Job finding and participation rates in the OECD: identification with job tenure data

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Abstract

It is common practice in the literature to compute labor flows from data on stocks. To use these flows in standard search models, it is assumed that the economically relevant movements occur between employment and unemployment. If there are significant flows between labor force participation and inactivity, ignoring the participation decision can lead to biased results. This paper shows that while with three states it is impossible to identify all the flows from publicly available data on stocks, partial identification is possible with the help of data on unemployment duration and job tenure. A new method is described, which allows the computation of the transition probabilities that are most relevant from a macroeconomic perspective. The method is easy to use, and the paper describes the detailed steps for its implementation to potential users.

1 Introduction

Measuring and explaining labor flows has become a fundamental part of the macroeconomics of labor markets. Search and matching models (Mortensen 1970. Pissarides 1985 and Mortensen-Pissarides 1994) have made it clear that without understanding gross flows we cannot hope to explain changes in stocks. Therefore. measuring labor market flows is crucial for the research program based on the search model.

Table 1 shows the relationsip between stocks and flows. Let E. U. I denote the size of employment. unemployment and inactivity within the relevant population. The latter can change over time: P^{in} is the inflow into. and P^{out} is the outflow from the studied population

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segment. In this paper we study the labor market status of the 15-64 age group. Therefore. P^{in} is the number of people who turn 15 in the given quarter. and similarly P^{out}measures those who turn 65. Flows between different labor market states are denoted by f^{ij}. and the rows in the table naturally sum up to 1. In what follows - and similarly to the literature - we assume that population changes are unimportant.[1] One way to state this is to assume that $P_t^{in} = P_t^{out}$ and $f_t^{in,j} = f_t^{j,out}$. where $j = e, u, i$.

Table 1: Stocks and flows

	E_t	U_t	I_t	P_t^{out}
E_{t-1}	$1 - f_t^{eu} f_t^{ei} - f_t^{e,out}$	f_t^{eu}	f_t^{ei}	$f_t^{e,out}$
U_{t-1}	f_t^{ue}	$1 - f_t^{ue} - f_t^{ui} - f_t^{u,out}$	f_t^{ui}	$f_t^{u,out}$
I_{t-1}	f_t^{ie}	f_t^{iu}	$1 - f_t^{ie} - f_t^{iu} - f_t^{i,out}$	$f_t^{i,out}$
P_t^{in}	$f_t^{in,e}$	$f_t^{in,u}$	$f_t^{in,i}$	

Changes in stocks over time are *net flows*. in employment. for example. $E_t - E_{t-1}$. Results from the Labor Force Survey (LFS) are published quarterly by Eurostat. and contain information on the three main stocks (E_t. U_t. I_t). Gross flows - the f_t^{ij} rates -. on the other hand. are not available. To measure these. we need either more information. or identification restrictions.

If we have access to individual panel data on labor market status. we can calculate flows directly. This possibility exists in some countries like Hungary. where the LFS ideally follows a given household for 6 months. hence it can be used as a rotating panel. Cseres-Gergely (2011) and Mihályffy (2012) computed labor market flows in Hungary. using individual LFS data.

A limitation of the LFS panel. however. is that it is not representative of the general population. and the flows constructed from it are typically not consistent with the aggregate stocks computed from the full cross-section. This problem can be treated using *statistical methods* (Frazis et al. 2005. Mihályffy 2012). we cannot be sure that the adjusted flows represent the true underlying *economic* processes.

A further difficulty with methods based on micro data is that results cannot be replicated from frequently updated. public databases. Moreover. for cross-country studies. individual level data is hard or impossible to access. Therefore. it is worth looking at the possibilities of identifying gross flows from aggregate stocks. whose time series are easily available in public databases.

[1] Methods using panel data - which we will discuss shortly - can also measure this channel. but the aggregate approach detailed in this paper cannot.

It is clear from table 1 that the full system cannot be identified from aggregate. public stock data. As stated above. we will ignore inflows and outflows into/from the age group of interest. so we can work with normalized stocks. Let $e_t/E_t/P_t$. $u_t = U_t/P_t$ and $i_t = I_t/P_t$ be the empoyment. unemployment and inactivity shares in the *population*.[2] Under constant population. we need to compute 6 independent transition probabilities (see rows and columns 2-4 in the table). but at this point there are only two independent observations. since $e_t + u_t + i_t = 1$. This is the fundamental *identification problem* in the computation of gross flows. The main topic of the paper is to present an easy-to-use method. which can help in treating this issue.

The generally applied method in the literature is to concentrate on *employment* and *unemployment* only. and compute unemployment inflow and outflow probabilities (Shimer 2005a). Shimer's method is based on the assumption that the participation decision can be ignored. and the labor market can be modeled and understood by focusing on just the two other states. Under this assumption. the unemployment inflows and outflows can be interpreted as job destruction and job finding rates. Apart from assuming two relevant states. a fundamental part of the method is to use data on unemployment duration. which is also publicly available.

Recently. however. the omission of inactivity has been questioned both by the empirical literatue of labor flows. and by the macor literature of business cycles (Elsby. Hobijn and Sahin 2015. and Campolmi and Gnocchi 2014). These papers find that the participation decision is an important adjustment margin for labor market adjustment. It is thus important to extend the stock-based method into a direction that can identify relevant flows among all three states.

This paper takes a step in this direction. We show that full identification is not possible with available aggregate data. but using the structure provided by the search and matching model we can compute the main probabilities associated with the destruction and creation of jobs. These are sufficient to calibrate and test a macroeconomic model with three states. Our results show that in most European countries the fluctuation of jobs is higher than the two-state method based on unemployment duration suggests.

In our empirical implementation we rely crucially on quarterly data on *job duration*. available since 2005. In addition on labor market stocks. this information makes it possible to compute *search intensity*. the *job finding rate*. and the *job destruction rate*. To our best knowledge this is the first paper that discusses this possibility.

As mentioned above. the two-state method was developed in Shimer (2005a). who used it to

[2] When working with shares. $f_t^{in,j} = f_t^{j,out} = 0$ by construction.

measure flows in the United States. Hobijn and Sahin (2009) presents average flows for OECD countries. Hobijn and Sahin (2009) also use job duration to compute the job destruction rate. but they maintain the two-state assumption. A further difference is that our data are quarterly. while Hobijn and Sahin (2009) use and annual frequency. Morvay (2012) applies the Shimer method to Hungary and the other Visegrad countries. He computes unemployment inflow and ooutflow rates. also assuming two relevant states.

It is worth mentioning the paper by Casado. Fernandez és Jimeno (2015). The authors use the EU-LFS micro dataset[3] to measure gross flows. A limitation of this dataset. however. is that individual identifiers are not available. and the panel property cannot be utilized. Instead. Casado. Fernandez és Jimeno (2015) rely on a question in the survey that asks participants about their labor market status a year before. This allows for the measurement of flows. but only at the annual frequency. It is likely. moreover. that measurement error is more severe in case of a retrospective question. Finally. as with other micro methods. the underlying data is hard to get. which makes extension and replication difficult.

In the remainder of the paper we first outline the two-state method. and discuss its problems and limitations. Next we present how data on job duration can be used to identify flows in the three state case that are relevant from a macroeconomic perspective. Then we show results for Hungary and for most European countries. We also discuss to important. related issues: one is the estimation of the mathicng function. a crucial ingredient in search models. and the other is the possibility of fully identifying all gross flows. Finally. the conclusion summarizes the method. and the main results.

2 Flows without inactivity

Shimer (2005a) shows how to compute labor market flows from data on the unemployment rate and on unemployment duration. Under the two-state assumption. the procedure identifies the job finding rate and the job destruction rate. In the basic search and matching model (Pissarides 2000. chapter 1) these two rates determine changes in unemployment and employment. since the labor force participation decision is not taken into account.

In this section I briefly present Shimer's method. While the original model was cast in continuous time. here I work in discrete time to maintain compatibility with later calculations

[3] This is the harmonized version of the Labor Force Survey that is available for a cross section of European countries.

under three states. Under two states. employment and unemployment constitute a closed system. hence the size of the labor force is constant ($L = E_t + U_t$). Based on this. let us introduce the unemployment rate: $\upsilon_t = U_t/L_t$ and the employment share within the labor force: $\epsilon_t = 1 - \upsilon_t$.

The timing of job search and job finding are not obvious in discrete time. In this and later sections I assume that successful searchers can start work in the same period. It follows that if someone loses his job at the end of period $t-1$. if his search is successful. he can be employed again already in the next period t. This timing is useful for two reasons. First. the unemployed who find jobs more quickly than a quarter do not appear in the unemployment statistics (*time aggregation problem*). They are important. however. to properly measure the dynamics and tightness of the labor market. since they compete with the other unemployed for vacant positions. Second. our timing also makes it possible to include those who change jobs without formally introducing *on-the-job search*.

Based on these. let us define the number (fraction) of those who search:

$$\sigma_t = \varrho_t \epsilon_{t-1} + \upsilon_{t-1},$$

where ϱ_t is the job destruction rate (or separation rate). Since there are no flows between the labor force and inactivity. searchers in period t are those were unemployed in the previous period. ot who just lost their jobs. The unemployed are those who search unsuccessfully. Finally. let us use ϕ_t to denote the job finding rate.

Using the definitions and the timing assumption. we can write down the flow equation of the unemployment rate:

$$\upsilon_t = (1 - \phi_t)\,\sigma_t = (1 - \phi_t)\left[1 - (1 - \varrho_t)(1 - \upsilon_{t-1})\right],$$

where the second inequality uses the definition of searchers. The equation can be rearranged to relate changes in unemployment to inflows and outflows:

$$\upsilon_t - \upsilon_{t-1} = \underbrace{\varrho_t\,(1 - \phi_t)\,(1 - \upsilon_{t-1})}_{\text{Inflow}} - \underbrace{\phi_t \upsilon_{t-1}}_{\text{Outflow}}. \tag{1}$$

Shimer's method is based on the observation that the outflow probability can be measured by the duration of unemployment:

$$\phi_t = 1 - \frac{\upsilon_t - \upsilon_t^s}{\upsilon_{t-1}},$$

where υ_t^s is the share of those who became unemployed less than a quarter ago.This statistics is available both in the United States and in the countries of the European Union. which means that ϕ_t can be computed directly. Given the outflow. the inflow probability $\varrho_t (1 - \phi_t)$ can be computed from changes in the unemployment rate. based on (1). Finally. having the inflow and outflow rates also yields ϱ_t. the job destruction probability.

The identification of job flows with two states comes from the fact that while the state are linearly dependent ($\upsilon_t + e_t = 1$). with information on unemployment duration we have two independent time series to compute the two flow rates (ϕ_t and ϱ_t). With three states the method cannot be used directly. since we only have three time series (the two independent states and unemployment duration). which is insufficient to identify six independent gross flows.

Although the literature uses unemployment duration for identification. we can also start with the flwo equation of employment:

$$\epsilon_t - \epsilon_{t-1} = \phi_t^e (1 - \epsilon_{t-1}) - \varrho_t^e (1 - \phi_t^e) \epsilon_{t-1}. \tag{2}$$

Eurostat publishes data on job duration since 2005.[4] Based on this information - and using the logic discussed previosly - one can compute the outflow rate of employment:

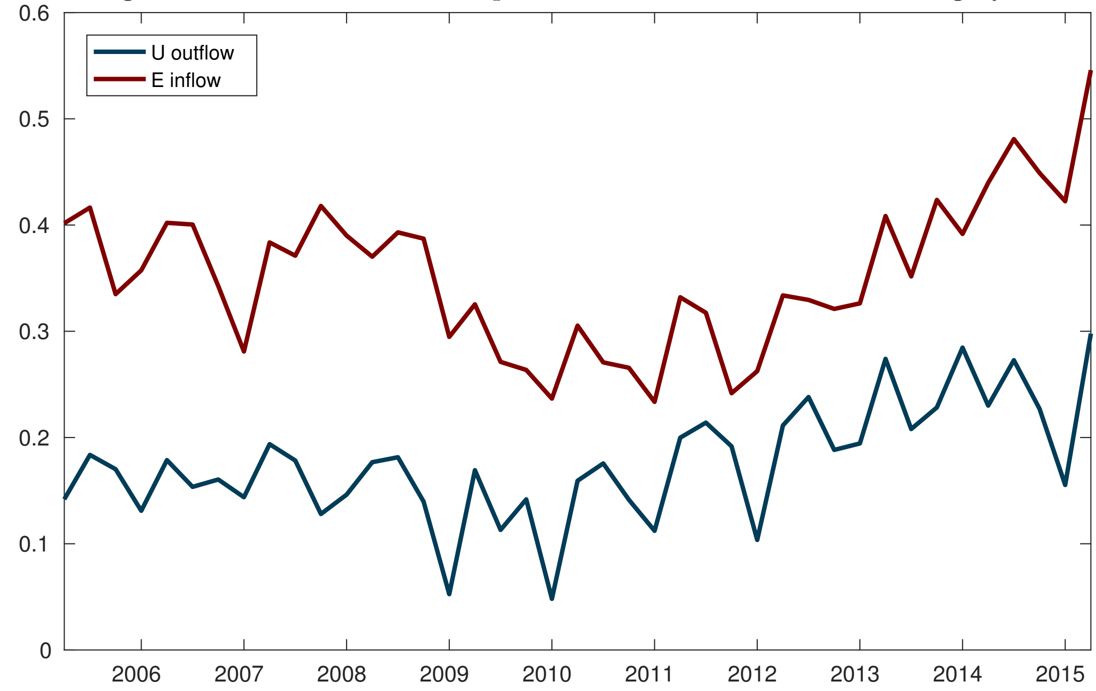
$$\varrho_t^e (1 - \phi_t^e) = 1 - \frac{\epsilon_t - \epsilon_t^s}{\epsilon_{t-1}},$$

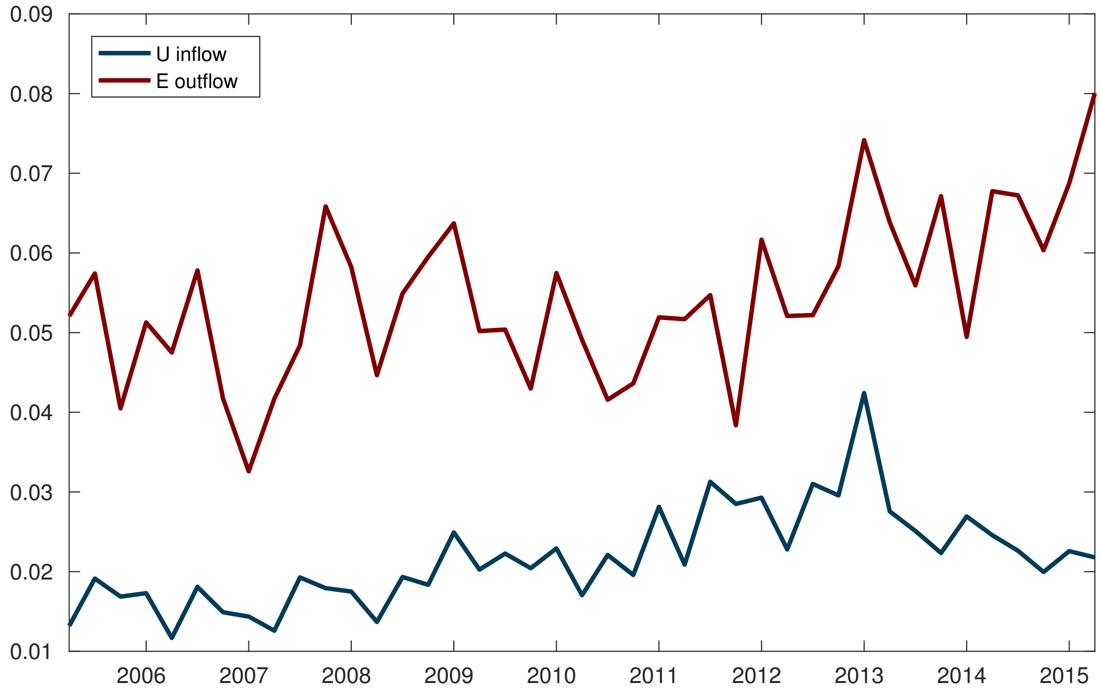
where ϵ_t^s is the fraction of jobs younger than 3 months. Using (2) and the employment outflow rate one can compute the underlying two probabilities. ϕ_t^e and ϱ_t^e.

If the two state assumption is a good approximate description of the underlying labor market processes. the job finding and job destruction rates computed with the alternative methods should not be very different from each other. As Figure 1 shows. this is far from true in the Hungarian data. Labor flows appear to be significantly bigger if calculated from job duration data. Cyclical properties are somewhat different as well: job inflows fell more in 2008-2009 than unemployment outflows. Recovery also started later when we use jobs data compared to the unemployment measure. Further. while the unemployment inflow increase substantially from

[4]Data used in the analysis is described in detail in the Appendix.

Figure 1: Estimated transition probabilities with two states in Hungary





The figure plots unemployment (blue lines) and employment (red lines) inflow and outflow rates in Hungary. The calculation is based on two states. and uses unemployment and job duration. alternatively. Data are not seasonally adjusted. Source: Eurostat and own calculation.

2008. this trend is much less apparent for jobs outflows.

To explain the causes of the differences we need more information. but we can discuss some probable factors. It is documented (Shimer 2005b) that job-to-job transitions paly an important role in job flows. Those who change jobs directly. or find jobs within one quarter. do not appear in the unemployment statistics. This is partly a question of definitions. and partly due to the time aggregation problem. The other obvious issue is that measures based on uenmployment contain flows to and from employment. but also to and from inactivity. Increased unemployment inflows after 2008 might very well have been caused by increased labor market participation of previously inactives.

3 Labor flows with three states

The previous section showed that the two state approach does not properly identify the job finding and job destruction rates. In this section I show that these problems can be treated by taking into account *inactivity* and *job duration* together. We will see below that using a simple modelling framework (see Campolmi and Gnocchi 2014 for the full general equilibrium setup) helps us identify the transitional probabilities relevant for macroecnomic analysis.

The main difficulty for the calculation is that with three labor market states - employment. unemployment and inactivity - there are six. independent gross flows (see Table 1). Since we do not have six independent time series on stocks. we cannot identify all the flows without additional assumptions. Using data on jobs duration. however. allows for the calculation of a few crucial probabilities.

3.1 Flow equations

Let us take the population shares[5] of employment. unemployment and inactivity as defined above (e_t. u_t. i_t). Moreover. let s_t denote the number of searchers (relative to the population) at the beginning of period t. The fraction of jobs that dissolve at the beginning of period t is given by ρ_t This means that the number of *potential job seachers* - those without a job - is $\rho_t e_{t-1} + u_{t-1} + i_{t-1}$. Let λ_t be the share of those among potential seekers who decide to search. either by staying in the labor force or coming back from inactivity. From these. the total number

[5]We maintain the assumption that the size of the population is constant. In the remainder of the paper we will use - somewhat inaccurately - the terms rate. probability and number interchangably.

of *job searchers* is given by

$$s_t = \lambda_t \left(\rho_t e_{t-1} + u_{t-1} + i_{t-1}\right). \tag{3}$$

Those whose search is not successful become *unemployed*. Let f_t denote the job finding rate. then

$$u_t = (1 - f_t)\, s_t. \tag{4}$$

Finally. inactives are those who as potential job searchers chose not to participate:

$$i_t = (1 - \lambda_t)\left(\rho_t e_{t-1} + u_{t-1} + i_{t-1}\right). \tag{5}$$

Using these definitions. let us write down the flow equation of employment:

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

After substituting for the number of searchers and rearranging. we get that:

$$e_t - e_{t-1} = \underbrace{\lambda_t f_t \left(1 - e_{t-1}\right)}_{\text{Inflow}} - \underbrace{\rho_t \left(1 - \lambda_t f_t\right) e_{t-1}}_{\text{Outflow}}. \tag{6}$$

The first term in the right hand side is the employment inflow: these are the active searchers who find jobs. The second part is the employment outflow: those former employees who either could not. or did not want to. find a job.

3.2 Identification

The equations in the previous part showed that the relevant (from a macroeconomic perspective) flows depend on three probabilities. These are the job finding rate (f_t). the job destruction rate (ρ_t). and the search participation rate (λ_t). Below we show how these probabilities can be identified from available. aggregate labor market data.

Public. aggregate data from the Labor Force Survey (Eurostat) contain time series on labor market stocks. There are quarterly series on the number of unemployed. employed and inactive. Since these add up to the total population. and we assume this to be exogenous (and constant). the three shares represent two independent observations.

The third time series used for identification is job duration. which was described earlier (see also the Appendix for details). We can recall from Section 2 that job duration can be used to calculate the inflow rate into employment:

$$\lambda_t f_t = \frac{e_t^s}{1 - e_{t-1}}, \tag{7}$$

where e_t^s is the number of employees whose tenure is less than three months. Using (6). we can now compute the outflow rate. and hence the job destruction rate:

$$\rho_t = \frac{1}{1 - \lambda_t f_t} \left(1 - \frac{e_t - e_t^s}{e_{t-1}}\right). \tag{8}$$

Finally. using the data on stocks and eq. (5). we can separately calculate λ_t. and hence f_t:

$$\lambda_t = 1 - \frac{i_t}{\rho_t e_{t-1} + u_{t-1} + i_{t-1}}. \tag{9}$$

Altogether. equations (7). (8) and (9) together determine the probabilities f_t. ρ_t and λ_t that we are looking for.

It is worth discussing briefly what makes possible the identification of the three parameters. We already saw under the two state assumption that data on job duration can be used to calculate employment inflows and outflows. Knowing the nmber of inactives makes it possible to separate the active searchers within these flows. Finally. based on this separation we can determine the job finding and job destruction rates as well.

We stressed earlier that the three identified probabilities are sufficient to calibrate a macroeconomic model of *employment*. To understand macroeconomic aggregates (GDP. inflation). employment - and its associated flows - are the key labor market variables. Our method can identify these properly. In contrast. our calculations cannot answer the following question: what is the probability that a person who was previously *unemployed* finds a job? Our job finding rate is an *average* among job searcher with different labor market backgrounds. Flows for individual groups are very important for social policy - for example. when looking at the job prospects of the long term unemployed -. but are somewhat less relevant for the *macro modeller*.

Apart from the three time series used so far. data is also available for unemployment duration (as discussed above). We showed earlier that this identifies unemployment inflows and outflows. In contrast to the two state case. under three states these no longer correspond to the job finding and job destruction rates.

To see this. let us write down the flow equation of unemployment under three states:

$$u_t - u_{t-1} = \underbrace{\rho_t \lambda_t^e \left(1 - f_t^e\right) e_{t-1} + \lambda_t^i \left(1 - f_t^i\right) i_{t-1}}_{\text{Inflow}} - \underbrace{\left[1 - \lambda_t^u \left(1 - f_t^u\right)\right] u_{t-1}}_{\text{Outflow}},$$

where $1 - \lambda_t^u$ is the labor force exit probability of the *unemployed.* and f_t^u is the job finding rate of the *unemployed.* The probabilities λ_t^e. λ_t^i and f_t^e. f_t^i are similarly defined for the other two relevant groups. We can see that these jointly determine inflows into unemployment. Without making further assumptions. the individual parameters cannot be separated. We will examine later what conclusions can be drawn from the available information.

3.3 Data

The main advantage of our method is that it uses easily available. public data. Labor markets stock can be downloaded from the Eurostat website. at the quarterly frequency for all European Union member states. and for some other European countries as well. In addition to stocks. data on job duration (job tenure) and data on unemployment duration are also easily available.

The time series are not seasonally adjusted. and are available from 2005Q1. We mostly work with the raw data. except when - for presentational purposes - we seasonally adjust the computed transition probabilities on Figures 5-7. When computing time series averages. we use the available sample period for each country. This is 2005Q1-2015Q2 for most nations. with a few exceptions. These and other data related issues are explained in detail in the Appendix.

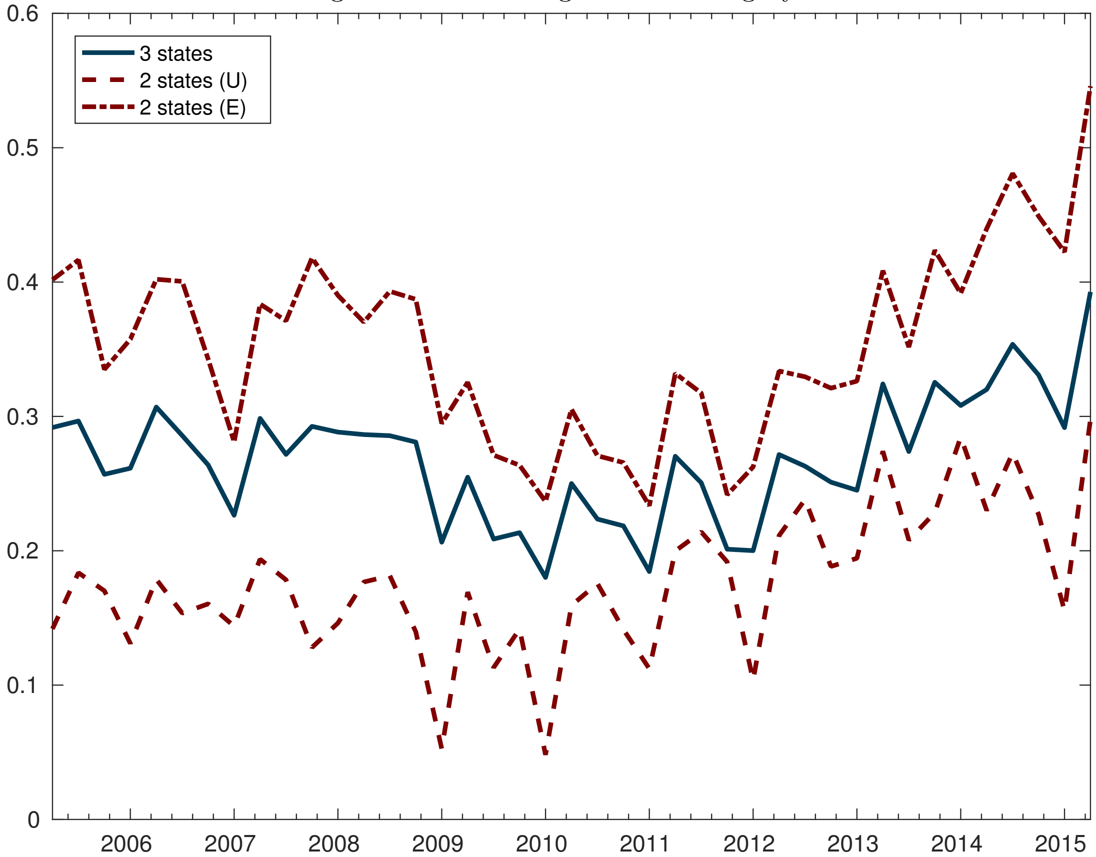
4 Results

4.1 Flows in Hungary

Figures 2-4 show the results for Hungary. where for comparison we also include rates computed under the two state approach. Figure 2 plots job finding rates. Numbers from the three state method are higher than values based on unemployment duration. but lower than when using job duration with two states. This is intuitive. since our three state method takes into account inflows into and outflows from the labor force.

The job finding rate fell singificantly from its pre-crisis level. and after large fluctuations started rising again from 2012. The pronounced increase at the end of the period is partly due to the public works program of the Hungarian government. It is worth mentioning that

Figure 2: Job finding rates in Hungary



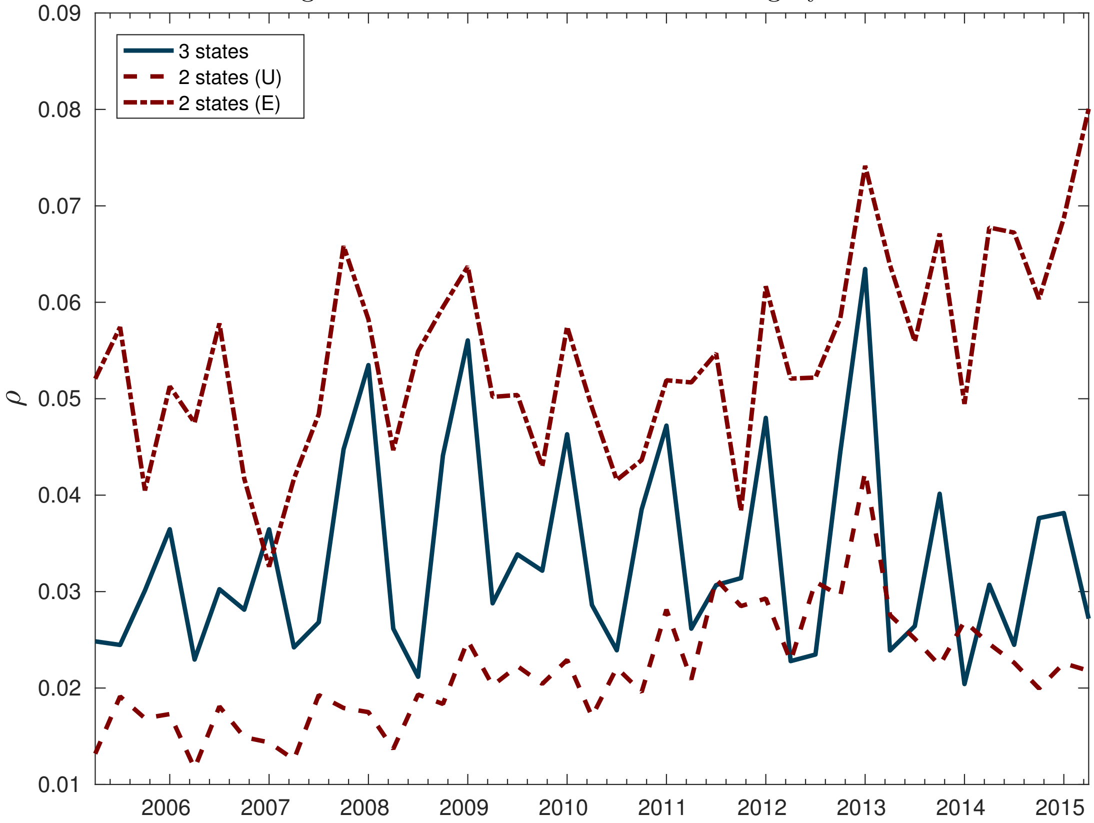
The figure plots the job finding rate for Hungary. using two and three state methods. Data is not seasonally adjusted. Data source: Eurostat and own calculation.

the indicator based on unemployment duration starts increasing much earlier. apparently not because of job finding. but because the unemployed gave up searching and became inactive.

Figure 3 presents the job destruction rate. again compared with two state estimates. The rate is very volatile - partly due to seasonality-. but its average value rose during the financial crisis. and returned to the pre-crisis level only by 2013. We can also see that job destruction in general is significantly higher than suggested by indirect. the two state estimate based on unemployment duration (Shimer 2005a). Both the participation margin and job-to-job transition is likely to be responsible for this result. Separating these two effects. however. is not possible with the data used for the calculations.

Finally. Figure 4 shows the fraction of searcher among those who are not employed (job search intensity). The chart also includes the activity rate for comparison. on the right scale. We can see that search intensity increased significantly. from 2008. and fell somewhat after 2013. In contrast. activity only started rising after 2011. but this increase is still going on. The rise in search intensity may be explained by an increase in the search effort of the inactive before

Figure 3: Job destruction rates in Hungary



The figure plots job destruction rates in Hungary. using two and three state methods. Data are not seasonally adjusted. Data source: Eurostat and own calculation.

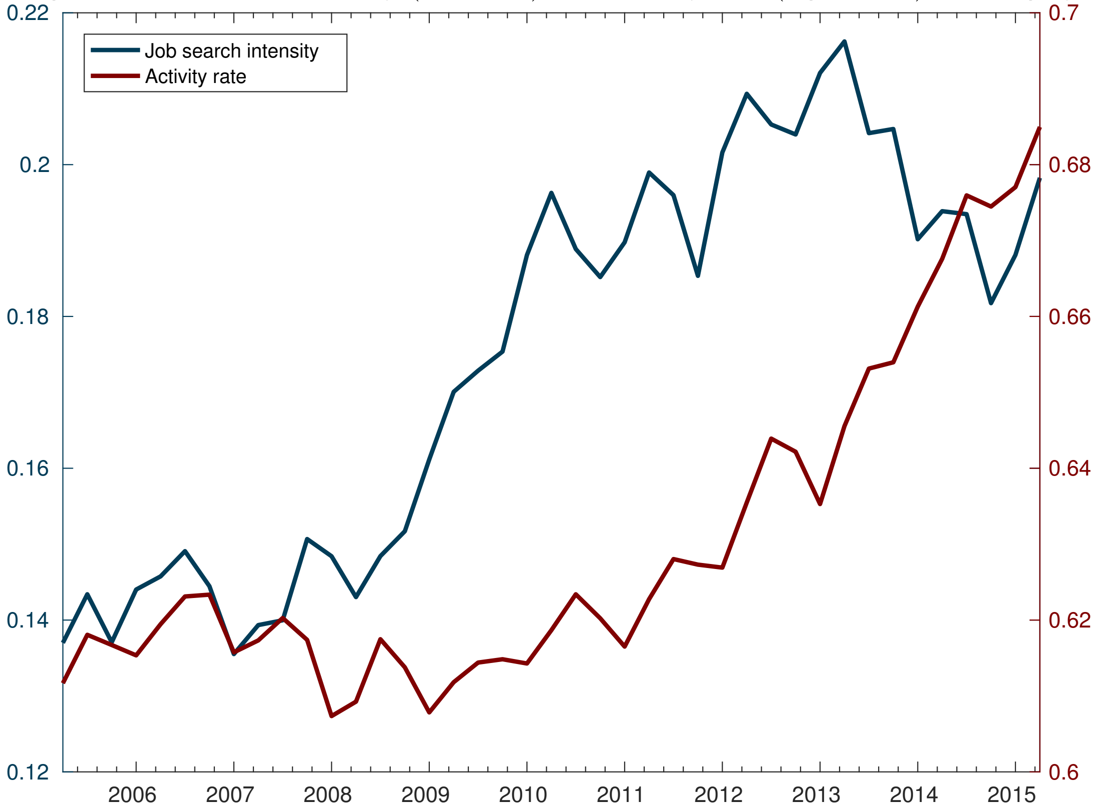
they formally entered the labor market. Another option is that inflows into inactivity may have shifted away from the unemployed and towards the employed.

To summarize the above. we can conclude that measures based on job duration indicate higher labor market flows than measures based on unemployment duration. It is also important. however. to take into account flows into and out of the labor force. Ignoring the participation margin and using job durations under only two states overestimates flows related to employment. The three state method described in the previous section is able to paint a momre realistic picture of the labor market.

4.2 International comparisons

In this section we compare the Hungarian flows with other countries. We shows detailed results for 5 economies: Hungary (HU). Czech Republic (CZ). Poland (PL). Austria (AT) and United Kingdom (UK). The three Visegrad countries are a natural comparison group. Austria's geographical location and history makes it a good reference point among the advanced members of the European Union. The United Kingdom is a frequent example of a labor market that is

Figure 4: Job search intensity (left scale) and activity rate (right scale) in Hungary



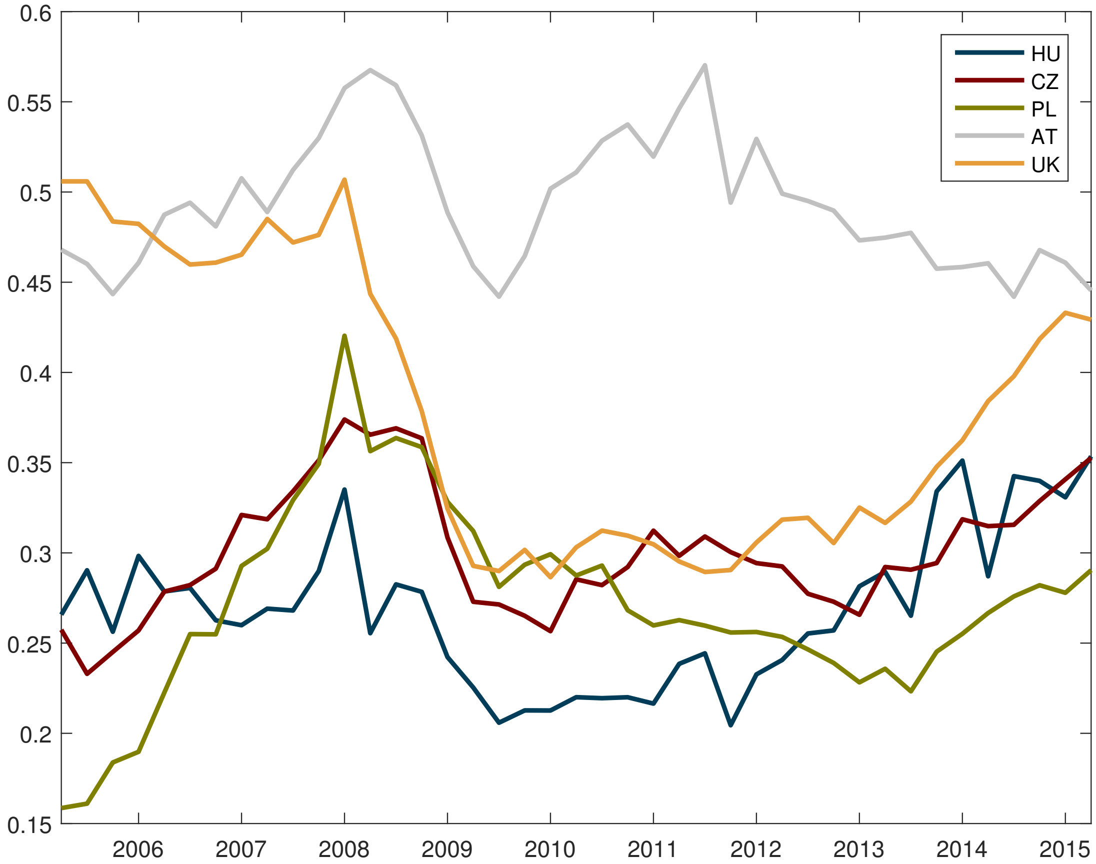
The figure plots the number of searchers among the non-employed (λ_t) and the activity rate ($e_t + u_t$) in Hungary. Data are not seasonally adjusted. Data source: Eurostat and own calculation.

more flexible than those of the continental economies. After calculating the transition rates. we seasonally adjust the resulting time series to filter out short-run factors that are less relevant for cross-country comparisons.

Figure 5 shows job finding rates. These are quite similar for the Visegrad countries. and significantly lower than Austrian or British levels. There has been. however. a significant improvement ion Hungary since 2012. It would be important to know. however. how much of this improvement is due to the public works program. Unfortunately data on job duration is not available separately for public works participants. It is somewhat surprising that the Austrian job finding rate is higher than the British one. One reason for this in the sample period might be the particularly severe impact of the financial crisis in the UK. Even taking this into account. however. does not show the British labor market to be more flexible than the Austrian.

Figure 6 shows the job destruction rates. These are very volatile even after seasonal adjustment. but basicaly confirm results seen on the previous chart. Job destruction rates are largest in Austria. and they fell significantly during the crisis in Britain. This might explain why - despite the falling job finding rate - British unemployment remained reatively low after 2008.

Figure 5: Job finding rates in five countries



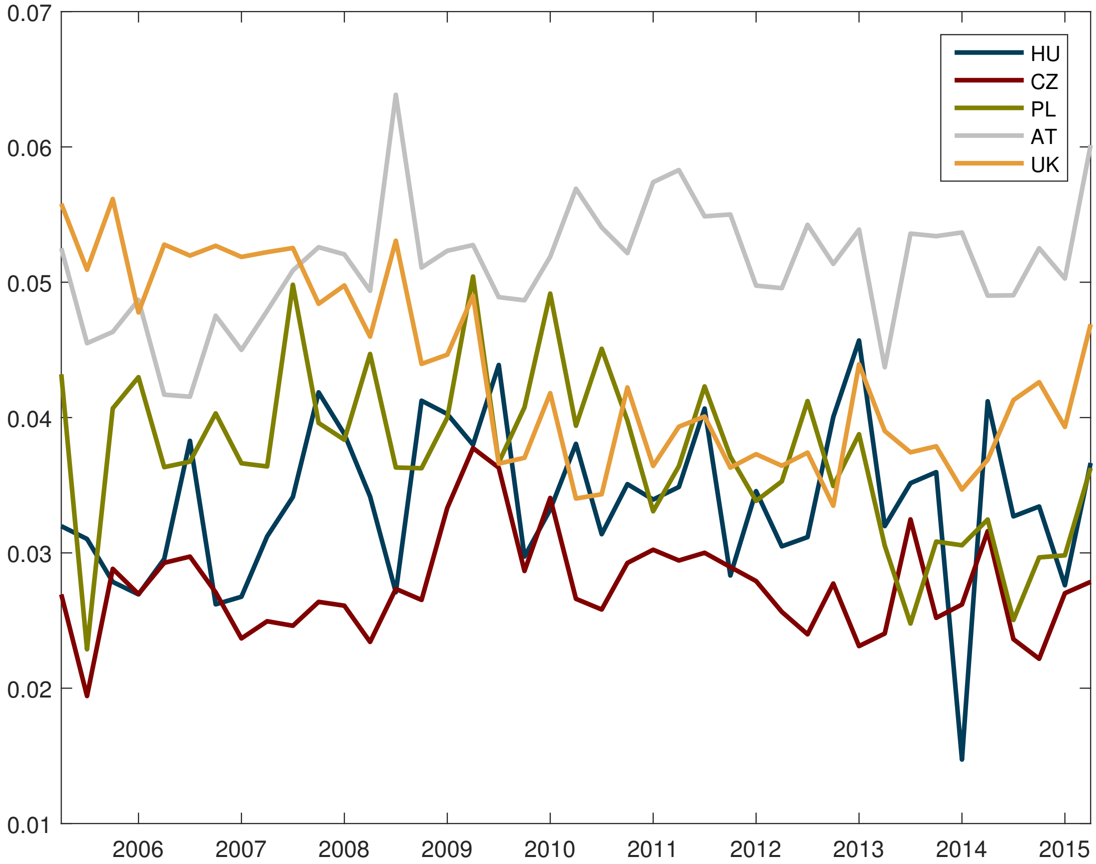
The figure plots job finding rates in five European countries. using the three state method. Data are seasonally adjusted. with the X-13 ARIMA-SEATS method. Data source: Eurostat and own calculation.

Figure 7 presents the job search intensity of the non-employed. It is lower in the Visegrad countries. with no major differences in the second half of the sample. In contrast to the previous two figures. it is the British rate that is highest here. It seems that the flexibility of the UK job market appears more in the number of searchers. and less in the job finding and job destruction probabilities. To summarize. overall it is the Austrian labor market that Hungary should aim to replicate.

We now present labor market flow statistics for the full sample of 33 countries. Table 2 shows time series averages for all countries, where the columns contain the job destruction rate (f_t), the job destruction rate (ρ_t), and the job search intensity (λ_t). For comparability with the previous literature, we also include rates computed with the two state method based on unemployment duration (ϕ_t and ϱ_t).

Countries are grouped into three categories, based on the magnitude of the job finding rate. The largest values can be see among the Northern European countries, with Turkey, Austria and Switzerland added. In general, job destruction rates and job search intensity are also highest

Figure 6: Job destruction rates in five countries



The figure shows job destruction rates in five European countries. calculated with the three state method. Data are seasonally adjusted. using the X-13 ARIMA-SEATS method. Data source: Eurostat and own calculation.

among these countries. The latter is not true for Turkey, however: in Turkey, a relatively small fraction of the non-employed participate in the otherwise dynamic labor market movements.

The second group consists of mostly Western European countries. These have lower job finding and job destruction rates, and also lower search intensities. The comparison is particularly striking with respect to Scandinavian countries: while in Sweden the share of searchers is 40%, in France, the UK and Germany it is only 25%. We again find that the British labor market does not seem particularly flexible, at least according to our indicators based on job duration.

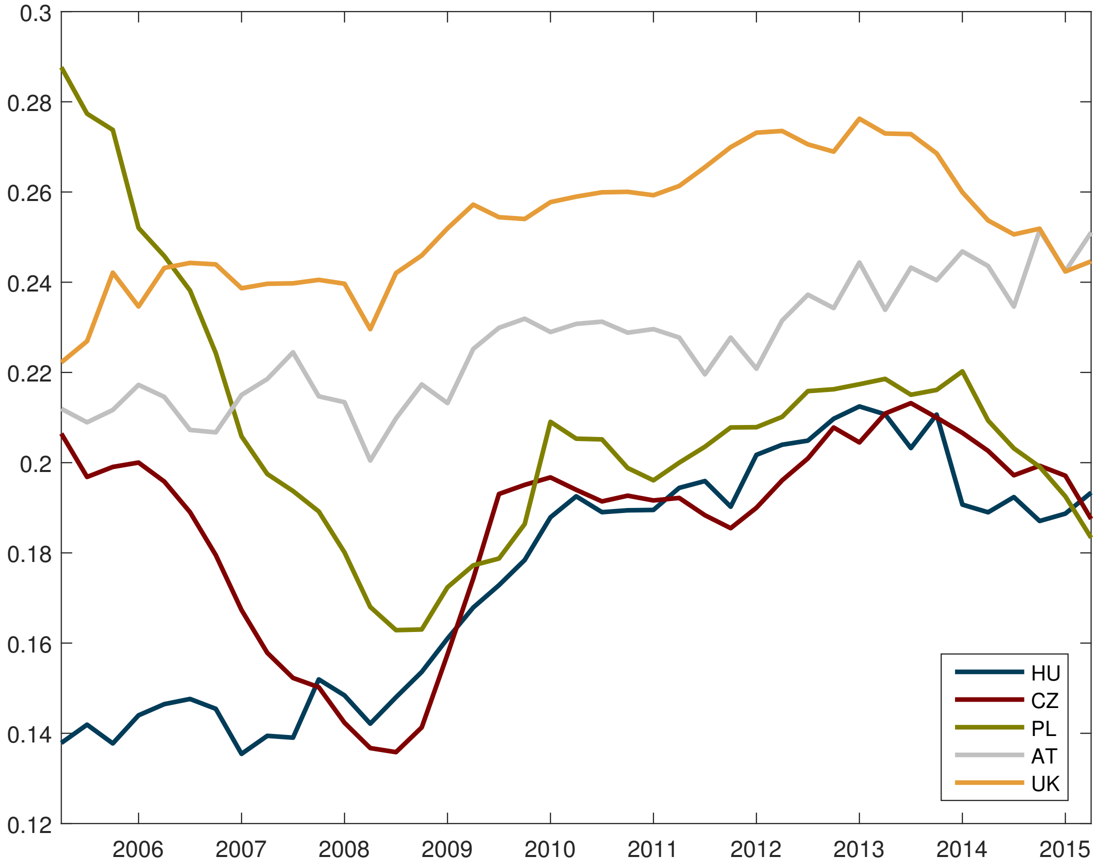
The third group contains Mediterranean and East-Central European countries.Here job finding rates are very low, and jobs are relatively durable. The fration of searchers is much lower than in the first group, but it is similar to the second group. Hungary is in the middle of the group. It is worth emphasizing, however, that In Hungary the time series averages are significantly lower than values seem towards the end of the sample period. If the increased churning after 2012 remains persistent (and it is not only the effect of the public works program), Hungary will move to the bottom of the second country group.

Table 2: Flow probabilities for European countries

		f_t	ϕ_t	ρ_t	ϱ_t	λ_t
NORTHERN EUROPE	Iceland	0.657	0.715	0.107	-	0.480
	Norway	0.628	0.455	0.065	0.030	0.253
	Denmark	0.595	0.448	0.093	0.051	0.361
	Switzerland	0.554	0.300	0.057	0.020	0.330
	Sweden	0.552	0.425	0.102	0.063	0.408
	Turkey	0.542	0.339	0.124	0.056	0.191
	Austria	0.494	0.354	0.051	0.030	0.226
	Finnland	0.491	0.437	0.084	0.069	0.325
WESTERN EUROPE	Cyprus	0.396	0.291	0.054	0.036	0.266
	France	0.390	0.275	0.062	0.037	0.257
	Germany	0.387	0.239	0.045	0.022	0.272
	Holland	0.385	0.274	0.033	0.019	0.225
	Luxembourg	0.385	0.373	0.033	-	0.153
	United Kingdom	0.380	0.346	0.043	0.038	0.253
	Estonia	0.371	0.265	0.052	0.041	0.286
	Slovenia	0.356	0.188	0.042	0.019	0.218
	Latvia	0.333	0.229	0.062	0.038	0.325
	Belgium	0.324	0.214	0.041	0.024	0.194
	Ireland	0.323	0.198	0.049	0.027	0.256
	Malta	0.314	0.330	0.028	0.039	0.131
	Czech Republic	0.301	0.203	0.027	0.017	0.186
SOTHEASTERN EUROPE	Spain	0.284	0.299	0.074	0.084	0.387
	Litvania	0.279	0.247	0.038	0.036	0.254
	Italy	0.277	0.167	0.036	0.020	0.172
	Poland	0.273	0.215	0.037	0.027	0.208
	Bulgaria	0.269	0.148	0.034	0.018	0.208
	Hungary	**0.268**	**0.177**	**0.033**	**0.022**	**0.175**
	Portugal	0.253	0.176	0.044	0.029	0.297
	Romania	0.222	0.222	0.020	0.022	0.141
	Croatia	0.176	0.100	0.032	0.020	0.229
	Slovakia	0.149	0.097	0.024	0.014	0.254
	Greece	0.120	0.141	0.025	0.031	0.259
	Macedonia	0.076	0.063	0.034	0.028	0.038

The table presents job finding and job destruction rates for 33 countries using the two state (ϕ_t, ϱ_t) and three state methods (f_t, ρ_t). The last column is the job search intensity of the non-employed (λ_t). The numbers are time series averages for the country-specific sample periods. Data are not seasonally adjusted. Source: Eurostat and own calculation.

Figure 7: Job search intensity in five countries



The figure shows job searchers among the non-employed in five European counties. using the three state method. Data are seasonally adjusted. with the X-13 ARIMA-SEATS method. Data source: Eurostat and own calculation.

Let us compare values calculated using the three state method with values computed using two states and job duration information. The job finding rate (f) is typically higher than the unemployment outflow rate (ϕ). This means that in most countries filling vacant jobs the inactive and job changers play a significant role, and/or flows from unemployment to inactivity are high. Interestingly, the two numbers are most similar in the United Kingdom, which indicates that job search is more connected to unemployment here than in other continental economies. The job destruction rates show similar patterns. Numbers based on the two state method are lower, since we compute them from the unemployment outflow rate.

To sum up, we see that in the vast majority of countries labor market flows are higher than what is suggested by indicators based on the two state method using unemployment duration. The main cause is probably that the link between unemployment and employment is looser than the two state model assumes. There are significant flows between employment and inactivity, and it is also important to take into account job changers. Flows from unemployment to inactivity, on the other hand, seem less of an issue, probably because these are relatively small compared to changes in employment.

5 Additional results

In this section we present other interesting results, returning to the case of Hungary. We discuss the estimation of the *matching function* using the two state and three state estimates, then we turn briefly to the question of fully identifying gross labor market flows from aggregate stock data.

5.1 The matching function

A fundamental ingridient of the search and matching model of the labor market is the matching function:

$$m_t = m\left(v_t, s_t\right),$$

where m_t is the number of newly filled jobs, v_t is the number (fraction) of open vacancies, and s_t is the number of searchers defined earlier. It is general practice to assume constant returns to scale for the matching function. In this case the relationship can be rewritten in terms of the job dinding rate and labor market tightness ($\theta_t = v_t/s_t$):

$$f_t = m\left(\theta_t\right).$$

To estimate the matching function, let us assume that it is Cobb-Douglas, subject to random shocks to matching efficiency (μ_t). These assumptions lead to the following, log-linear relationship:

$$\log f_t = \alpha + \beta \log \theta_t + \mu_t,$$

where constant returns to scale imply that $0 < \beta < 1$.

We estimate this specification using ordinary least squares (OLS). It is possible that the OLS coefficients are biased, if job creation and search intensity is endogenous to the matching function shock μ_t (Borowczyk-Martins, Jolivet és Postel-Vinay, 2013). If this is the case, then labor market tightness is not independent of the shock, which violates a fundamental assumption of OLS estimation.Our purpose here, however, is not to construct the best unbiased estimator for β, but to compare the estimates when we calculate the job finding rate using the two state or three state method. If the extent of the bias is independent of the method to construct the indicators, the comparison is valid under OLS.

Table 3 presents the results. The first column contains estimation based on three states, while the second column uses two states and unemployment duration in the construction of the job finding rate. We can see that the fit is significantly better when using the three state approach, and parameter estimates are also quite diferent. Therefore, when estimating the matching function it is important to use the measure advocated by this paper. It is closer to the theoretical job finding rate than the unemployment outflow rate that is identified in previous papers.

Table 3: Comparing matching function estimates

	(1)	(2)
Constant	$-5,775^{**}$	-8.592^{**}
	(0.621)	(1.454)
Job finding rate	0.322^{**}	0.481^{**}
	(0.045)	(0.103)
R^2	0.568	0.359

The table shows estimation results for the matching function. Column (1) uses job finding rates calculated with the three state method, while column (2) uses job finding rates calculated with the two state (Shimer) method. The regressions are estimated with ordinary least squares. Two stars indicate significance at bthe 1% level; standard errors are in parentheses. Data source: Eurostat and own calculation.

5.2 Full identification?

Let us recall that our approach only partially identifies labor market flows. The fundamental reason for this is that we use only three time series: employment, unemployment, and job duration. There is a fourth series we have not used yet, which is the number of fresly unemployed (unemployment duration). Overall, we have at most four time series to compute potentially six different gross flows among the three labor market states.

An important question is whether we can calculate the missing flows with appropriate identification restrictions. Note that are job finding, job destruction and search intensity rates are averages: the job finding probability, for example, can be different for those who were previously unemployed, and for those who were previously inactive. The required identification restrictions restrict the number of such differences that we can allow for.

We investigate only the simplest case, where we assume that $f_t^e = f_t^u = f_t^i$ and $\lambda_t^{eu} \equiv \lambda_t^e = \lambda_t^u$, where the superscripts indicate those who in period $t-1$ were employed, unemployed and inactive, respectively. We thus postulate that the job finding rate is independent of previous labor market status, and the probability of searching is the same between the formally employed and the formally unemployed. We 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, generic 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:

$$u_t - u_{t-1} = \rho_t \lambda_t^{eu} \left(1 - f_t\right) e_{t-1} + \lambda_t^i \left(1 - f_t\right) i_{t-1} - \underbrace{\left[1 - \lambda_t^{eu} \left(1 - f_t\right)\right]}_{\phi_t} u_{t-1}. \tag{10}$$

As we showed earlier, using data on unemployment duration we can calculate the outflow rate ϕ_t. Substituting this into equation (10) we can also compute the unemployment inflow rate. Given our previous estimates for the job finding rate f_t, the job destruction rate ρ_t, and the average search intensity $\lambda_t = \left(\rho_t e_{t-1} + u_{t-1}\right) \lambda_t^{eu} + i_{t-1} \lambda_t^i$, we can recover the two separate search intensities, λ_t^{eu} and λ_t^i. This means that we 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 - as we saw in Table 2 - the unemployment outflow rate in most countries is smaller, than the job finding rate. This is inconsistent with eq. (10), 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 or 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 i either direction, hence we do not see full identification possible from aggregate data.

6 Summary

This paper presented a method to compute labor market transition probabilities using agregate data. Although identification is partial, we can calculate the job finding and job destruction rates, which are crucial for macroeconomic modelling. Identification relies crucially on jobs duration data, which is available from Eurostat since 2005 at the quarterly frequency. Based on the method, we carried out an empirical analysis for Hungary and most of the European countries, using the sample period 2005Q1-2015Q2.

Our method is easy to apply. To help others, let us summarize the main steps:

1. From the Eurostat homepage, download quarterly time series for employment, unemployment and inactivity (E_t, U_t and I_t) for the age group 15-64, or whichever is used for the analysis.

2. Convert numbers to shares (e_t, u_t and i_t), by dividing the absolute magnitudes by the size of the relevant population, which is simply the sum of the three labor market groups.

3. Also download from Eurostat the number of empoyed broken down by job tenure (duration). Use the fraction of those within the population whose job tenure is less than 3 months (e_t^s).

4. Compute the job finding rate, the job destruction rate, and the job search intensity of the non-employed using equations (7), (8) and (9).

Results show that employment fluctuations are larger than if we rely on the two state mathod of Shimer, who used unemployment duration for identification. To get a more complete picture, it is necessary to take into account the participation decision. Our indicators based on three states partialy modify the prevailing picture about the flexibility of European labor markets, but leave the relative position of countries mostly intact.

Our method is useful to gain information about movements into and out of employment, but we cannot separately identify job finding rates for the unemployed. As we argued in the paper, this is not necessary to model the evolution of the macro economy. For social policy, on the other hand, it is important to understand the employment prospects of the unemployed. It is likely that while the evolution of employment looks similar in Britain and in the continental European economies, in the former it is much easier to find a job when unemployed. To investigate this question, we would need additional identification restrictions, but there are no obvious candidates. It is probably more fruitful to combine our approach with micro data, if they are available for the country or countries we would like to analyze.

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Data appendix

Data comes from Eurostat[6]. Time series contain raw data, they are not seasonally adjusted. Availability is defined more pricesely as: Database by themes -> Population and Social conditions -> Labour market -> Employment and unemployment -> LFS series – Detailed quarterly survey results. Within this group, we use the following time series:

Unemployment Total unemployment – LFS series -> Unemployment by sex, age and duration of unemployment (lfsq_ugad)

Employment Employment – LFS series -> Employment by sex, age, time since job started and economic activity (lfsq_egdn2)

Inactivity Inactivity – LFS series -> Inactive population by sex, age and willingness to work (lfsq_igaww)

The sample period is in general 2005Q1 - 2015Q2, which is determined by the starting date of the job duration time series (unemployment and inactivity is available for some countries from 1998Q1). Periods by country are as follows:

2005Q1–2015Q2 Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finnland, France, Germany, Greece, Holland, Hungary, Iceland, Ireland, Italy, Latvia, Litvania, Luxembourg, Malta, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, United Kingdom

2006Q1–2015Q2 Macedonia, Norway, Turkey

[6] http://ec.europa.eu/eurostat/data/database

2006Q4–2015Q2 Croatia

2010Q1–2015Q2 Switzerland

Jobs are divided into two categories by duration: those under three months, and those over three months. For some countries and periods there is a third option with nonzero observations, no response. When this happens, I divide the latter category in accordance to the shares in the other two groups. For Hungary, the no response category is nonempty only after 2014Q1, but the share of nonresponse is at most 1%. similarly small numbers can be seen in most cases, expect for a few countries - like Norway - at the beginning of the sample period.

Sample periods for unemployment duration are the same as for job tenure. Answers, however, are broken down into many more categories. Given the quarterly frequency, short term unemployed are those whose duration is either less than 1 month, or is from 1 to 2 months. Nonrespondents are divided into the two categories the same way as indicated above for job tenure. It is worth noting that compared to the job duration data, the number and occurance of nonresponse is much more rare in the case of unemployment duration.

Rates presented on Figures 5-7 for five countries are seasonally adjusted. Adjustment was done by the free and open source IRIS Toolbox, which is an add-on to Matlab. IRIS uses the X13 ARIMA-SEAT method developed by the US Census Bureau.