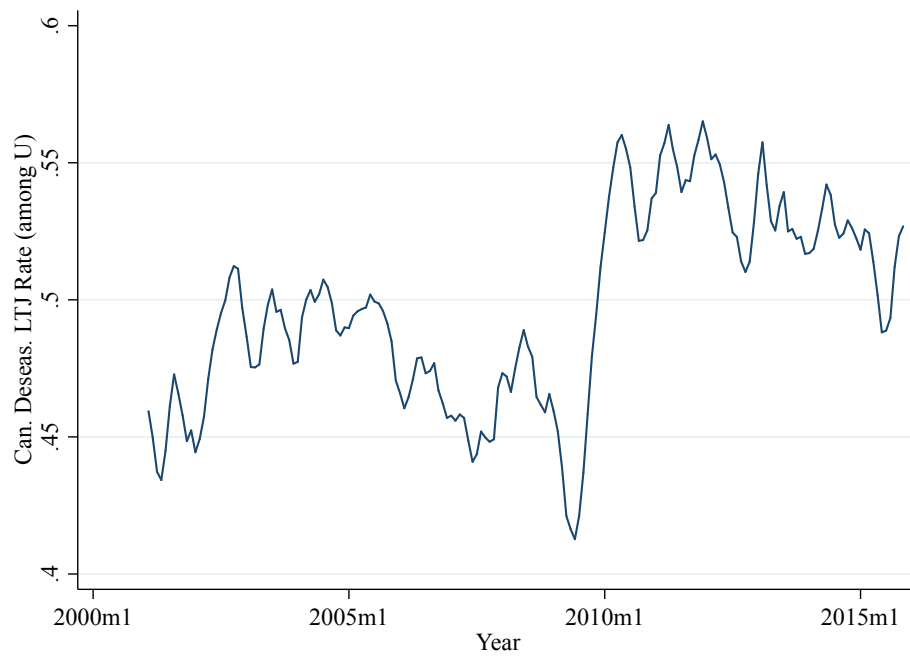
Figure 6 shows the share of long-term joblessness for non-participants. Rates of long-term joblessness are much higher for non-participants than they are for the unemployed. This reflects the fact that this

Figure 4: Long-Term Unemployment in Canada and the U.S., 1/2001 - 10/2015



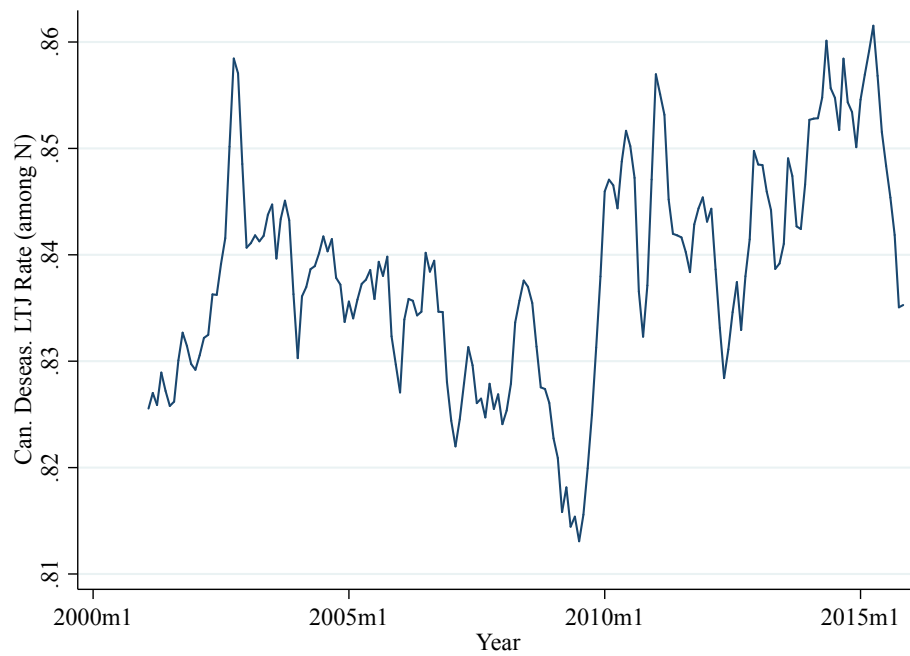
Notes: Both data series combine men and women, restrict to ages 25-55, have been age-adjusted to hold age distribution constant at the initial year age distribution, and have been deseasonalized by regressing the series on month fixed effects and taking the residuals. In Canada, Long-Term Unemployment refers to unemployment durations exceeding 26 weeks; in the US, the cut-off is 6 months.

Figure 5: Long-Term Joblessness among the Unemployed in Canada



Notes: Both data series combine men and women, restrict to ages 25-55, have been age-adjusted to hold age distribution constant at the initial year age distribution, and have been deseasonalized by regressing the series on month fixed effects and taking the residuals. Long-term joblessness refers to jobless durations exceeding 26 weeks.

Figure 6: Long-Term Joblessness among OLF in Canada



Notes: Both data series combine men and women, restrict to ages 25-55, have been age-adjusted to hold age distribution constant at the initial year age distribution, and have been deseasonalized by regressing the series on month fixed effects and taking the residuals. Long-term joblessness refers to jobless durations exceeding 26 weeks.

group is composed of many individuals who are not on the margin of entering the labor market. Similar to the trends for the unemployed, the LTJ share among non-participants declined prior to the recession and increased moderately during the recession. While most of the increase in long-term joblessness concentrated in the first few months of the Great Recession among the unemployed, the increase in LTJ among non-participants has been much more gradual. It is indeed not clear whether this increase in LTJ has run its course by October 2015, when our data ends. Overall, the relative increase in LTJ is much more pronounced among the unemployed since the share of LTJ is of course much lower among the unemployed. Nevertheless, since there are many more non-participants as compared to unemployed, an increase of 4 percentage points in the LTJ share among non-participants is an important empirical pattern.

3.3 Transition Rates

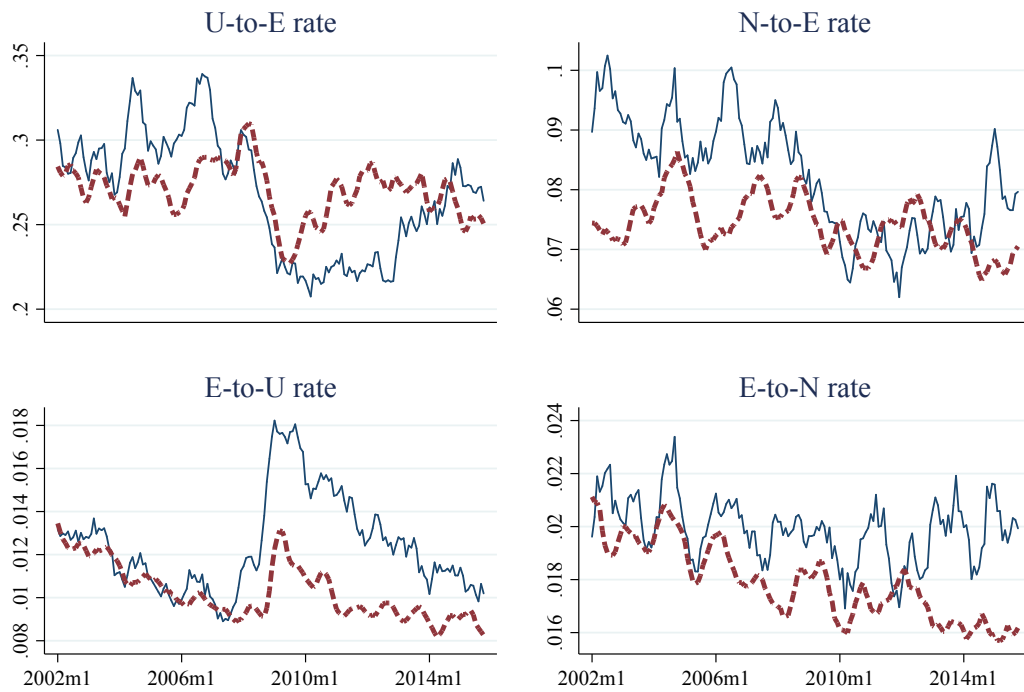
Figure 7 provides another way of examining the relative labor market performance in Canada and the U.S. over time. It shows the job finding rates and the job loss rates depending on whether they involve unemployment or non-participation. We present smoothed data by taking 6-month moving averages. The top two panels show the job finding rates conditional on U or N and the bottom two panels show the rates at which the employed transition into U or N.

Starting with the job loss rates, we see that for Canada, the E-to-U rate increased slightly from 1 percent to about 1.5 percent, but quickly returned back to normal levels. By contrast, in the U.S. the E-to-U rate increased from about 1 percent to around 2 percent and remained elevated during the Great Recession. In both countries, the rates at which individuals transitioned from employment to non-participation remained relatively stable. Considering the job finding rates, we observe an initial decline for the unemployed that is similar in size in both Canada and the U.S. However, Canada returned to its prior levels more rapidly. Among non-participants, unlike the U.S. which experienced a drop in the job finding rate, we do not observe a significant decline in job finding rates in Canada. It is striking that in the U.S., job finding rates among non-participants so far have not fully recovered to their pre-recession levels.

It is thus not the initial decline in job finding rates among the unemployed that explains why the 2008-2009 recession was “Great” in the U.S. and not in Canada. Rather, the persistence in the decline of job finding rates and job loss rates account for the severity of the recession in the U.S.. Canada escaped a Great Recession primarily because its labor market rebounded more quickly and because job finding rates among those out of the labor force did not deteriorate substantially.

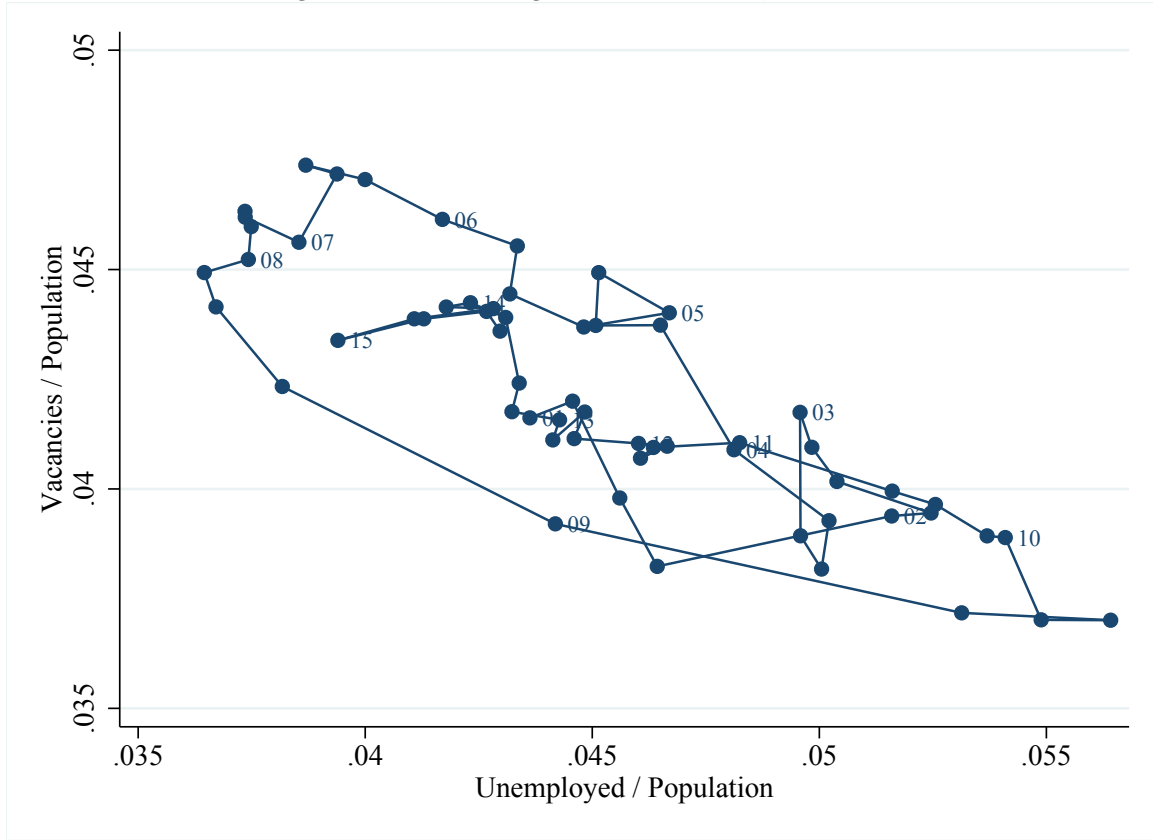
Figure 7: Job Finding and Job Loss Rates in Canada and the U.S.

US = solid, thin line; Canada = thick, dashed line



Notes: All data series combine men and women, restrict to ages 25-55, have been age-adjusted to hold age distribution constant at the initial year age distribution, and have been deseasonalized by regressing the series on month fixed effects and taking the residuals. The deseasonalized series are then smoothed by taking a 6-month moving average.

Figure 8: The Beveridge Curve in Canada, 2001-2015



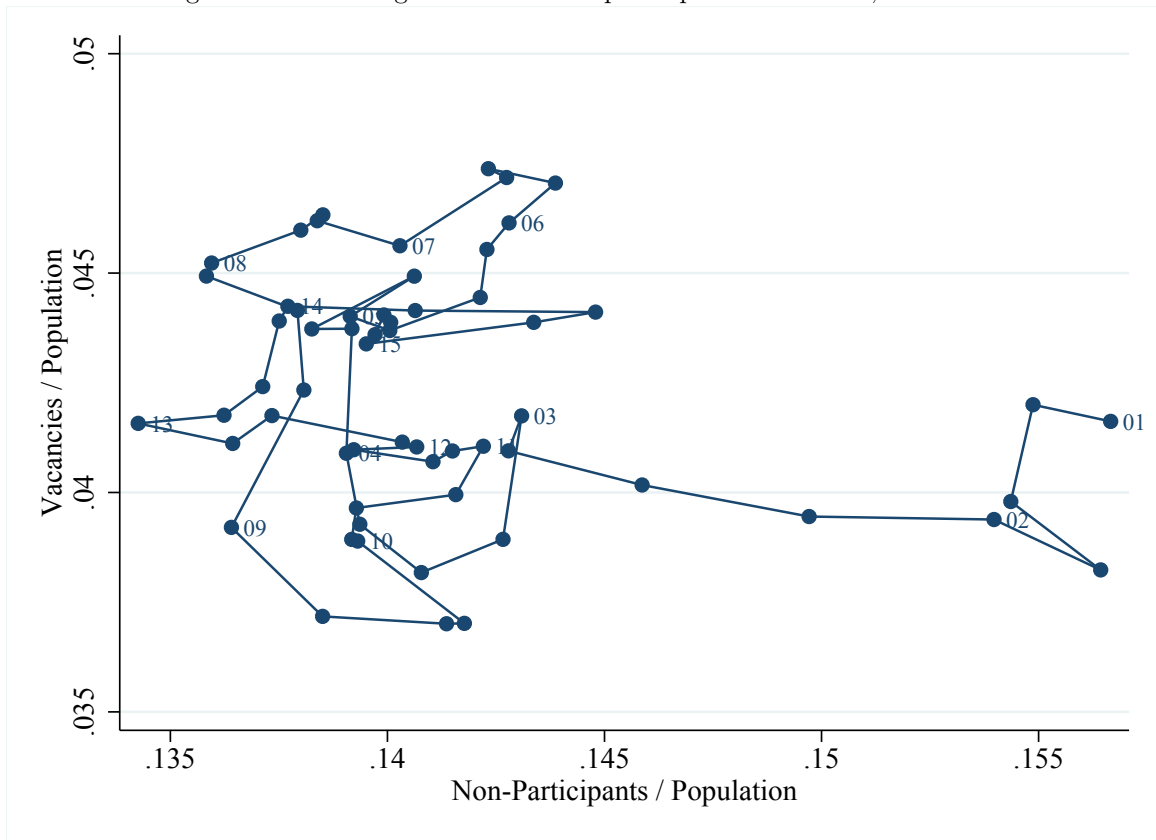
Notes: This figure uses the recruiter-producer ratio as proxy for vacancy/population ratio and relates this to the unemployment/population ratio.

3.4 Beveridge Curve

The Beveridge curve is one of the main diagnostic tools used to understand the labor market performance over the business cycle. Using the vacancy series constructed according to the recruiter-producer ratio we are in a position to produce what we believe to be the first monthly Beveridge curve for Canada covering this entire time period.

Figure 8 shows this Beveridge curve depicting the vacancy-to-population rate and the unemployment-to-population rate in our data. The data depicted here are quarterly averages running from Q1 2001 to Q3 2015. Figure 8 clearly depicts the downward-sloping relationship familiar from Beveridge curves in other countries such as the U.S. or the UK. Compared to the U.S., we do not see a substantial “outward shift” in the Beveridge curve in Canada. We also show the analogous relationship between vacancies and non-participants in Figure 9. It is clear that there is less of a systematic relationship between vacancies and non-participants than between vacancies and unemployment.

Figure 9: A Beveridge Curve for Non-participants in Canada, 2001-2015



Notes: This figure uses the recruiter-producer ratio as proxy for vacancy/population ratio and relates this to the non-participants/population ratio.

4 The Role of Composition for Trends in Long-Term Unemployment and Long-Term Joblessness in Canada

As described above (see Figures 5 and 6), the rates of long-term unemployment and long-term joblessness in Canada rose sharply at the end of 2009 and have since remained elevated. Roughly half of the increase still remains. We now explore this increase in more depth. We first assess how much of the increase can be accounted for by changes in the observable composition of the unemployed and non-participants. Specifically, we consider education (high school dropout, high school graduate, some college, and college graduate), age (six 5-year age groups between 25 and 55), region, and gender. We proceed to separately investigate the role of composition across these categories in the time-patterns of the LTU among the unemployed and LTJ among non-participants. Long-term unemployment and long-term joblessness are both defined using a 6-month cut-off.

In the Appendix, we present both the incidence and share of LTU conditional on each of the above listed characteristics among the unemployed. These figures illustrate that the variation in LTU over time is quite similar across different characteristics. Furthermore, when there is variation in LTU across observable characteristics, the share of the different groups among the unemployed does not change dramatically when the recession hits. Consequently, these figures suggest that there is limited scope for changes in the composition of the unemployed to account for the overall change in LTU for unemployed workers.

Figure 10 combines all of these characteristics together to predict the change in LTU from compositional changes in the sample of unemployed individuals using a shift-share procedure. We find that the predicted change in the overall LTU share based on compositional changes is very small, mirroring the results we found in Kroft et al. [2016] for the U.S. To create this figure, we go through each characteristic (gender, age, etc.) and we predict the change in LTU based on the change in composition after 2008 and the 2002 incidence of LTU for this characteristic. We then sum these predicted changes across all of the characteristics.¹⁰ Our projection uses each of the characteristics shown in Appendix.

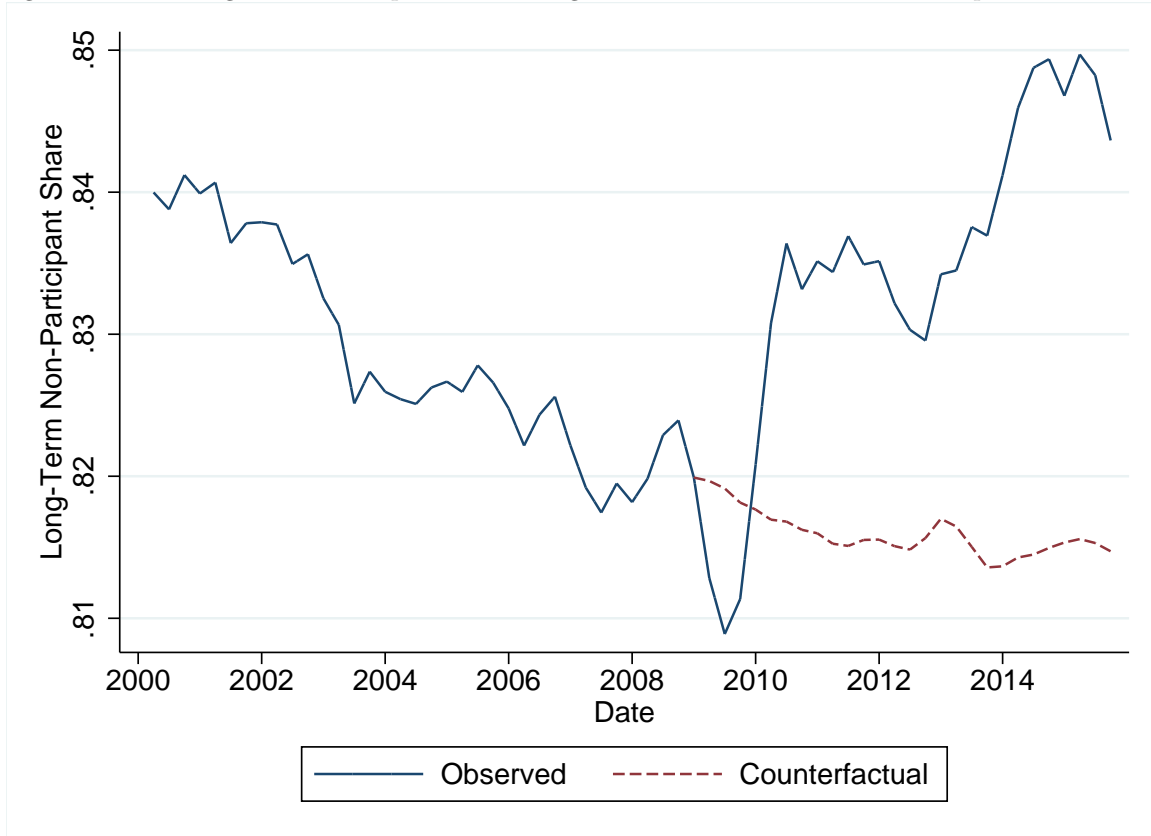
We repeat the same exercise for non-participants. In the Appendix, we show a similar pattern of long-term joblessness across education groups, but large differences in levels. In addition to the large

¹⁰As noted to us by Andrew Berger-Gross, our procedure may overstate the role of composition if there are correlated compositional changes among groups with a high incidence of LTU in the initial period. An alternative procedure would instead calculate the incidence of LTU for narrower cells (e.g., LTU for each gender-age-region-education cell) and then follow the same procedure but using only this one “combined characteristic” defined by this mutually exclusive and collectively exhaustive set of cells. This procedure is less prone to upward bias, but in practice it likely limits the number of characteristics one can use due to the curse of dimensionality. In public-use CPS data, we have verified that this alternative procedure produces extremely similar results to our procedure. In either case, one concludes that there is no strong role for composition in understanding overall trends in LTU.

Figure 10: Assessing Role of Composition in Long-Term Unemployment in Canada



Figure 11: Assessing Role of Composition in Long-Term Joblessness for Non-Participants in Canada



pre-recession differences in LTJ levels by education, there are also meaningfully different trends in the composition of long-term jobless non-participants, with more long-term jobless non-participants having high education in recent years (as compared to earlier years). Despite these differences in levels and trends by education, however, the limited overall role of compositional changes in accounting for LTJ trends among non-participants is shown in Figure 11. As with the long-term unemployed in both U.S. and Canada, the results suggest no meaningful role for compositional changes in accounting for national trends in long-term joblessness.

Thus, the overall rise in LTU and LTJ in Canada after 2009 was not isolated to specific demographic groups, but rather was experienced broadly across the labor market. These results using observables do of course not speak directly to the potential for compositional changes based on unobservables. Nevertheless, they do suggest that changes in the composition of the unemployed are not driving the observed patterns in LTJ during the recession.

5 Replicating and Extending Kroft et al. [2016]

So far, we have shown how the labor market experience in Canada during the last recession differed from the U.S. experience. For the remainder of the paper, we explore the ability of a standard matching model augmented with duration dependence in labor market flows to match the observed patterns in unemployment and non-participation as well as long-term unemployment and joblessness over the business cycle. This work builds substantially on Kroft et al. [2016], and we begin by reviewing the methodology employed in that paper.¹¹ Our treatment here is sparse, and we refer the reader to Kroft et al. [2016] for details.

The Matching Function

At the core of our analysis of the U.S. labor market in Kroft et al. [2016] is a matching function which determines the number of meetings between job openings and both unemployed and non-participants.

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

The (U_t, N_t) variables are the stocks of unemployed and non-participants; V_t are vacancies and (m_0, s, α) 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 deemed out of the labor force. 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 non-participants.¹²

The function $A(d)$ is defined as the relative job finding rates of the unemployed with durations of unemployment d . This function captures “true” duration dependence (sometimes called “structural duration dependence”); i.e., the genuine causal effect of longer durations on the job finding rate. As described in Kroft et al. [2016], this modeling assumption is motivated partly by recent field experimental evidence on duration dependence in “callbacks” for interviews (Ghayad [2013], Kroft et al. [2013]). It is also consistent with recent structural econometric work that finds evidence of “true” duration dependence using population-level data from Spain (Bentolila et al. [2017]) and with recent work finding a causal effect of duration of joblessness on re-employment wages (Nekoei and Weber [2017], Schmieder et al. [2016]), since these papers interpret these results as suggesting human capital depreciation, which would cause “true” duration dependence. We emphasize that understanding how much of the $A(d)$ function

¹¹Some of the formulations in this section are lifted directly from that paper and edited for brevity.

¹²See Hornstein et al. [2014] for an index of labor search that aggregates various different groups among the non-employed including the marginally attached, the discouraged and those with diverse labor search histories in a similar manner.

that we estimated from observation data represents “true” duration dependence remains very much an open question, with a range of recent evidence suggesting a smaller role for “true” duration dependence in generating observed pattern of duration dependence (Farber et al. [2017], Ahn and Hamilton [2016], Jarosch and Pilossoph [2016]). In this paper, we will proceed under the assumption that we have access to the function $A(d)$ representing “true” duration dependence. The job finding rates of the unemployed with duration d and the non-participants in Kroft et al. [2016] are given by

$$\lambda^{UE}(x_t; d) = A(d)m_0x_t^{1-\alpha} \quad (2)$$

$$\lambda^{NE}(x_t) = sm_0x_t^{1-\alpha} \quad (3)$$

We normalize $A(0) = 1$ and assume 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. 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 need to measure or model flows between all three labor force states (E, U, N). In addition, we need to measure or model the duration distribution of the flows into unemployment. Above, we showed how to model the endogenous flows into employment: $\lambda_t^{UE}(d)$ and λ_t^{NE} . The remaining flows in the labor market are exogenous processes 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.” Similarly, when employed workers move into unemployment, they draw an unemployment duration from the empirical distribution of unemployment durations.¹³ These two empirical distributions are defined as $\theta_t^{NU}(d)$ and $\theta_t^{EU}(d)$, respectively. The dynamic equations governing changes in the stocks are then

$$N_{t+1} = N_t \left(1 - \lambda_t^{NU} - \hat{\lambda}_t^{NE} \right) + E_t \lambda_t^{EN} + U_t \lambda_t^{UN} \quad (4)$$

¹³One of the lessons we draw from the analysis in this paper as well as in Kroft et al. [2016] is that it is crucial to account for the fact that transitions between unemployment and non-participation vary across the duration distribution. The assumptions made in Kroft et al. [2016] are ad-hoc, but, as we will see below, they do succeed in roughly accounting for the fact that the durations reported by non-participants that transition to unemployment are relatively long. The advantage of the data on long-term joblessness for both U and N available in Canada is that we can replace these ad-hoc assumptions with direct measurements of the durations of those transitioning.

$$U_{t+1}(0) = E_t \theta_t^{EU}(0) \lambda_t^{EU} + N_t \theta_t^{NU}(0) \lambda_t^{NU} \quad (5)$$

$$U_{t+1}(d) = U_t(d) \left(1 - \hat{\lambda}_t^{UE}(d) - \hat{\lambda}_t^{UN}(d)\right) + E_t \theta_t^{EU}(d) \lambda_t^{EU} + N_t \theta_t^{NU}(d) \lambda_t^{NU} \quad (6)$$

$$E_t = P_t - N_t - U_t \quad (7)$$

where P_t denotes the total population aged 25-55. We place a “ $\hat{\cdot}$ ” symbol above the endogenous flow variables and treat the other flow variables as exogenous driving variables (together with the vacancies) in our analysis.

5.1 Updating Kroft et al. [2016] to Oct. 2015

The analysis in Kroft et al. [2016] use data up until April 2013. In this Section, we explore the implications and performance of the model since then.

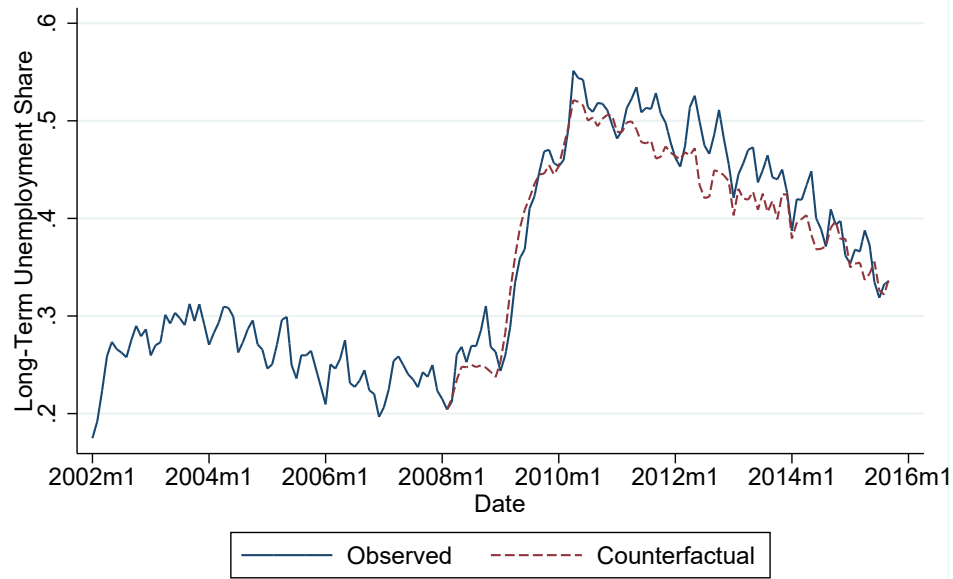
Discrepancy from Kroft et al. [2016]

Before we turn to the updated analysis, we regret to report that 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 Kroft et al. [2016] and discovered a coding error in the dynamic equations used to construct the flows. In particular, the code did not exactly implement equations (4) - (7) (which were written correctly in the published paper). Upon re-running the analysis, we found that this mistake did not affect our main conclusions, but it did have some effect on a few of the quantitative results.

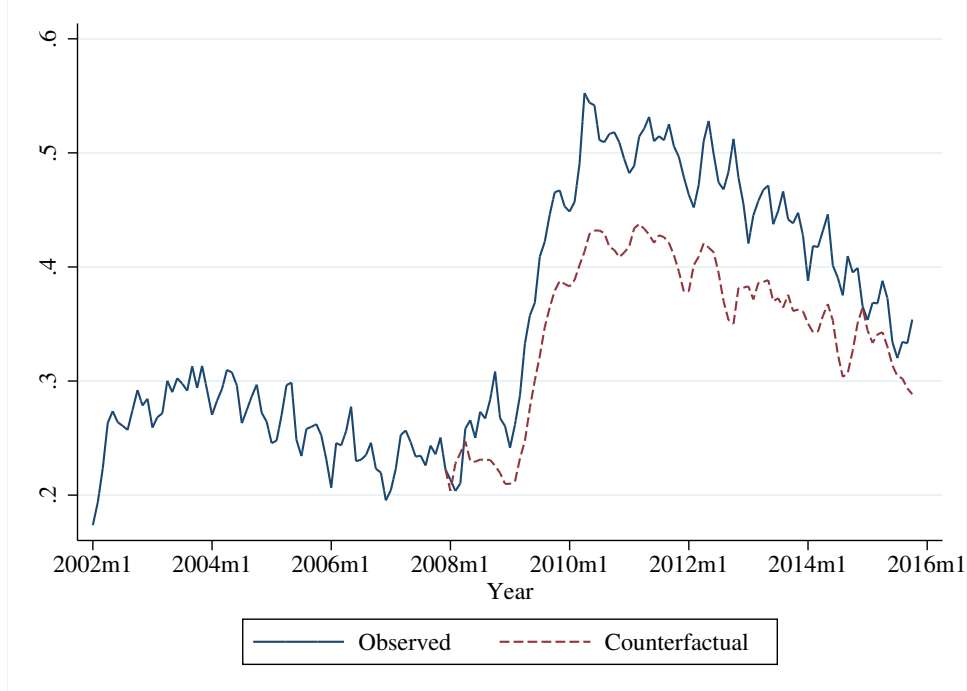
In Figure 12, we compare the predicted and observed shares in LTU in Panel A and B. Panel A shows the results updated to October 2015 using our original code. By contrast, Panel B shows results using the updated code. Using the corrected code, Panel B shows that we underestimate the actual share of long-term unemployed during the Great Recession by about 5 to 10 percentage points. The mean error in the (out-of-sample) prediction is about -6.8 percentage points (with a mean squared prediction error of 0.0057, or 57 squared percentage points).

Comparing Panels A and B, one sees that the consequence of the coding mistake is that Kroft et al. [2016] reported a higher LTU share in our counterfactual series than warranted. By implication, our reported counterfactual job finding rate for the unemployed 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 Panel A

Figure 12: Predicted and Observed Long-Term Unemployment Share in the U.S.
 Panel A: Predicted and Observed LTU Share Among Unemployed [Flawed Code]



Panel B: Predicted and Observed LTU Share Among Unemployed [Corrected Code]



in 13). 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. Thus, this does not substantively affect the ability of the model to fit the simulated stocks in the labor market and leaves our main conclusions largely unchanged. We still find that the model can account for a large share of the increase in LTU and some of the outward shift in the Beveridge curve, and we continue to find (as before) that the model does not do a good job accounting for trends in non-participation during and after the Great Recession.¹⁴

Kroft et al. [2016] 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 (Figure 12) and the job finding rates conditional on unemployment (Figure 13). Indeed, on both dimensions the model does better after April 2013. Figure 12 shows that the stock of LTU declines rather slowly but steadily. By the end of 2015, the observed and counterfactual share of LTU has declined to 35 and 30 percent respectively from about 50 and 40 percent respectively right after the Great Recession.

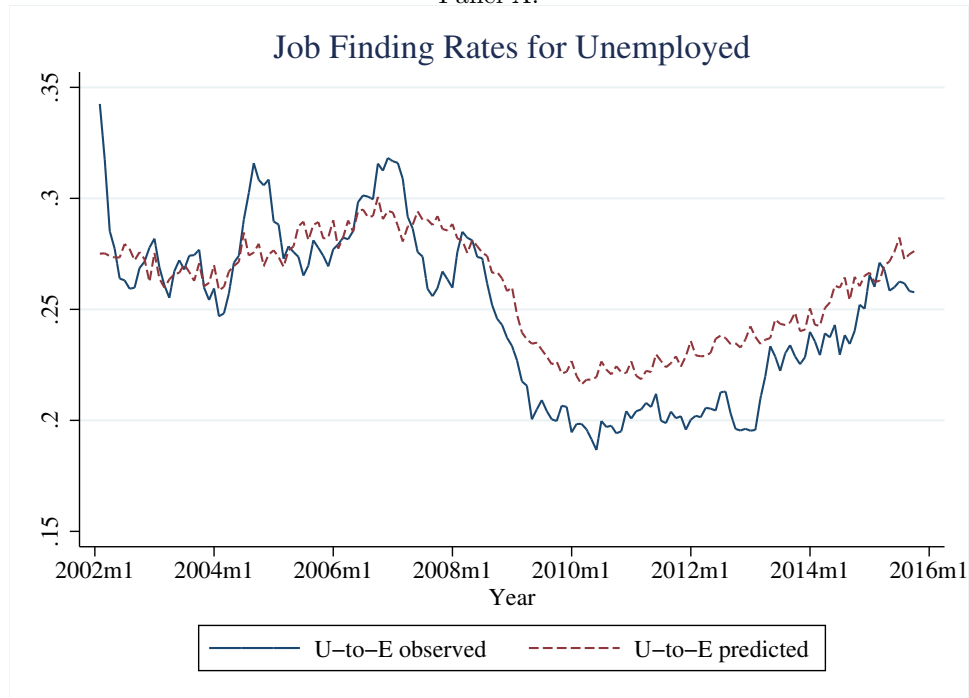
The model, however, fits the data much less well when we consider job finding rates among the non-participants. Those rates are consistently overestimated after 2008 (see Panel B of Figure 13,). The persistent feature of the U.S. labor market that is most difficult to explain is not unemployment or long-term unemployment, but non-participation since 2008.

Consider next the Beveridge curve shown in Figure 14. Since April 2013, labor demand as measured by 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.

In Kroft et al. [2016] we reported that we could explain about half of the shift in the Beveridge curve until April 2013 using the changing duration structure. A gap of about 1 percentage point however remained to be explained outside of our model. Since then, we have seen the gap between the observed and the counterfactual Beveridge curve close from a little above 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.

¹⁴We can use the average error (bias) and the mean squared error – calculated both “in sample” and “out of sample” – in order to assess the goodness-of-fit for both panels of Figure 13. In Panel A, the “in sample” average error is -0.0022 and the MSE is 0.00034; the analogous “out of sample” statistics are 0.0199 and 0.00051, respectively. In Panel B, the “in sample” average error is -0.0002 and the MSE is 0.00004, and the analogous “out of sample” statistics are 0.011 and 0.00018. Relative to the average job finding rates in each panel in the “in sample” pre-period, there is a greater bias in the predictions for the N-to-E flows relative to the U-to-E flows.

Figure 13: Job Finding Rates for Unemployed and Non-Participants
Panel A:



Panel B:

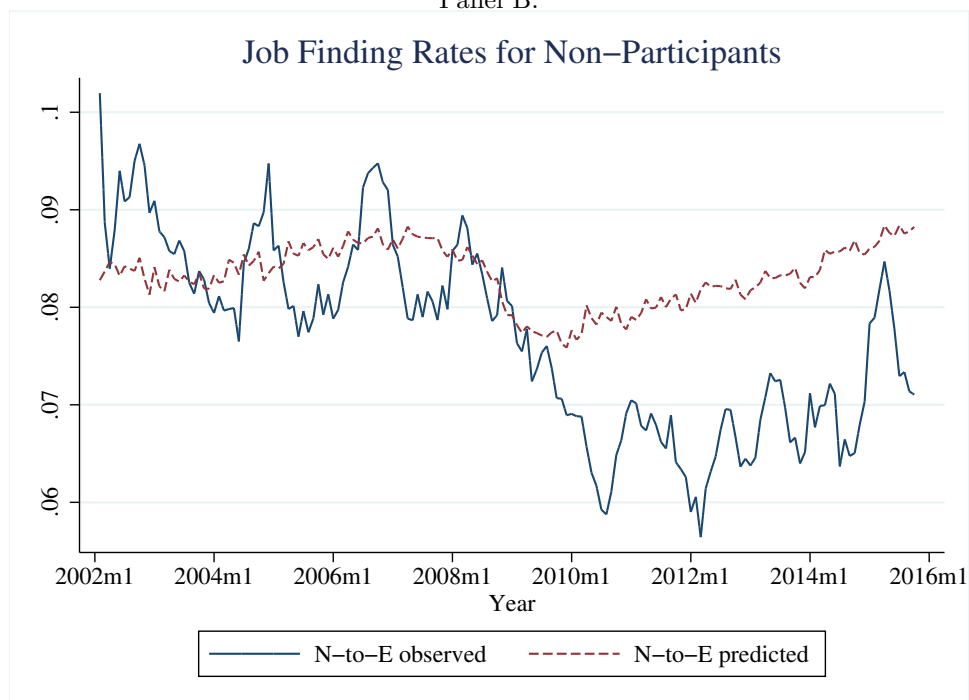
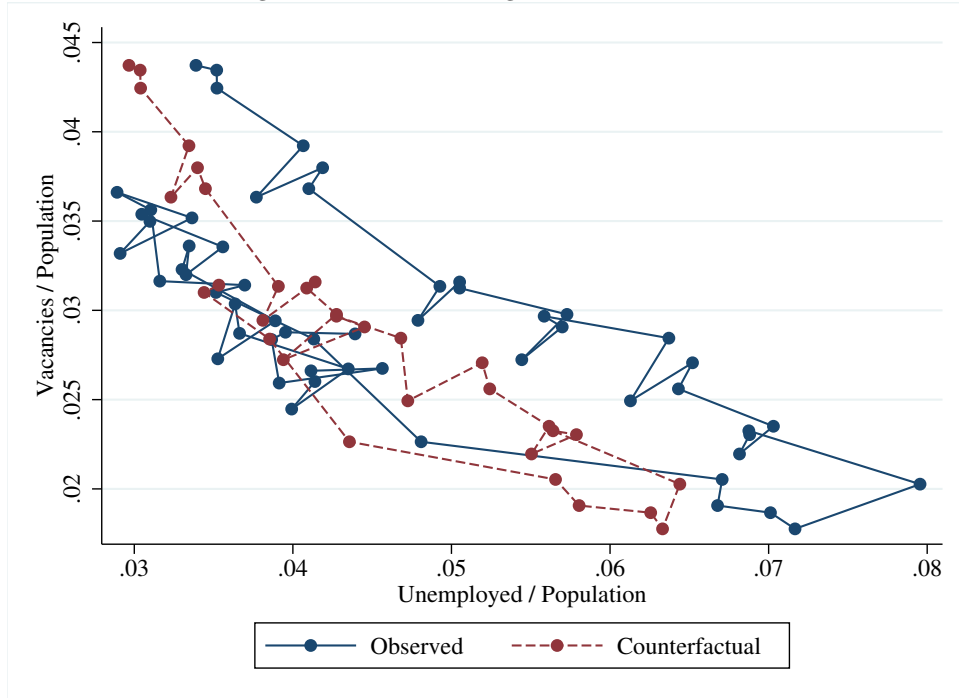


Figure 14: The Beveridge Curve in the U.S.



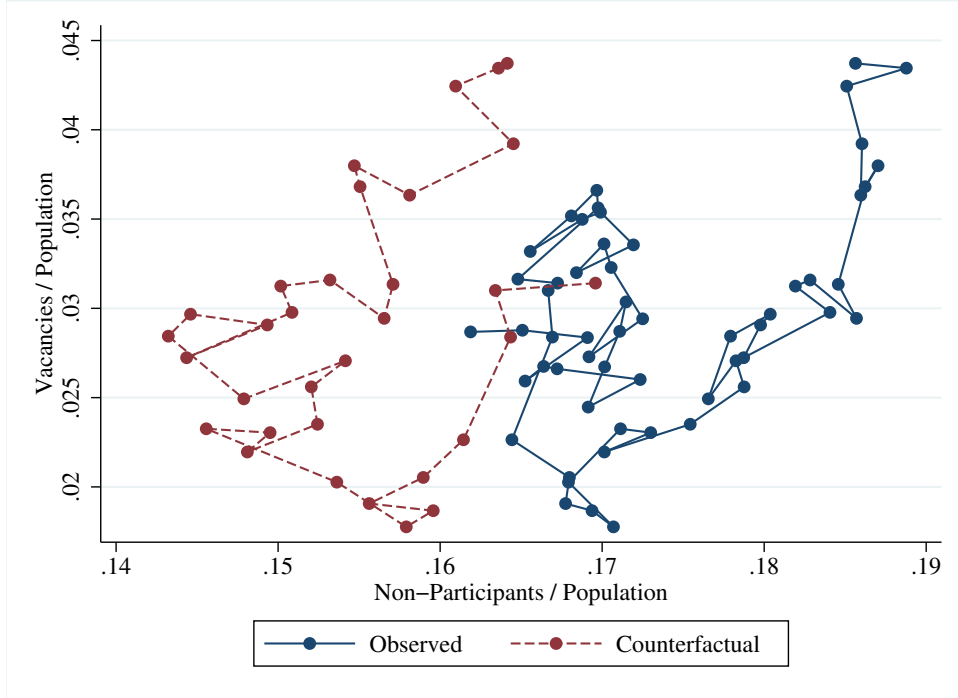
As noted in Kroft et al. [2016], the model fails to explain by how much non-participation increased during the Great Recession. This failure of the model persists after April 2013. This becomes apparent when one considers the Beveridge curve in non-participation in Figure 15, which depicts the relation between non-participation and vacancies. It should be noted however that the failure comes almost entirely from the counterfactually predicted sharp decline in non-participation up until April 2013 at a time when we observed actual non-participation rates to increase. Since then, the model has tracked the changes in the stock of non-participants quite well.

Overall, we conclude that over the additional two years out-of-sample, the model calibrated on 2002-2007 data continues to perform very well when matching the dynamics in long-term unemployment, reasonably well when fitting the evolution of unemployment overall, but (as reported before) fails to match the persistent decline in the stock of non-participants.

6 The 2008-2009 Recession in Canada: A Laboratory to Understand Counterfactuals

We now turn to the Canadian Labor market. The Canadian LFS, in contrast to its American counterpart the CPS, contains data on how long individuals have been without work, regardless of whether they are

Figure 15: Non-Participation and Vacancies in the U.S.



currently unemployed or non-participants. This allows us to extend the matching model to account for a richer specification of how the duration of joblessness affects labor force transitions. The obvious extension is to allow the job finding rate of both the unemployed and those out of the labor force to depend on how long individuals have been out of employment. Thus, we model the job finding rate for those out of the labor force as follows:

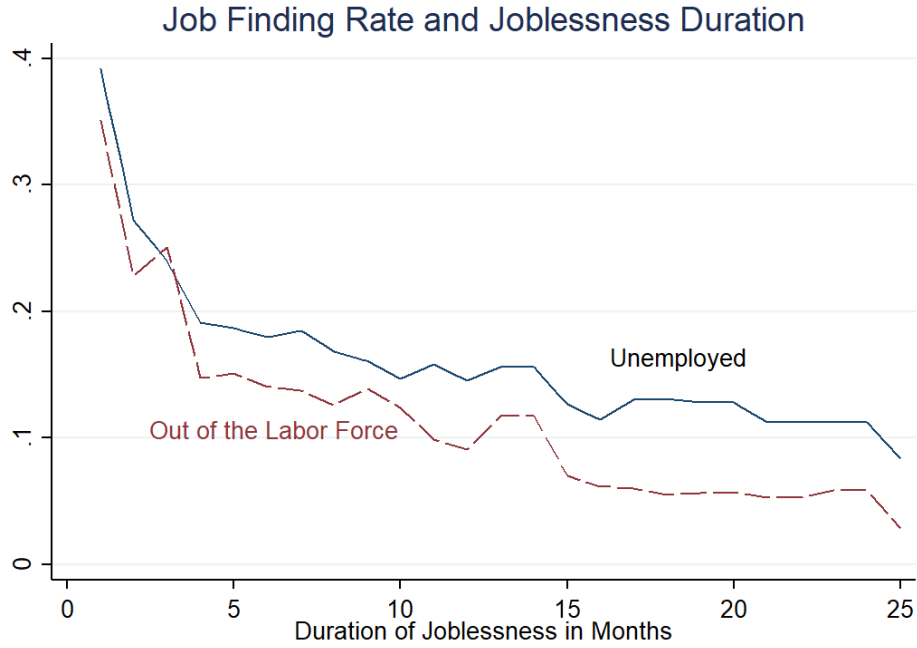
$$\lambda^{NE}(d; x_t) = sB(d)m_0x_t^{1-\alpha} \quad (8)$$

where $B(d)$ captures the duration dependence in the job finding rate among those out of the labor force. This function is analogous to $A(d)$ in equation (2).

In addition, with the LFS, we can now model how transitions between unemployment and non-participation depend on the duration of joblessness. To capture these, we model the duration-dependent transition rates from U-to-N ($\lambda_t^{UN}(d)$) and from N-to-U ($\lambda_t^{NU}(d)$) to be given by a time-specific shifter and a time-invariant function capturing the duration dependence. These duration-dependent transition rates are therefore

$$\lambda_t^{UN}(d) = \lambda_t^{UN}C(d) \quad (9)$$

Figure 16: Job Finding Rate and Joblessness Duration in Canada



Notes: This figure reports average job finding rates by joblessness duration for unemployed individuals and non-participants.

and

$$\lambda_t^{NU}(d) = \lambda_t^{UN} D(d) \quad (10)$$

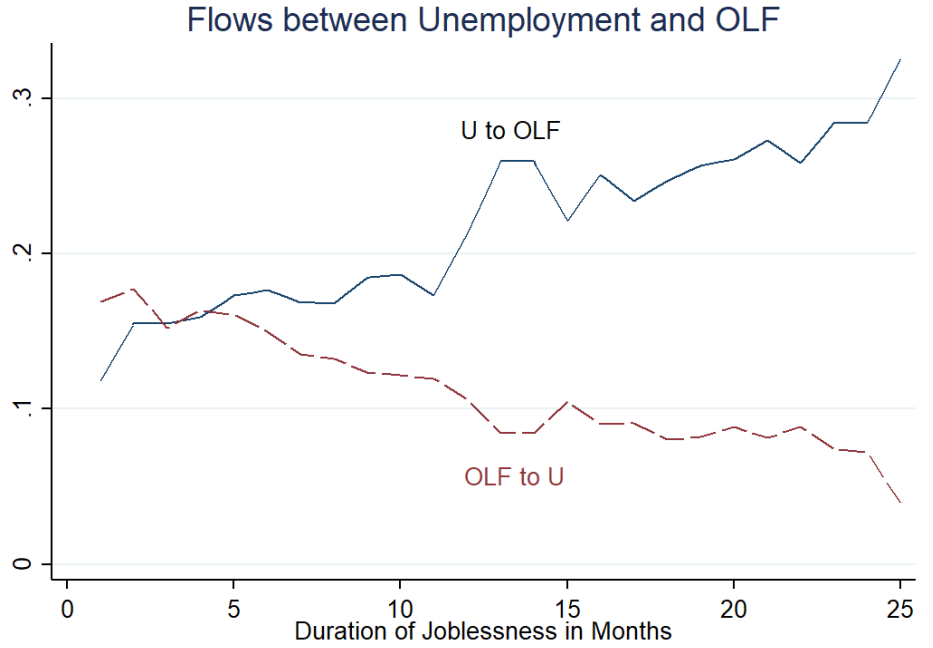
where $C(d)$ and $D(d)$ are functions capturing the duration structure in these transition rates. These functions are obtained by averaging the transition rates over the entire data period and then allowing for the relative transition rates to vary month-by-month up to duration of 24 months. After 2 years of joblessness, transition rates are postulated not to vary with the length of joblessness any further.

6.1 Observed Duration Dependence in Labor Market Flows

Using the Canadian LFS between January 2001 and October 2015, we next describe how joblessness durations affect labor market flows, including flows originating among those out of the labor force. These flows are shown as functions of the duration of joblessness in Figure 16 for job finding rates and Figure 17 for flows between unemployment and non-participation.

For both groups, the job finding rate declines sharply over the first few months of joblessness and then flattens out somewhat. At a duration of one year, the job finding rate is about one-third that of a newly jobless individual, whether the individual is unemployed or out of the labor force. We also observe strong

Figure 17: Transitions $U \rightleftharpoons N$ by Duration of Joblessness in Canada



Notes: This figure reports average monthly transition rates between unemployment and non-participation by joblessness duration.

duration patterns in flows between unemployment and non-participation. Figure 17 shows that the probability of transitioning from unemployment to non-participation increases and the probability of making a reverse transition from non-participation to unemployment declines steadily with joblessness duration. These findings are consistent with research in the U.S. that finds that individuals are increasingly likely to withdraw from the labor market the longer they are out of a job (Krueger et al. [2014]).

We use $A(d)$ to describe duration dependence (in jobless duration) for unemployed workers, and $B(d)$ to describe duration dependence (in jobless duration) for non-participants. To capture these relationships, we estimate two separate flexible nonlinear functions over the spell to allow for the possibility that the pattern of duration dependence differs across these two groups. The functional form for both $A(d)$ and $B(d)$ depends on two parameters and is $(1 - a) + a * \exp(-b * d)$. For both functions, we estimate the parameters (a, b) using non-linear least squares (NLLS) regression based on the “cell” averages (i.e., average job finding rate by joblessness duration) across the time-period from January 2001 to October 2015. The NLLS estimation is weighted using the number of observations at that duration. The estimated parameters are reported in Table 1.

Overall, we find that these functions fit the job finding rates across the duration distribution well (see Appendix Figure 38.) Both functions show steep declines (of more than 50 percent) over the first several

Table 1: Parameterizing the Matching Model with Duration Dependence in Joblessness

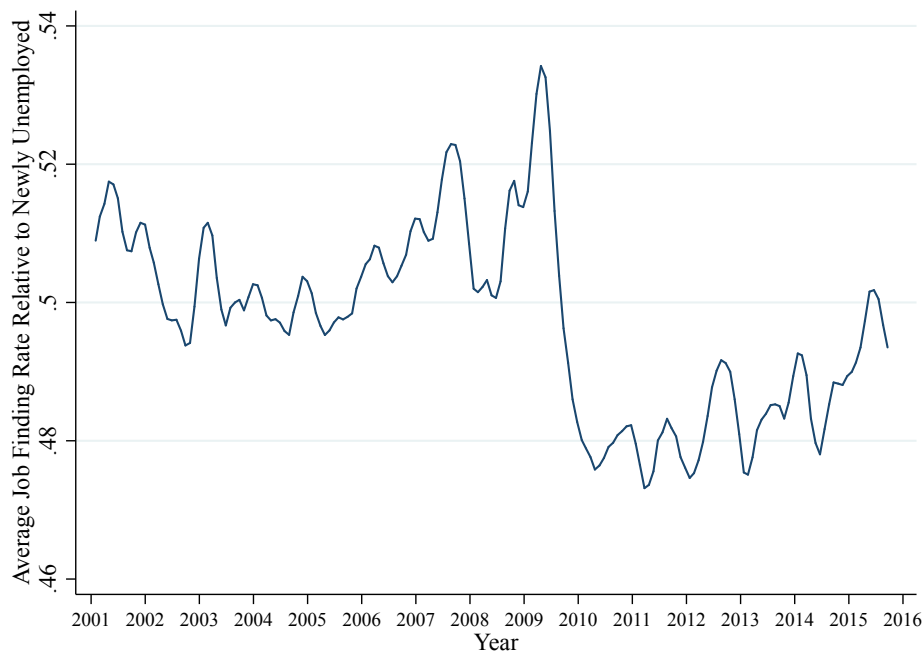
Table 1

Model-Based Estimates

<u>Duration Dependence Parameters (Jobless Duration)</u>			
a (intercept parameter unemployed)			0.671
b (slope parameter unemployed)			0.448
a (intercept parameter non-participant)			0.862
b (slope parameter non-participant)			0.283
$A(d) \text{ or } B(d) = (1-a) + a \exp(-b * d)$			
<u>Matching Model Parameters</u>			
	No Duration Dependence	Duration Dependence in U, but not N	Duration Dependence in U and N
α	0.831	0.871	0.835
m_0 (scale parameter)	0.342	0.666	0.693
s (relative search intensity of inactive)	0.277	0.140	0.580
ρ	2.067	1.247	2.644
$M(U+sN, V) = m_0(U+sN)^\alpha V^{1-\alpha}$			

Notes: The top panel reports NLLS estimates of duration dependence parameters for unemployed and non-participants using jobless duration for both groups. The second panel reports estimates from model calibration to match the pre-recession data. These parameters are then used to construct counterfactual predictions of unemployment, employment, long-term joblessness, and other labor market outcomes. See text for details.

Figure 18: A Measure of the Search Relevant Duration Structure in Unemployment in Canada: $\overline{A(d)}$

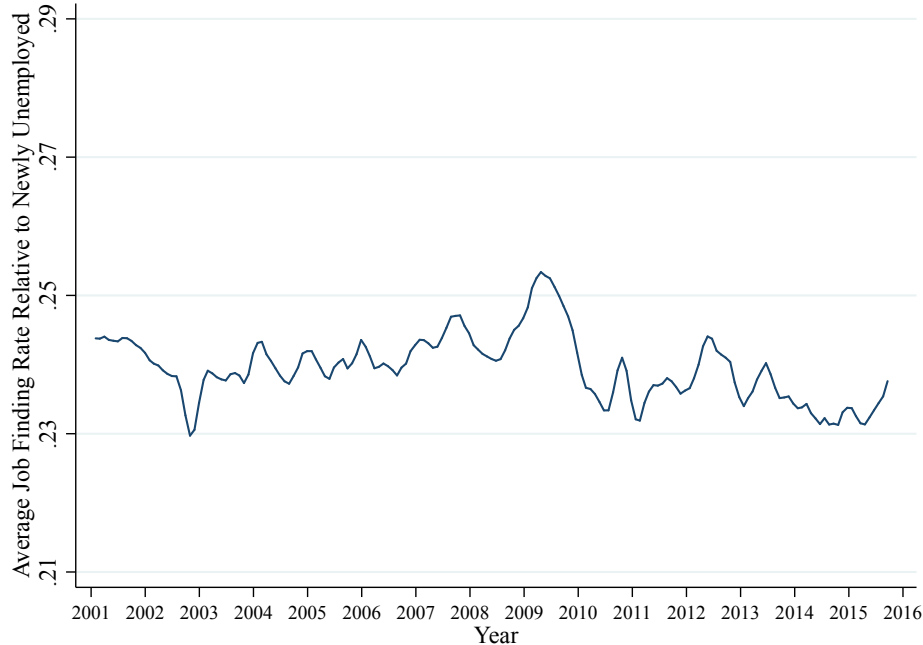


months. For the unemployed, the function “flattens out” considerably after roughly six months, which mirrors what has been found in the U.S. (Kroft et al. [2016]). For non-participants, the function also steeply declines, but does not flatten out quite as rapidly, and also declines further in absolute terms: after 12 months, the job finding rate of non-participants is less than 20 percent of a non-participant with a jobless duration of 0, while for unemployed individuals the job finding rate (at 12 months) is roughly 30 – 40 percent of the job finding rate of an unemployed individual with duration of 0.

With these estimates, we next examine how job finding rates change over time based solely on changes to the distribution of joblessness durations. For the unemployed, this is the average of the $A(d)$ function (averaged across stock of joblessness durations). Intuitively, in a recession, longer spells receive more weight and so pull down the mean $A(d)$. For Canada, the mean is roughly 52 percent in the pre-recession period and drops to about 48 percent during the recession as can be seen in Figure 18. This compares with a drop from about 75 percent to about 65 percent during the Great Recession in the US. The smaller decline in $A(d)$ in Canada compared to the U.S. is consistent with the trends in LTU/LTJ for both countries, showing that the recession was much deeper in the U.S. and generated much more long-term unemployment.

For non-participants, we report how the job finding rate conditional on non-participation evolved solely based on the distribution of the duration of joblessness. This measure is obtained by averaging

Figure 19: A Measure of the Search Relevant Duration Structure among Non-Participants in Canada: $\frac{B(d)}{A(d)}$



$B(d)$ using the observed duration distribution among non-participants. Figure 19 shows that the average $B(d)$ is much lower than the average $A(d)$, starting around 25 percent in the pre-recession period and falling to about 23 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 during the recession.

6.2 Calibrating the Extended Matching Model with Canadian data

To calibrate the matching model in equations (2) to (8), we require estimates of the parameters entering the matching function (s, m_0, α, ξ) as well as the functions $A(d)$, $B(d)$, $C(d)$, and $D(d)$. We described in the previous section the functional form and estimation of $A(d)$ and $B(d)$. For the functions $C(d)$ and $D(d)$, we use the transition rates by month of joblessness duration averaged over the period from January 2001 to October 2015. We do not impose a functional form on $C(d)$ and $D(d)$ and show them in Figure 17.

To estimate the matching parameters (s, m_0, α, ξ) we only use the data up to the onset of the recession in October 2008. The parameter estimates of the matching model as well as estimates of $A(d)$ and $B(d)$ are shown in Table 1.¹⁵

¹⁵As in Kroft et al. [2016], we estimate the model parameters using a minimum distance procedure that minimizes the sum

Figure 20: Observed and Fitted Job Finding Rates for Unemployed in Canada

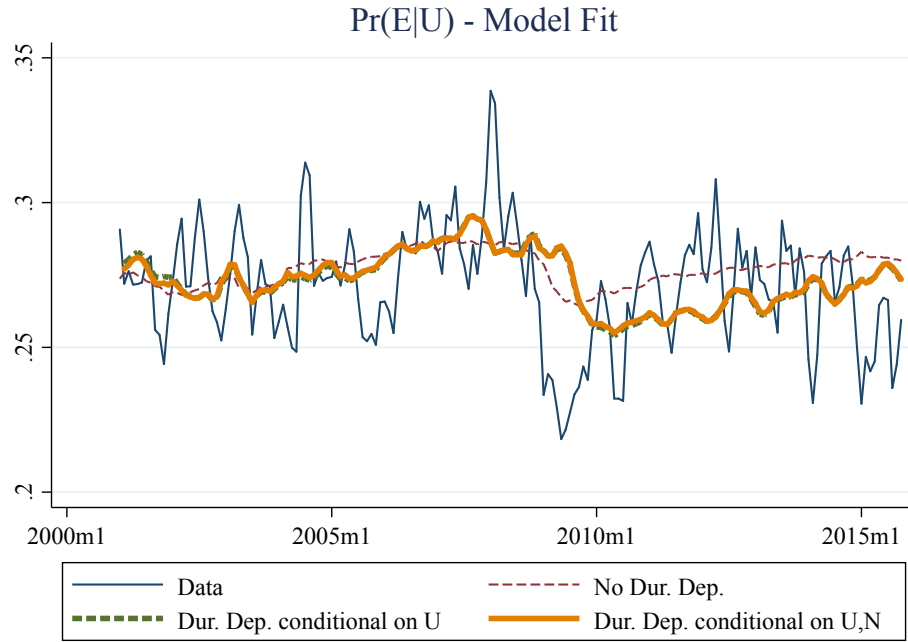
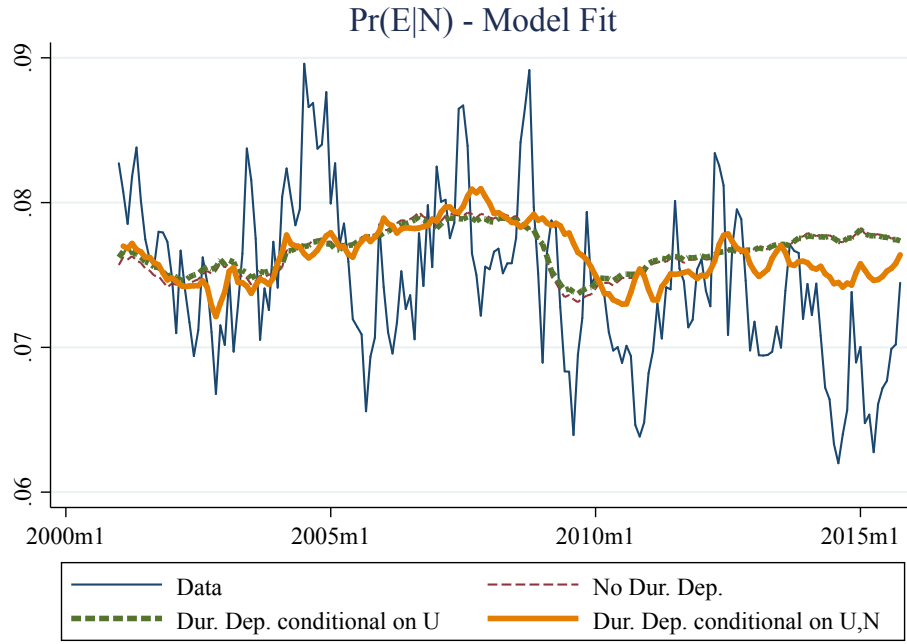


Figure 20 shows the observed and fitted job finding rates for the unemployed from January 2001 to October 2015. The figure shows both the fit for the full model allowing for both duration dependence among the unemployed and those out of the labor force, as well as the fit for a model that is restricted to allow only for duration dependence among the unemployed. The predicted values for these two models overlap almost perfectly. Overall, we see that the model fits the overall decline in job finding rates fairly well, with the exception of the initial decline in observed job finding rates.

As we calculated for the model predictions for the U.S. data (see Figure 13 and footnote 14), we calculated the average error (bias) and the mean squared error (MSE) – both “in sample” and “out of sample” – in order to assess goodness-of-fit. In Figure 20, the “in sample” average error is -0.00002 and the MSE is 0.0003 for the “No Duration Dependence” model. For the full model with duration dependence among both the unemployed and those out of the labor force, the average error is -0.00004 and the MSE is 0.0003. The analogous out-of-sample statistics are 0.0129 and 0.0005 for the “No Duration Dependence” model and 0.0048 and 0.0006 for the full model. Thus, the full model has similar MSE out of sample as the model with no duration dependence, but has much smaller average error (bias).

Figure 21 shows the observed and fitted job finding rates among non-participants. Here we find that of squared differences between the model-predicted U-to-E and N-to-E flows and the observed flows. We prefer to evaluate the model fit using the average error and mean squared error for the predicted flows to employment (from unemployment and non-participation), but an alternative measure of model fit could be constructed based on test statistics from the minimum distance procedure.

Figure 21: Observed and Fitted Job Finding Rates for Non-participants in Canada



allowing for duration dependence in both U and N improves the fit of the model. The thick line shows the fit of our preferred model, while the dashed line shows the fit without duration dependence among those out of the labor force. The restricted model overestimates the job finding rate among non-participants after 2012, while the unrestricted model does a reasonable job of fitting these later periods as well. Overall, we note that the model fits the decline in the job finding rate reasonably well.

It is noteworthy that in Canada, but not in the U.S., the matching model estimated on the pre-recession period matches the job finding rates even after the recession. This is true even if we estimate the restricted model in Kroft et al. [2016] rather than the model with enriched dynamics (equations (8), (9), and (10)). In either case, the matching model estimated on Canadian data fits the job finding rates both quantitatively and qualitatively, while in the U.S. we underestimate the decline in the job finding rate especially among those out of the labor force.¹⁶

¹⁶Using the same goodness-of-fit statistics reported for previous figures showing model-based job finding rates, the “in sample” average error is 0.00006 and the MSE is 0.00003 for the “No Duration Dependence” model. For the full model with duration dependence among both the unemployed and those out of the labor force, the average error is 0.0001 and the MSE is 0.00002. The analogous out-of-sample statistics are 0.0043 and 0.00005 for the “No Duration Dependence” model and 0.0037 and 0.00004 for the full model. Thus, the full model has somewhat smaller average error than the “No Duration Dependence” model, and both of these models have smaller average error than the analogous statistics for predicted N -to- E flows in the U.S. data.

6.3 Counterfactual Results

Figures 20 and 21 were constructed using the observed distributions of the duration of joblessness across the entire time period. These figures therefore do not speak to how well the model performs in generating counterfactual distributions across (U, N, E) and across the duration of joblessness. We now turn to counterfactual simulations that allow us to probe how well the model of labor force flows developed here describes the dynamics of the labor market overall.

In particular, we simulate the model using as exogenous forcing variables the vacancy series, the job loss rates conditional on U and N , and the transition rates between U and N observed in the data.¹⁷ We keep constant the parameters of the matching model (equations (2) and (8)) and the relative transition rates $A(d)$, $B(d)$, $C(d)$, and $D(d)$.

We begin by using the dynamic equations to simulate long-term joblessness (>26 weeks) among the unemployed and those out of the labor force. Figure 22 shows the observed share of long-term joblessness (>26 weeks) among the unemployed as well as for 3 different counterfactual scenarios starting in October 2008. The dashed thin line refers to the model without any duration dependence. Surprisingly, this model does fairly well in fitting the long-term joblessness distribution conditional on unemployment. The thick dashed line (labeled “DD in U”) shows the counterfactuals based on a model that allows only for duration dependence among the job finding rates of the unemployed, but not among non-participants, nor in $U \rightleftharpoons N$ flows. This model predicts a larger share of long-term joblessness than observed in the data. It does so because it does not account for the fact that many of those unemployed for long periods become non-participants (see Figure 17). By contrast, the full model allowing for duration dependence in job finding rates among both the unemployed and those out of the labor force and also for duration dependence in flows $U \rightleftharpoons N$ fits the observed data better than the other models.

Figure 23 shows the same data and counterfactuals for the long-term jobless conditional on being out of the labor force. Models that do not allow for duration dependence in the job finding rates of non-participants as well as in flows between unemployment and non-participation under-estimate the share of long-term joblessness among the non-participants. This is because these models do not capture the large unbalanced flows between unemployment and non-participation at high durations of joblessness. Once we allow for duration dependence in these flows, we can fit the patterns in long-term joblessness quite well using the stable matching framework and a duration structure that is unchanged over the study period. Another way of assessing the performance of the model presents the counterfactual stocks

¹⁷For the latter, we take the average transition rates λ_{UN} and λ_{NU} as well as the duration distribution observed in the data to construct the rates of transitioning between U and N conditional on duration 0. These are used as the forcing variables in the dynamic simulation.

Figure 22: Long-term Joblessness among Unemployed in Canada (>26 weeks)

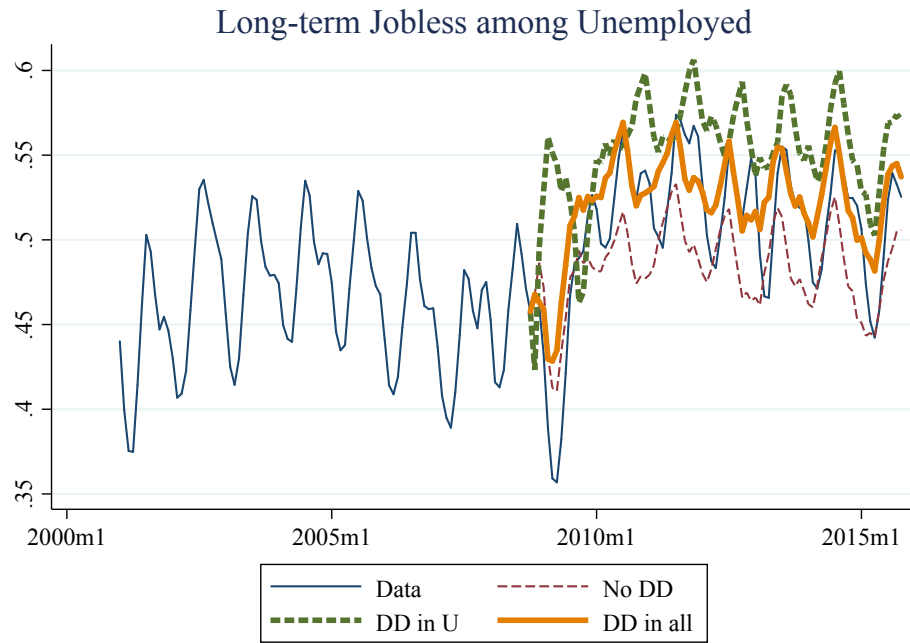


Figure 23: Long-Term Joblessness among OLF in Canada (>26 weeks)

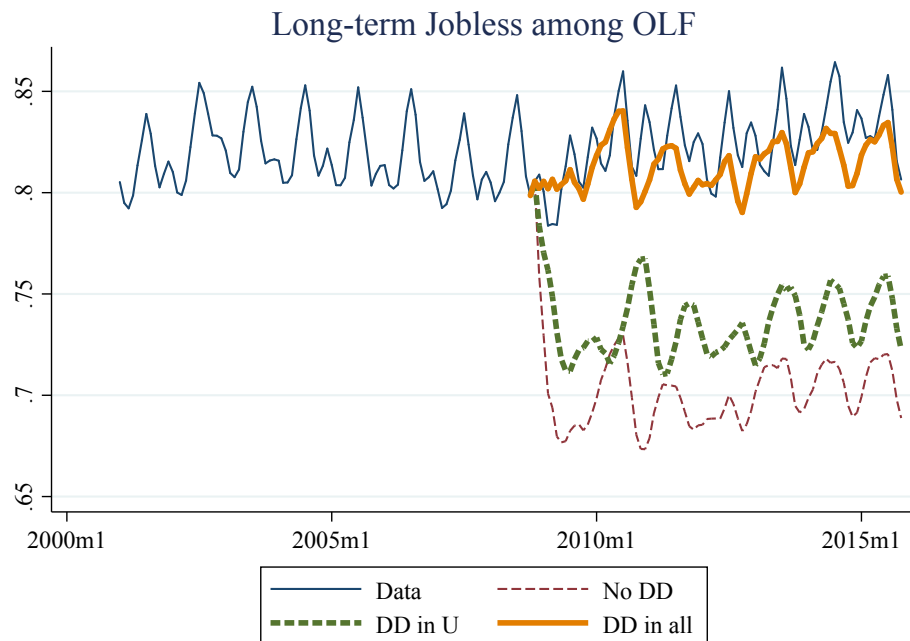
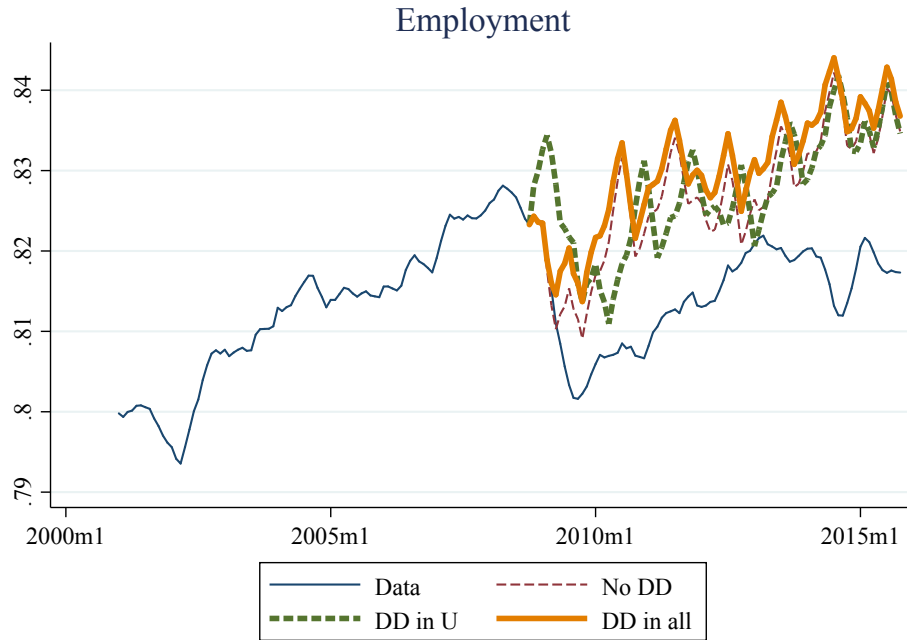


Figure 24: Employment during the Canadian Recession



of employment and unemployment during the recession. These are shown in Figures 24 and 25, where both stocks are normalized by the population (so these are employment-population and unemployment-population ratios). Here we see that all of the models trace out a path for employment that exceeds the observed path, and a path for unemployment that falls short of what is actually observed. Part of this comes from the fact that the model-based job finding rate was predicted to be slightly higher than what was actually observed during the recession.

Figure 26 traces out the counterfactual Beveridge curve in unemployment using the full model with duration dependence in all flows since the onset of the recession in October 2008. Also displayed is the observed Beveridge Curve over this time period. We see that the model predictions trace out the same general shape of the Beveridge curve, but we observe a difference (between predicted and actual unemployment-population ratio) of around one-half to one percentage point over the recession. The fit of the counterfactual $N - V$ curve (see Figure 27) is not as good as the fit of the Beveridge curve in unemployment in that the model persistently underestimates the share out of the labor force by about 1 percentage point.

Thus, we have so far seen that the dynamics of long-term joblessness conditional on unemployment and non-participation are sensitive to correctly modeling the duration dependence in both job finding rates and in the flows between unemployment and non-participation. Overall, the full model does well in

Figure 25: Unemployment during the Canadian Recession

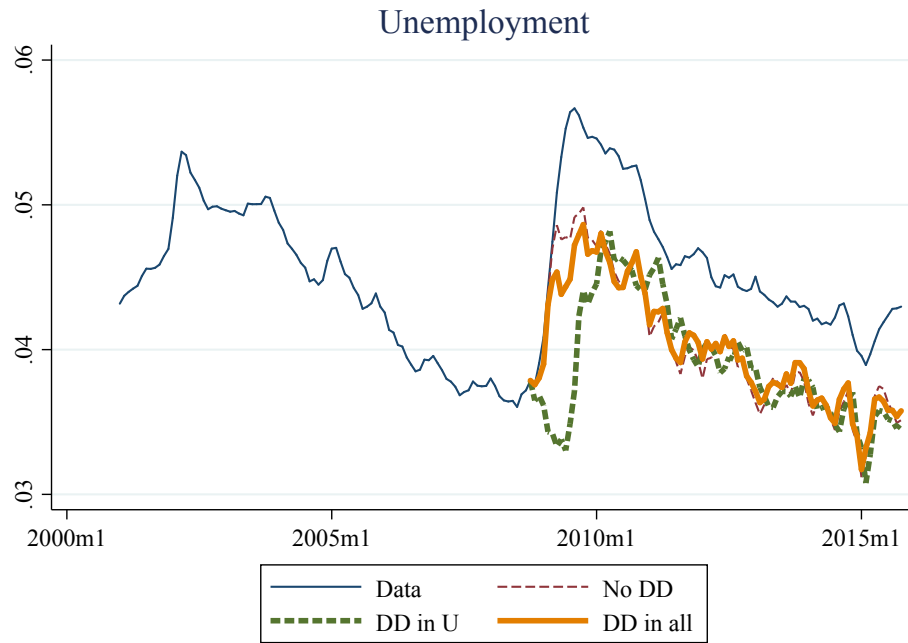


Figure 26: A Counterfactual Beveridge Curve - Canada

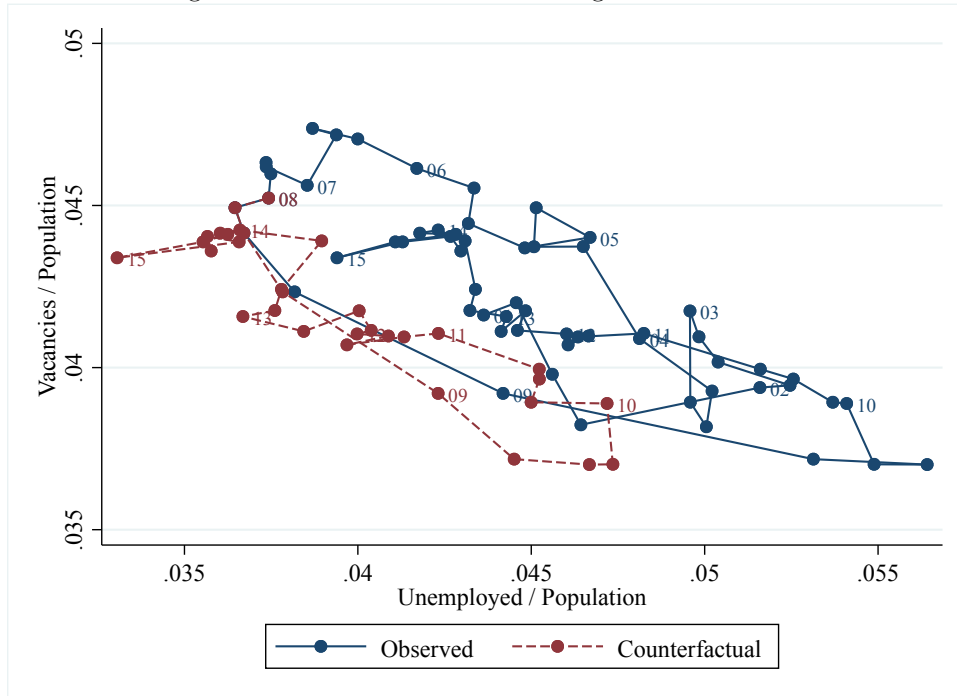
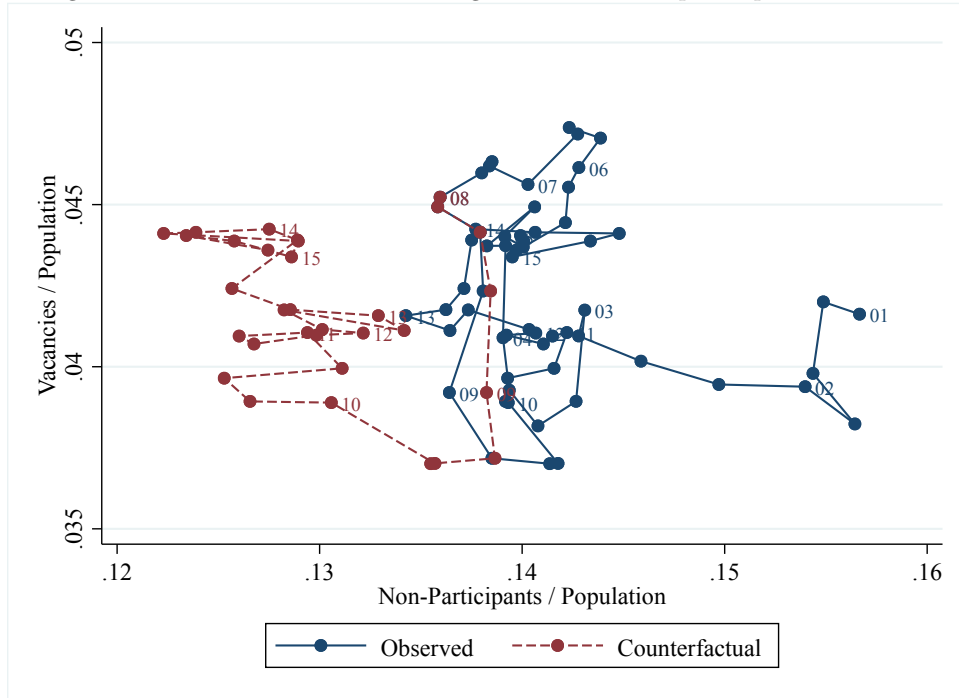


Figure 27: A Counterfactual Beveridge Curve for Non-participants - Canada



matching the stocks of unemployed and non-participants over the recession.

6.4 A Canadian Great Recession in Labor Demand

The final question we want to take up using our full counterfactual model is whether the Canadian labor market performed better than the U.S. labor market primarily because of differences in the demand for labor over the recessionary period. Perhaps Canada avoided a Great Recession because Canadian employers continued to create vacancies at higher rates and because Canadian employers did not lay-off as many workers during the recession itself. To investigate this question, we take the counterfactual model that we saw fits the data well over the recession and apply to it the same time series pattern in job separation rates and in vacancies observed in the U.S. during the Great Recession. That is, we apply the percentage decrease in vacancies observed during the Great Recession to the vacancy series in Canada starting in October 2008 and we likewise apply the increase in the job loss rate over the Great Recession. To illustrate, the vacancy rate in the U.S. in December 2008, one year after the onset of the Great recession stood at 66 percent of the vacancy rate in December 2007. In our next set of counterfactual simulations we thus postulate that the vacancy rate in Canada in October 2009 stands at 66 percent of that in October 2008, the onset of the Canadian recession. At that point, the vacancy rate in Canada had in fact only declined by about 19 percent. We proceed in the same fashion for job loss rates and thus

impose higher job losses on the Canadian economy.

The two panels in Figure 28 show the implied time series of the unemployment rate and non-participation rate from the full counterfactual model as well as the counterfactual model that does not allow for duration dependence.¹⁸ We have highlight three results from this exercise. First, by coincidence both of the counterfactual models closely approximate the observed patterns in the unemployment rate in Canada. Second, even under the conditions of the Great Recession in terms of labor demand, the full model and the model without any duration dependence do not diverge widely in predicted unemployment and non-participation over the recession. This reinforces the conclusion that duration dependence is significantly more important for understanding the patterns in long-term joblessness than it is for understanding the overall performance of the labor market in terms of the broad labor force stocks (E, U, N) . We believe this to be the case because these latter stocks and their dynamics are quite sensitive to the flows early during jobless spells, since the majority of jobless spells are relatively short.

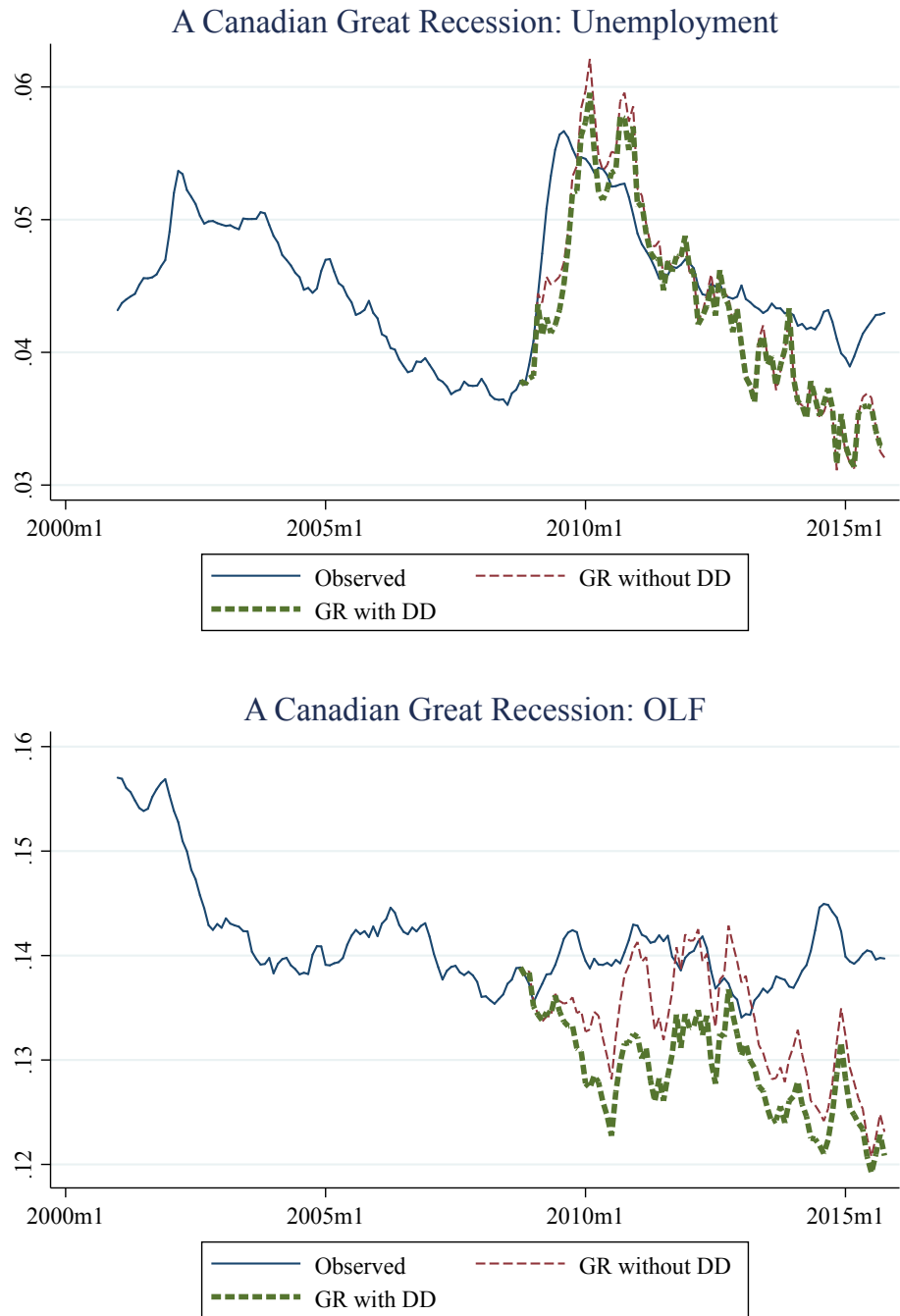
Third, the two panels in Figure 28 show that the much greater decline in labor demand and the larger and more persistent increase in job loss rates in the U.S. compared to Canada is not enough to explain the different labor market experiences of the two countries over the last decade. Clearly, imposing U.S.-style deterioration in labor demand would have significantly worsened the recession in Canada, but it does not seem as if this would have induced a Canadian Great Recession. Rather, it seems that the recession in Canada was mild compared to the recession in the U.S. in large part because the rate at which job seekers were matched to vacancies did not break down to the same extent in Canada as it did in the U.S. In other words, the matching model was more stable in Canada during this time period.

7 Conclusion

Long-term unemployment rose sharply in both Canada and the U.S. during the Great Recession. The levels of long-term unemployment continue to remain elevated in both countries and are not explained by shifts in the observable characteristics of the unemployed. Similar to our previous analysis of the Great Recession in the U.S., we turned to a matching model to try to understand these labor market dynamics. The Canadian labor market data permitted us to extend the matching model in one important direction – since we observe joblessness spells for both unemployed individuals and non-participants, we could model how job finding rates vary with the duration of joblessness for both groups, something that we were unable to do in the U.S. analysis. Additionally, we could allow for duration dependence in all flows between unemployment and non-participation. Our results indicate that job finding rates for non-participants

¹⁸The “full” counterfactual model here includes duration dependence in both U and N .

Figure 28: A Canadian Great Recession



are strongly negatively associated with the duration of joblessness. Flows between unemployment and non-participants also depend significantly on the duration of joblessness. When we broaden the matching model to include these features for Canada, we find that the fit of the model improves.

Our analysis suggests several important directions for future research. First, there are gaps in the measurement framework of the BLS that should be addressed. Our paper and the work by Kudlyak and Lange [2017] suggest that durations of joblessness and durations of unemployment are distinct economic phenomena. Joblessness durations and unemployment durations do not measure the same thing and researchers interpreting the duration of unemployment as the time since an unemployed individual was last employed will be mistaken. Additionally, we demonstrate in this paper that accounting for joblessness durations among the unemployed and non-participants has important quantitative implications for modeling the dynamics of the labor market. Thus, we believe that the CPS should consider following the LFS in collecting data on time since last employment for both the unemployed and the non-employed. Given rising interest in trends in labor force participation (see, e.g., Abraham and Kearney [2018]), this seems like a worthwhile data investment. In the meantime, the panel nature of the CPS can serve to provide some information on the duration of joblessness that can be used to supplement the cross-sectional measure of unemployment duration.

Second, our findings point to the importance of understanding flows between U and N , both overall and by duration of joblessness. Only part of the newly unemployed are continuously actively searching for employment and thus observed to be unemployed throughout their jobless spells. Many others move in and out of the labor force and between non-participation and employment. When they become employed, many are often in precarious jobs of short durations (see also Krueger et al. [2014] and Kudlyak and Lange [2017]). One way to interpret this evidence is to postulate the existence of a dual labor market and to think of part of the population as either being caught in – or choosing to engage in – a labor market with short attachments and many transitions across unemployment, non-participation, and employment. This suggests room for future work developing models that can capture this kind of labor market behavior.

Third, we hope other researchers will extend these results to more recent years and also apply them to the study of future business cycles. Additionally, we have focused throughout our analysis on prime-age workers (age 25-55). This excludes older workers, who are working longer in both Canada and the U.S. One approach to include older workers would be to combine traditional matching models of the labor market with traditional labor demand models that allow for imperfect substitution between older and younger workers. This is the approach taken in Cosksun [2018], building on Card and Lemieux [2001], and it may provide a useful template for studying a broader range of joblessness trends.

Fourth, in this paper we have applied the methodology of Landais et al. [2018] to calculate a new

vacancy series for Canada. This is a new measure that still needs more testing and validation, but we believe it has promise. One important caveat is that this measure may capture variation in both “pure” vacancies as well as variation in what Davis et al. [2013] describe as “recruiting intensity.” An interesting avenue for future work is assessing how much of the variation in the recruiting proxy captures each of these distinct forces.

Fifth, we believe that a more geographically disaggregated analysis might provide useful insights. We reported that the more severe contraction observed in the U.S. relative to the Canadian labor market cannot be explained simply by the greater decline in labor demand or the more persistent degree of job losses observed in the U.S. Rather, we found the matching model to be more stable in Canada than the U.S. However, it is hard to know whether the severity of the recession itself might have lead the matching function to break down or if something else caused this decline in the matching function. One way to make progress would be to examine how the matching model did at a sub-national level, looking across states, regions, or commuting zones. Do we observe that the matching model was particularly unstable in those regions of the U.S. and Canada most severely hit by the recession? Similarly, “border comparisons” focusing on areas on either side of the U.S.-Canada border might help control for differences in the structures of the two national economies. Such regional analyses, however, are currently difficult to carry out since vacancy measures are typically not available at the regional level. However, we believe that regional analyses may be able to construct a recruiter-producer following Landais et al. [2018] ratio at a sub-national level. This could allow researchers to construct “local Beveridge curves” and study labor demand questions at a local level using this methodology to construct a proxy for local vacancies.

This paper provides some initial evidence that a matching framework provides a useful way to understand the performance of labor market in Canada in the recent past. It provides a parsimonious framework, expanded in a transparent manner, to account for duration dependence in modeling flows out of non-participation and unemployment as well as other forms of heterogeneity. Overall, we interpret the results from this paper as providing suggestive evidence that joblessness may be a useful measure for analyzing labor market trends.

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Online Appendix

This Appendix contains additional results and figures described in main text.

The Negligible Role of Age Adjustment in 25-55 Sample

We begin with figures which show the negligible role of “age adjustment” in our main sample of 25-55 year olds. Following Aaronson (2014), we calculate contribution of aging to change of Y from month M_0 to month M_1 as

$$C = \sum_{age} Y_{age, M_0} * (share_{age, M_1} - share_{age, M_0}),$$

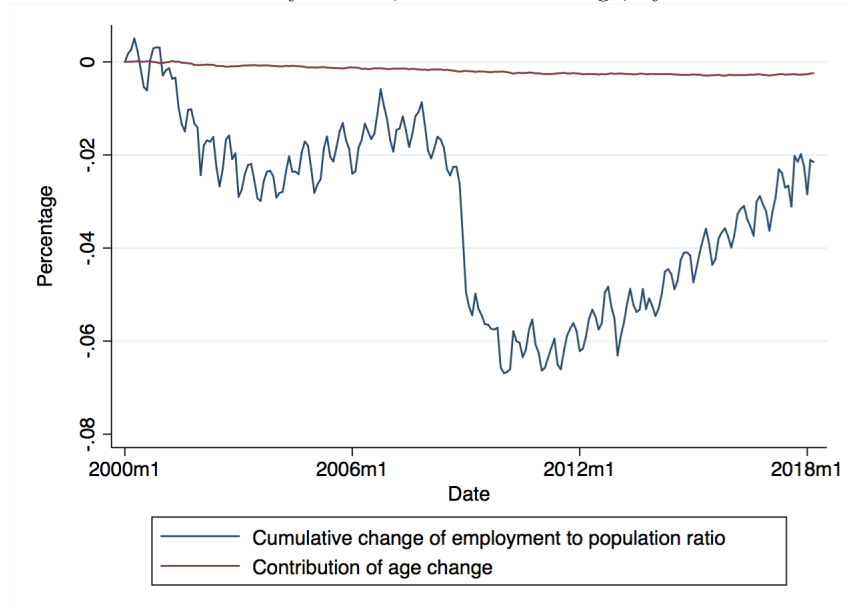
where m denotes month; Y denotes unemployment rate, labor force participation rate, or employment to population ration. Age is restricted to 25-55 or 25-65 years old.

We plot change of Y and contribution of aging for employment rate and labor force participation rate in Figures 29 and 30. Contribution of age change is much smaller in the 25-55 years-old sample than in the 25-65 years-old sample.

Appendix Figures

[See additional figures on subsequent pages]

Figure 29: Contribution of aging to employment rate
 Panel A: 25-55 years-old, cumulative change, by month



Panel B: 25-65 years-old, cumulative change, by month

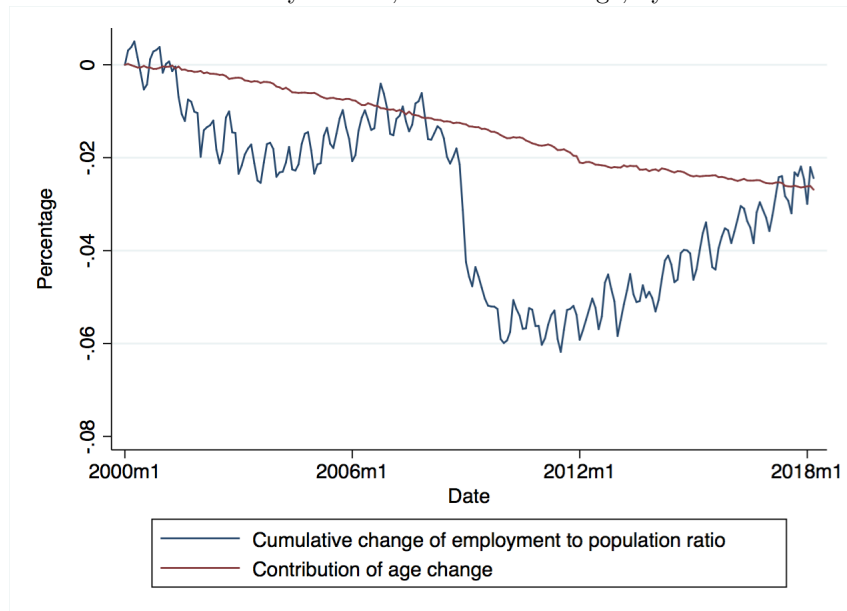
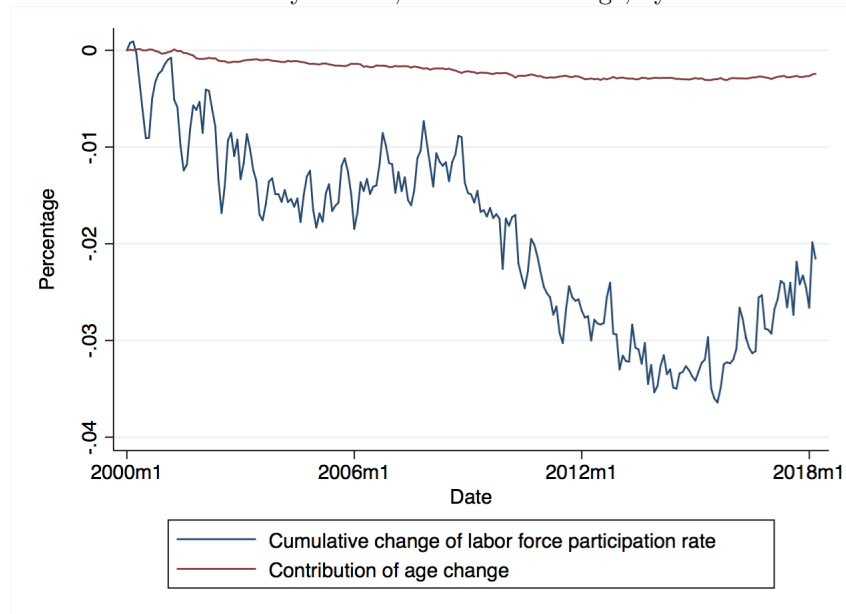


Figure 30: Contribution of aging to labor force participation rate
 Panel A: 25-55 years old, cumulative change, by month



Panel B: 25-65 years old, cumulative change, by month

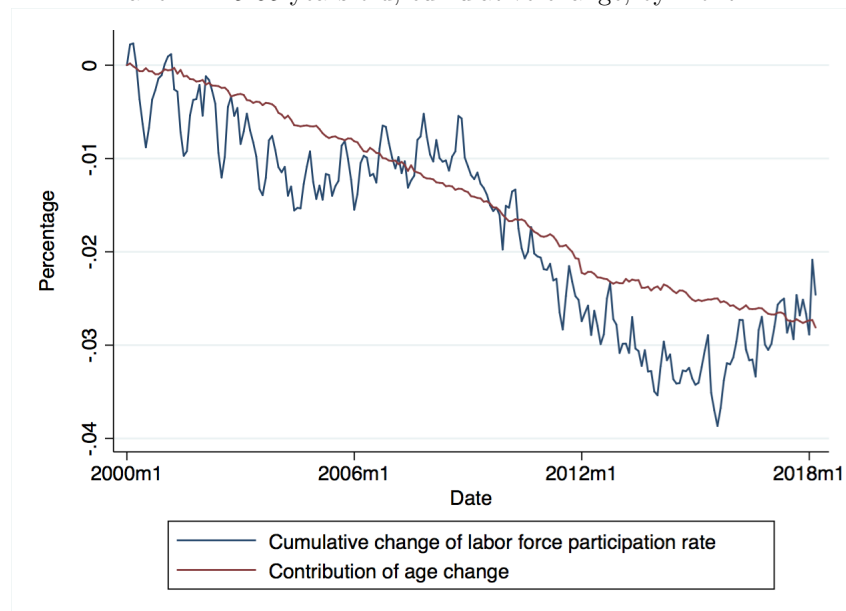


Figure 31: Age Distribution from CPS, 2000 and 2016

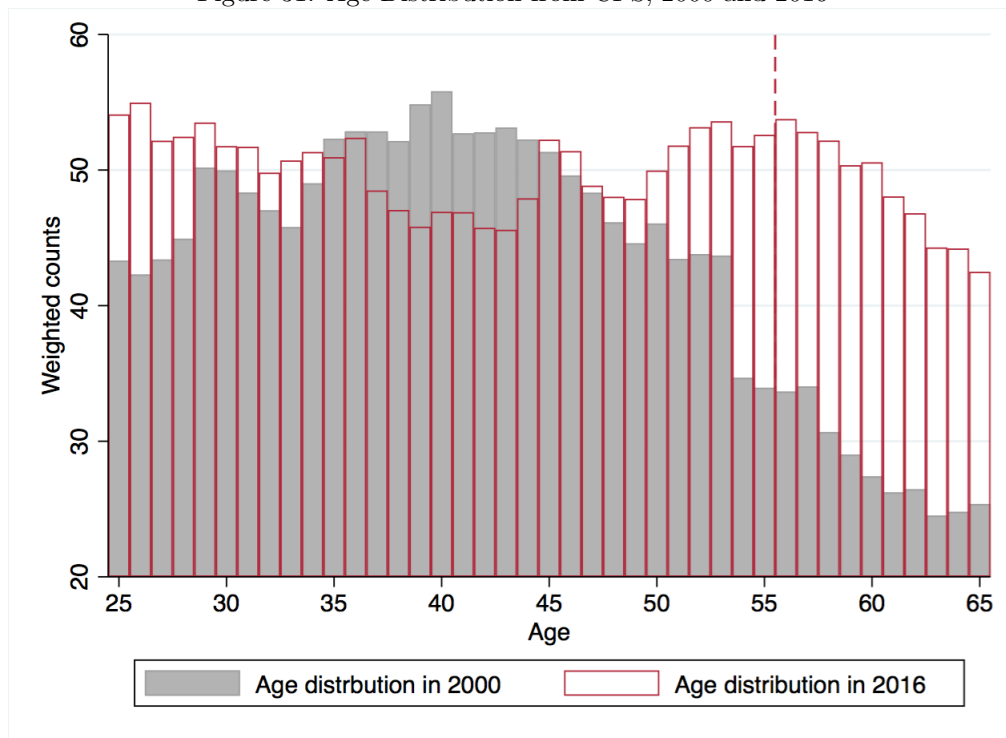


Figure 32: Long-Term Unemployment by Age

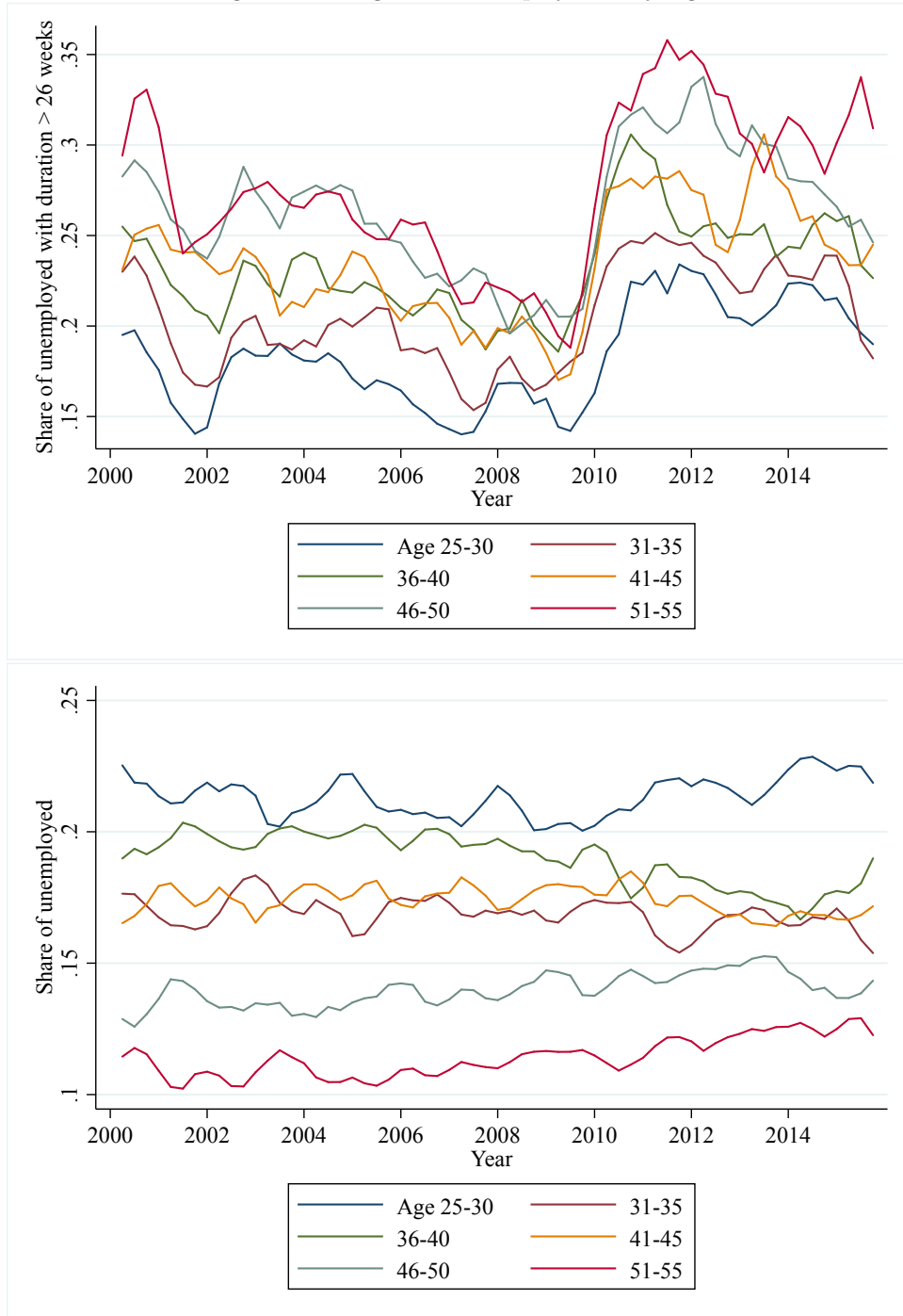
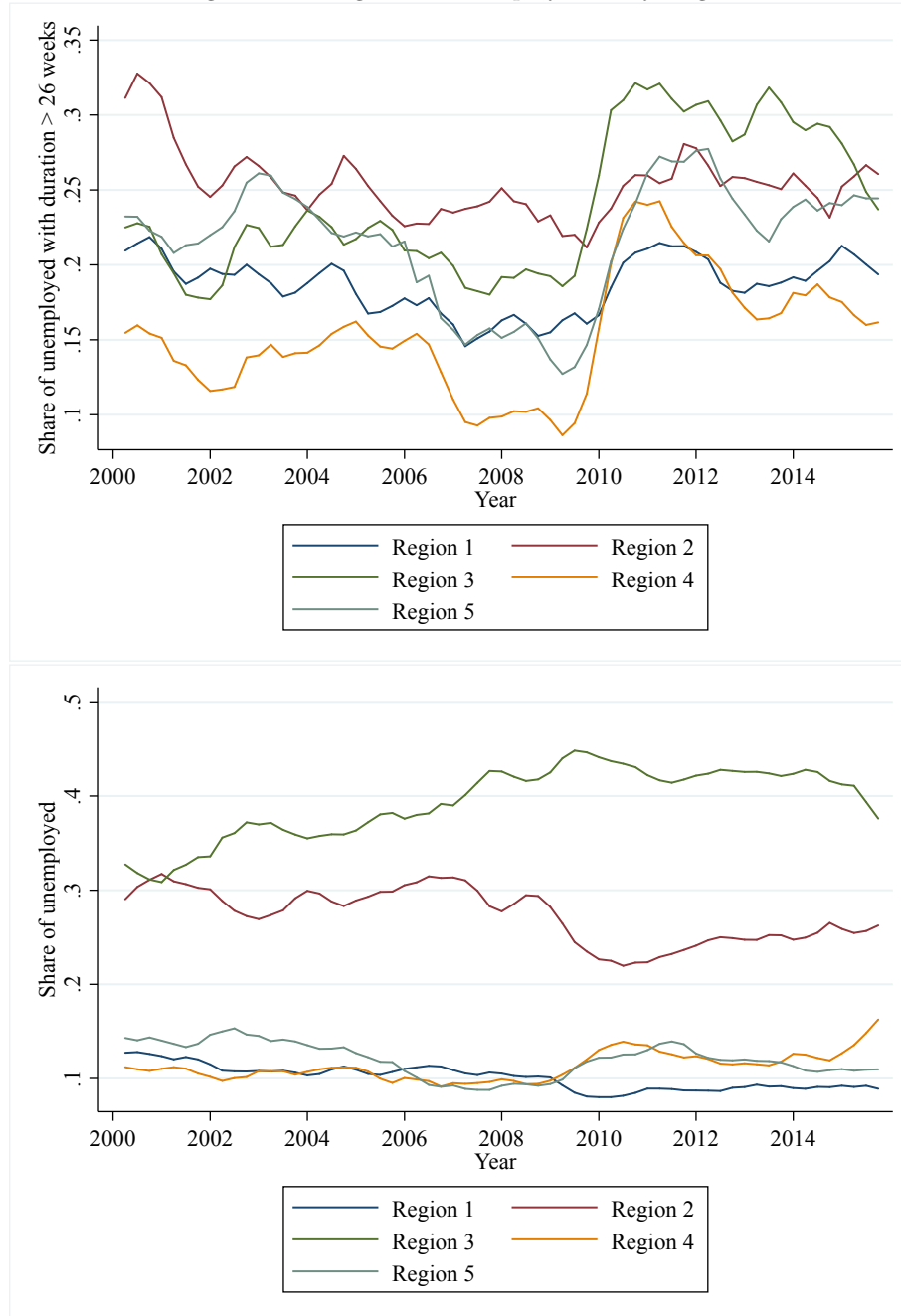


Figure 33: Long-Term Unemployment by Region



Notes: Region codes are Atlantic Provinces (1), Quebec (2), Ontario (3), Prairie Provinces (4), British Columbia (5).

Figure 34: Long-Term Joblessness for Non-Participants by Education

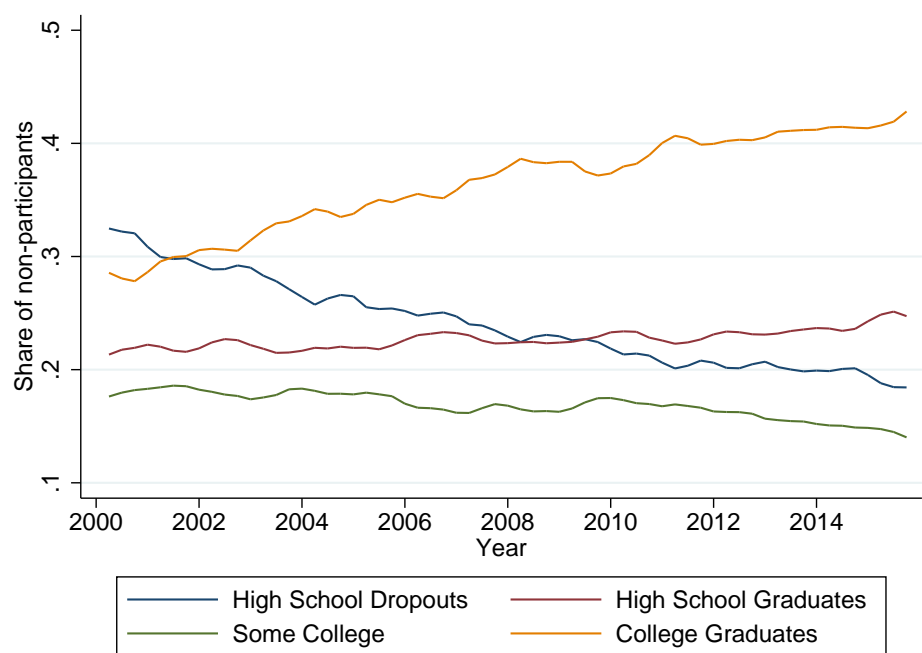
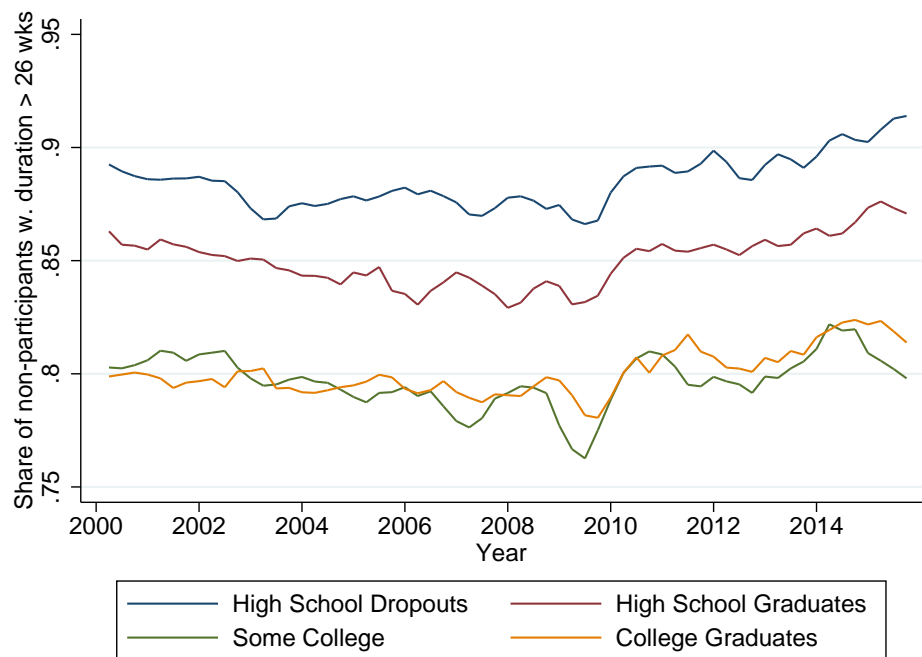


Figure 35: Long-Term Joblessness for Non-Participants by Gender

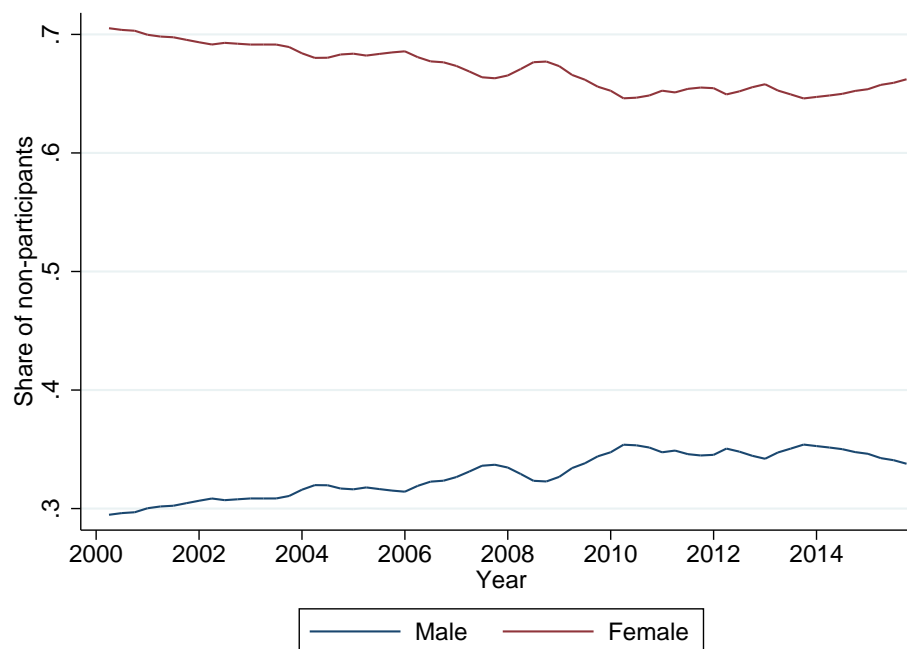
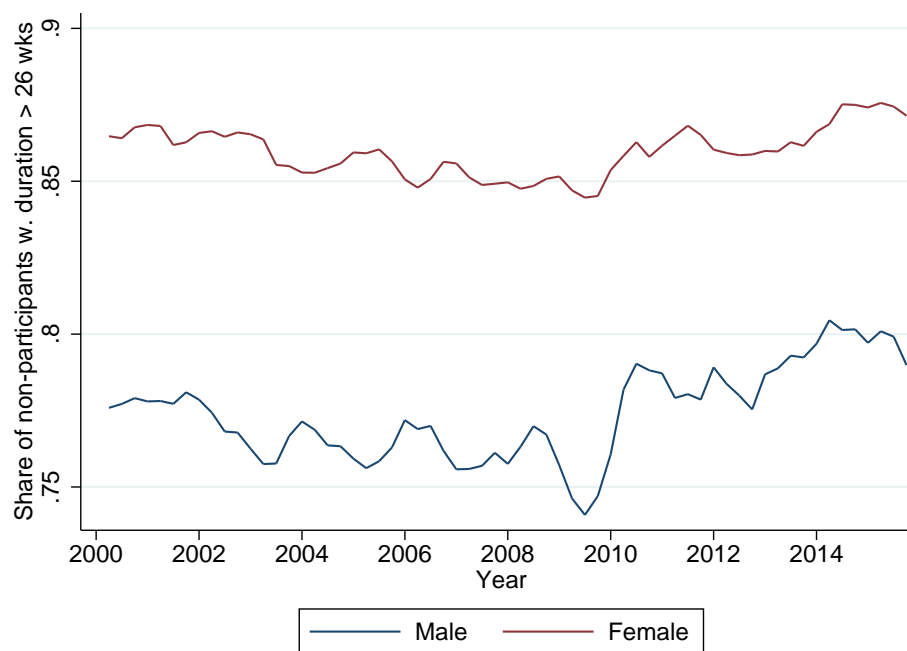


Figure 36: Long-Term Joblessness for Non-Participants by Age

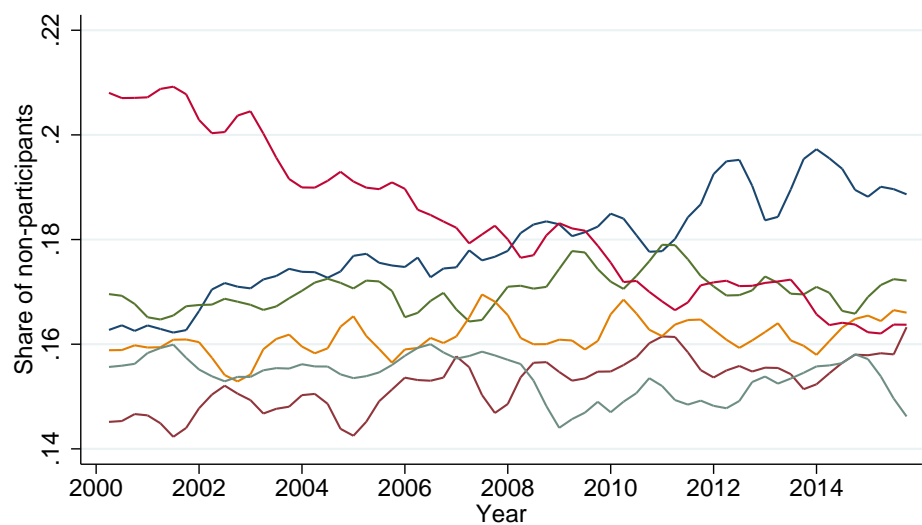
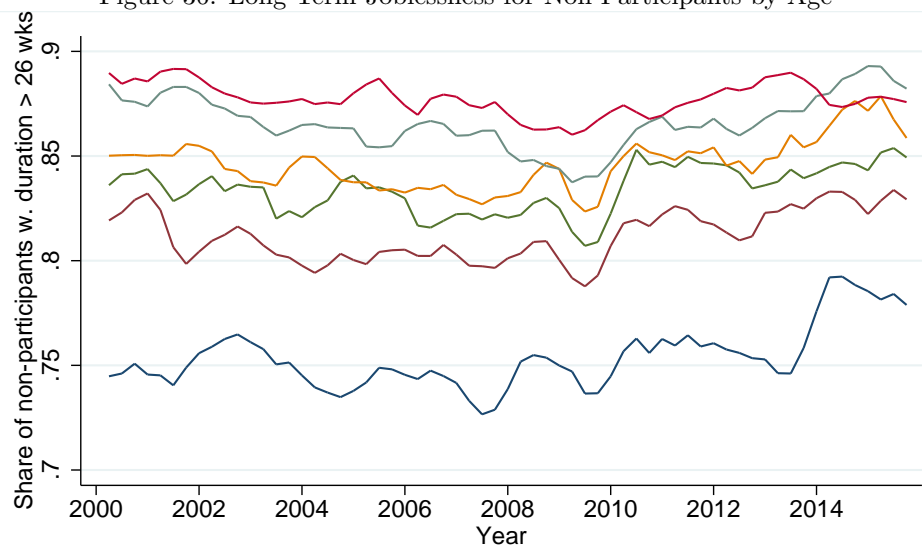
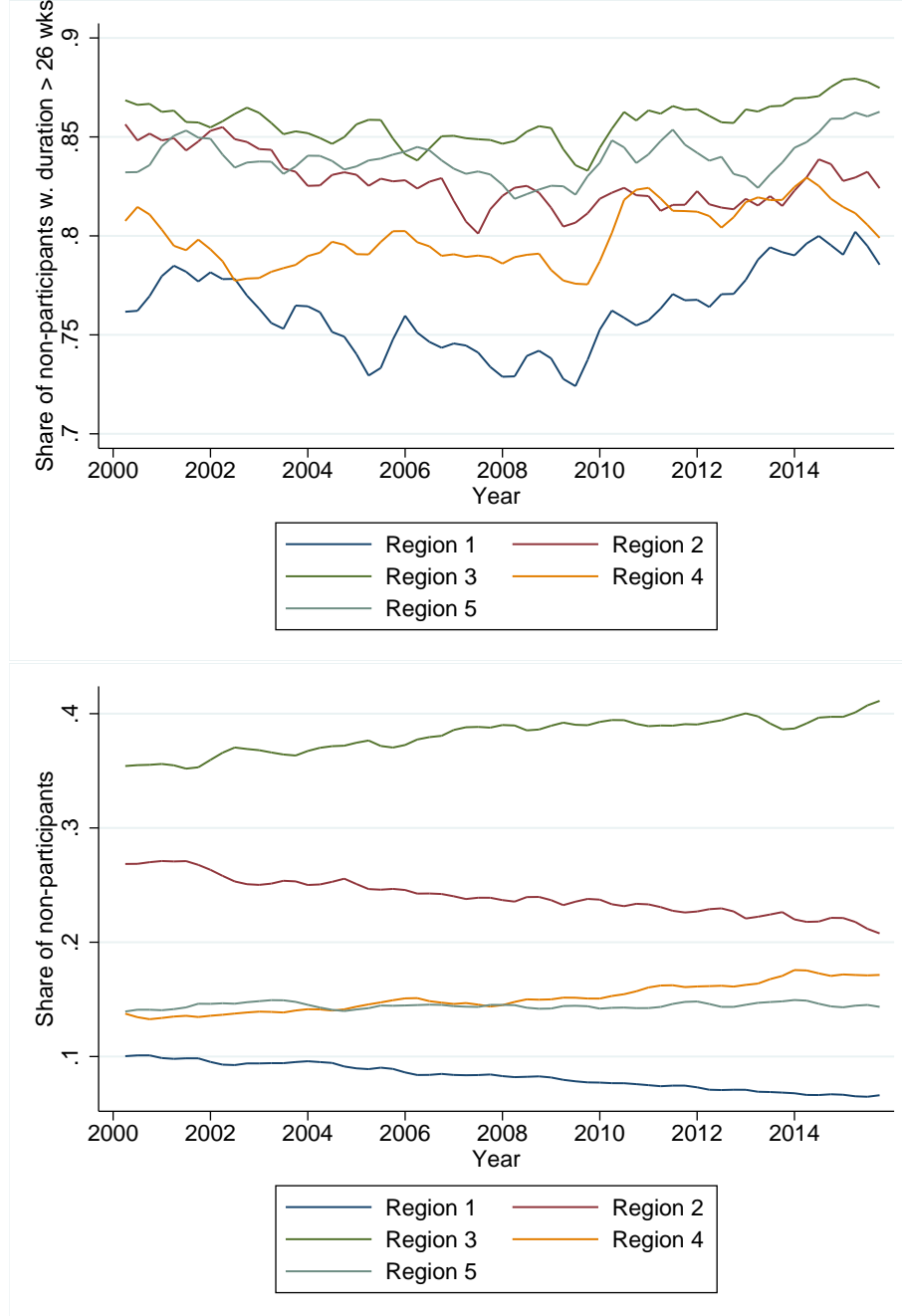


Figure 37: Long-Term Joblessness for Non-Participants by Region



Notes: Region codes are Atlantic Provinces (1), Quebec (2), Ontario (3), Prairie Provinces (4), British Columbia (5).

Figure 38: Fitted Job Finding Rates by Duration for Unemployed and OLF

