Swedish Labour Market Flows

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1 Introduction

2 Literature

Our study relates to a body of literature, which discusses the decomposition of variation in unemployment into variation coming from inflow into and outflow from unemployment, respectively.

The findings from the early literature can be summarised in the catch-phase *the ins win.*[1] This phase summarises the notion that variations in the inflow to unemployment accounts for the lions share of the observed variation in the unemployment.

This result was found by Darby et al. (1986) who construct a framework for decomposing the variation in the level of unemployment in the United States. Specifically, they show how the current level of unemployment can be written as a function of an initial level and subsequent in- and outflow rates. They apply this framework to the monthly flow rates between labor market states, constructed from the Current Population Survey. Using this setup they construct two counterfactual time-series for unemployment: One where the inflow rate into unemployment is held fixed, and one where the outflow rate from unemployment is held fixed. The ratio of variance in these series to the variance of actual unemployment is then computed, and it is shown that this ratio is higher for the counterfactual serie where the outflow rate is held constant. Darby et al. (1986) take this as evidence for fluctuations in the inflow rate being the driving factor behind the observed variation in the level of unemployment. The result is strengthened when the authors account for compositional effects.[2] The authors take the overall finding to be important, as the contemporaneous macroeconomic literature focused on variations in the inflow to unemployment in explaining fluctuations in unemployment[TBD: Cite Dornbusch/fisher or Gordon]. Here a recession was characterised by a downwards shift in the wage-offer distribution. Being unaware of this shift, would then be more likely to decline incoming job-offers why outflows from unemployment would diminish. The findings by Darby et al. (1986) go against this story.

More supporting evidence of the *the ins win* hypothesis is found by Blanchard and Diamond (1990). They also construct gross worker flows from CPS data, as well as gross flows in and out of manufactoring employment from firm data. Using this data the paper focuses on two aspect of the labor market. First, it focuses on the creation and destruction of jobs over the business cycle. Here the paper finds that reduced employment in recessions(booms) are more driven by higher(lower) job-destruction rates than of lower(higher) job-creation rates. Second, the paper maps the flows of workers between different labor market states. Specifically, the flow from employment to unemployment is found to increase in a recession, while the flow from employment to out-side the labor market decreases. Conversely, the flow from unemployment

[1] This sentence is coined by Darby et al. (1986)

[2] The study does this by regressing the in- and outflow rates on compositional factors as well as lagged flow rates. Using the resulting regressors counterfactual flow rates are constructed, where the rates only vary due to composition. Using these counterfactual flow rates the two counterfactual time-series for unemployment are again created: one where the inflow rate is held constant, and one where the outflow rate is held constant.

to employment is found to increase in a recession, while the flow from outside the labor force to employment decreases.

NOTE: Darby et al. (1985) paper is not related

Later, Shimer (2012)[3] challenged these results. This paper uses information on the unemployment duration as well as the stock of unemployed from the Current Population Survey (CPS) and develops a continous time model, where data is observed at discrete times. This allows for the correction of time-aggregation issues. Data is de-trended using HP-filtering. To decompose the fluctuations in employment into contributions stemming from seperation and job-finding rates, the paper uses that the steady state level of unemployment can be written as a function of the job-finding and seperation rate. This steady state level of unemployment can be shown to track the actual level closely. The expression also allow for the construction of two counterfactual unemployment rates: one where the seperation rate is held constant at its average level and the job-finding rate is allowed to vary, and one where the opposite is true. The variance contribution from each flow rate is then gauged by computing the ratio of the covariance between the counter-factual and the actual unemployment rate to the variance of the actual unemployment rate. Doing so the paper finds that the job-finding rate accounts for two-thirds of the variation in the unemployment rate. This result is at odds with the previous literature, and Shimer (2012) argues that two reasons are behind this. First, fluctuations in the inflow to unemployment has become quantitatively less important in the last two decades. Second, ignoring the issue of time-aggregation will bias the analysis towards finding a counter-cyclical inflow rate into unemployment. This is because a lower outflow rate *ceteris paribus* makes it more likely that a unemployment worker is *measured* as being unemployment during a spell of unemployment.

Supporting evidence for for this result is found by Hall (2005). He inspects movements in the seperation rate using six different data sources. First, the Job Openings and Labor Turnover Survey (JOLTS), which since 2000 measures the seperation rate from the firm side. Second, he construct a time-serie going back to 1948 the seperation rate by regressing the seperation rate in the JOLTS on industry-growth rates, and then using the historical industry-growth rates to construct a computed seperation rate before 2000. Third, he presents Shimer's measure of seperation from the CPS. Fourth, he measures seperations directly from the CPS via a question included since 1994. Fifth, measures the seperation rate from the Survey of Income and Program Participation, which covers the period 1983 to 1995 and surveys 30 000 workers.[4] Finally, he uses data from the hiring rates in the CPS, which traditionally is closely correlated with the seperation rate. Hall's conclusion from this inspection of evidence is that a constant seperation rate over the last decades is a good approximation.

Fujita and Ramey (2008) on the other hand find that the seperation rate plays a larger role in explaining the unemployment variability. This paper takes a different approach to Shimer (2012) both in terms of data

[3]The first version of this paper appeared in 2005 (**?**).

[4]This data is originally compiled by Gottschalk and Moffitt (2000).

and and methodology. In terms of data they use CPS data on the individual level. From this compute month-to-month transitions and correct for bias stemming from margin error[5] as well as time-aggregation. In terms of methodology, they also rely on the steady state approximation on unemployment from Shimer (2012), but instead of constructing counter-factorial time-series they log-linearise the steady state equation and do a traditional variance decomposition of the resulting terms. They take out the high-frequency trend of the time-series by means of HP-filtering or first differencing. Doing so they find that 40-50 percent of the business cycle fluctuation in unemployment can be explained by the seperation rate. Although, this is somewhat higher than the share reported by Shimer (2012) the two papers both find that the contribution from the seperation rate has declined in the last two decades.

Elsby et al. (2009) also find a somewhat larger role for seperations than Shimer (2012) Like Shimer (2005) they rely on data from the repeated cross-section of the CPS rather than the gross-flow data used by Fujita and Ramey (2008). [TBD: Describe differences in time-aggregation method compared to Shimer] They also take point of departure in the observation, that the actual level of unemployment can be well approximated using the expression for steady state unemployment which is written as a function of the seperation and job-finding rate. This expression can be log-linearised, which allows for the calculation of contributions unemployment changes coming from changes in the separation and job-finding rate, respectively. They do this decomposition for 10 recessions covering the period 1948-2004, and show that on average approximately 35 percent of the increase in unemployment came from higher inflow while the remaining 65 percent came from lower outflow. This split has however changed over time, as the contribution coming from higher seperation has been lower in more recent recessions.

Yashiv (2007)

In addition to the literature focusing on the United States, a number of studies have studied the role of seperation and job-finding rates in other other countries.

Petrongolo and Pissarides (2008) study France, Spain and United Kingdom. They use administrative data on the stock and inflow of unemployed workers as well as data on gross-flows from labor force surveys. Using the time-aggregation correction from Shimer (2012) and the decomposition method from Fujita et al. (2009) they show that (i) approx. 30 % of the historical variation in UK unemployment is explained by variation in the inflow to unemployment, (ii) in France only 20 % of the the variation is driven the inflow, while (iii) the variation in Spain is explained evenly by inflow and outflow.

Elsby et al. (2013) study 14 OECD countries. They use yearly data on the stock of unemployed workers broken down by duration. The data stems from national labor force surveys but is compiled the OECD. For time-aggregation they take point of departure in the method from Shimer (2012), but extend it to account for noisy time-series of short-run unemployed. The idea is that surveys in countries with a low proportion of

[5]Due to sample rotation and temporary absence of individuals transition information is unavailable for a subset of the sample

short-run unemployed might measure the stock of short-run unemployed with a high variance. To account for this they propose to estimate the job-finding rate not only by means of the stock of total and short-run unemployment, but by means of the entire distribution of unemployment. The underlying assumption for this approach to yield a consistent estimate of the average outflow rate among the unemployed is that the job-finding rate is not duration dependent. They test this for all countries, and apply the extended method where the test can be accepted and the approach from Shimer (2012) where the test is rejected. In addition, they develop a method that allows for a decomposition of the variance in unemployment in cases where the actual level of unemployment is not well-approximated by the steady state. In such cases, changes in unemployment will be a function of (i) convergence towards the steady state and (ii) changes in the level of steady state. They find that unemployment variation in Anglo-Saxon economies approximately is explained by a 15:85 inflow-outflow split, while the approximate split in continental Europe is 45:55.

Gomes (2012) studies the United Kingdom. He uses gross-flow time series from the labor force survey, corrects these for the time-aggregation problem by means of the method proposed by Shimer (2012) and decomposes the variation in unemployment both using the method from Shimer (2012) as well as from Fujita and Ramey (2008). He finds that the in- and outflow are roughly equally important.

Silva and Vazquez-Grenno (2013) analyses Spain. They use gross-flow rates from the Spanish labor force survey and correct for time-aggregation using XXXX. Then, the set up a 4 state model, allowing for both regular and temporary employment, and uses this to decompose the variation in unemployment using both the method proposed by Shimer (2012) and Fujita et al. (2009). They find that temporary jobs explain a large part of the the fluctuations in the unemployment rate. Specifically, the transition rates involving temporary contracts accounts for roughly 60 % of the fluctuation in the unemployment rate.

?

3 Method

We derive our decomposition method by first fully defining the assumed underlying stochastic process, and then show what moments from the stochastic process our method identifies. This means an upfront cost in notation to clarify everything, but we think this is outweighed by the gain in being clear in all assumption underlying the estimation procedure.

[I will weaken the following formulation but internally I'll be clear with the gist]. Given that there is a large number of conflicting ways of doing this, and the literature has not yet settled on any standard method, it seems to be useful to show the whole working of an estimation procedure, starting with a fully parametrized stochastic process and go from there.

We will also be fully general in allowing for an arbitrary number of states. This clarifies the underlying logic of the estimation procedure for the general case.

3.1 Environment and notation

So we start by defining the stochastic process that we assume generate our data. We assume that workers can be in S different states from the set $\mathcal{S} = \{\infty, \dots, \mathcal{S}\}$. In our particular case, we will have $S = 4$. Other studies has looked at $S = 2$ and $S = 3$ respectively.

Each individual jumps between states according to a flow matrix $Q(t)$. This means that an individual at time t in state s flows to state s' according to a poisson process with rate $Q(t)_{s,s'}$. The diagonal elements on $Q(t)$ are such that each row sum to zero, i.e.

$$Q(t)_{s,s} = -\sum_{s' \neq s} Q(t)_{s,s'}.$$

With this setup, workers are flowing between states according to a *time-inhomogenous continuous time Markov chain generated by* $Q(t)$. The process is a continuous time Markov chain as it has this property of people flowing to other states at a poission rate. The process is a time-inhomogenous as the flow matrix $Q(t)$ changes over time.

We write $x(t)$ to denote the stochastic process defined above. It is fully defined by the flow matrix function $Q(t)$. It is often convenient to analyze the transition matrix P between two arbitrary time periods as well. This is defined for $t < t'$ as

$$P(t, t')_{s,s'} = \mathbb{P}(x(t') = s' | x(t) = s).$$

It is a well-known theorem in continuous time markov chain theory that the transition matrix is given by

$$P(t, t') = \exp\left(\int_t^{t'} Q(z) dz\right)$$

where $\exp(\cdot)$ denotes matrix exponentiation. We can illustrate the intuition behind this equation for a two state system. For small δ we have

$$\begin{aligned}
\exp\left(\int_t^{t+\delta} Q(z)dz\right) &\approx \exp\left(\delta Q(t)\right) \\
&= \begin{pmatrix} 1-\delta(Q(t)_{1,2}) & \delta Q(t)_{1,2} \\ \delta Q(t)_{2,1} & 1-\delta Q(t)_{2,1} \end{pmatrix} \\
&\approx P(t, t+\delta)
\end{aligned}$$

The last equation is because we consider a small time interval δ, and agents leave state 1 at rate $Q(t)_{1,2}$ which becomes roughly $\delta Q(t)_{1,2}$ for small time intervals. By using that we obtain $P(t,t')$ by repeated multiplication we can let $\delta \to 0$ and obtain the integral.

3.2 Expected unemployment share and law of large numbers **

[tl;dr version of this: with this formulation of stochastic processes, the expected share of individuals in a particular state $\mathbb{E}\sigma(t)$, which is a vector of length S (element s gives the share of that particular element), satisfies the equation

$$\mathbb{E}\sigma(t) = \mathbb{E}\sigma(0)P(0,t)$$

i.e. we can think of expected value vectors of shares being transformed by the transition matrix. Therefore, going forward we will write $\sigma(t)$ for the expected share vector in different states, with initial share $\sigma(0)$ given. We will assume that expected share is equal to actual share, i.e. that sampling error causes negligible errors in measures shares compared to expected shares.]

When other papers do decomposition analyses, they usually neglect the sampling error which results as the share of workers in a particular state does not always equal the expected share of workers given the underlying stochastic process. This neglect can be justified if the sample is large by reference to the law of large numbers.

However, as we have the ambition of starting from a stochastic process and derive everything from there, we will be explicit with defining the shares in terms of the stochastic processes of individual workers, and then show exactly where we refer to the law of large numbers. This is also good to do because when we see where the law of large numbers is called upon, we can see whether it is justified in particular cases, which can be important if we subdivide the labor market into many states.

So let's get started. Assume that there are N workers and we write $x_i(t), i \in \{1, \ldots, N\}$ for the stochastic process for each worker. Worker i start in state $s_{0,i}$. The processes $x_i(t)$ follow the process $x(t)$ in the sense that

$$\mathbb{P}(x_i(t) = s) = P(0,t)_{s_{0,i},s}$$

i.e. the probability that worker i is in state s at time t is given by the transition matrix $P(0,t)$ given that we start from state $s_{0,i}$.

With this formulation, the share of workers in state s is

$$\sigma_s(t) = \frac{\sum_{i=1}^n \mathbb{I}(x_i(t) = s)}{N}$$

where $\mathbb{I}(\cdot)$ is the indicator function which takes value one if the condition is true and zero otherwise. The expected value of this share is given by

$$\begin{aligned} \mathbb{E}\sigma_s(t) &= \frac{\sum_{i=1}^n \mathbb{E}\mathbb{I}(x_i(t) = s)}{N} \\ &= \frac{\sum_{i=1}^n \mathbb{P}(x_i(t) = s)}{N} \end{aligned}$$

We want to re-express this in terms of the initial distribution of the initial state of workers and the transition matrix from 0 to t. It is intuitive that this should be the case, as we have that the expected value "should" be the transition matrix times the initial probability distribution. We prove this by collecting terms which start on the same initial state s_0. Write N_{s_0} for the number of individuals that start in state s_0 and note that

$$\mathbb{E}\sigma_{s_0}(0) = \frac{N_{s_0}}{N}.$$

i.e. the proportion of elements in each state. This equation just says that the expected share of workers in state s_0 at time 0 is the proportion of workers in that state. As the initial state is deterministic, this is no problem.

With this formulation, we get

$$\begin{aligned} \mathbb{E}\sigma_s(t) &= \frac{\sum_{i=1}^n \mathbb{P}(x_i(t) = s)}{N} \\ &= \frac{\sum_{i=1}^n}{N} \\ &= \frac{\sum_{s_0 \in \mathcal{S}} \sum_{i \in \{1,\ldots,N\}; s_{0,i}=s} P(0,t)_{s_{0,i},s}}{N} \\ &= \frac{\sum_{s_0 \in \mathcal{S}} P(0,t)_{s_{0,i},s} N_{s_0}}{N} \\ &= \sum_{s_0 \in \mathcal{S}} (\mathbb{E}\sigma_{s_0}(0)) P(0,t)_{s_{0,i},s} \\ &= (\mathbb{E}\sigma(0) P(0,t))_s \end{aligned}$$

3.3 Identifying the flow matrix $Q(t)$

We observe the distribution vector $x(t) \in \mathbb{R}^S$ at discrete time points

$$t = 0, \ldots, T$$

and we also observe the transition matrix $P(t, t+3)$ (here, the unit of time is one month, and we get the transition probabilities over three month periods). The aim of our analysis is to use our data to first estimate the flow matrix $Q(t)$.

To do this, we use that

$$P(t, t+3) = \exp\left(\int_t^{t+3} Q(z)dz\right)$$

where $\exp(\dots)$ is matrix exponentiation.

To identify Q we further make the assumption that $Q(t)$ is constant on each measurement interval $[t, t+3)$. Under this assumption, we estimate $Q(t)$ by

$$Q(t) = \frac{\log(P(t, t_3))}{3}$$

Can we be sure that we just can take this matrix logarithm and get a unique answer? The answer is yes under some conditions. The matrix logarithm exists and is real-valued if and only if the negative eigenvalues of P in the Jordan composition has an even block size. If this is not true, P is not "embeddable" which means that it cannot be the result from a continuous time Markov chain with constant flow matrix. If this is the case there exist algorithms to derive an approximate generating flow matrix Q. [When I write this I see that our assumption is very strange, as we disconfirm it when we use $P(t+1, t+4)$. Writing this actually makes me want to change it to something else, maybe that $Q(t)$ is linearly interpolated between measurement times or similarly].

3.4 Stationary distribution approximation and the convergence rate to the stationary distribution

In some cases, we can approximate the observed distribution $x(t)$ by the corresponding steady state distribution of the estimated $Q(t)$ for the interval $t \in [t-3, t)$ (we write Q_t for this value going forward.

When Q_t have S distinct eigenvalues, it has on zero eigenvalue λ_1 and the rest of the eigenvalues have negative real parts:

$$Re(\lambda_S) < Re(\lambda_{S-1}) < \cdots < Re(\lambda_1) = 0.$$

The eigenvector $\bar{x}_t$ corresponding to λ_1 is the unique stationary distribution provided that $\sum \bar{x}_t = 1$ where $\sum$ denotes component-wise summation.

All other eigenvectors sum to zero. As the full share vector in the previous quarter $x(t-3)$ sums to 1, we know that there must be a coefficient 1 on the steady state eigenvector $\bar{x}_t$. Thus, we can write

$$x(t-3) = \bar{x}_t + \sum_{i=2}^{S} q_t^i x_t^i$$

i.e. the stationary distribution has coefficient one and the others have arbitrary coefficients q_s^i.

We can use this eigenvalue decomposition of $x(t-3)$ to place bounds on the distance between $x(t)$ and $\bar{x}_t$, i.e. between $x(t)$ and the corresponding steady state vector. The key is that $\exp(3Q_t)$ has eigenvalues $1, \exp(3\lambda_2), \ldots, \exp(3\lambda_S)$ with the same eigenvectors as Q. Thus, we have

$$\exp(3Q)x(t-3) = \bar{x}_t + \sum_{i=2}^{S} q_t^i \exp(\lambda_i) x_t^i.$$

Thus, the terms which are not the steady state decay at rate $\lambda_i < 0$. Thus, we can formulate the distance between them as

$$\begin{aligned} ||x(t) - \bar{x}_t|| &= ||x(t-3)\exp(3Q_t) - \bar{x}_t|| \\ &= ||\sum_{i=2}^{S} q_s^i \left(\exp(3Q^s)\right) x_s^i|| \\ &\leq \sum_{i=2}^{S} |q_s^i| || \exp(3\lambda_i) x_s^i|| \\ &\leq \exp(3\lambda_2) \sum_{i=2}^{S} |q_s^i| ||x_s^i|| \end{aligned}$$

So we see that the distance between $x(t)$ and its corresponding steady state is bounded above by $\exp(3\lambda_2)$ where λ_2 is the second largest eigenvalue of Q_t.[6]

3.5 Taylor approximation

Insofar λ_2 is very negative and convergence is rapid, the sequence of observations can be closely approximated as a function only of Q_t where Q_t is the value $Q(t)$ takes on the interval $[t-3, t)$.

So we obtain a sequence of observations steady states $f(Q_t)$ and want to derive how much of the variation in f can be attributed to different components of Q_t.

We want to focus on cyclical variations in Q_t and $f(Q_t)$ so we want to remove trends. Thus, we extract the trend $\bar{Q}_t$ and see how $f(Q_t) - f(\bar{Q}_t)$ is driven by the different components of Q.

The natural way to do this is to do a Taylor expansion of $f(Q_t) - f(\bar{Q}_t)$ which allows us to linearly decompose. We do a log-linear transformation and obtain

$$\log\left(\frac{f(Q_t)}{f(\bar{Q}_t)}\right) = \sum_{i,j;i\neq j} \frac{\partial f}{\partial Q_{i,j}} \frac{(\bar{Q}_t)_{i,j}}{f} \log\left(\frac{(Q_t)_{i,j}}{(\bar{Q}_t)_{i,j}}\right) + \mathcal{O}\left(||Q_t - \bar{Q}_t||^2\right)$$

With this formulation, we can define the percentage contribution of flow matrix element $Q_{i,j}$ as

$$\beta_{i,j} = \frac{Cov\left(\log\left(\frac{f(Q_t)}{f(\bar{Q}_t)}\right), \frac{\partial f}{\partial Q_{i,j}} \frac{(\bar{Q}_t)_{i,j}}{f} \log\left(\frac{(Q_t)_{i,j}}{(\bar{Q}_t)_{i,j}}\right)\right)}{Var\left(\log\left(\frac{f(Q_t)}{f(\bar{Q}_t)}\right)\right)}$$

and this will sum to 1 apart from the quadratic error term.

[6]In some papers, the important term for convergence is $f+s$ where f is job finding rate and s is job separation rate. This is because in a two-dimensional model $\begin{pmatrix} -s & s \\ f & -f \end{pmatrix}$ is the transition matrix and $-(f+s)$ is the second largest eigenvalue.

3.6 Eigenvalue analysis and appropriateness of decomposition

The convergence rate of a Markov chain to steady state can be analyzed using eigenvalue analysis. In the generic case, the flow matrix Q_t (short-hand for the value $Q(t)$ takes for the interval $[t, t+s)$) has $n$distinct eigenvalues $\lambda_1(t), \ldots, \lambda_n(t)$ which satisfy

$$\lambda_1 < \ldots \lambda_{n-1} < \lambda_n = 0$$

with corresponding eigenvectors $v_1(t), \ldots, v_n(t)$. Here, $v_n(t)$ has only non-negative value and is the unique invariant probability distribution associated with Q_t once we normalize its sum to 1.

This means that $\{v_i(t)\}_{i=1}^n$ form a basis for $\mathbb{R}^n$. Thus, we can decompose the labor market state $x(t)$

$$x(t) = \sum_{i=1}^{n} q_i(t) v_i(t)$$

for some real values q_i. It can be shown that $q_n(t) = 1$ for all Q_t which means that the invariant probability distribution vector $v_n(t)$ always gets weight 1 when we decompose the probability distribution $x(t)$ with respect to the flow matrix Q_t. Writing $\bar{x}(t)$ for this steady-state, we obtain

$$x(t) = \bar{x}(t) + \sum_{i=1}^{n-1} q_i(t) v_i(t).$$

Now, we use that if v is a left eigenvector of Q with eigenvalue λ, then v is also an eigenvalue of $\exp(sQ)$ with eigenvalue $\exp(s \times \lambda)$. Indeed

$$\begin{aligned} v \exp(Q) &= v \sum_{j=0}^{\infty} \frac{(sQ)^j}{j!} \\ &= \sum_{j=0}^{\infty} \frac{s^j \lambda^j v}{j!} \\ &= \exp(s\lambda) v \end{aligned}$$

as required. This means that we can use the decomposition to obtain

$$\begin{aligned} x(t+s) &= x(t) exp(Q_t s) \\ &= \bar{x}(t) + \sum_{i=1}^{n-1} q_i(t) v_i(t) \exp(sQ_t) \\ &= \bar{x}(t) + \sum_{i=1}^{n-1} q_i(t) \exp(s\lambda_i) v_i(t) \end{aligned}$$

As $\exp(s\lambda_i) \to 0$ for $s \to \infty$ whenever $\lambda_i < 0$ (i.e. for $i = 1, \ldots, n-1$), we obtain the classic result that $x(t+s) \to \bar{x}(t)$. Moreover, we get that that the convergence rate is determined by λ_{n-1}, the second largest eigenvalue (as all other terms become insignificant compared to the $\exp(\lambda_{n-1}s)$-term asymptotically. Thus, to analyze whether a steady-state approximation is justified we can analyze the second eigenvalue of the flow matrix.

3.7 Eigenvalues in our data

When we do an eigenvalue analysis of our estimated flow matrices, we get that the second largest eigenvalue is approximately -0.02. This means that the convergence rate is only 2% monthly and 6% on a quarterly basis. This means that a steady state analysis can be inappropriate with our data. (In standard two-state analysis in the US, the flow matrix is

$$Q = \begin{pmatrix} -s & s \\ f & -f \end{pmatrix}$$

which has a second largest eigenvalue $-(s+f)$ which has an approximate size 0.5). [To be added: Redoing our analysis without permanent/temporary partition etc].

The main problem in the data is that the loss rate is extremely low from permanent jobs in Sweden, which means that it takes a long time for the economy to adjust to a new steady state. [Could be added here: "decompose" the causes of a large second eigenvalue].

3.8 Decomposition without steady-state approximation

In this section, we outline how to decompose the cyclical component of unemployment without using a steady-state approximation.

We begin with some notation. Let λ_t^{ij} for $1 \leq i,j \leq 4$ and $i \neq j$ be the estimated flow from state i to state j between time t and $t+1$. Write

$$Q_t(\{\lambda_t^{i,j}) = \begin{cases} \lambda_t^{i,j} & \text{if } i \neq j \\ -\sum_{j \neq i} \lambda_t^{i,j} & \text{if } i = j \end{cases}$$

(We do not write $Q_t^{i,j}$ for the flow rate to emphasize that when we vary $\lambda_t^{i,j}$, we automatically vary the diagonal element of Q to make it a flow matrix, i.e. the flow matrix is a *function* of the $n(n-1)$ defined flows).

We write $\hat{\lambda}_t^{i,j}$ for the trend of the flow $\lambda_t^{i,j}$ and we write $\hat{Q}_t$ for the associated trend flow matrix obtained from $\{\hat{\lambda}_t^{i,j}\}_{i,j;i\neq j}$.

Define the trend state $\hat{x}_t \in \mathbb{R}^4$ by

$$\hat{x}_t = x_0 \exp\left(\sum_{s=0}^{t-1} \hat{Q}_s\right).$$

By the definition of Q_t, the actual state is given by

$$x_t = x_0 \exp\left(\sum_{s=0}^{t-1} Q_s\right).$$

Hence, the deviation can be decomposed into deviations between $\hat{Q}_s$ and Q_s, which in turn is driven by deviations between $\{\lambda_s^{i,j}\}$ and $\{\hat{\lambda}_s^{i,j}\}$.

We make a log-linear approximation of x to get

$$\log\left(\frac{x_t}{\hat{x}_t}\right) = \sum_{s=0}^{t-1} \sum_{i,j} \sum_{i\neq j} \left.\frac{\partial \exp(\sum_{s=0}^{t-1} Q_s)}{\partial \lambda_t^{i,j}}\right|_{Q_s=\hat{Q}_s, s=0,\ldots,t-1} \hat{\lambda}_t^{i,j} \log\left(\frac{\lambda_t^{i,j}}{\hat{\lambda}_t^{i,j}}\right) + \varepsilon_t$$

where $\varepsilon_t$is an error term which is quadratic in $\{\lambda_t^{i,j}\}$. Define

$$\Delta_t^{i,j} = \sum_{s=0}^{t-1} \left.\frac{\partial \exp(\sum_{s=0}^{t-1} Q_s)}{\partial \lambda_t^{i,j}}\right|_{Q_s=\hat{Q}_s, s=0,\ldots,t-1} \hat{\lambda}_t^{i,j} \log\left(\frac{\lambda_t^{i,j}}{\hat{\lambda}_t^{i,j}}\right)$$

as the contribution of variations in the flows from $i$to $j$to overall variations in x. Let $x(k)$ be the k^{th}component of x and $\Delta_t^{i,j}(k)$the k^{th} component of Δ. Then define the contribution of i, j as

$$\frac{Cov(\Delta_t^{i,j}(k), \log\left(\frac{x_t(k)}{\hat{x}_t(k)}\right)}{Var\left(\log\left(\frac{x_t(k)}{\hat{x}_t(k)}\right)\right)}.$$

This expression sums to 1apart from the covariance between trend deviations in $x_k(t)$ and the quadratic error term $\varepsilon_t(k)$.

4 Relation to other papers

Shimer looks at covariance between $\frac{\bar{f}}{x_t+f}$ to $\frac{f}{x+f}$ once both have been detrended. It is not clear that this is a linear decomposition or where the approximation is made around. $\bar{f}$ is the long-run average, but deviation is from trend. ah Fujita & Ramey: Use similar method but in two dimensions.

5 Data

5.1 Data source and selection

Data derives from the Swedish Labour Force Survey (LFS) during the period 1987-2012 (**?**). The survey began in 1961, but micro data is available for 1987 and onwards. During this period the survey samples 17 000-29 500 individuals each month sampled from a register containing the Swedish population (RTB). Up to 2001 the sample includes all ages 16-64, but in 2001 the age interval was expanded to 15-74. For consistency, we will however confine our sample to ages 16-64.

The survey uses a rotating sample (Figure 1). Specifically, a participating individual is interviewed about his or her employment status at a given week every third month during two years. In each month 8 groups of individuals are interviewed. 7 of these 8 groups have been interviewed previously, while 1 group is being interviewed for the first time. Consequently, one group is rotating out(in) of the sample at each point in time.

Overall, the surveyed population is divided into the following categories (i) employed, (ii) unemployed or (iii) outside the labour force (Figure 1). The individual is characterised as *employed* if she was working at least one hour during the reference week as (a) self-employed (including helping spouse) (c) on a permanent contract (*tillsvidereanstallning*) or (d) on a time-limited contract. An individual who has a job but was absent work due to illness, leave, vacation, military service, a conflict or similar is also counted as employed. So is an individual in a labour market program, if she receive some enumeration from the employer. The individual is characterised as *unemployed* if she is not employed, but has been applying for work within the last four weeks and is able to start work within the reference week or the two following weeks. An individual is also characterised as unemployed if the person is set to start a job within the next three months, provided that the individual would be ready to start already in the reference week or during the following two weeks. Finally, an individual is characterised as *outside the labor force* if she is not covered by the definitions above. This includes individuals who would and could be able to work, but who did not actively seek jobs (*latent unemployment*).

In 2007 the treatment of students was altered, so as to comply with ILO definitions. Up to this point full-time students who also applied for jobs were counted as outside the labour force. But from 2007 these are counted as unemployed. For the age group 16-64, which we confine our sample to, this definition is applied through the entire sample.

THIN DATA CORRECTION.

5.2 Labor market stocks and flows

Figure 3 shows the stock of employed, unemployed and inactive in Sweden since 1987. The period covers approx. two business cycles as unemployment troughs and peaks in 1990/2008 and 1996/2001, respectively. The overall employment rate is falling approximately 10 percentage points through the period (from 82 to 70 percent), with inactivity rising similarly. The change in the overall employment rate covers diverse changes for permanent and temporary employment, however. While the share of the population on permanent employment is down 10 percentage points, the share on temporary employment has risen slightly. Consequently, the share of workers on temporary contracts has increased from 20 to 24 percent.

Figure 4-5 show the flows moving between the four groups as hazard rates. From these figures two trends are visible. First, all the flow rates into permanent and temporary employment have decreased. Second, the probability of flowing from employment into unemployment has increased. There is no clear trend in the hazard rates for movements into inactivity.

5.3 Cyclicality of flows

Table 2 illustrates the sensitivity of labour market flows with respect to the business cycle. We gauge this by regressing the relevant hazard rate (logged) on the the unemployment rate and a linear trend. Table 2 reports the coefficient on the unemployment rate from this regression. A positive(negative) value in Table 2 indicates that the correlation between the relevant flow and unemployment is positive(negative). Consequently, a negative(positive) value indicates that the flow is pro-cyclical (counter-cyclical). Thus, from Table 2 we see that all flows into permanent and temporary employment are procyclical, while all flows into unemployment are countercyclical. The flow from permanent employment to inactivity is from regular(temporary) employment is procyclical(acyclical), while the flow from temporary employment to inactivity is countercyclical.

Table 1: Illustration of the rotating panel structure

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8
Month 0	$\mathbf{G_0}$	G_{-3}	G_{-6}	G_{-9}	G_{-12}	G_{-15}	G_{-18}	G_{-21}
Month 1	G_1	G_{-2}	G_{-5}	G_{-8}	G_{-11}	G_{-14}	G_{-17}	G_{-20}
Month 2	G_2	G_{-1}	G_{-4}	G_{-7}	G_{-10}	G_{-13}	G_{-15}	G_{-19}
Month 3	G_3	$\mathbf{G_0}$	G_{-3}	G_{-6}	G_{-9}	G_{-12}	G_{-14}	G_{-18}
Month 4	G_4	G_1	G_{-2}	G_{-5}	G_{-8}	G_{-11}	G_{-14}	G_{-17}
Month 5	G_5	G_2	G_{-1}	G_{-4}	G_{-7}	G_{-10}	G_{-13}	G_{-16}
Month 6	G_6	G_2	$\mathbf{G_0}$	G_{-3}	G_{-6}	G_{-9}	G_{-12}	G_{-16}
Month 7	G_7	G_4	G_1	G_{-2}	G_{-5}	G_{-8}	G_{-11}	Gdv_{-14}
Month 8	G_8	G_5	G_2	G_{-1}	G_{-4}	G_{-7}	G_{-10}	G_{-13}
Month 9	G_9	G_6	G_3	$\mathbf{G_0}$	G_{-3}	G_{-6}	G_{-9}	G_{-12}
Month 10	G_{10}	G_7	G_4	G_1	G_{-2}	G_{-5}	G_{-8}	G_{-11}
Month 11	G_{11}	G_8	G_7	G_4	G_1	G_{-2}	G_{-5}	G_{-8}
Month 12	G_{12}	G_9	G_6	G_3	$\mathbf{G_0}$	G_{-3}	G_{-6}	G_{-9}

Notes: G_n is group of individuals who entered the survey in month n. Each group is surveyed with an interval of 3 months. In each month 7/8 of the sample has been surveyed before. 1/8 of the sample is surveyed for the first time.

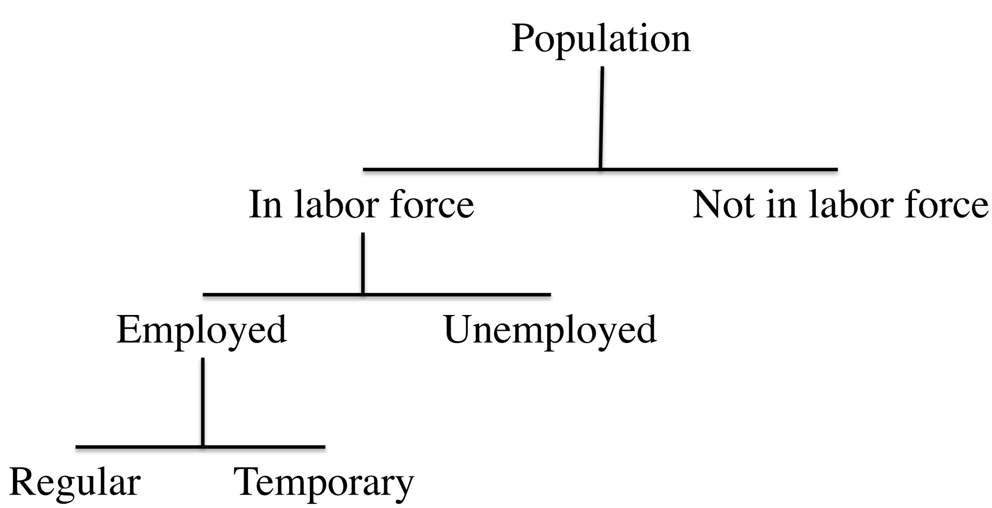

Figure 1: Basic classification of population in labor force survey

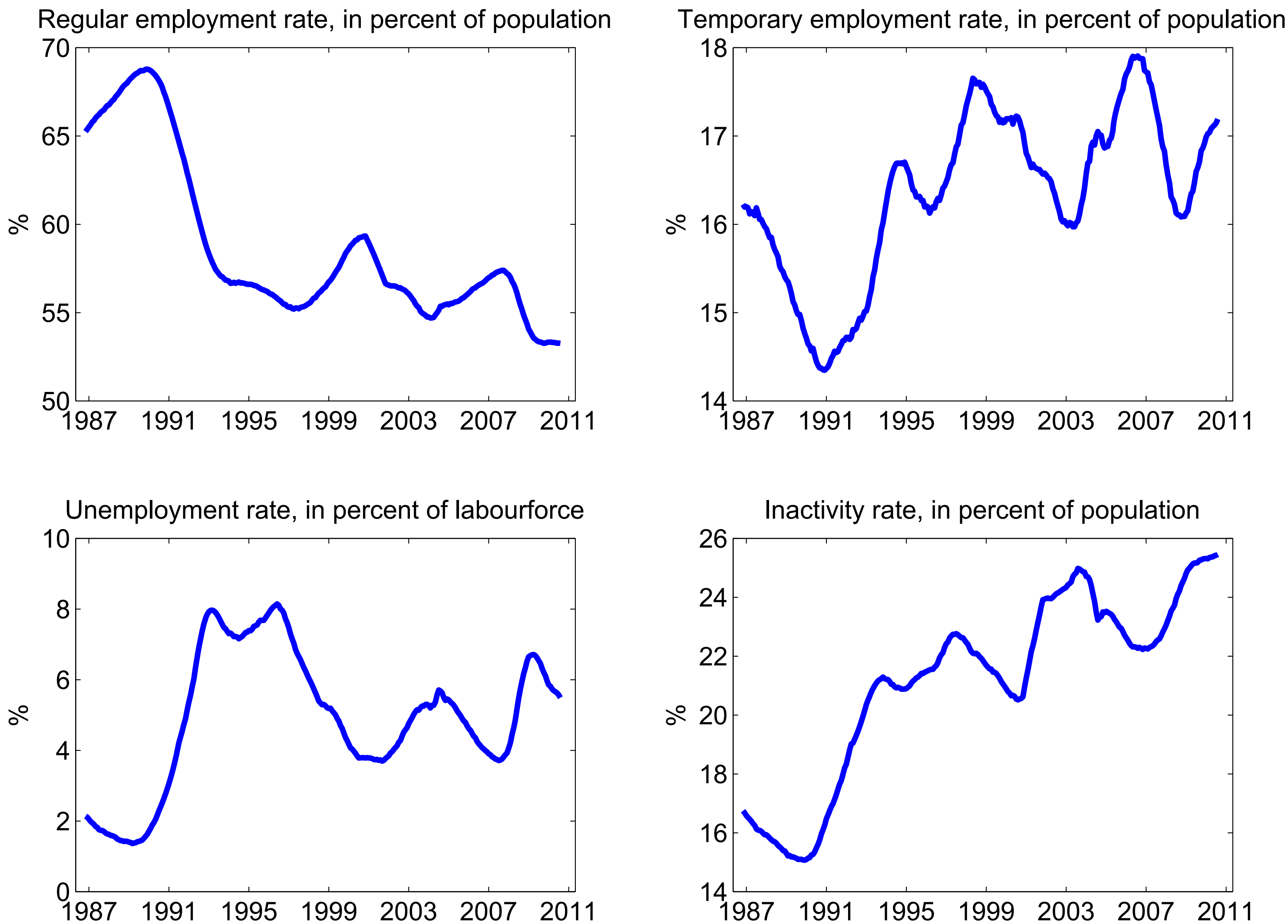

Figure 2: Labour market stocks across time

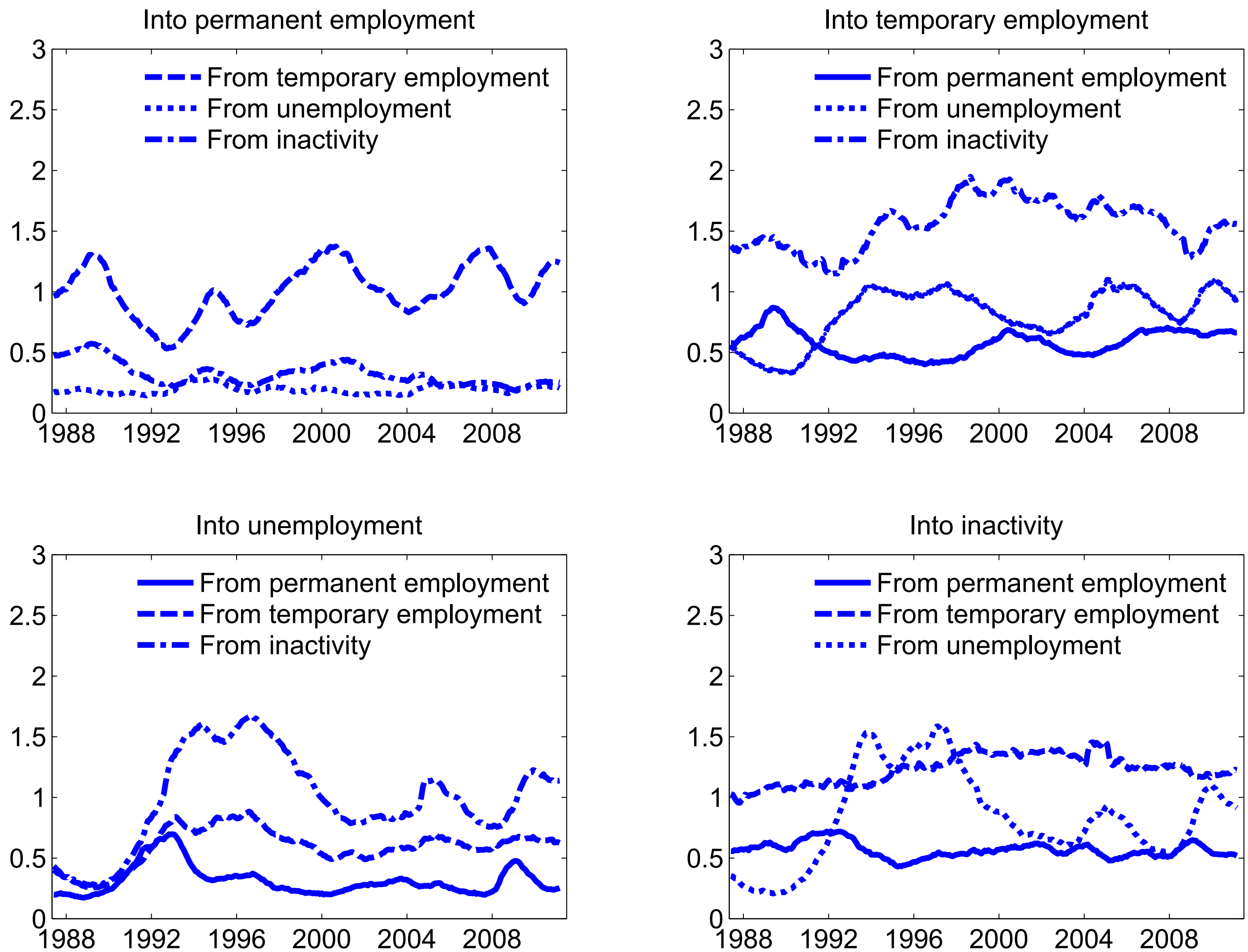

Figure 3: Gross flows between labour market states

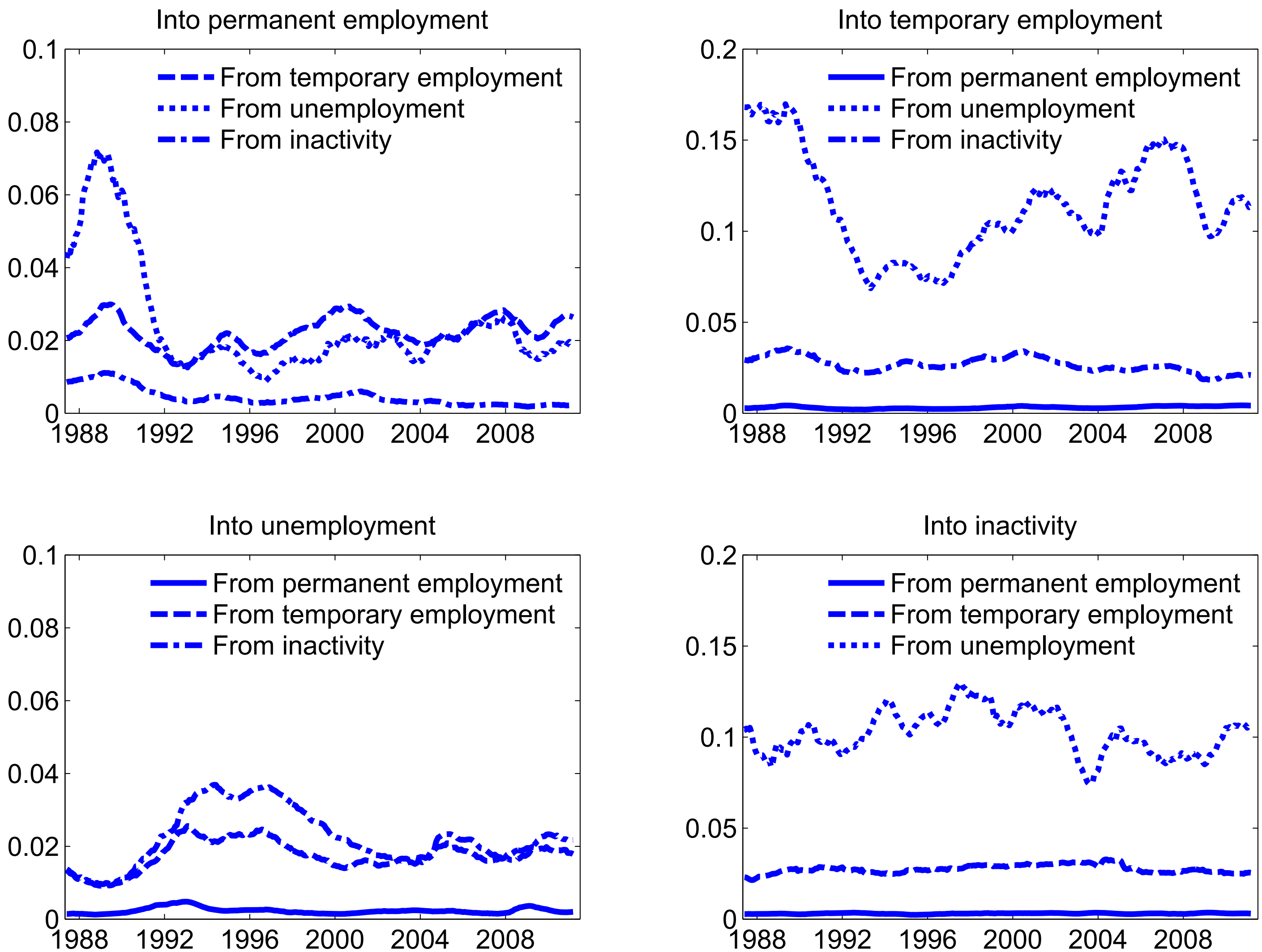

Figure 4: Hazard rates for transition across labour market states

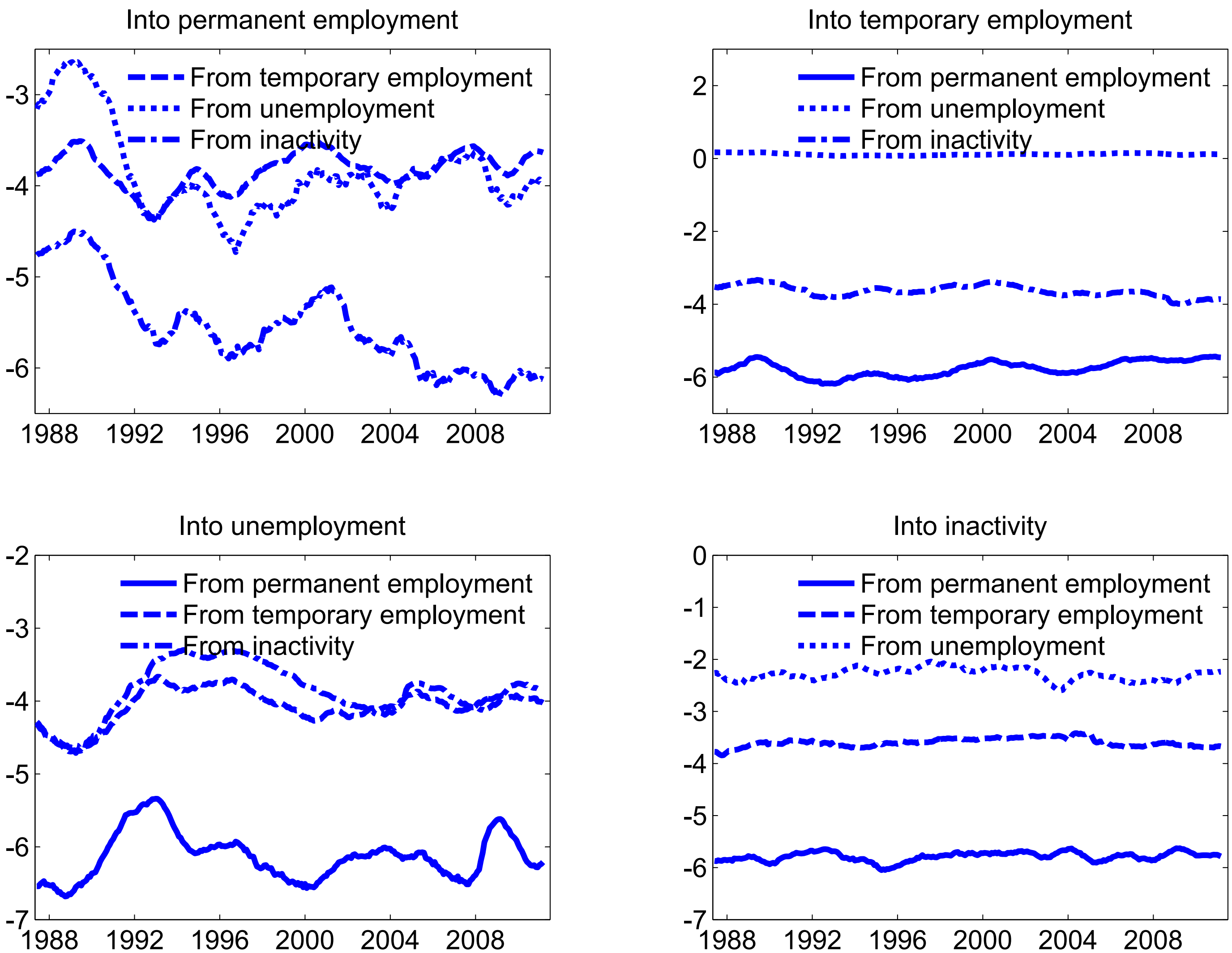

Figure 5: Hazard rates for transition across labour market states, logged

Table 2: Cyclical variation in hazard rates

	Permanent emp.	Temporary emp.	Unemployment	Inactivity
Permanent emp.		-6.8117^{***}	8.0218^{***}	-0.9282^{***}
Temporary emp.	-6.6049^{***}		11.3282^{***}	-0.0401
Unemployment	-20.5563^{***}	-12.1247^{***}		3.1729^{***}
Inactivity	-10.5943^{***}	-2.9194^{***}	18.5694^{***}	

Notes: The reported figure is the the coefficient of the unemployment rate in a regression of the relevant hazard rate logged. Time trends are included in the regression. *(**)[***] denotes significance on 10(5)[1] pct. level. Sample period is 1987m1-2011m9.

6 Conclusion

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