Job market transitions: identification from cross-sectional data

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Abstract

It is common practice to compute labor market transition rates assuming that the economically relevant transitions occur between employment and unemployment only and using data on unemployment duration. However, if there are significant flows between labor force participation and inactivity, ignoring the participation margin can lead to biased results. This paper proposes an alternative approach based on a three-state framework that is easily estimable using publicly available data on labor market stocks and employment tenure. We show that such data carries more, and more relevant information than unemployment duration, including information on job-to-job transitions. We use the case of Canada and the United Kingdom as illustrative examples, contrasting our method with commonly used alternatives. Results show that the extra information provided by our method can be crucial, especially when looking at economies in an upswing.

JEL codes: E24, J63, J64

Keywords: labor market flows, job tenure, measurement, job search

1 Introduction

Measuring and explaining job creation and job separation rates is a fundamental part of labor economics (Mortensen 1970, Pissarides 1985, Mortensen and Pissarides, 1994). Transition rates between labor market states can be calculated using data on gross flows in an unrestricted way. In some countries, statistical offices publish labor market flows based on panel datasets, such as the Labor Force Survey (LFS) in the European Union and the Current Population Survey (CPS) in the United States. A limitation of the panel method is that the data are not representative of the general population, and flows constructed from it are not consistent with aggregate stocks computed from the full cross-section. This problem can be treated using *statistical methods* (Frazis et al., 2005), but these do not make use of the logic of the underlying *economic* processes. Unfortunately, for many countries, gross flows data are not reported, and it is hard or impossible to acquire the original micro-level panel dataset.[1]

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[1] A possible way out is the approach of Casado, Fernandez és Jimeno (2015), using cross-sectional microdata with retrospective information on labor market status. This method allows for the measurement

An alternative method widely used in the literature is to concentrate on *employment* and *unemployment* only, and approximate job separation and job creation rates by unemployment inflow and outflow rates (Shimer 2005). Shimer's method is based on the assumption that the participation decision can be ignored and that job to job transitions are not important, therefore data on unemployment duration is sufficient to calculate the rates of interest. Despite the questionable assumptions, the method is popular, perhaps because it is straightforward anduses publicly available data on unemployment duration.

Recently both the empirical literature on labor flows, and the macro literature on business cycles (Elsby, Hobijn and Sahin 2015; Campolmi and Gnocchi 2014) have questioned the omission of inactivity. Research in labor economics has been looking at the differences between unemployment and out of the labor force status (see an overview in Dunson and Stone, 2017). Also, Krause and Lubik (2006) and Karahan et al. (2017) provide evidence the importance of job to job transitions, especially in booms. This idea has reflections also in research on labor market transitions. Hobijn and Sahin (2009), in particular, used job tenure information to compute the job separation rate. However, they use unemployment duration data for the job finding rate. This is in line with their maintained two-state assumption and is likely to miss important dynamics. Also, their estimation method is relatively complex, making it a less likely candidate for widespread adoption than that of Shimer (2015).

This paper overcomes the limitations, but retains the practical simplicity of the approach of Shimer (2015). It provides a straightforward method for the estimation of job finding- and job separation rates based on job tenure data. The method is consistent with both job to job transitions and the structure provided by the search and matching model, yielding also a *search participation rate*. The method has the added benefit of using only openly available data, often at the quarterly frequency[2]. We illustrate the use of the method by applying it to data from Canada and the United Kingdom.

In what follows, we first outline a simple model leading to employment flow equations and show identification based on that. Then we discuss alternative measures and thirdly, we introduce the data we use and provide empirical results to illustrate our approach. Finally we discuss the possibility for further identification based on the data we have at hand.

2 Labor flows from job tenure: a model and identification

Shimer (2005) shows how to compute unemployment inflow and outflow rates using data on the unemployment rate and on unemployment duration. He interprets these as the *job finding rate* and the *job separation rate*. In the basic search and matching model (Pissarides 2000, Chapter 1) these two rates determine changes in unemployment and

of flows, but only at the annual frequency and is likely to be contaminated by measurement error due to recall.

[2]Hobijn and Sahin (2009) and Casado, Fernandez és Jimeno (2015) work on annual frequency

employment since the labor force participation decision is not taken into account. However, if three labor market states are relevant instead of two,the concepts of job finding and job separation are wrongly identified from unemployment dynamics and this approach is not sufficient to correctly identify the relevant transition rates. This section shows how to overcome this restriction in a straightforward and consistent way. In particular, using information on *inactivity* and *job tenure,* besides that on employment and unemployment, along with some structure imposed by theory, makes it possibleto identify key transition probabilities relevant for macroeconomic- and labor market analysis.

2.1 Employment flows

Our model assumes that time is discrete, but the model frequency can be arbitrarily high. Data is available at a quarterly frequency, but it is possible that over a quarter at least workers experience multiple transitions. This is the well-known time aggregation problem, introduced into the labor flow literature by Shimer (2005). While Shimer treated the problem using a continuous time framework, our setup is more conducive to discrete time methods, applicable to the daily frequency, the highest realistic one.

To fix ideas, we will assume that decisions are made daily, and we aggregate these daily flows into quarterly probabilities. Let t denote the start of the current quarter, and we use the index τ to index days within a quarter. There are $T = 365/4$ days in a quarter (we ignore leap years and the minimal differences that come from the unequal lengths of months). The crucial assumption - in line with the literature - is that the daily flow rates are constant over a quarter. This allows us to derive the changes in stocks between the beginning of two quarters, and identify the underlying flow rates from quarterly data.

Let $e_{t+\tau-1}$, $u_{t+\tau-1}$, and $i_{t+\tau-1}$ denote shares of employment, unemployment, and the inactive (not in the labor force) *in the population* at the end of period $t + \tau - 1$. A ρ_t fraction of the formerly employed lose their jobs at the beginning of period $t+\tau$ (recall that transition rates are constant within a quarter). Therefore, the population share of *potential* job searchers at $t+\tau$ is $\rho_t e_{t+\tau-1}+u_{t+\tau-1}+i_{t+\tau-1}$.These include the previously unemployed who stay in the labor force, the previously inactive who return to the labor force, and also those who change jobs within the period. The timing assumption for changing jobs allows us to account for job-to-job transitions, which is likely to be quantitatively important for job churning.[3] Out of this pool, a fraction λ_t decides to look for a job. The number of searchers is thus given by

$$s_{t+\tau} = \lambda_t \left(\rho_t e_{t+\tau-1} + u_{t+\tau-1} + i_{t+\tau-1}\right). \tag{1}$$

It is important to emphasize that we *do not assume an equal search participation rate* for all types of searchers. Equation (1) defines λ_t as an average rate, and it is perfectly compatible

[3]This setup was used, for example, in Campolmi and Gnocchi (2016). They incorporate labor market search and the participation decision into an otherwise standard New Keynesian framework. Their focus on monetary policy and inflation. They do not explore the measurement implications of the labor market setup, which is the main contribution of our paper.

with different participation rates for the unemployed, inactive, and job changers. The main point is that while we cannot identify these rates separately, we can calculate an average as we show below.

A fraction f_t of the searchers ($f_t s_{t+\tau}$ fraction of the total population) finds jobs during the period. Again, *this is an average rate*, and rates for different groups can - and are likely to - differ from each other. We can only calculate the number of new jobs relative to the searching population, which yields f_t as an average job finding rate. Unsuccessful searchers become *unemployed*:

$$u_{t+\tau} = (1 - f_t)\, s_{t+\tau}. \tag{2}$$

Potential job searchers who chose not to participate are inactive:

$$i_{t+\tau} = (1 - \lambda_t)\, s_{t+\tau} = (1 - \lambda_t)\,(\rho_t e_{t+\tau-1} + u_{t+\tau-1} + i_{t+\tau-1})\,. \tag{3}$$

Using these definitions, the flow equation of employment is

$$e_{t+\tau} = (1 - \rho_t)\, e_{t+\tau-1} + f_t s_{t+\tau}.$$

After substituting for the share of searchers and rearranging, the equation becomes

$$e_{t+\tau} = \lambda_t f_t + (1 - \rho_t)\,(1 - \lambda_t f_t)\, e_{t+\tau-1}. \tag{4}$$

Now we use this equation to solve for the employment rate at $t+T$, which is the start of the next quarter. To simplify notation, let us define $\eta_t = \lambda_t f_t$ and $\varphi_t = (1 - \rho_t)\,(1 - \lambda_t f_t)$. One can think about the first as the job finding rate of a random person in the potential searcher population (that is: taking into account the probability of participation), while the latter gives the share of those with stable employed status between the periods. Then the following derivation links e_{t+T} and e_t:

$$\begin{aligned}
e_{t+T} &= \eta_t + \varphi_t e_{t+T-1} \\
&= \eta_t + \varphi_t\,(\eta_t + \varphi_t e_{t+T-2}) \\
&\vdots \\
&= \eta_t \sum_{\nu=0}^{T-1} \varphi_t^{\nu} + \varphi_t^T e_t \\
&= \frac{\eta_t}{1 - \varphi_t}\left(1 - \varphi_t^T\right) + \varphi_t^T e_t.
\end{aligned}$$

Substituting back the original rates, we get the following flow equation for quarterly employment:

$$e_{t+T} = \frac{\lambda_t f_t}{1-(1-\rho_t)(1-\lambda_t f_t)} \left\{1-\left[(1-\rho_t)(1-\lambda_t f_t)\right]^T\right\} + \left[(1-\rho_t)(1-\lambda_t f_t)\right]^T e_t \tag{5}$$

Similarly, we can also derive how the number of the inactive changes between two quarters. Using eq. (3), eq. (5) and the identity that $e_{t+\tau} + u_{t+\tau} + i_{t+\tau} = 1$, we can write this as follows:

$$\begin{aligned} i_{t+T} &= (1-\lambda_t)(\rho_t e_{t+T-1} + 1 - e_{t+T-1}) \\ &= 1 - \lambda_t - (1-\rho_t)(1-\lambda_t) e_{t+T-1} \\ &= (1-\lambda_t)\left\{1-(1-\rho_t)\left[\frac{\eta_t}{1-\varphi_t}\left(1-\varphi_t^{T-1}\right) + \varphi_t^{T-1} e_t\right]\right\}, \end{aligned} \tag{6}$$

where η_t and φ_t are defined as above.

2.2 Identification

Now we are ready to discuss the identification of the three flow rates, λ_t, ρ_t and f_t. Information on job tenure includes the share of the newly employed (e_t^s), whose tenure is less than one quarter. Using the simple fact that those employed in $t+T$ are composed of those employed through the period and of the newly employed,, the job separation rate ρ_t is directly identified as follows:

$$(1-\rho_t)^T = \frac{e_{t+T} - e_{t+T}^s}{e_t}. \tag{7}$$

The right-hand side is the fraction of those who are employed at the beginning of the current quarter, and remain employed at the same job by the beginning of the next quarter. The left-hand side defines this as the probability that a job survives over the T periods within the quarter.

Next, we can use eq. (5) to solve for the product $\eta_t = \lambda_t f_t$, given quarterly data on employment and the job separation rate ρ_t calculated from eq. (7). For any t, this is a simple non-linear equation that can easily be solved numerically. Note that ρ_t and $\lambda_t f_t$ are sufficient to calculate the auxilliary variable $\varphi_t = (1-\rho_t)(1-\lambda_t f_t)$. Using these in eq. (6), along with quarterly employment and inactivity data, we can solve for the search participation rate λ_t. Finally, the job finding rate is given by $f_t = \eta_t/\lambda_t$.

The quarterly job finding and job separation probabilities can easily be calculated from the high-frequency rates:

$$F_t = 1-(1-f_t)^T \tag{8}$$

$$R_t = 1-(1-\rho_t)^T. \tag{9}$$

The first equation is the probability that someone who is searching for a job at the beginning of the current quarter finds one by the next quarter (assuming that she does not give up search earlier). The second equation defines the survival probability of a job from the current quarter to the next. Note that we do not need to adjust the search participation rate λ_t, since it is (by assumption) a constant ratio of stocks within a quarter.

The identified rates and probabilities are sufficient to calibrate a macroeconomic model of *employment*. To understand macroeconomic aggregates (GDP, inflation, etc.), employment and its associated flows are the key labor market variables. As we noted earlier, however, the job finding rate f_t (along with the search participation rate λ_t) is an *average* among job searchers with different labor market backgrounds. Flows for individual groups (such as the unemployed) are of great interest to social policy, but are less relevant for the *macro modeler*.

Our method, due to the timing assumption that searchers may find and start work within one period, incorporates job-to-job transitions. This is important since much of the churning in employment is due to these transitions (Mukoyama, 2014), which data on stocks or even gross flows fail to capture.

2.3 The source of new information - some intuition

To see where the new information comes in our procedure with respect the the existing, two-state one, using unemployment duration data, it is worth discussing the intuition behind the identification further. First, let us recall the key equations between periods t and $t+1$:

$$\begin{aligned} e_{t+1} &= (1-\rho_t)\, e_t + f_t \lambda_t \left(\rho_t e_t + 1 - e_t\right) \\ i_{t+1} &= (1-\lambda_t)\left(\rho_t e_t + 1 - e_t\right) \\ (1-\rho_t)\, e_t &= e_{t+1} - e^s_{t+1}, \end{aligned}$$

this latter identifying the job separation rate directly. Using the link between the three labor market states, $i_{t+1} = 1 - e_{t+1} - u_{t+1}$, in the second equation, we can write that

$$\lambda_t \left(\rho_t e_t + 1 - e_t\right) = e_{t+1} + u_{t+1} - (1-\rho_t)\, e_t.$$

Substituting this back into the first equation yields

$$e_{t+1} = (1-\rho_t)\, e_t + f_t \left[e_{t+1} + u_{t+1} - (1-\rho_t)\, e_t\right].$$

Finally, using the third equation for the job separation rate above, we can express the job finding rate as follows:

$$f_t = \frac{e^s_{t+1}}{e^s_{t+1} + u_{t+1}}. \tag{10}$$

The derivation above assumes that the population $P_t = E_t + U_t + I_t$ is constant between two periods. Even if this is reasonable both at daily and quarterly frequency, the calculations can be easily extended to include population change. Using capital letters for levels and denoting the size of the population with P_t, one obtains

$$f_t = \frac{E^s_{t+1}}{E^s_{t+1} + U_{t+1} - (P_{t+1} - P_t)},$$

which is the pool of searchers adjusted with population change, almost equivalent to the earlier result.

An important implication of these calculations is that while we worked with a three-state setup, most of the extra information comes directly from the use of short-term employment data. The intuition is that the short-term employed come from all states, including inactivity, thus their number carries more relevant information than that of the short-term unemployed. An added benefit of our approach is the ability to account for job to job transitions, as the number of short-term employed include those coming from another job. Neither of these is true of the approach of Shimer (2005) and the use of data on short-term unemployment.

Although the above did not consider time aggregation directly, equation (7) does not depend on the assumed frequency if the population is stationary and one can show that the difference is small in any case.

3 Alternative measures

To facilitate comparison of our identified quarterly probabilities, we also calculate alternative measures used in the literature. Below we briefly discuss the usage of gross flow data (whenever available) and unemployment duration data, and how to correct these for time aggregation.

3.1 Data on gross flows

One obvious way to calculate quarterly probabilities is to use labor flow data. Although subject to time aggregation, flow data reveal more details, since one can see all six possible transitions among the three labor market states. Job-to-job flows, however, cannot be calculated from flow data without further breakdown - this is an advantage of our method that relies on job tenure information.

We follow Shimer (2012) to calculate quarterly probabilities from gross flow data, correcting for time aggregation using the high frequency approach of the previous section. Let us define the matrix of daily transition probabilities - assumed constant within a quarter - as follows:

$$m_t = \begin{bmatrix} 1 - m_t^{EI} - m_t^{EU} & m_t^{IE} & m_t^{UE} \\ m_t^{EI} & 1 - m_t^{IE} - m_t^{IU} & m_t^{UI} \\ m_t^{EU} & m_t^{IU} & 1 - m_t^{UE} - m_t^{UI} \end{bmatrix}.$$

Also, let $n_{t+\tau}$ be the following matrix:

$$n_{t+\tau} = \begin{bmatrix} n_{t+\tau}^{EE} & n_{t+\tau}^{IE} & n_{t+\tau}^{UE} \\ n_{t+\tau}^{EI} & n_{t+\tau}^{II} & n_{t+\tau}^{UI} \\ n_{t+\tau}^{EU} & n_{t+\tau}^{IU} & n_{t+\tau}^{UU} \end{bmatrix}.$$

A typical element of $n_{t+\tau}$ is people who started period t in labor market position i, and are in labor market position j at $t+\tau$, where $i, j = E, I, U$. It is clear that within a quarter, the evolution of $n_{t+\tau}$ is given by

$$n_{t+\tau+1} = m_t n_{t+\tau}.$$

To correct for time aggregation, one needs to calculate the transition matrix m_t from the quarterly flows. Let M_t denote the matrix of observed flows, where the elements are normalized into shares using the sum of possible flows from a given state. Then given regularity conditions that hold in our data, M_t can be diagonalized.

$$M_t = p_t \mu_t p_t^{-1},$$

where p_t is a matrix with the eigenvectors of M_t in its columns, and μ_t is a diagonal matrix with the eigenvalues of M_t along the diagonal. Then the daily transition matrix is simply given by

$$m_t = p_t \mu_t^{\frac{1}{T}} p_t^{-1}.$$

With the daily transition matrix we calculate the adjusted quarterly probabilities as follows:

$$\begin{aligned}
\rho_t^{gf} &= 1 - \left(m_t^{EE}\right)^T \\
f_t^{gf} &= 1 - \left[1 - \frac{m_t^{UE} u_t + m_t^{IE} i_t}{\left(m_t^{UE} + m_t^{UU}\right) u_t + \left(m_t^{IE} + m_t^{IU}\right) i_t}\right]^T \\
\lambda_t^{gf} &= \frac{\left(m_t^{UE} + m_t^{UU}\right) u_t + \left(m_t^{IE} + m_t^{IU}\right) i_t}{u_t + i_t}.
\end{aligned}$$

3.2 Two states with unemployment duration data

The most widely used method to calculate transition probabilities from stock data was proposed in Shimer (2005). This method uses data on unemployment duration to calculate unemployment inflow and outflow probabilities, correcting for time aggregation. Since the procedure is described in detail in the original article, we keep the exposition brief. The only difference is that instead of continuous time, we derive the equations using our previous high frequency assumption.

The quarterly unemployment outflow probability (interpreted as the job finding rate) is calculated as follows:

$$F_t^{ts} = 1 - \frac{u_{t+1} - u_{t+1}^s}{u_t},$$

where u_t^s is the number of those who have been unemployed for less than a quarter at the beginning of the next quarter. The daily unemployment inflow rate ρ_t^{ts} (interpreted as the job separation rate) is then calculated from the following equation:

$$u_{t+T} = \frac{\rho_t^{ts}}{\rho_t^{ts} + f_t^{ts}} \left[1 - \left(1 - \rho_t^{ts} - f_t^{ts}\right)^T\right] + \left(1 - \rho_t^{ts} - f_t^{ts}\right)^T u_t,$$

where $f_t^{ts} = 1 - \left(1 - F_t^{ts}\right)^{\frac{1}{T}}$. Finally, the quarterly job separation rate is given by

$$R_t^{ts} = 1 - \left(1 - \rho_t^{ts}\right)^T.$$

4 Data, estimation and results

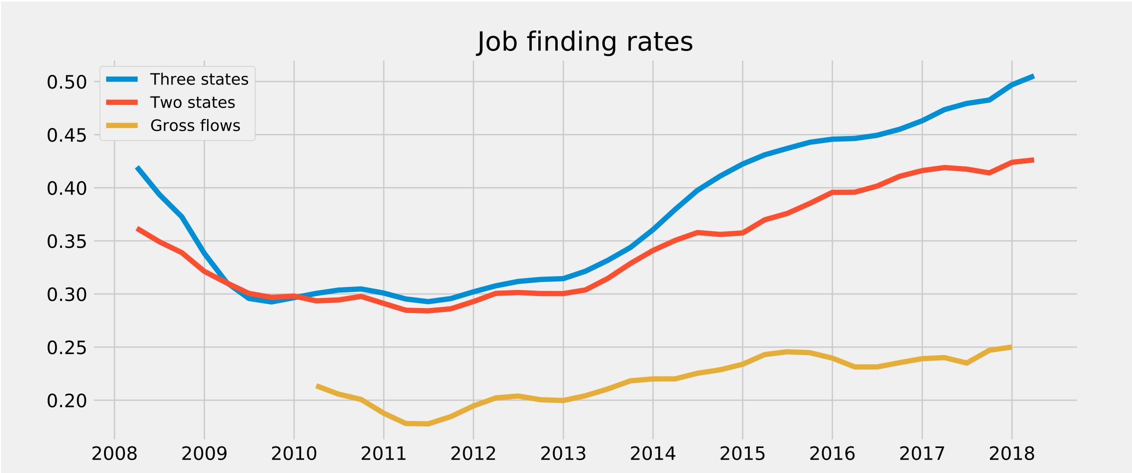
Data availability is constrained primarily by information on job tenure. For the EU, Eurostat reports quarterly figures since 2008Q1. Since 2010Q1, Eurostat also started publishing data on gross flows, which allows us to compare our method with flow rates calculated from gross flows directly. We present results for the United Kingdom as an example.

Long time series for job tenure and stocks are available for Canada, starting in 1976. This allows us to compare job finding and separation rates between our three-state method, and the original two-state Shimer method. Unfortunately, there are no public gross flow data available for Canada.

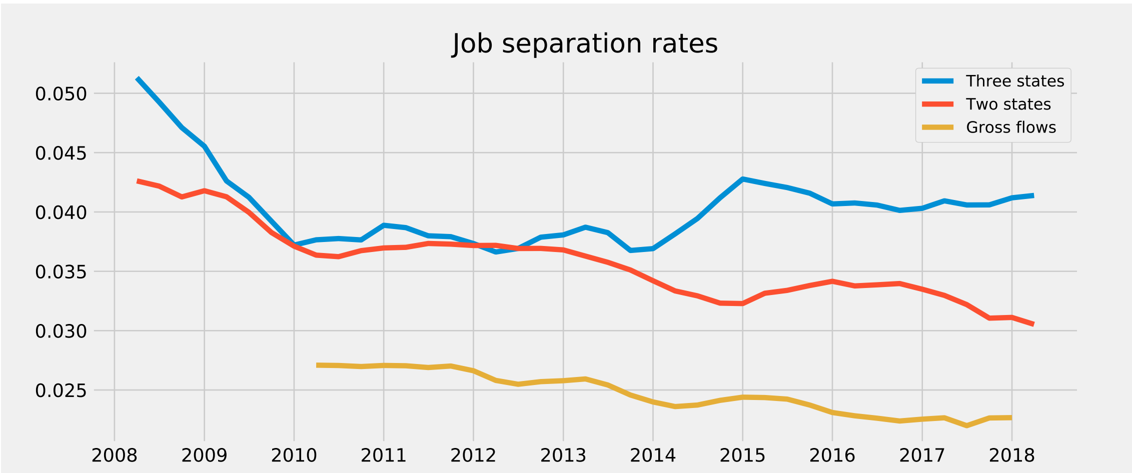
Figure 1 plots the UK results. For comparison, we present results from the two-state method and from using gross flows directly. For the latter, we use the unemployment-employment flow rate (first panel), the flow rate from employment to unemployment or inactivity (second panel), and the flow rate from inactivity into either employment or unemployment (third panel). We remove seasonality from all the calculated rates.

The two-state and three-state methods yield notably similar outcomes for the UK, especially when considering the overall business cycle properties of the job finding and separation rates and the different nature of the data used. Note however the almost exact match of the measures in the crisis period and the divergence before and after that. A reason for this is having information on job to job flows, one of the advantages of using employment tenure data. Indeed, as the theoretical model of Krause and Lubik (2006) confirms everyday observation, matches to better jobs and thus job to job transitions are much more likely in upswings and in downturns. Our approach is able to capture that, while the commonly used alternative cannot.

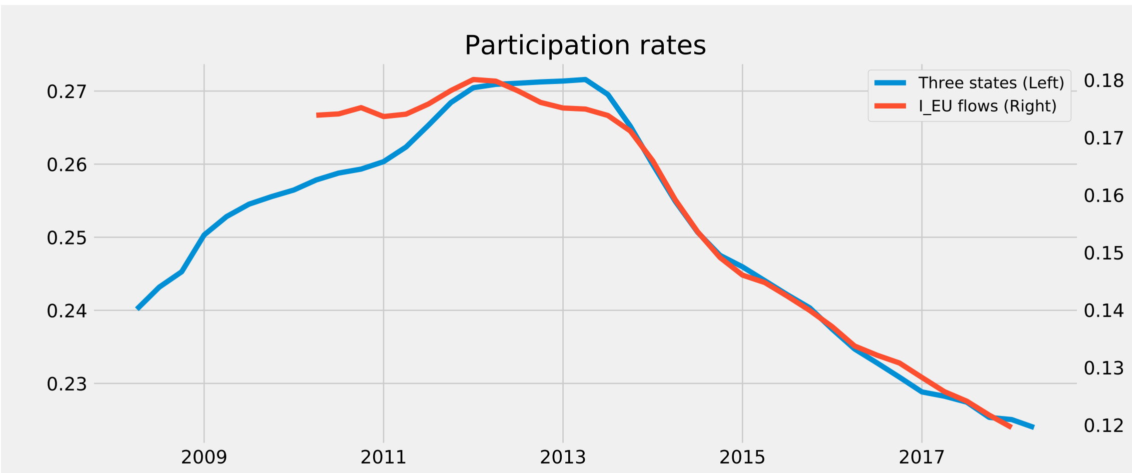
Comparing the three-state method with the gross flows, the level differences are much bigger. The average job finding and separation rates are bigger then the unemployment-



The panel plots the job finding rate f_t, the unemployment outflow rate based on unemployment duration data, and the unemployment-employment flow rate from gross flows.



The panel plots the job separation rate ρ_t, the unemployment inflow rate based on unemployment duration data, and the employment outflow rate from gross flows.



The panel plots the search participation rate λ_t, and the inactivity outflow rate from gross flows. Note the different scales for the two measures.

Figure 1: Results for the UK

employment flow rate or the employment outflow rate. The main reason behind this is likely to be job-to-job transitions, which are picked up by our method, but not by the gross flow data. The match between the two measures of participation, is of no surprise: job to job transitions play no part there. Although the levels are different (note the different scales on the figure), the dynamics are virtually identical.

Figure 2 presents the Canadian results. The dynamics between the two and three state methods are again similar. The job finding rate remains broadly stable after 1996, while the unemployment outflow rate increases sharply. The opposite is true when we compare the job separation rate and the unemployment inflow rate. The former drops significantly after 1996, while the latter remains broadly stable. The discrepancies might be explained by the behavior of the search participation rate (λ_t), which declines significantly during the mid-1990s, but which is not taken into account by the two-state method.

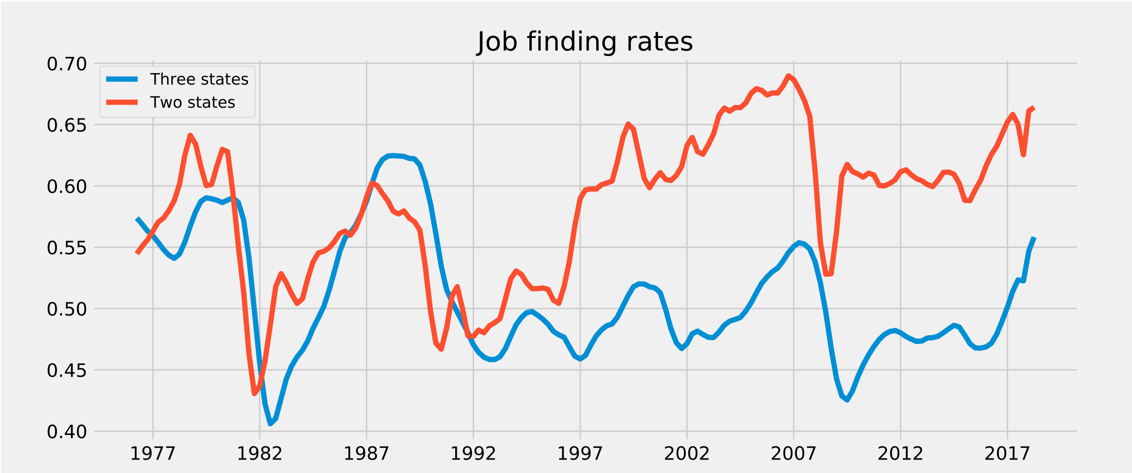
5 Discussion: group-level identification

As we stressed above, the identified job finding rate is an average over the various groups that make up job searchers. These groups are the formerly unemployed, the formerly inactive, and those changing jobs. There is no reason why the job finding probabilities should be the same for these three sub-groups. Unfortunately stock data with job duration information is not sufficient to identify group-level transition rates. The question is whether it is possible to impose additional restrictions on the flow rates to identify the separate probabilities.

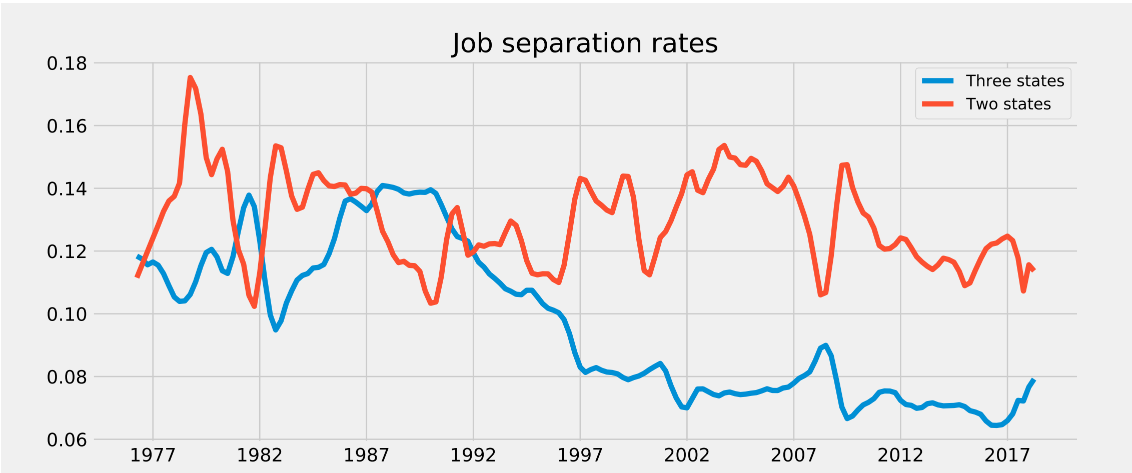
Note that there is one additional time series that we have not used so far. In particular, Shimer (2005) uses unemployment duration data (see below) to calculate unemployment outflow and inflow rates. Although he interprets the outflow rate as a job finding probability, this is not accurate, since some of those who leave unemployment become inactive. Our question in this section is whether adding unemployment duration to our list of observables is useful to calculate separate job finding rates for the three groups of searchers, and if not, what additional restrictions might be needed.

The answer to the first question is no. The additional information allows us to calculate the unemployment outflow rate, as shown by Shimer (2005). Without knowing how many of the unemployed remain active, we cannot separately calculate the job finding rate of the unemployed. Unless we assume that the search participation rate λ_t is the same for each subgroup, we cannot go further. This assumption is unlikely to hold in the data, since it is likely that the search participation rate of the currently unemployed (u_t) is higher than the search participation rate of the currently inactive (i_t), i.e. $\lambda_t^u > \lambda_t^i$.

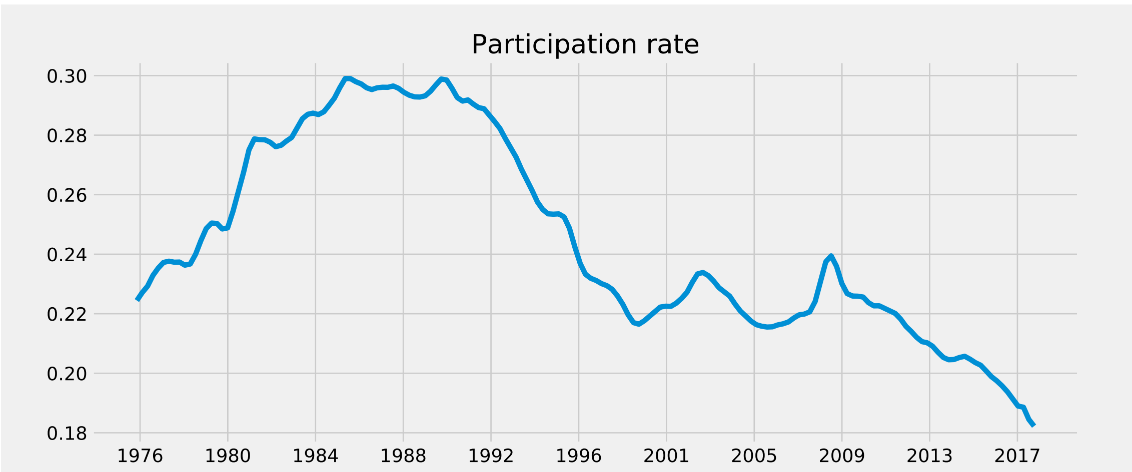
To study the second question, let us impose - contrary to the above - a set of identification restrictions to eliminate heterogeneity across different groups. In particular, let us assume that $f_t^u = f_t^e = f_t^i \, (= f_t)$ and $\lambda_t^u = \lambda_t^e (= \lambda_t^{eu})$. The assumptions mean that the job finding rate is independent of previous labor market status, and the search participation rate is the same between the formally employed and the formally unemployed. We do



The panel plots the job finding rate f_t and the unemployment outflow rate based on unemployment duration data.



The panel plots the job separation rate ρ_t, the unemployment inflow rate based on unemployment duration data.



The panel plots the search participation rate λ_t.

Figure 2: Results for Canada

allow for lower search intensity among the inactive relative to the other two groups of potential searchers.

It is easy to verify that under these assumptions all flows are identified. Compared to the previous case we need to compute one additional indicator, which is the probability that an inactive becomes an active searcher (λ_t^i). Let us write down the flow equation of unemployment, using the identification restrictions:

$$u_{t+1} - u_t = \rho_t \lambda_t^{eu} (1 - f_t) e_t + \lambda_t^i (1 - f_t) i_t - \underbrace{[1 - \lambda_t^{eu} (1 - f_t)]}_{\phi_t} u_t. \tag{11}$$

Using data on unemployment duration we can calculate the outflow rate ϕ_t. Substituting this into equation (11) we can also compute the unemployment inflow rate.[4] Given our previous estimates for the job finding rate f_t, the job destruction rate ρ_t, and the average search intensity $\lambda_t = (\rho_t e_{t-1} + u_{t-1}) \lambda_t^{eu} + i_{t-1} \lambda_t^i$, we can recover the two separate search intensities, λ_t^{eu} and λ_t^i. This means that we would have all the necessary information to reproduce the gross flows among all three states.

Unfortunately, this identification strategy does not work in practice. The simple reason for this is that the unemployment outflow rate ϕ_t tends to be smaller than the average job finding rate f_t (see Figure 1). This is inconsistent with eq. (11), which requires that $\phi_t > f_t$. Our strong identification restrictions cannot be maintained: the job finding rate of the unemployed is apparently lower than average. Reasons for this can be the better labor market position of the newly unemployed and job changers, or that people returning from inactivity might find it easier to get a job, or probably a combination of both.

If we relax the $f_t^e = f_t^u = f_t^i$ assumption, full identification is no longer possible, since we would need to calculate at least five rates from four time series. Either we find new data, or we introduce some other restrictions. There are no obvious choices in either direction, hence we do not see full identification possible from aggregate data.

6 Conclusion

We presented a method to estimate key labor market transition rates using publicly available data on employment, unemployment, inactivity and job tenure. The method is easy to implement and improves measurement compared to methods that ignore movements into and out of inactivity. Data are more broadly available than direct measures of labor market flows, and stock-flow consistency is not an issue. Finally, the method takes into account job-to-job transitions that are important in understanding employment dynamics, in particular over the business-cycle.

We highlight two topics for further research. First, longer job tenure time series are available at the annual frequency. These can be utilized combining the current methodology with the techniques developed in Hobijn and Sahin (2009). Second, a more detailed

[4] In this section we ignore time aggregation and focus only on identification at the baseline frequency. Time aggregation would complicate the calculations, but would not change the identification results.

comparison of our results with gross flows may lead to improvements in the raking procedure used to ensure stock-flow consistency in the latter.

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