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ABSTRACT

Assessing Labor Market Conditions in Canada with Public-Use Microdata*

We extend Nakamura et al. (2019, 2020)'s approach of using the publicly available microdata files of the Labour Force Survey (LFS) to construct worker transition rates across employment, unemployment, and inactivity. Our approach involves estimating and applying a scaling factor that has been proposed in earlier research as a way of capturing the relative intensity of job search from inactivity compared to unemployment. This factor provides enough structure to prevent arbitrary splitting of unemployment outflows between employment and inactivity. In turn, the estimated job search factor can be used in a few simple step-by-step instructions applied to the LFS public files to assess near real-time labor market conditions in Canada. An analysis of the recent dynamics of worker flows illustrating the practicality of our approach highlights that transition rates: (a) from employment to unemployment have fallen over time (b) from unemployment to employment were unusually high during the pandemic and (c) have regional differences.

JEL Classification: E24, J21, J63

Keywords: employment, unemployment, labor force participation, gross worker flows

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1 Introduction

Worker flows across employment, unemployment and out of the labor force are a key source of empirical information to assess the state of the labor market and guide policy-making. During recessions, these data reveal whether soaring unemployment rates are a result of firm shutdowns and layoffs, or due to extended periods of joblessness caused by reduced job creation and investment (Darby, Haltiwanger, and Plant (1986); Blanchard and Diamond (1990); Elsby, Michaels, and Solon (2009); Shimer (2012)). At secular frequencies, labor force entry and exit shape the participation rates which in turn play a major role in driving the long-run employment performance of an economy (Elsby et al. (2019); Hobijn and Sahin (2022)).

In principle, researchers and analysts in Canada are well equipped to obtain information on worker flows. Each month, Statistics Canada's Labour Force Survey (LFS) collects data from a large number of individuals through a rotating panel sampling design. By longitudinally matching individuals over consecutive interviews, users of the LFS can construct measurements of worker flows across labor force states at a relatively high frequency to measure the impact of rapidly disseminating shocks and economic policies. In practice, however, the situation is different. Since the microdata files of the LFS that contain the individual identifiers for longitudinal tracking are subject to restricted access, researchers and analysts must first go through an application process; upon approval of the application, and after obtaining security clearance, they are allowed to access the microdata in designated Research Data Centres;[1] finally, to ensure confidentiality is preserved, calculations based on these data files must undergo a vetting procedure before public release of the results is authorized.

While these are real costs, a researcher who pursued this route would bear most of them only once, with the process then repeatable each month. However, there is still an advantage to using only the publicly available microdata files of the LFS for an even faster and publicly-verifiable alternative to measure transition rates and assess labour market conditions. Hence in this paper we propose such an alternative. Our starting point is the analysis of the LFS presented in Nakamura et al. (2019, 2020) (henceforth NNPS20). NNPS20 point out that three out of the six worker transition rates across employment, unemployment, and out of the labor force, can be obtained directly from the public-use LFS data. We depart from NNPS20 in our treatment of the three "missing" transition rates, namely those

[1] While there is also the option of using Statistics Canada's online system called Real Time Remote Access, this portal allows users only to submit programs, not to work directly with the data; see Brochu (2021).

governing flows from inactivity into employment and the two unemployment outflows.[2] Indeed, we show that NNPS20's treatment of these transitions has some counterfactual implications. As an alternative to their approach, we introduce a scaling factor between the inflows towards employment coming from respectively unemployment and inactivity. Conceptually, this scaling factor corresponds to the intensity of job search from inactivity compared to unemployment, which is stressed in several search-theoretic models of the labor market featuring a participation margin (Garibaldi and Wasmer (2005); Pries and Rogerson (2009); Lalé (2018)). The notion also appears in key contributions by Jones and Riddell (1999, 2006), Kroft et al. (2016), and Kroft et al. (2019). In these empirical studies, besides the interpretation in terms of job search, the scaling factor is viewed as capturing the share of out-of-the-labor-force workers who are 'marginally attached' to the labor market. We propose a method to estimate this factor, and we implement this method at the level of Canadian provinces.

To illustrate the practicality of our approach, we report monthly estimates of worker transition rates until the most recent publicly available LFS data as of this writing (November 2023), and use these estimates to put the recent COVID-19 recession into perspective. We document that, compared to the previous major recessionary episodes covered by the data, the main distinctive feature of the COVID-19 recession is the collapse of transition rates from unemployment to out of the labor force. While puzzling at first, these dynamics ought to be related to the unprecedented increase of the employment-to-unemployment transition rate at the onset of the pandemic. By sending an unusually high number of employed workers to unemployment, the initial shock likely shifted the composition of the unemployment pool towards workers with a stronger attachment to the labor force. Hence the observed lower rate at which the average unemployed worker drops from the labor force. Relatedly, we document that in all Canadian provinces the transition rates from unemployment to employment remained stable, or even increased, during the COVID-19 recession.

The paper contributes to a (very) large literature on worker flows and labor market dynamics. This literature provides empirical information that is essential for the development of search models of the labor market and, as mentioned in the opening paragraph, it offers valuable insights for the conduct of macroeconomic policies. Within this literature, the dynamics of Canada's labor market has been a topic of keen study; see Jones (1993), Jones and Riddell (1999), Heisz (2005), Campolieti (2011), among others, and Brochu, Créchet, and Deng (2020), Jones et al. (2020), Lemieux et al. (2020) and Jones et al. (2023) for analyses of the COVID-19 recession. Many studies have used a comparative approach between the

[2] Given the importance of transitions from unemployment to employment in driving labor market dynamics (Shimer (2012)), it is important to develop an accurate and robust treatment of these worker flows.

United States and Canada to gain a deeper understanding of the dynamics of unemployment and labor force participation; see Card and Riddell (1993), Baker, Corak, and Heisz (1998), Macklem and Barillas (2005), and Kroft et al. (2019). The comparison is naturally appealing due to the similarities between the structure of the LFS and that of the Current Population Survey, the U.S. household survey of the labor market.[3] Yet, we note that in a recent paper by Donovan, Lu, and Schoellman (2023) that studies worker flows based on microdata from rotating panel labor force surveys from 49 countries, Canada is not included due to the difficulties of working with the restricted-access microdata files (see Table A2 in Donovan, Lu, and Schoellman (2023)). With the objective of alleviating such hurdles, at the end of Section 3 which presents our empirical approach, we provide some simple step-by-step instructions for its implementation. Users of the LFS can directly utilize our estimated job search factors and these instructions to construct worker transition rates from the public files of the survey. We hope that this will help researchers and analysts track labor market conditions in Canada in a straightforward and timely manner that can also be easily publicly verified and challenged.

The paper proceeds as follows. Section 2 provides a brief presentation of the LFS data. Our approach to using these data for the measurement of worker flows and estimation of worker transition rates across employment, unemployment, and out of the labor force, is presented in Section 3. Section 4 is our descriptive analysis of labor market dynamics in recent decades and during the COVID-19 recession. Section 5 concludes.

2 The Labour Force Survey

The data that we analyze in this paper come from Statistics Canada's Labour Force Survey (LFS). The LFS is a monthly household survey. It is the main source of information for measuring unemployment statistics in Canada and is used in the administration of the Employment Insurance program. The LFS is also widely used by researchers to understand and analyze the state of the labor market and to track trends over time. The LFS is conducted nationwide, in provinces and territories. It is designed to be representative of the civilian non-institutionalized population in Canada. Each month, the survey collects labor force information from about 56,000 households for all household members aged 15 and over, in addition to basic demographic information. The LFS relies on a rotating panel design. Each household is interviewed for six consecutive months, and each month one-sixth of the sample is replaced with a new

[3] Both surveys are carried out every month, based on a rotating panel design, and available to run analyses that stretch back to January 1976. The structure and content of the questionnaire of the two surveys are also similar.

cohort of respondents (Statistics Canada (2017)).

The LFS has a long history going back to 1945; see Usalcas and Kinack (2017) and Brochu (2021). The current monthly format of the LFS was adopted in 1976. It underwent major changes in 1996 and 1997, when the questionnaire was deeply redesigned to fully exploit computer-assisted interviewing. We use data from January 1997 onwards for our main analysis to minimize the impact of these changes on our estimates. We report longer time series that include the 1976–1996 data in Appendix C.

A major advantage of the LFS for users interested in analyzing the Canadian labor market in a timely manner is that the microdata become publicly available about three weeks after the survey is conducted. To be precise, the reference week of the LFS is usually the week containing the 15th of the month; LFS interviews are conducted during the week that follows the reference week; and the microdata file is posted at the web address `https://doi.org/10.25318/71m0001x-eng` on the first Friday of the month that follows. The flip side of the coin is that the public microdata file does not include some of the information contained in the full version of the LFS microdata. Most importantly, it does not include the individual identifiers required to longitudinally match respondents across consecutive months of interviews. While this undermines some of the usefulness and potential application of the public-use data, as noted in the Introduction there are hurdles to using the full version of the LFS microdata within a Research Data Centre. And as also noted in the Introduction, there are advantages to the verifiability of using public-use microdata.

COVID-19 and the LFS

The COVID-19 pandemic raises a significant concern regarding the quality of the LFS data. The non-response rate of the survey almost tripled at the beginning of the pandemic and remained elevated throughout 2020. Brochu and Créchet (2022) thoroughly analyze the factors driving the non-response rate.[4] They show that these may have caused the LFS to underestimate the decline in employment and labor force participation between March and July of 2020. Given the uncertainty about quality, we remove data from March 2020 onwards for our main estimation.

[4] The interview modalities of the LFS changed during COVID-19: most notably, face-to-face interviews were suspended. Brochu and Créchet (2022) argue that these changes explain a large portion of the increased non-response rate of the survey.

3 Constructing worker transition rates from the public files of the LFS

With the LFS data at hand, researchers and analysts would typically describe the labor market in the following way. At any point in time, individuals are classified as being either employed (E), unemployed (U), or out of the labor force (O). Formally, the labor market in period t can be condensed in the vector

$$\ell_t = \left[\begin{array}{ccc} E_t & U_t & O_t \end{array} \right]'. \tag{1}$$

Each element of ℓ_t denotes the stock (or count) of workers in each labor market state. The evolution of ℓ_t over time is governed by the dynamics of transition probabilities across labor market state, denoted as p_t^{ij} with i and j elements of $\{E, U, O\}$. Note that there are six independent transition probabilities, since $\sum_j p_t^{ij} = 1$ for all $i \in \{E, U, O\}$.

In principle, one can estimate the p_t^{ij}'s with counts of workers computed from cross-sectional data and worker flows derived from longitudinally linked data. For example, to estimate the unemployment-to-employment transition rate p_t^{UE}, one would use the number of unemployed workers at $t-1$ to divide the number of workers who switch from unemployment (U) in $t-1$ to employment (E) in t. In practice, however, the worker flows data may be difficult to come by. This data availability issue motivates the alternative approaches presented in the next two sections.

3.1 Nakamura et al. (2020)'s approach

An unusual and advantageous feature of the LFS is that it collects information about the duration of joblessness in addition to the duration of unemployment spells.[5] In a key contribution, Kroft et al. (2019) exploit this feature to study duration dependence and gain insights into the sources of long-term joblessness. We follow NNPS20 and use this information, contained in the public microdata files of the LFS, to count N_t^s, the number of workers who are not employed in t (i.e., they are either in unemployment or out of the labor force) but were employed recently, that is to say less than four weeks before t (the superscript s stands for *s*hort term). By conditioning on the current labor force status, we in addition obtain counts of the stock of short-term unemployed workers, denoted as U_t^s. The other key measurement derived from public LFS, is the flow of workers who have switched from employment to unemployment in t, which we denote as f_t^{EU}. It is readily available from the distinction made in the LFS between

[5] Labor force surveys in most countries, including the Current Population Survey in the Unites States, collect information only about the duration of an ongoing unemployment spell.

unemployed workers who have been recently employed as opposed to those who have entered for the first time or re-entered the labor force.

As NNPS20 explain, the measurements of N_t^s, U_t^s, f_t^{EU}, together with those of E_t, U_t, O_t, are related to the transition probabilities p_t^{ij}'s through the following relations:

$$U_{t+1} = \left(1 - p_t^{UE} + p_t^{UO}\right) U_t + p_t^{EU} E_t + p_t^{OU} O_t, \tag{2}$$

$$E_{t+1} = \left(1 - p_t^{EU} - p_t^{EO}\right) E_t + p_t^{UE} U_t + p_t^{OE} O_t, \tag{3}$$

$$U_{t+1}^s = p_t^{EU} E_t + p_t^{OU} O_t, \tag{4}$$

$$N_{t+1}^s = \left(p_t^{EU} + p_t^{EO}\right) E_t, \tag{5}$$

$$f_{t+1}^{EU} = p_t^{EU} E_t. \tag{6}$$

The above is a system of five linear equations. Recall that there are six unknown p_t^{ij}.

NNPS20 then do two things. The first is to rearrange Equations (4) to (6) to calculate three out of the six transition rates, namely p_t^{EU}, p_t^{EO}, p_t^{OU}. These can be obtained through:

$$p_t^{EU} = \frac{f_{t+1}^{EU}}{E_t}, \tag{7}$$

$$p_t^{EO} = \frac{N_{t+1}^s}{E_t} - p_t^{EU}, \tag{8}$$

$$p_t^{OU} = \frac{U_{t+1}^s - p_t^{EU} E_t}{O_t}. \tag{9}$$

For the remaining unknowns, namely p_t^{UO}, p_t^{UE}, p_t^{OE}, the combination of (2) and (4) yields

$$p_t^{UO} = \frac{1}{U_t} \left(E_t - E_{t+1} + U_t - U_{t+1} + U_{t+1}^s - N_{t+1}^s + p_t^{OE} O_t\right), \tag{10}$$

while Equations (3) and (5) put together give

$$p_t^{UE} = \frac{1}{U_t} \left(E_{t+1} - E_t + N_{t+1}^s - p_t^{OE} O_t\right). \tag{11}$$

Equations (10) and (11) show clearly that knowledge of p_t^{OE} – the only unknown on the right-hand side of these equations – is enough to obtain the two probabilities of transitioning out of unemployment, p_t^{UO}

and p_t^{UE}.

We show in Appendix A that the rest of NNPS20's approach to measuring worker transition rates from the public files of the LFS involves postulating that:

$$p_t^{UO} = p_t^{UE} \tag{12}$$

to pin down p_t^{OE}. This is an appealing solution because Equation (12) together with Equations (2)–(6) yields a linear system of six equations with six unknown for any given time period t. The major downside to this solution, however, is that Equation (12) is counterfactual. In Appendix A, we show, using estimates based on the restricted LFS files from Kostyshyna and Luu (2019), that $p_t^{UO} = p_t^{UE}$ does not hold in the data, not even on average, and is also not an accurate description of the cyclical behaviors of the two transition probabilities. This motivates us to develop an alternative solution method.

3.2 New proposed approach

Our approach to address the calculation of the remaining transition rates, p_t^{UO}, p_t^{UE}, and p_t^{OE}, is motivated by a set of theoretical studies that extend the standard equilibrium job search model to include a labor force participation margin; see Garibaldi and Wasmer (2005), Pries and Rogerson (2009), and Lalé (2018). In these studies, workers who are out of the labor force in a given period t may still receive a job offer to become employed in $t+1$. That is, they search for jobs, but at a lower rate compared to the unemployed who are supposed to be individuals who put in the highest effort to search. In other words, we should have $p_t^{OE} > 0$ and $p_t^{OE} \leq p_t^{UE}$. A convenient way to capture these relations is to introduce a new parameter, which we denote as r, to measure the $r$elative search intensity of individuals out of the labor force, compared to unemployed workers.[6] We have:

$$p_t^{OE} = r p_t^{UE}. \tag{13}$$

Note that we assume r to be constant over time. The approach presented below to estimate r exploits variations of the transition rates over time, and as such it makes it difficult to recover a time series for r. We did explore a few specifications allowing r to contain a cyclical component or a slow-moving trend,

[6] In the key contributions by Jones and Riddell (1999, 2006), Kroft et al. (2016), and Kroft et al. (2019), r is related to the subset of out-of-the-labor-force workers who are 'marginally attached' to the labor market.

but the results were mostly inconclusive.[7] In sum, even if it is conceivable that r varies over time, we focus on a method that recovers the average value of r.

Equation (13) is appealing not only because r has a direct interpretation in terms of search theory, but also because it provides a simple approach to computing p_t^{UO} and p_t^{UE}. Indeed, by plugging (13) into Equations (10) and (11), we obtain

$$p_t^{UO} = \frac{1}{U_t}\left(E_t - E_{t+1} + U_t - U_{t+1} + U_{t+1}^s - N_{t+1}^s + r p_t^{UE} O_t\right), \tag{14}$$

and

$$p_t^{UE} = \frac{E_{t+1} - E_t + N_{t+1}^s}{U_t + rO_t}. \tag{15}$$

That is, r gives us p_t^{UE}, and then we obtain p_t^{OE} and p_t^{UO} from respectively Equations (13) and (14).

There remains the question of how to determine r. To answer this question, we build on a well-known property of labor market stocks and flows in markets with high turnover rates – such as the Canadian labor market – that the steady-state labor market stocks associated with the contemporaneous p_t^{ij}'s come very close to the actual ones (Shimer (2012); Elsby, Hobijn, and Şahin (2013)). That is, when labor market transition rates are high, convergence towards the steady state can be almost completed within a few periods, so that ℓ_t is well approximated by $\bar{\ell}_t$, the vector of steady-state labor market stocks. Consider further the steady-state labor market vector $\bar{\ell}_t(r)$ that can be computed for any given r. We use it to pin down the arguably preferred value of r, denoted as r^*, through:

$$r^* = \min_r \left\{\frac{1}{T}\sum_{t=1}^{T}\left\|\bar{\ell}_t(r) - \ell_t\right\|\right\}, \tag{16}$$

s.t.

$$0 \leq p_t^{UE} \leq 1 \quad , \quad 0 \leq p_t^{UO} \leq 1, \quad \text{for all } t = 1, \ldots, T. \tag{17}$$

In (16), T denotes the sample size; the objective function is the average distance between the actual labor market stocks and those implied by the steady-state approximation from a given r; and the constraints (17) ensure that the implied transition rates out of unemployment are probabilities in any period t.

Table 1 presents our estimates of r^* for the larger Canadian provinces or groups of provinces.[8] The

[7] We considered variants of a simple model where $r_t = \exp(\alpha_0 + \alpha_1 y_t^c)$, where α_0 and α_1 are the parameters to be estimated and y_t^c the cyclical component of GDP. The estimation returned α_1 close to zero. We obtained similar inconclusive results when we allowed for a linear time trend in r_t, as well as when we combined cyclical and time trend components.

[8] We use data from January 1997 through February 2020 to estimate r^* to minimize the impact of the 1996-1997 methodological changes and the disruptions brought about by the COVID-19 pandemic; see Section 2.

Table 1: Estimated relative search intensity from out of the labor force

	British Columbia	Prairies	Ontario	Québec	Atlantic
	(1)	(2)	(3)	(4)	(5)
r^*	16.2	15.2	12.3	13.4	11.3

Notes: The table report the estimated relative search intensity from out of the labor force, r^*, for each province or group of provinces. All table entries are expressed in percent.

values that we obtain are typically between 11 and 16 percent. This finding is remarkable because it lines up closely to the ratio between p_t^{OE} and p_t^{UE} from the restricted access LFS data described in Table A1 of Appendix A. Indeed, when we analyze p_t^{OE}/p_t^{UE}, we find that it ranges between 11.7 and 22.8 percent over the sample period, with an average value of 16.5 percent. When we exclude 2000-01 from this analysis, which is when p_t^{OE} seems to jump above trend, we find that the average of p_t^{OE}/p_t^{UE} is 15.9 percent, with values ranging between 11.7 and 19.4 percent. Given the overlap, we are confident that the estimates of r^* in Table 1 can reliably be used to construct estimates from the public files of the LFS.

3.3 Putting it all together

We summarize our approach as a series of simple step-by-step instructions that can be applied by users of the LFS who are interested in obtaining timely estimates of labor market conditions:

1. Compute E_t, U_t, O_t, U_t^s, N_t^s, f_t^{EU} directly from the public microdata files of the LFS;
2. (Optional) Remove systematic seasonal variation. This can be done by applying the U.S. Census Bureau's X-13ARIMA-SEATS program;
3. Compute p_t^{EU}, p_t^{EO}, p_t^{OU} by using Equations (7), (8), and (9), respectively;
4. Obtain r^* by solving the minimization problem described in (16)–(17). Alternatively, use the r^* reported in Table 1 to move on to the next step;
5. Compute p_t^{OE}, p_t^{UE}, p_t^{UO} by using Equations (13), (14), and (15);
6. (Optional) Clear the transition probabilities from time aggregation bias.

In Step 4 of the proposed approach, we suggest using the r^* from Table 1 to skip solving problem (16)–(17). While doing this, users of the LFS should be wary of the fact that the constraints $0 \leq p_t^{UE} \leq 1$ and $0 \leq p_t^{UO} \leq 1$ might not be always satisfied, if they use data for other time periods and/or restrict the data to certain groups of workers or segments of the labor market.

While Steps 2 and 6 in the above set of instructions may be considered as optional (and are flagged as such), we include them as part of our proposed approach and recommend implementing them. Since Step 2 is common practice in the literature, it improves the comparability of the resulting p_t^{ij}'s with existing available estimates.[9] Regarding Step 6, we note that the literature on labor market dynamics has long demonstrated the importance of clearing data from time aggregation bias, i.e. adjusting for the fact that the discrete-time (monthly) probabilities miss some of the transitions that occur at a higher frequency (see Elsby, Michaels, and Solon (2009), Shimer (2012) and Elsby, Hobijn, and Şahin (2015)). In Step 6, we adapt Shimer (2012)'s continuous-time correction to our setup to address this bias. It should be pointed out that this correction *jointly* adjusts the transition probabilities. So, even though $p_t^{EU}, p_t^{EO}, p_t^{OU}$ can be computed out of the LFS data independently of the estimated r^* (Step 3), in our final estimates they are impacted by r^* through the correction of time-aggregation bias. A formal description of Step 6 is provided in Appendix B.

4 Recent labor market dynamics

In this section, we use the estimated transition probabilities to provide a brief account of the recent dynamics of worker flows in Canada's labor market. We begin with a description of the average behavior of the time series, then we analyze changes over time, and focus on the dynamics during the pandemic recession.

4.1 Average behavior

Table 2 reports the average of transition rates across employment, unemployment, and inactivity, in the larger Canadian provinces or groups of provinces. The first remark concerns the comparison of p_t^{UE} and p_t^{UO} in this table vs. those based on the restricted access LFS microdata in Table A1, and vs. those implied by NNPS20's approach. As can be seen, Table 2 puts p_t^{UE} at between 21.9 and 26.7 percent, depending on the province considered. This is well in line with the national average of 23.4 percent from

[9]Obviously, one should skip Step 2 when seasonality is the explicit topic of interest, as in Jones (1993).

Table 2: Average of monthly transition rates, 1997–2019

	British Columbia (1)	Prairies (2)	Ontario (3)	Québec (4)	Atlantic (5)
p_t^{EE}	96.4	96.8	96.7	96.1	94.7
p_t^{EU}	1.6	1.4	1.4	1.8	2.8
p_t^{EO}	2.0	1.8	2.0	2.1	2.5
p_t^{UE}	21.9	26.7	22.7	23.9	25.9
p_t^{UU}	58.1	53.2	62.0	63.9	64.9
p_t^{UO}	19.9	20.0	15.3	12.2	9.2
p_t^{OE}	3.0	3.4	2.5	2.5	2.5
p_t^{OU}	3.1	3.8	3.3	2.9	2.8
p_t^{OO}	93.9	92.9	94.1	94.6	94.7

Notes: LFS (public) data, 1997m01–2019m12. The table reports, for each transition rate, its average value over the period analyzed. All table entries are expressed in percent.

Kostyshyna and Luu (2019)'s data in Table A1 of the Appendix. Also, we find that p_t^{UO} is on average lower than p_t^{UE}. The average values for British Columbia and the Prairies are very close to the national average of 18.8 percent in Table A1, while for Ontario, Québec and the Atlantic, we find average values that are lower by several percentage points.[10] We note that NNPS20's approach implies, by construction, that p_t^{UE} and p_t^{UO} should have the same average value within each province or groups of provinces. This implication is clearly rejected by the data in Table 2.

Second, the estimates reveal differences across provinces in the rates at which workers leave employment, i.e. differences in p_t^{EU} and p_t^{EO}. As can be seen in Table 2, the employment-to-unemployment transition rate is on average twice higher in the Atlantic than in the Prairies or Ontario (2.8 vs. 1.4 percent). Further analyses not reported here show that these differences are driven by a few occupations and industries that have different turnover rates across provinces. For instance, 'natural resources, agriculture and related production occupation' have a much higher rate of job separation in the Atlantic compared

[10] One of the sources of difference between the estimates reported in Table 2 and those based on Kostyshyna and Luu (2019)'s Table A1 of the Appendix is that the latter are not adjusted for time aggregation bias. The correction for time aggregation typically shifts transition rates from unemployment to inactivity downwards by several percentage points.

with the other provinces.[11] While these differences are interesting in their own right, they are also useful to point out in light of the step-by-step instructions presented at the end of Section 3. Recall that p_t^{EU} and p_t^{EO} are only indirectly impacted by the calculation of r^*. This suggests that the differences in worker turnover uncovered in Table 2 are genuine as opposed to being a consequence of the different values of r^* from Table 1.

Last, Table 2 shows differences across provinces in the persistence of unemployment measured by p_t^{UU}. One possible interpretation is that these differences stem from the trade-off between searching for work from unemployment vs. searching from out of the labor force. Consider for example the differences between Québec and the Prairies. In Québec, search from out of the labor force as captured by r^* is less effective than in the Prairies (Table 1). It could be that, due to this difference, workers in Québec are less likely to move back and forth between unemployment and out of the labor force (lower p_t^{UO} and p_t^{OU} on average), and more likely to remain in unemployment (higher p_t^{UU}) to search for jobs than workers in the Prairies. Another way to think about these differences is that r^* could be measuring average search effort among the cross-section of workers who are out of the labor force. Suppose that the workers who search harder remain in the pool of unemployment in Québec. Then this would explain the lower p_t^{UO} and result in lower average search effort r^* among those who are out of the labor force.

4.2 Recent dynamics

Next, we take a look at the dynamics behavior of the six transition rates. Figure 1 shows their time series along with the gray bands that denote the recession episodes of the sample period.[12] Figure C1 in the Online Appendix extends these plots to include data from the period 1976–1996. In both sets of plots, readers who are familiar with the literature on worker flows and labor market dynamics will recognize a number of common patterns. First, job separation rates, measured by p_t^{EU} and p_t^{EO}, increase markedly during recessions. Second, the probability to find a job from either unemployment or out of the labor force, i.e. p_t^{UE} and p_t^{OE}, decreases during downturns and remains lower for a prolonged period of time following the recession trough. These cyclical movements are not as pronounced as those observed in U.S. time series (see Elsby, Michaels, and Solon (2009), Fujita and Ramey (2009), and Shimer (2012)). Third,

[11]It is also interesting to note that, with exception of the Atlantic, the provinces exhibit higher rates of job separation towards inactivity (p_t^{EO}) than to unemployment (p_t^{EU}).

[12]We use the dates of recession periods identified by the C.D. Howe Institute Business Cycle Council; see https://www.cdhowe.org/council/business-cycle-council. The Council performs functions similar to the Business Cycle Dating Committee of the National Bureau of Economic Research in the United States. According to the Council, the Great Recession in Canada started in October of 2008 and lasted until May of 2009, while for the COVID-19 recession the beginning and end dates are February and April of 2020.

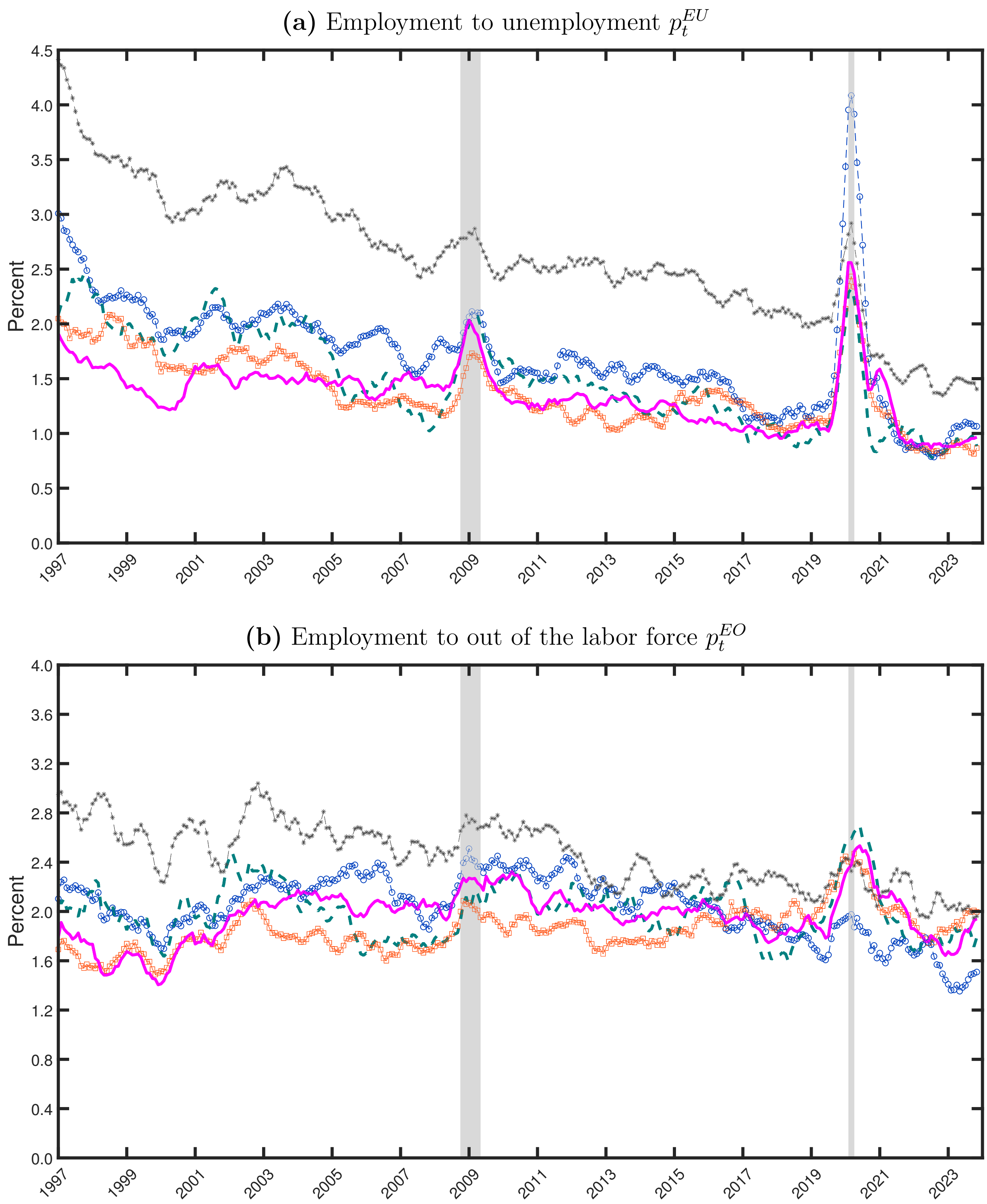
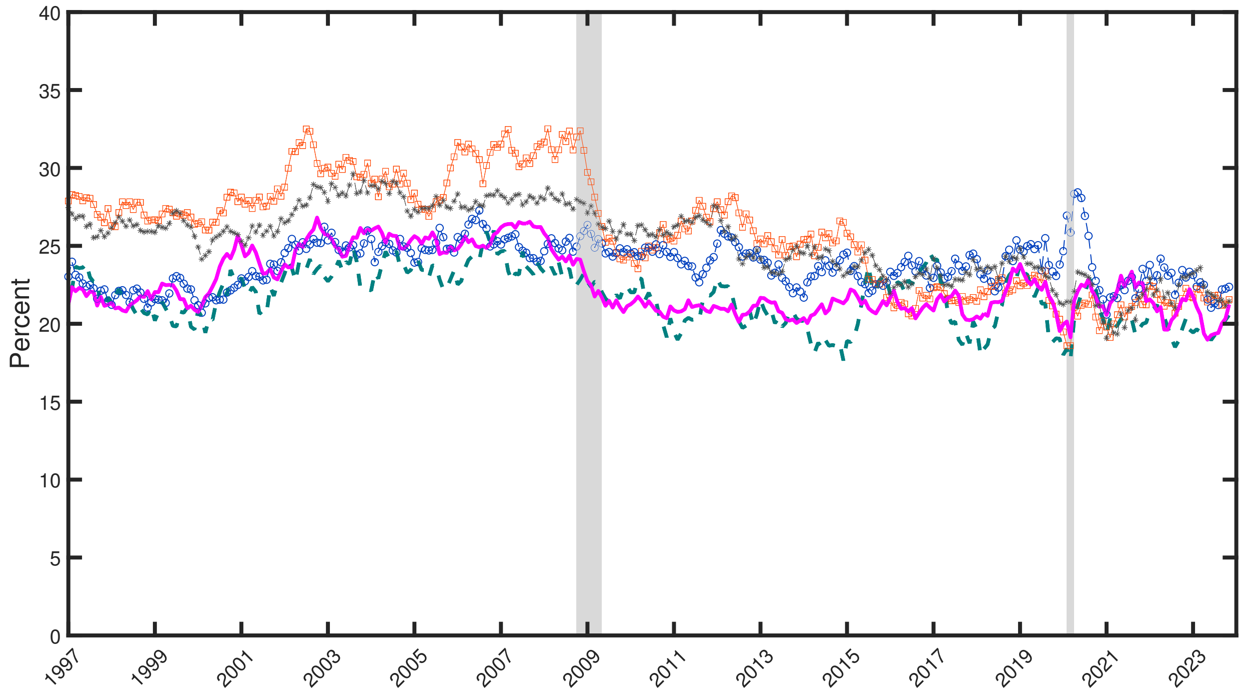


Figure 1: Monthly transition rates, 1997–2023

Notes: LFS (public) data, 1997m01 – 2023m11. The figure shows the time series of monthly transition rates. All series are adjusted for seasonality and time aggregation bias, and smoothed using a three-period, two-sided moving-average. All series are expressed in percent. Gray-shaded areas indicate recession periods. Dashed lines (--): British Columbia; Squares (□): Prairies; Solid lines (–): Ontario; Circles (○): Québec; Asteriks (*): Atlantic.

(c) Unemployment to employment p_t^{UE}



(d) Unemployment to out of the labor force p_t^{UO}

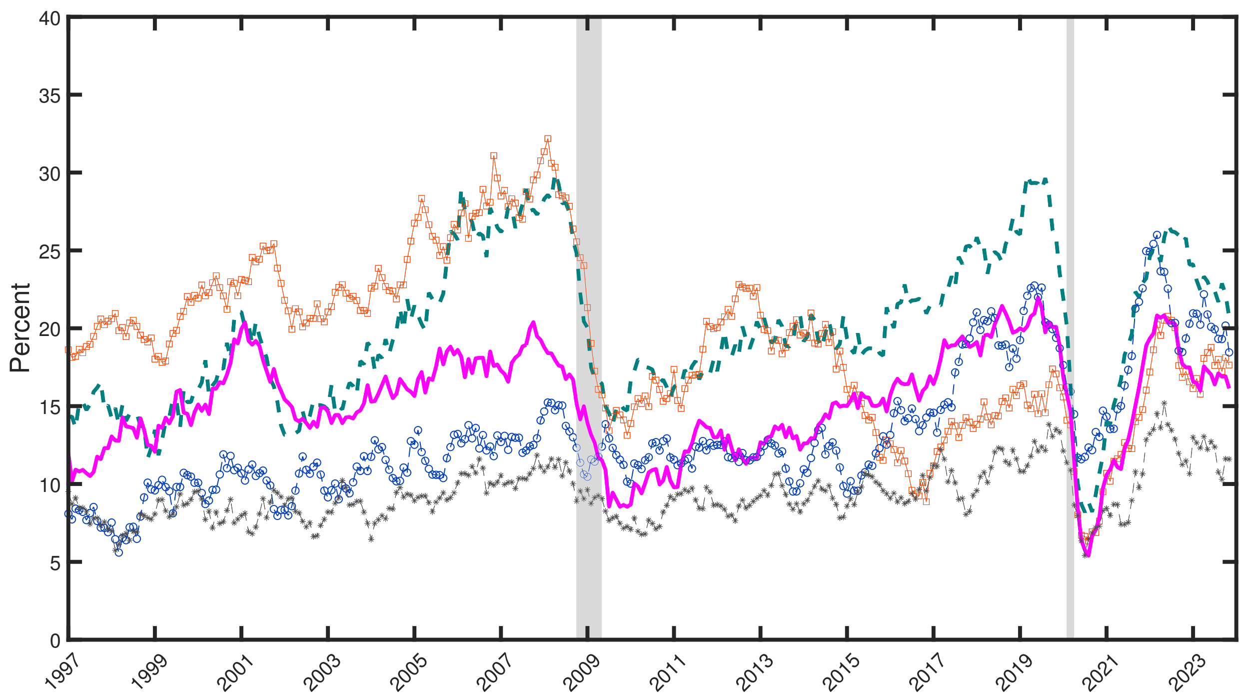
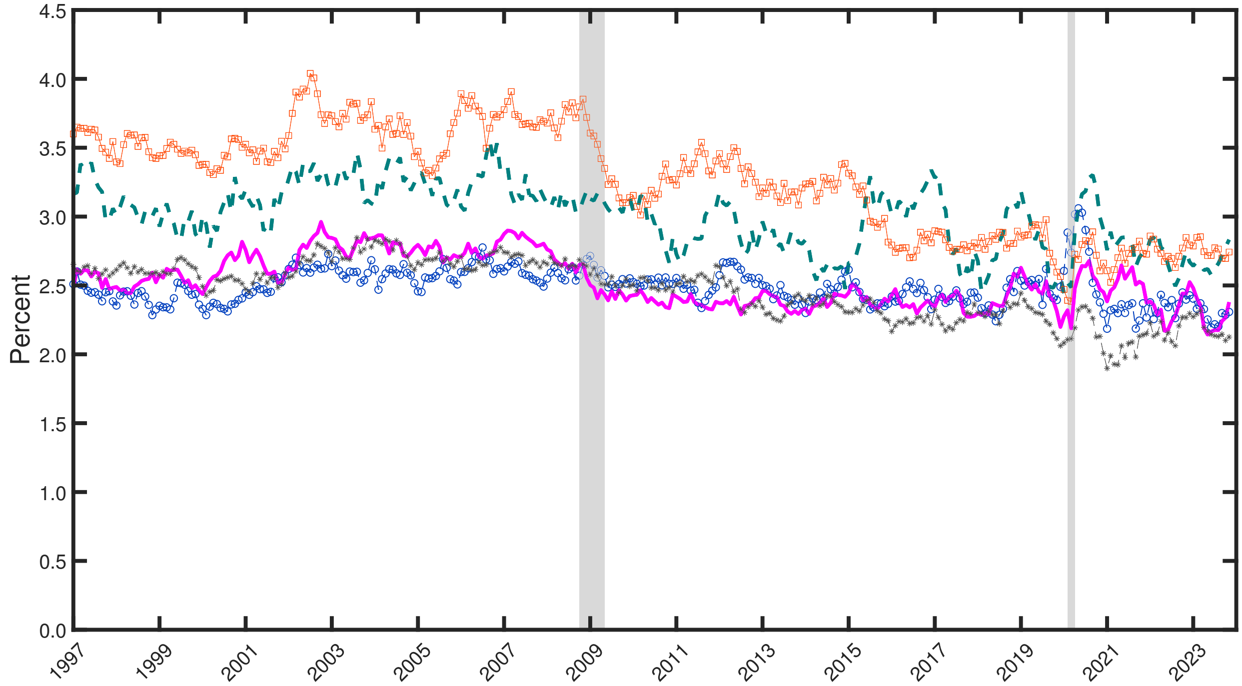


Figure 1(cont'd): Monthly transition rates, 1997–2023

Notes: LFS (public) data, 1997m01 – 2023m11. The figure shows the time series of monthly transition rates. All series are adjusted for seasonality and time aggregation bias, and smoothed using a three-period, two-sided moving-average. All series are expressed in percent. Gray-shaded areas indicate recession periods. Dashed lines (--): British Columbia; Squares (□): Prairies; Solid lines (–): Ontario; Circles (○): Québec; Asteriks (*): Atlantic.

(e) Out of the labor force to employment p_t^{OE}



(f) Out of the labor force to unemployment p_t^{OU}

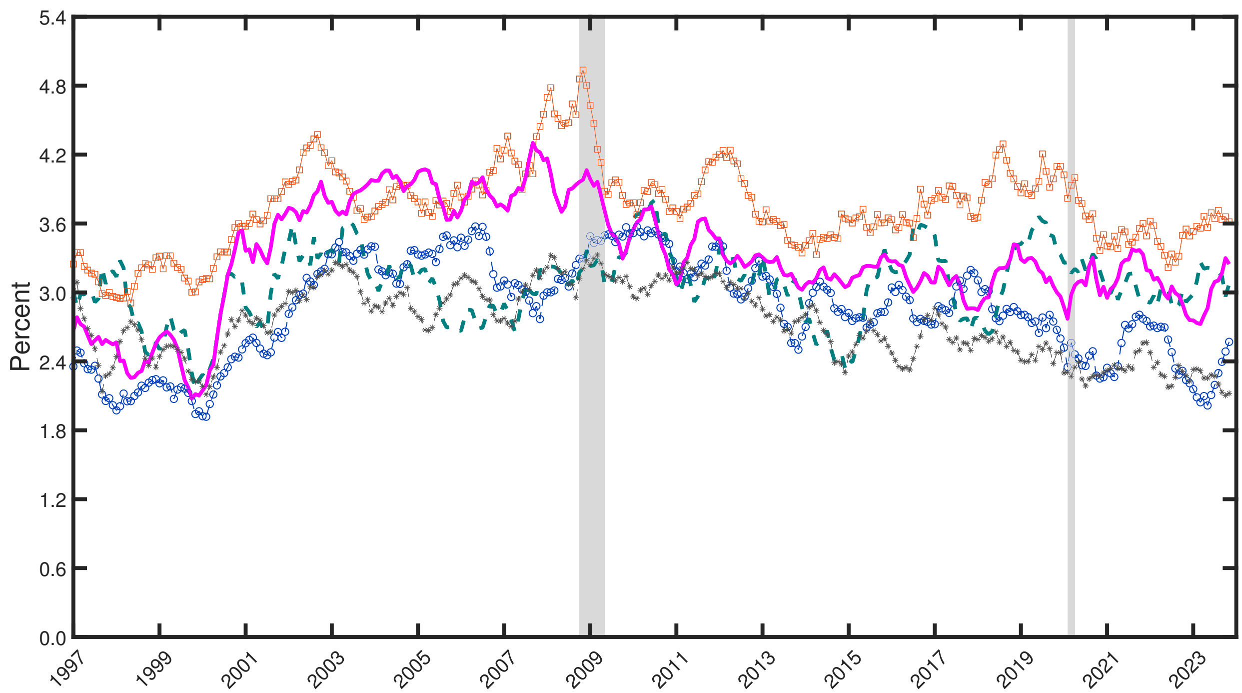


Figure 1(cont'd): Monthly transition rates, 1997–2023

Notes: LFS (public) data, 1997m01 – 2023m11. The figure shows the time series of monthly transition rates. All series are adjusted for seasonality and time aggregation bias, and smoothed using a three-period, two-sided moving-average. All series are expressed in percent. Gray-shaded areas indicate recession periods. Dashed lines (--): British Columbia; Squares (□): Prairies; Solid lines (–): Ontario; Circles (○): Québec; Asteriks (*): Atlantic.

the probability to drop from the labor force from unemployment, that is to say p_t^{UO}, is procyclical.[13] Last, in the long run, there is a decrease in the employment-to-unemployment transition rate. A similar secular decline of p_t^{EU} has been observed in data for the U.S. (see, e.g., Fujita (2018)).

It is interesting to point out a few differences between Canadian provinces in the cyclical behavior of worker flows that emerge in Figure 1. Most strikingly, the unemployment-to-employment transition rate, p_t^{UE}, is less clearly synchronized with the business cycle in Québec than in Ontario or the Prairies. A similar pattern holds for the transition rate from out of the labor force to employment, p_t^{OE}. We note that these results for the Prairies are consistent with Campolieti (2011) who finds that the unemployment-to-employment hazard rate accounts for more than 90 percent of unemployment fluctuations in Manitoba. Another difference between Canadian provinces concerns the transition rate from unemployment to out of the labor force p_t^{UO} during the Great Recession. It remained roughly constant in Québec during the downturn, while it fell precipitously in the other provinces. In the remaining paragraphs, we discuss the sources of cyclical changes of p_t^{UO} alongside changes in the other transition rates.

COVID-19 recession

Last, we seek to provide a more detailed analysis of the COVID-19 recession. As mentioned in Section 2, there is a major caveat to this analysis. The LFS suffered a large increase in non-response at the beginning of the pandemic. As this non-response is correlated with worker characteristics such as education and age, it may bias unemployment and labor force participation estimates derived from the 2020 LFS data (Brochu and Créchet (2022)). Besides this, comparisons of the standard labor force categories – employment, unemployment, out of the labor force – between the beginning of the pandemic and 'normal times' are potentially misleading due to the large changes in the underlying composition of each category. At the beginning of the COVID-19 recession, there is a large increase in the number of workers classified as "Employed – Absent" and "Unemployed – Temporary layoff" that typically make up only a small share of, respectively, employment and unemployment, and there are also large changes in the composition of the pool of out-of-the-labor-force workers; see Jones et al. (2020, 2023) for details and further discussions.

In Table 3, we report the pre-pandemic average of transition rates as well as their value at the end of the first lockdown, when unemployment was at its highest. The italicized numbers in parentheses in the Table show the percent changes between the two points in time. It is clear, in both Figure 1 and Table 3, that the largest change in quantitative terms was the increase in the unemployment-to-employment

[13] Similar movements in p_t^{UO} are found in U.S. data; see Elsby, Hobijn, and Şahin (2015) and Elsby et al. (2019).

Table 3: Monthly transition rates during the COVID-19 recession

		British Columbia (1)		Prairies (2)		Ontario (3)		Québec (4)		Atlantic (5)	
p_t^{EU}	2019Q4	1.4	*(+68.0)*	1.6	*(+46.9)*	1.5	*(+75.9)*	2.0	*(+115)*	2.3	*(+18.8)*
	2020Q2	2.4		2.3		2.6		4.2		2.7	
p_t^{EO}	2019Q4	2.3	*(+10.5)*	2.4	*(-1.3)*	2.3	*(+6.7)*	2.1	*(-4.5)*	2.3	*(+1.4)*
	2020Q2	2.5		2.3		2.5		2.0		2.3	
p_t^{UE}	2019Q4	17.2	*(+18.8)*	20.2	*(+1.5)*	21.0	*(+3.5)*	20.8	*(+41.6)*	21.3	*(+8.0)*
	2020Q2	20.5		20.5		21.8		29.4		23.0	
p_t^{UO}	2019Q4	30.2	*(-62.9)*	18.5	*(-54.8)*	18.3	*(-53.1)*	19.2	*(-40.6)*	16.1	*(-65.4)*
	2020Q2	11.2		8.4		8.6		11.4		5.6	
p_t^{OE}	2019Q4	2.2	*(+32.2)*	2.5	*(+5.8)*	2.4	*(+6.9)*	2.2	*(+46.5)*	2.1	*(+14.1)*
	2020Q2	2.9		2.7		2.6		3.2		2.4	
p_t^{OU}	2019Q4	3.4	*(-6.1)*	4.1	*(-5.8)*	2.9	*(-2.2)*	2.8	*(-15.8)*	2.3	*(-9.6)*
	2020Q2	3.2		3.8		2.9		2.4		2.1	

Notes: LFS (public) data. The table reports, for each transition probability, its average value during the fourth quarter of 2019 and second quarter of 2020, and in parenthesis the relative change between the two values. All table entries are expressed in percent.

transition rate, p_t^{EU}. This is not surprising, however, given decisions to shut down the economy to curb the COVID-19 pandemic. What is perhaps more surprising is the very large drop in the transition rates from unemployment to out of the labor force during the pandemic: -62.9 percent in British Columbia, -53.1 percent in Ontario and -40.6 percent in Québec. p_t^{UO} suffered a larger drop (by a peak-to-through percent change metric) during COVID-19 than in the Great Recession.

As discussed in Elsby, Hobijn, and Şahin (2015), Hall and Schulhofer-Wohl (2018), and also in Jones et al. (2023) in the context of the pandemic, heterogeneity among the non-employed is key to understand patterns of changes in the outflow rates.[14] This suggests thinking of p_t^{UO} as the average rate measured across a population of unemployed workers with varying degrees of labor force attachment. Consider the

[14] Jones et al. (2023) provide an insightful description of the dynamics of the Canadian labor market through the lens of search and matching theory. They contrast the initial period of the pandemic, which they called "tied" or "attached", to the period from about May 2020 onwards, called the "non-tied" or "unattached" phase (although, as the authors point out, elements of the first phase persist throughout 2020). In the tied phase, most workers have been separated from their jobs only temporarily, and as a result they may quickly return to employment when conditions improve. In contrast, in the non-tied phase, most individuals who are not working can regain employment only by going through the usual search and matching process.

very large increase of the employment-to-unemployment transition rate at the onset of the pandemic. By sending an unusually high number of employed workers to unemployment, the initial shock likely shifted the composition of the unemployment pool towards workers with a stronger attachment to the labor force. As a result, the rate at which the average unemployed worker drops from the labor force, p_t^{UO}, decreases. In line with this interpretation, we note that the transition rates from unemployment to employment, p_t^{UE}, remain elevated during the pandemic – this transition rate actually increases during the COVID-19 recession. This suggests that the pool of unemployment shifted markedly towards workers who could return to employment quickly, presumably because they were getting recalled to their previous job.[15]

5 Conclusion

We develop a method to obtain monthly rates of worker turnover between employment, unemployment, and inactivity, from the publicly available microdata files of the Labour Force Survey (LFS). Our key contribution lies in estimating and applying a scaling factor that has been proposed in earlier research as a way of capturing the relative intensity of job search from inactivity compared to unemployment. This factor provides enough structure to avoid splitting the unemployment outflows between employment and inactivity in an arbitrary manner. A major advantage of our method is its applicability, through a few simple step-by-step instructions, to near real-time LFS data, enabling timely assessments of labor market conditions in Canada. Another important advantage is the verifiability of calculations associated with public-use data. More generally, the proposed method expands the possibilities afforded by the public files of the LFS, which should prove valuable given the costs associated with accessing and working with the confidential microdata.

While we illustrate the usefulness of our approach by using the estimates to describe the labor market impacts of the COVID-19 pandemic, there exist several additional empirical applications to explore. First, our estimates reveal some differences across Canadian provinces not only in the average rates of worker turnover but also in their cyclical behaviors. It would be interesting for future work to analyze the sources of these differences. Second, we document that the transition rates from employment to unemployment have fallen secularly over time, a trend observed in U.S. data as well. This prompts the question of whether Canada's labor market is also experiencing decreased dynamism. Lastly, our proposed method

[15] As pointed out by Jones et al. (2023) (see the previous footnote), during the "tied" phase, there is an usually high number of individuals who have a job but are absent from work and individuals on temporary layoff unemployment. Having maintained linkages with their employer, these workers contribute to shifting upwards the average p_t^{UE}.

can also be applied to obtain rates of worker turnover between employment, unemployment, and inactivity separately for different demographic groups. This would be a worthwhile avenue for future work to explore heterogeneity in worker's trajectories in the Canadian labor market.

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Appendices

A Details and discussion of NNPS20

In this Appendix, we provide details on NNPS20's approach of calculating p_t^{OE}. We then discuss some of its implications by using estimates based on data from the restricted LFS files.

The following citation from NNPS20 describes the authors' calculation:

> *"We assume that the probability of a transition from labor force inactivity to employment, p^{OE} is the midpoint of its boundary values in each period. We can bound p^{OE} by noting that p^{UO}, p^{UE}, and p^{OE} should be non-negative."* (Nakamura et al. (2020, p.7)).

We seek to make the above citation explicit by translating it into a few equations. The first task is to derive the two boundary values of p_t^{OE} implied by the non-negativity constraints $p_t^{UO} \geq 0$ and $p_t^{UE} \geq 0$ (recall from Equations (10) and (11) that, given measurements of the different stocks, p_t^{UO} and p_t^{UE} are fully determined by p_t^{OE}). We have

$$\begin{aligned} p_t^{UO} \geq 0 &\Leftrightarrow \frac{1}{U_t}\left(E_t - E_{t+1} + U_t - U_{t+1} + U_{t+1}^s - N_{t+1}^s + p_t^{OE} O_t\right) \geq 0 \\ &\Leftrightarrow p_t^{OE} \geq \frac{1}{O_t}\left(E_{t+1} - E_t + U_{t+1} - U_t + N_{t+1}^s - U_{t+1}^s\right), \end{aligned}$$

which yields the lower bound

$$\underline{p}_t^{OE} = \frac{1}{O_t}\left(E_{t+1} - E_t + U_{t+1} - U_t + N_{t+1}^s - U_{t+1}^s\right). \tag{A.1}$$

The other constraint yields

$$\begin{aligned} p_t^{UE} \geq 0 &\Leftrightarrow \frac{1}{U_t}\left(E_{t+1} - E_t + N_{t+1}^s - p_t^{OE} O_t\right) \geq 0 \\ &\Leftrightarrow \frac{1}{O_t}\left(E_{t+1} - E_t + N_{t+1}^s\right) \geq p_t^{OE}, \end{aligned}$$

which in turn gives the upper bound

$$\overline{p}_t^{OE} = \frac{1}{O_t}\left(E_{t+1} - E_t + N_{t+1}^s\right). \tag{A.2}$$

Next, NNPS20's approach is to set p_t^{OE} to "the midpoint of its boundary values in each period, i.e.

$$\begin{aligned} p_t^{OE} &= \frac{1}{2}\left(\underline{p}_t^{OE} + \overline{p}_t^{OE}\right) \\ \Leftrightarrow p_t^{OE} &= \frac{1}{O_t}\left(E_{t+1} - E_t + N_{t+1}^s + \frac{U_{t+1} - U_t - U_{t+1}^s}{2}\right). \end{aligned} \tag{A.3}$$

Plugging this back into (10) to compute p_t^{UO}, we obtain:

$$\begin{aligned} p_t^{UO} &= \frac{1}{U_t}\left(E_t - E_{t+1} + U_t - U_{t+1} + U_{t+1}^s - N_{t+1}^s + \left(E_{t+1} - E_t + N_{t+1}^s + \frac{U_{t+1} - U_t - U_{t+1}^s}{2}\right)\right) \\ \Leftrightarrow p_t^{UO} &= \frac{1}{U_t}\left(U_t - U_{t+1} + U_{t+1}^s + \frac{U_{t+1} - U_t - U_{t+1}^s}{2}\right) \\ \Leftrightarrow p_t^{UO} &= \frac{1}{2}\frac{U_t + U_{t+1}^s - U_{t+1}}{U_t}. \end{aligned} \tag{A.4}$$

Similarly, plugging (A.3) into Equation (11) to obtain p_t^{UE}, we have:

$$\begin{aligned} p_t^{UE} &= \frac{1}{U_t}\left(E_{t+1} - E_t + N_{t+1}^s - \left(E_{t+1} - E_t + N_{t+1}^s + \frac{U_{t+1} - U_t - U_{t+1}^s}{2}\right)\right) \\ \Leftrightarrow p_t^{UE} &= \frac{1}{2}\frac{U_t + U_{t+1}^s - U_{t+1}}{U_t}. \end{aligned} \tag{A.5}$$

Equations (A.4) and (A.5) put together imply that $p_t^{UO} = p_t^{UE}$, i.e. Equation (12) in the main text.

It is also useful to note that the probability of remaining unemployed going from t to $t+1$ is given by

$$p_t^{UU} = \frac{U_{t+1} - U_{t+1}^s}{U_t} \Leftrightarrow 1 - p_t^{UU} = 1 - \frac{U_{t+1} - U_{t+1}^s}{U_t} = \frac{U_t + U_{t+1}^s - U_{t+1}}{U_t}. \tag{A.6}$$

This last result shows that $p_t^{UO} = p_t^{UE} = \frac{1}{2}\left(1 - p_t^{UU}\right)$.

Discussion of $p_t^{UO} = p_t^{UE}$ (Equation (12))

To confront Equation (12) to the data, we use Kostyshyna and Luu (2019)'s estimates of worker transition rates across employment, unemployment, and out of the labor force. The authors have access to the restricted microdata files of the LFS and generously agreed to share their estimates with us. Table A1 presents several descriptive statistics that characterize the behavior of these transition rates. While our focus is on p_t^{UO} and p_t^{UE}, we report results for all the p_t^{ij}'s for sake of completeness.

From the first column of Table A1, we see that the transition rate from unemployment to employment is higher than that from unemployment to out of the labor force (respectively 23.4 and 18.8 percent). The second column of the table shows that p_t^{UE} is also an order of magnitude more volatile than p_t^{UO} at business cycle frequencies: the standard deviation of its cyclical component is almost three times higher. At the same time, it is less strongly correlated with (the cyclical component of) GDP, with correlations of respectively 0.16 and 0.41 percent, as shown in the last column of Table A1. The results are readily summarized: Equation (12) does not hold in the data, not even on average, and is also not an accurate description of the cyclical behaviors of p_t^{UO} and p_t^{UE} as these are quite different from each other.

Table A1: Monthly transition rates from the restricted access files of the LFS

	Average	Cyclical component Standard deviation	Correlation with GDP
	(1)	(2)	(3)
p_t^{EE}	96.2	0.6	0.03
p_t^{EU}	1.4	11.8	-0.26
p_t^{EO}	2.4	18.4	0.06
p_t^{UE}	23.4	16.0	0.16
p_t^{UU}	57.9	5.9	-0.33
p_t^{UO}	18.8	6.1	0.41
p_t^{OE}	3.8	15.3	0.04
p_t^{OU}	3.2	12.9	-0.29
p_t^{OO}	93.0	1.0	0.11

Notes: LFS (restricted access) data, 1997m01 – 2019m09. The table reports, for each monthly transition rate, its average value (Column 1), the standard deviation of its cyclical component (Column 2) and the correlation between its cyclical component and that of GDP (Column 3). Cyclical components are extracted from the time series averaged to the quarterly frequency and taken in log as deviations from a HP trend with smoothing parameter 1,600. All table entries are expressed in percent.

B Time aggregation bias

At the last step of our method for constructing transition rates based on the public files of the LFS, we adjust the estimate to control for time aggregation bias. Our adjustment procedure is based on the continuous-time correction developed by Shimer (2012). Denote by $\boldsymbol{H}_t$ the continuous-time analog of $\boldsymbol{M}_t$. If the eigenvalues of $\boldsymbol{H}_t$ are all distinct, then $\boldsymbol{H}_t$ can be written as: $\boldsymbol{H}_t = \boldsymbol{V}_t\boldsymbol{C}_t\boldsymbol{V}_t^{-1}$, where $\boldsymbol{C}_t$ is a diagonal matrix of eigenvalues and $\boldsymbol{V}_t$ is the matrix of associated eigenvectors. Furthermore, it can be shown that $\boldsymbol{M}_t$ can be decomposed as: $\boldsymbol{M}_t = \boldsymbol{V}_t\boldsymbol{D}_t\boldsymbol{V}_t^{-1}$, where $\boldsymbol{D}_t$ is a diagonal matrix whose elements are the exponentiated eigenvalues in $\boldsymbol{C}_t$, and that this relationship is unique if the eigenvalues of $\boldsymbol{D}_t$ are, in addition to distinct, real and nonnegative. These relationships can be used to obtain time series of estimates of the adjusted hazard rates, called λ_t^{ij}. Thus, in every month t, we compute the eigenvalues of the discrete transition matrix $\boldsymbol{M}_t$ and check whether they are all distinct, real and nonnegative. We then take their natural logarithm to obtain the eigenvalues of the continuous-time analogue $\boldsymbol{H}_t$. Finally, we compute λ_t^{ij}, and use the relationship: $p_t^{ij} = 1 - e^{-\lambda_t^{ij}}$ to obtain the series of time-aggregation adjusted transition probabilities.

Online appendix

C Additional figures

Figure C1 is the analogue of Figure 1 in the main text, but it includes monthly data from 1976 through 1996. As mentioned in Section 2, there were major changes to the LFS that were implemented in 1996 and 1997. These changes do not prevent us from obtaining the same inputs from the public files of the LFS, that is to say E_t, U_t, O_t, U_t^s, N_t^s, f_t^{EU}. However, they generate a discontinuity in some of the time series in 1996–1997. To obtain the estimates reported in Figure C1, we implement the step-by-step instructions presented at the end of Section 3 and proceed in the following way. In Step 2, we remove seasonal variations by dealing separately with the 1976–1996 data. In Step 4, we skip the calculation of r^* and instead use the scaling factor reported in Table 1 for each Canadian province or group of provinces. After the implementation of Step 6 (the adjustment for time aggregation bias), we make no attempt to reconcile the estimates obtained before and after the 1996–1997 break. As shown in Figure C1, they do suffer a discontinuity in January of 1997, denoted by the vertical dotted lines. This discontinuity raises a timing issue as to when the secular decline of the unemployment-to-employment transition rate (p_t^{EU}) started. Despite the difference in levels, however, most of the cyclical properties of the transition rates (see Section 4.2) seem to be preserved.

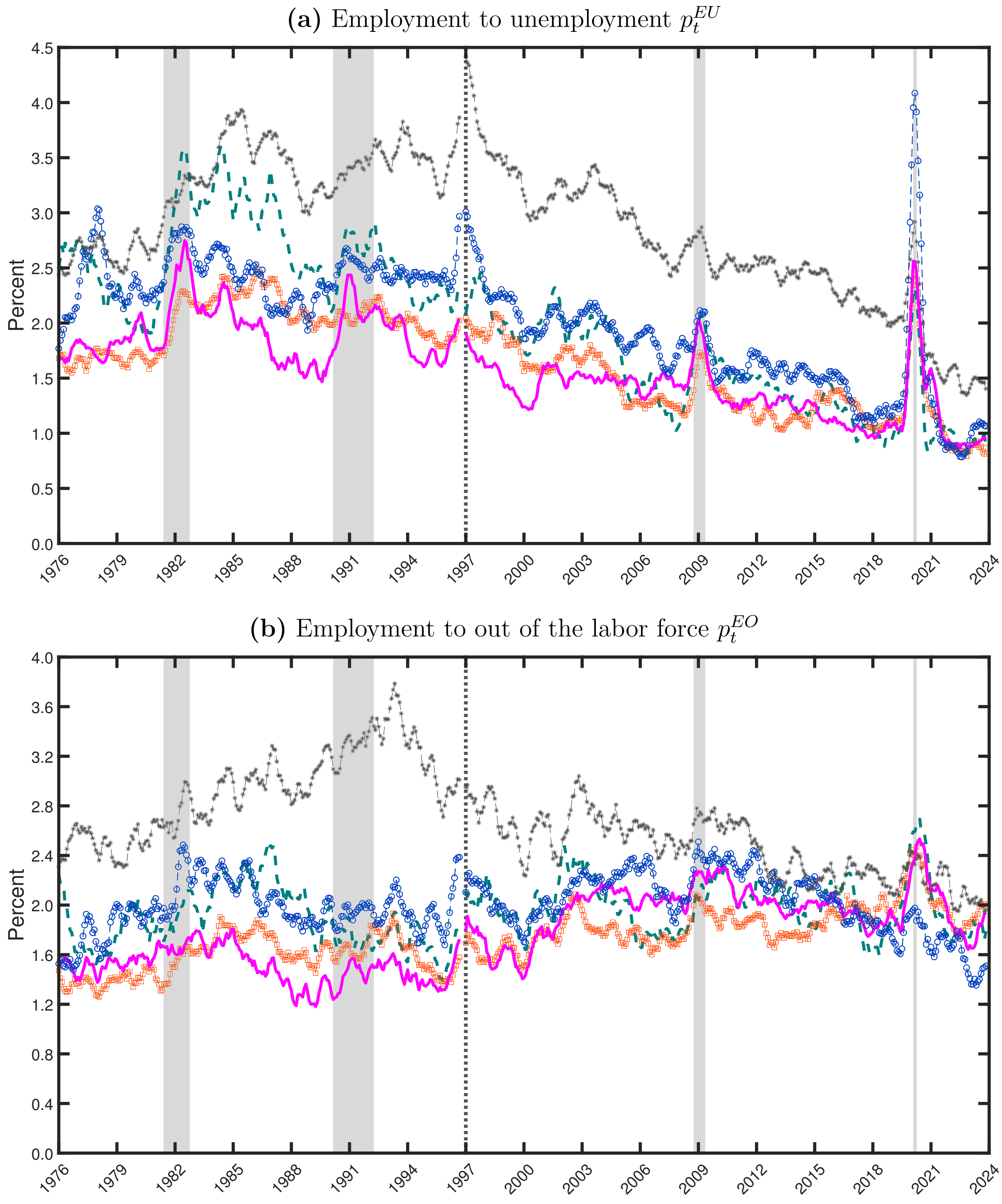
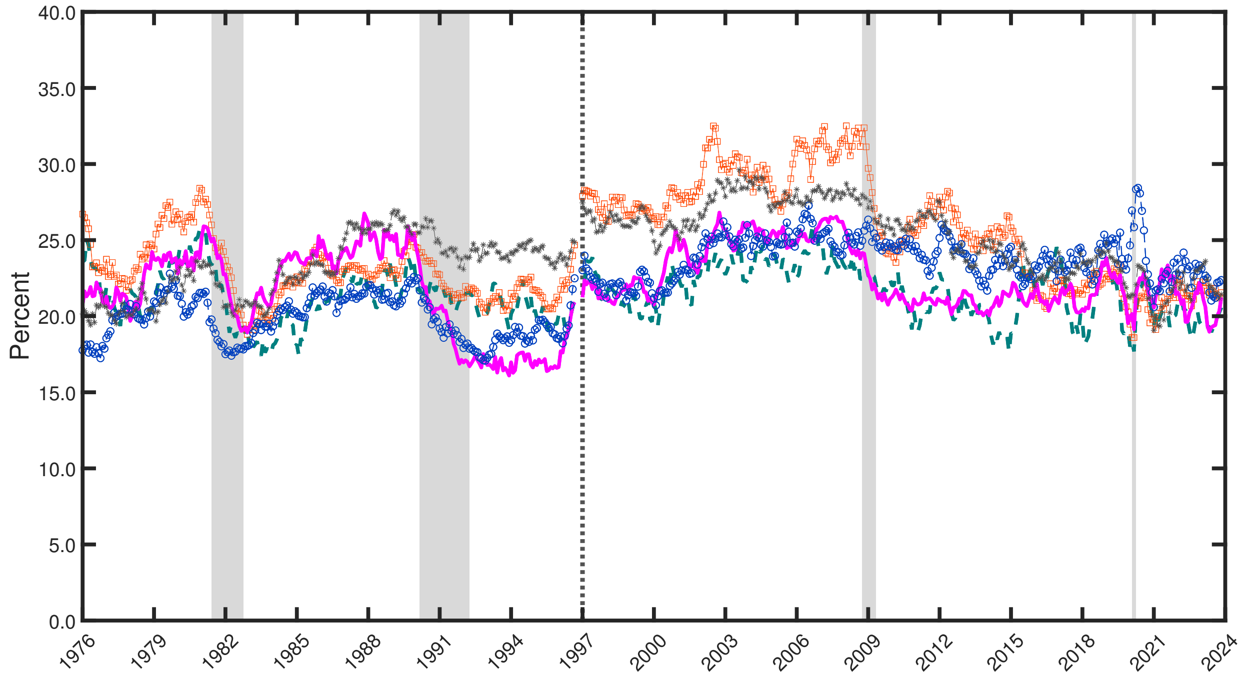


Figure C1: Monthly transition rates, 1976–2023

Notes: LFS (public) data, 1976m01 – 2023m11. The figure shows the time series of monthly transition rates. All series are adjusted for seasonality and time aggregation bias, and smoothed using a three-period, two-sided moving-average. All series are expressed in percent. The vertical dotted lines indicate January 1997; Gray-shaded areas indicate recession periods. Dashed lines (--): British Columbia; Squares (□): Prairies; Solid lines (–): Ontario; Circles (○): Québec; Asteriks (*): Atlantic.

(c) Unemployment to employment p_t^{UE}



(d) Unemployment to out of the labor force p_t^{UO}

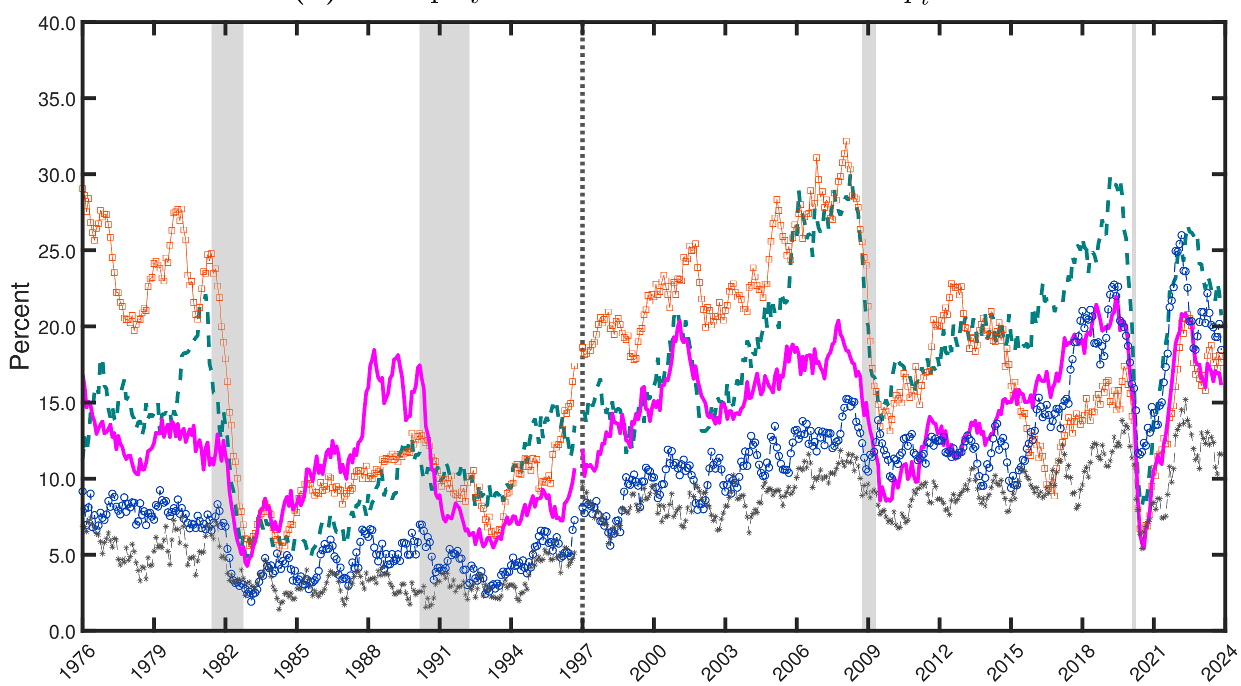
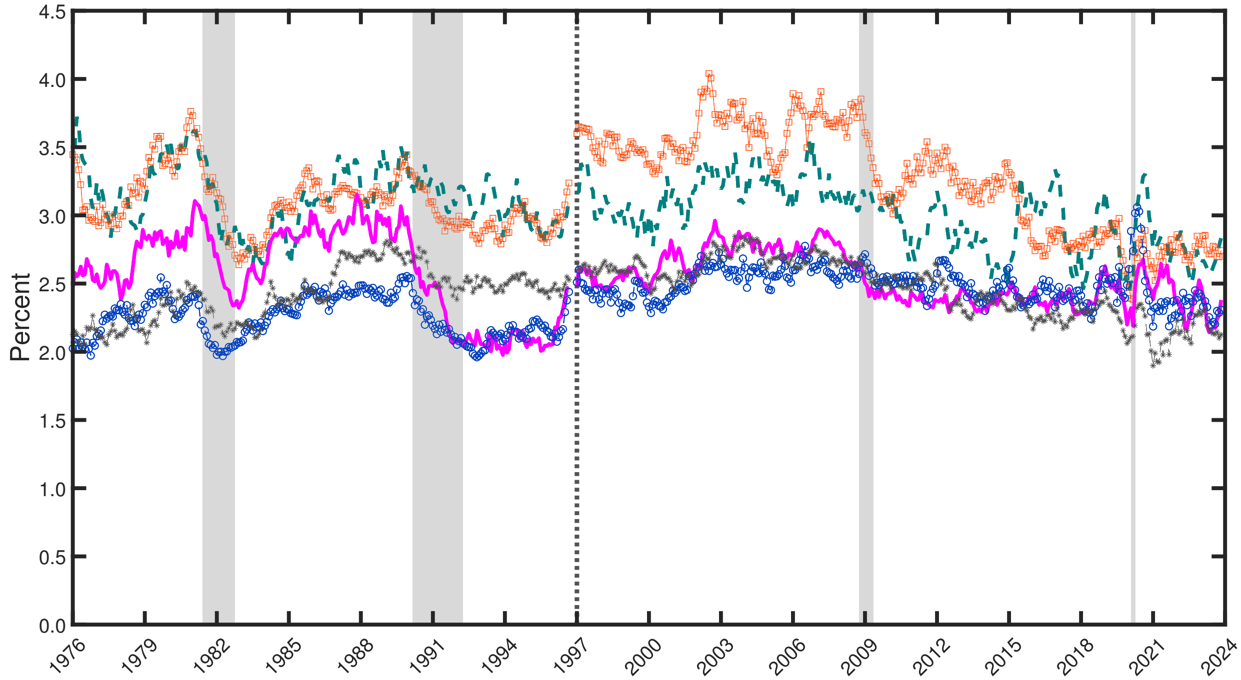


Figure C1(cont'd): Monthly transition rates, 1976–2023

Notes: LFS (public) data, 1976m01 – 2023m11. The figure shows the time series of monthly transition rates. All series are adjusted for seasonality and time aggregation bias, and smoothed using a three-period, two-sided moving-average. All series are expressed in percent. The vertical dotted lines indicate January 1997; Gray-shaded areas indicate recession periods. Dashed lines (--): British Columbia; Squares (□): Prairies; Solid lines (–): Ontario; Circles (○): Québec; Asteriks (*): Atlantic.

(e) Out of the labor force to employment p_t^{OE}



(f) Out of the labor force to unemployment p_t^{OU}

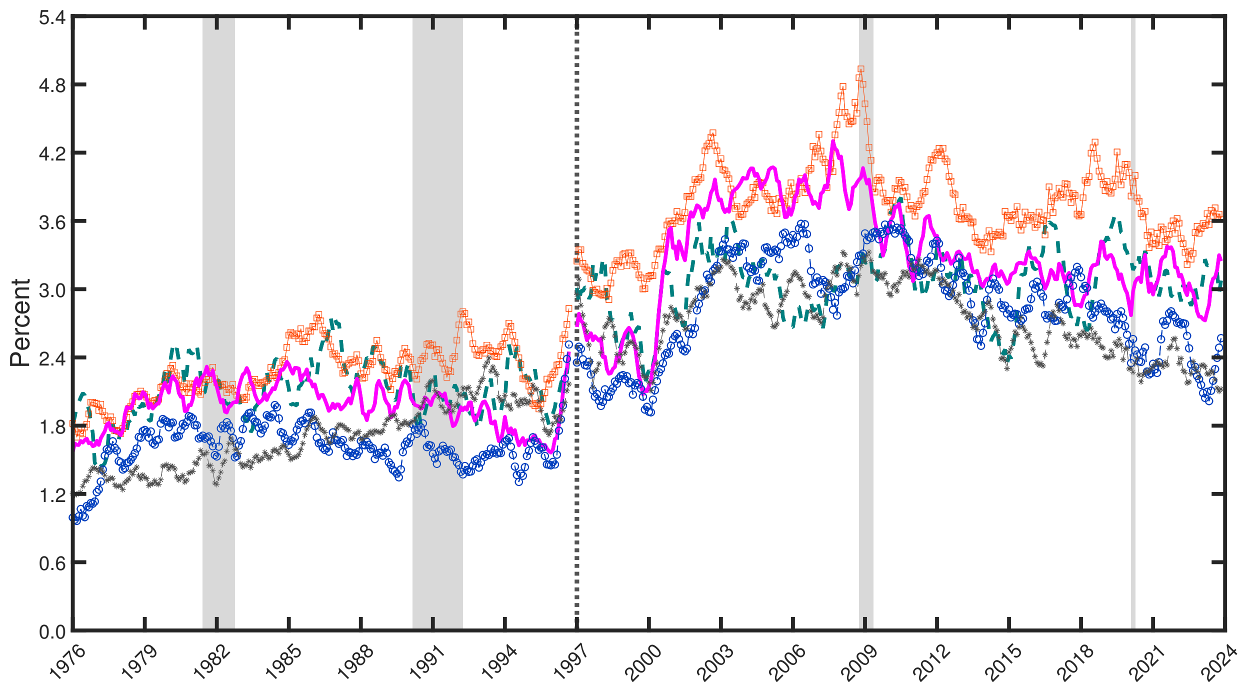


Figure C1(cont'd): Monthly transition rates, 1976–2023

Notes: LFS (public) data, 1976m01 – 2023m11. The figure shows the time series of monthly transition rates. All series are adjusted for seasonality and time aggregation bias, and smoothed using a three-period, two-sided moving-average. All series are expressed in percent. The vertical dotted lines indicate January 1997; Gray-shaded areas indicate recession periods. Dashed lines (--): British Columbia; Squares (□): Prairies; Solid lines (–): Ontario; Circles (○): Québec; Asteriks (*): Atlantic.