European Job Finding Rates: Evidence from the European Community Household Panel

Master Thesis

Oliver Sigrist
03-061-868

supervised by

Prof. Dr. Aleksander Berentsen
Matthias S. Hertweck
Department of Business and Economics
University of Basel

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1 Introduction

> "Increased unemployment during a recession could arise from an increase in the number of unemployment spells, an increase in the duration of unemployment spells, or both." (Elsby, Michaels and Solon, 2009:84)

However, one of the recent trends in modeling the aggregate labor market is to assume constant job separation rates. Thus, unemployment can change through altering job finding rates only, which is determined exogenously, for example by labor productivity, in standard job matching models.[1] As a consequence, an increase of the unemployment rate must be lead by a decrease of the job finding rate in such models. This also implies that labor market turnover declines when unemployment rises.

In empirically justifying constant separation rates, Shimer (2007) has been influential on other researchers with his conclusion that separation rates for the United States are "nearly acyclic" (Shimer, 2007:1). Since the publication of a first draft of Shimer's paper, it has been debated whether firstly, transition rates and secondly the cyclicality of transition rates and their contributions to unemployment variability are measured correctly.[2] Fujita and Ramey (2006, 2007, 2009) are part of the critics of the approach made by Shimer, notably his measurement of the cyclicality of the transition rates. The conclusion of their 2007 paper declines Shimer's results and the models based on his conclusion: "Our results establish that job matching models with constant separation rates are inconsistent with the empirical evidence" (Fujita and Ramey, 2007:10). Elsby, Michaels and Solon (2007) echo the finding, and Elsby, Hobijn ans Sahin (2008) come to a similar conclusion considering various OECD countries.

The aim of this thesis is first of all to specify job finding and job exit probabilities of France, Germany, Spain, and the United Kingdom from European Community Household Panel (ECHP) data for the period of 1994 to

[1] Throughout the thesis, we use the terms 'job separation' and 'job exit' equivalently to express movements from employment to unemployment. 'Job finding' stands for a movement from unemployment to employment. The term 'transition rate' is used as a generic term.

[2] The topic of worker flows and the cyclicality of the ins and outs of unemployment has been widely discussed, notably for the United States. See Elsby, Michaels and Solon (2009), Fujita and Ramey (2006, 2009), and Shimer (2007) for overviews.

2001.[3] The United States are also considered with the data provided by Shimer (2007).[4] The two-state model with employment and unemployment proposed by Shimer (2007) builds the basis of this analysis (hence, no movements in and out of the labor force are regarded).[5] Secondly, the cyclical behavior of the movements in and out of unemployment are assessed. Cyclicality is measured twofold: Once it is measured in terms of co-movements of the transition rates with the business cycle. Co-movements are measured in terms of correlations between the transition rates and business cycle indicators at various leads and lags. Once it is measured in terms of contributions of the transition rates to unemployment variability. The contributions are measured by "counterfactual steady state" unemployment rates and by decomposing unemployment variability into components that depend separately on job finding and job exit rates. Then, the contributions are measured by means of conventional factor analysis. In that, we follow Shimer (2007), Fujita and Ramey (2007, 2009), and Petrongolo and Pissarides (2008). The central question is whether constant separation rates are plausible for European labor markets as well as for the American labor market.

For the calculation of the European transition rates, we take official statistics and data from the ECHP, which up until now is available from 1994 to 2001 (see Section 3 for details). We deal with the data by adjusting the ECHP data for margin error, and by correcting the transition rates for the time aggregation bias.

The thesis proceeds as follows. In the next Section, theory is presented. In Section 3, the data necessary for the calculations is described. Section 4 follows with the presentation of job transition probabilities. Section 5 assesses the cyclicality ot the transition rates and their contribution to unemployment variability. Section 6 concludes, discusses the results and specifies fields for further research.

[3]Much work to estimate worker flows among European countries has been done. See Elsby, Hobijn and Sahin (2008), footnote 4, for references.

[4]The data are provided by the 'Bureau of Labor Statistics' and are corrected for the CPS redesign of 1994 by Abraham and Shimer (2001) and Shimer (2007). See their papers for details.

[5]The program is available on `http://robert.shimer.googlepages.com/flows`.

2 Theory

The aim of this section is to present the theoretical background this thesis is based on. In that, we will follow the theory proposed by Shimer (2007), constraining to the simplest case with two possible states: employment and unemployment. Hence, it is assumed that economic inactivity is inexistent. Furthermore, it is assumed that individuals are ex ante identical and thus that all employed workers have the same job exit probability X_t in every point of time t and that all unemployed have the same job finding probability F_t in every point of time t. This assumption rules out heterogeneity of workers and duration dependence of the job finding probability. Based on these assumptions Shimer (2007) shows that

> "the probability that an unemployed worker finds a job during a period is a simple function of the number of unemployed workers at the start of the period, the number of unemployed workers at the end of the period, and the number of unemployed workers at the end of the period who were employed at some point during the period ('short-term unemployment')." (Shimer 2007:1)

In order to get the job finding probability $F_t \in [0, 1]$ and the job exit probability $X_t \in [0, 1]$ during period t, a continuous time environment in which data are available only at discrete dates is modeled. A 'period t' is equivalent to $[t, t+1)$ for $t \in \{0, 1, 2, ...\}$. Shimer (2007) assumes job finding *rates* f_t and job exit *rates* x_t which are related tho their corresponding *probabilities* via a Poisson process $f_t = -\ln(1 - F_t) \geq 0$ and $x_t = -\ln(1 - X_t) \geq 0$, respectively. F_t expresses the probability that an unemployed finds *at least* one job during period t.

Let $\tau \in [0, 1]$ be the elapsed time in a period t. So, $E_{t+\tau}$ denotes the number of employed workers and $U_{t+\tau}$ the number of unemployed at time $t + \tau$, respectively. Short-term unemployed individuals who were employed at some time $t' \in [t, t + \tau]$ but are unemployed at time $t + \tau$ are denoted as $U_t^s(\tau)$. Note that $U_t^s(0) = 0$ for all t. Let $U_{t+1}^s = U_t^s(1)$ be the total amount of short-term unemployment at the end of period t.

On these assumptions and definitions, Shimer (2007) sets up two equations:

$$\dot{U}_{t+\tau} = E_{t+\tau}x_t - U_{t+\tau}f_t \tag{2.1}$$
$$\dot{U}_t^s(\tau) = E_{t+\tau}x_t - U_{t+\tau}^s f_t \tag{2.2}$$

The two equations capture the evolution of unemployment and short-term unemployment at time $t+\tau$, respectively. It can be followed that unemployment increases when workers exit employment and decreases when workers enter unemployment depending on the (instantaneous) rates x_t and f_t.

Merge (2.1) and (2.2) to get

$$\dot{U}_{t+\tau} = \dot{U}_t^s(\tau) - \left[U_{t+\tau} - U_t^s(\tau)\right] f_t. \tag{2.3}$$

The solution to the differential equation is[1]

$$U_{t+1} = (1 - F_t)U_t + U_{t+1}^s. \tag{2.4}$$

This result is intuitive: The number of unemployed workers at date $t+1$ are equal to the number of unemployed who do not find a job (first part of the right hand side) and the total amount of newly unemployed workers of period t at time $t+1$. Rearrange (2.4) to get

$$F_t = 1 - \frac{U_{t+1} - U_{t+1}^s}{U_t} \tag{2.5}$$

This fist key equation is used to calculate job finding probabilities. In order to derive the second key equation to calculate job exit rates and probabilities, Shimer (2007) solves the differential equation (2.1) which results in[2]

$$U_{t+1} = \frac{(1 - e^{-f_t - x_t})x_t}{f_t + x_t} L_t + e^{-f_t - x_t} U_t, \tag{2.6}$$

where $L_t \equiv U_t + E_t$ is the size of the labor force in t which is assumed to be constant. The right hand side of (2.6) is increasing in x_t because $L_t > U_t$. Given equation (2.5), (2.6) uniquely defines x_t and X_t. $1 - e^{-f_t - x_t}$ is the rate of convergence to steady state in one period t.

Equation (2.6) is easy to understand when $U_t = U_{t+1}$ is assumed. It gives

$$\frac{U_t}{L_t} = \frac{x_t}{x_t + f_t}, \tag{2.7}$$

which is called (stochastic) steady state unemployment rate.

[1] See appendix for details.
[2] See appendix for details.

The model proposed by Shimer (2007) corrects the probabilities and rates for the amount of workers who flow into unemployment between two measurement dates, and thus corrects for the so called time aggregation bias. Discrete time models lack this correction.

3 Data description

3.1 Measuring stocks and transitions

According to Shimer (2007), we need to measure employment, unemployment and transitions of individuals between these states. In particular, we need to observe the labor market status of an individual in two consecutive periods for the measurement of the potential transitions. There are four possible combinations of states: A person can be either unemployed or employed in two consecutive periods. In the first case, there is no transition, whereas in the latter there is a possible transition from one job to the next. This possible transition, however, is not explicitly measured. A person can further transit from unemployment to employment in one period. For our purpose, this transition simply adds to the stock of employed in a particular period. If a particular interviewee was employed in period $t - 1$, and gets unemployed at some point in period t, she is called "short-term unemployed", as explained in Section 2. If a person transits into unemployment and stays there for longer than one time period, she is called "long-term unemployed" from the beginning of the second time period onwards, subsequently.

For the measurement of the states and the transitions between them, we work with the European Community Household Panel (ECHP) provided by Eurostat which currently consists of eight yearly waves from 1994 until 2001. The data set aims at being cross-sectionally and longitudinally representative (Peracchi, 2002). The ECHP data on an individual level include the category "Calendar of Activities", which reports the monthly employment, unemployment or inactivity status of each individual interviewed for one year (see sub-category "Main Activity Status" in ECHP). ECHP data are valuable since firstly, the assessment of the raw data is standardized and secondly, available in a high frequency, which cannot be taken for granted across European countries. For the analysis, it is a reasonable approximation to assume that people cannot make two or more transitions in one month. Furthermore, it is assumed that all interviewed people indicate their labor market status at the same point of time (say, at the end of every month). This assumption is necessary, though not following the design of the sub-category "Main Activity

Status" of the ECHP. The characteristics of this data set which are relevant for the calculation of the transitions are discussed in the next paragraph.[1]

As we always need two consecutive periods to measure a potential transition within a given month, our time series starts in February 1994. Basically, there is information about the year and the month an individual last stopped working, so that we could start to count stocks and transitions from January. But the availability of data for the month the interviewed last stopped working is far from complete; most data fields are filled with either "not applicable" or "missing". Hence, because of lack of data, January 1994 is left out of our analysis. January in all subsequent years does theoretically not pose any problem, since many interviewed individuals completed the questionnaire for several consecutive years.[2] We matched the individuals from one year to the next by their personal identification number, their household identification number, their year of birth, their age (which had to be at least the age of the previous year), and their sex to measure transitions in January. This approach should eradicate the probability that mistaken transitions are measured due to the matching of different interviewees.[3]

The methodology to calculate the stocks of employment, unemployment and short-term unemployment is the following: Firstly, we pool the totally 12 categories to three, namely "employed", "unemployed" and "inactive/exclude". See Table 3.1 for details.

Thereafter, we count all the employed, unemployed and short-term unemployed in month t, depending on the labor market status in month $t-1$. An observation is excluded in month t if its status is inactive/exclude in month $t-1$ because transitions cannot be measured in that case. In order to avoid biases of population means and totals due to unequal selection probabilities and response rates, there are "Personal Weights" provided with every individual observation by the ECHP.[4] On average, these weights are normalized to one. So, instead of counting the valid observations to get a number for a particular status (employed, unemployed, or short-term unemployed), the weights for the valid observations of a group are summed up.

Our approach to correct the *margin error* is simply not to count observations assigned with the status "inactive/exclude". This approach called *miss-*

[1] In this thesis, we do not discuss the data structure of the ECHP in detail. For a discussion of the ECHP, see Peracchi (2002).

[2] For an overview on the pattern of participation of the interviewed individuals, see Peracchi (2002). For the matching of the Spanish data, problems were encountered. See below for details.

[3] Shimer (2007) applies similar matching criteria when he calculates transitions between unemployment, employment and not in the labor force status from US "Current Population Survey" (CPS) data.

[4] For details on the calculation of these weights and potential problems see Peracchi (2002).

ECHP Labels	*Pooled categories*
paid employment, whether full-time or part-time	employed
paid apprenticeship or training under special schemes related to employment	employed
self-employment (with or without employed)	employed
unpaid work in family enterprise	employed
in education or training	inactive/exclude
unemployed	unemployed
retired	inactive/exclude
doing housework, looking after children or other persons	inactive/exclude
in community or military service	inactive/exclude
other economically inactive	inactive/exclude
not applicable	inactive/exclude
missing	inactive/exclude

Table 3.1: Pooled ECHP data

ing at random implies the assumption that those observations appear randomly, imputing the measured population distribution to the those observations. Shimer (2007) uses the model for the measurement of short-term unemployment,[5] and Abraham and Shimer (2001) and Shimer (2007) use this model when they calculate transition rates between employment, unemployment, and not in the labor force status for the United States from CPS raw data.[6]

Abraham and Shimer (2001, Appendix B) emphasize the problem of the noisiness of US CPS data which certainly applies to ECHP data as well. Noise arises because of sample attrition and mistakes in recording data elements. The former problem is minimized by working with the "Personal Weights" provided by ECHP. The latter problem, however, could not be corrected entirely. Obvious mistakes in recording data elements were encountered. The method how we corrected them is described in the next paragraph. Single wrongly recorded elements could not be corrected, though. This problem will be addressed in Section 4.

Two obvious problems were encountered which stem from mistakes in data recording and which create spurious transitions:[7] Firstly, although we matched

[5]See Shimer (2007), Appendix A.

[6]Others also use this approach. See Fujita and Ramey, footnote 10, for references.

[7]As it will be explained below, these observations are removed before the time series are seasonally adjusted. All seasonal adjustments in this thesis are conducted using a TRAMO/SEATS filter. TRAMO/SEATS can handle missing observations when seasonally adjusting time series. TRAMO is "Time Series Regression with ARIMA Noise, Missing Observations, and Outliers" and SEATS is "Signal Extraction in ARIMA Time

individuals from one year to the next using several criteria, the Spanish unemployment rate dropped on average by 4.7 percentage points in January and rose by on average 4.4 percentage points in February from 1995 onwards. When having a closer look at the data, an unnatural rise in short-term unemployed people and an even more pronounced drop in long-term unemployed people can be observed. As a consequence, also a rise in employed people can be observed. This evidence suggests that there is a matching problem for Spanish ECHP data – at least what concerns the data used for this analysis. Hence, all the Spanish series used in this thesis were seasonally adjusted without their January values.

Secondly, the French data have huge defects every September from 1995 onwards. The first thing that strikes when one looks at French data is that from the year 1995, the number of not applicable observations drops from a positive number to zero every September. (In 1994, there are no not applicable observations.) Furthermore, the number of missing observations drops by 79 percent in the years 1995 and 1996 and by 94 to 99 percent from 1997 onwards every September. (Again, there is no missing data in 1994.) Additionally, the number of missing observations rises dramatically from August to September every year from 1997 onwards; numbers increase by almost 40 to 85 percent. Remarkably and reversed to the increase of missing observations, there is a severe drop by about 20 percent in the number of unemployed people every September from 1997 to 2001. At the same time, employment numbers stay about the same. This drop in the unemployment level causes a positive spike in the employment quota (and hence a negative spike in the unemployment rate) every September from 1997 onwards. The properties of the data do not only seem unnatural but also contradict official statistics – as far as they can be compared. Because the French data have deficits in September, also October is lost because we cannot measure the transitions correctly. For this reason, we seasonally adjust the French data without the September and October values from 1995 onwards.

Before we turn to the analysis of European job finding rates and probabilities Section 4, the generated series of the ECHP data are described and compared to (semi-)official statistics to get a feeling for their accuracy.[8] We take two indicators for this purpose: On the one hand, we compare actual seasonally adjusted unemployment rates[9] with the unemployment rates that can be generated from ECHP data. The data series from ECHP are season-

Series". For general information on the program and references to papers, see `http://www.bde.es/servicio/software/econome.htm`.

[8]Why some statistics are called 'semi-official', see Section 3.2.

[9]See Section 3.2 for details.

ally adjusted too. On the other hand, there are yearly figures on the quota of people who are unemployed for less than one month to total unemployment provided by OECD.[10] The same ratio was generated from ECHP data on a monthly basis, after it was seasonally adjusted, and for the comparison to official OECD statistics, yearly arithmetic averages of the monthly data were taken. Subsequently,

$$\frac{\text{short-term unemployment}_t}{\text{short-term unemployment}_t + \text{long-term unemployment}_t}$$

is called "short-term unemployment rate". The denominator is equal to total unemployment in time t. It shall be noted that this ratio is the only measure we use of the ECHP data. Other input data that is necessary for the computation of transition rates are the employment and unemployment level on a monthly basis. These figures are taken or computed from official statistics (for details, see Section 3.2).

The attention is turned to unemployment rates first, which are depicted in Figure 1. What strikes is that the calculated unemployment rates follow the trend of the actual unemployment rates. The German quota in the approximately first two years makes the only striking exception. Apart from this fact, the German unemployment rate calculated from the ECHP dataset is persistently between one and four percentage points higher than the actual unemployment rate. The correlation of the series is 0.36 for the whole series and 0.62 for the years 1996 to 2001.[11] The Spanish unemployment rate calculated from the ECHP data differs even more from the actual series: the series differ from around 5 percentage points up to 13 percentage points. The correlation, though, is relatively high with 0.92. The French ECHP data seem to be similar to actual unemployment rate as the level and the trend are regarded and have a correlation coefficient of 0.85. The unemployment rates of the United Kingdom are similar (correlation coefficient of 0.98) albeit the spread of the rates widens up to almost 2 percentage points from the year 1998 onwards. In addition, there is a noticeable spike at the end of 2000 in the ECHP data. It is not attempted to be corrected since the raw data do not seem to show obvious mistakes.[12]

[10] The series is called "Incidence of unemployment by duration" and can be downloaded from `http://stats.oecd.org`.

[11] All correlations in this paragraph are calculated on the basis of quarterly averages of monthly figures.

[12] Petrongolo and Pissarides (2008) calculate contributions of transition rates to unemployment variability for the United Kingdom, France, and Spain (see Section 5.2.2). They obtain higher correlations between the series from which they calculate contributions and actual unemployment rates, except for the United Kingdom in one subsample: For the United Kingdom, the correlation coefficient between the claimant count unemployment (from which the transition rates are calculated) and a survey-based unemployment rate is 0.955 for the

It can be concluded that the data quality from the viewpoint of the unemployment rate seems to be between sound and satisfactory. The two rates from United Kingdom and Spain (when the correlation is regarded) certainly are at the upper end of the scale. The French quota is somewhere in between, while the German quota is more at the lower end.

Our second indicator to measure the accuracy of the ECHP data is the short-term unemployment rate. The yearly quotas of the ECHP and the OECD can be found in Figure 2. OECD provides yearly figures on the quota of short-term unemployed exactly the way we calculated them on a monthly basis. A shortcoming of the OECD data is that it is not clear whether some disaggregated figures were averaged to get yearly figures or whether the statistic was collected at some specific point of time. It is assumed the OECD data were aggregated somehow. Except for France, the trends of the averaged ECHP data are very much the same as the OECD data. In the French OECD series, there is a peculiar spike in the year 1999. When the whole series provided by OECD (1975–2007) is considered, this spike is still highly visible.[13] So perhaps, the French OECD data for the year 1999 are mistaken. In France and Spain, the ECHP data lead to a higher short-term unemployment rate, whereas in United Kingdom and Germany, the quota is estimated to be lower than the OECD quota. The German and the Spanish quotas differ by approximately 1.5 percentage points and exhibit the smallest difference on average. The gap between the French data is around 2.3 percentage points not corrected for the spike. If replace the 1999-value by the average quota of all the years except for 1999, we get an average difference of almost 2.5 percentage points. United Kingdom data differ by almost 5.5 percentage points on average, and hence represent OECD data worst from this viewpoint.

When the indicators are compared, no systematic pattern can be determined. That is, the ECHP time series are not always either too high or too low compared to the two benchmarks. This could suggest that our method to calculate the series did not lead to any systematic mistakes.[14]

1997–2007 period, and 0.991 for the entire period ($1967Q3 - 2007Q2$). For France, the correlation coefficient between the claimant count data and the official ILO unemployment rate from $1991Q2$ to $2007Q3$ is 0.941. For Spain, the correlation coefficient between the claimant count data and actual unemployment is 0.974 for the $1987Q4 - 2006Q4$ period. The correlations were calculated on a quarterly basis.

[13] This series is not depicted here. The series, however, can be downloaded from `http://stats.oecd.org`.

[14] Our input data for the calculations of the transition rates were checked for their robustness by counting all individuals "in community or military service" as employed. The results for the United Kingdom do not change at all. The results of other countries differ only slightly: The unemployment rate that can be calculated from ECHP data differs by on (absolute) average 0.06 percentage points in France, 0.14 percentage points in Germany, an 0.16 percentage points in Spain. The short-term unemployment rate differs by on (absolute) average 0.23 percentage points in France, 0.07 percentage points in Germany and

3.2 Employment and unemployment levels

In order to calculate transition probabilities, we need the number of employed, unemployed and short-term unemployed for each point of time t. The number of employed and unemployed is taken or calculated from official statistics. The series are discussed below. The number of short-term unemployed people in month t is derived from multiplying the number of unemployed people by the short-term unemployed quota which is calculated from ECHP data.

The monthly German data were downloaded from the GENESIS database.[15] The series follow the ILO concept and are seasonally adjusted. The monthly United Kingdom data were downloaded from "UK National statistics"[16] and are seasonally adjusted.

For France and Spain, the monthly employment statistics could not be downloaded directly. We took the following approach: For both countries, the longest joint available non seasonally adjusted series of the unemployment rate and the unemployment level were taken to calculate (non seasonally adjusted) employment.[17] This was done to make the successive seasonal adjustment more robust. Employment E_t was calculated from

$$E_t = (\frac{1}{u_t} - 1)U_t,$$

where u_t is the unemployment rate and U_t it the unemployment level. Afterwards, the French and the Spanish series were seasonally adjusted. The seasonally adjusted unemployment level for both countries was taken from the Eurostat.

In this thesis, all unemployment quotas are calculated from the seasonally adjusted employment and unemployment levels described here. The so obtained unemployment rates differ by maximally 0.0029 percentage points from the official, monthly, and seasonally adjusted Eurostat series[18] and their correlation coefficients are around 0.999, so the series are virtually identical.

In the next section, job finding and job exit probabilities are analyzed descriptively. Then, the cyclicality of job finding rates and job exit rates to the fluctuations of the unemployment rate are analyzed according to the method of Shimer (2007) in Section 5.1, which leads to its critique and the application of alternative approaches.

0.1 percentage points in Spain. Because of these almost negligible differences, we will calculate transition probabilities on the basis of individuals "in community or military service" excluded only.

[15] `https://www-genesis.destatis.de/genesis/online/logon`

[16] `http://www.statistics.gov.uk/hub/index.html`

[17] France: 1983:M1-2009:M2; Spain: 1986:M4-2009:M2

[18] It is the United Kingdom series in July 1997.

4 Job finding and job exit probabilities

In Figure 3, the quarterly and monthly job finding and job exit probabilities are plotted. Table 4.1 shows average monthly job finding ($U \rightarrow E$) and job exit ($E \rightarrow U$) probabilities as well as standard deviations for all countries from 1994 to 2001. Apparently, US job finding and job exit probabilities are a lot higher than European. The average job finding probability of the USA (44.67%) is more than seven times higher than the average Continental Europe job finding probability (6.12%). The separation probability is 4.5 times higher in the USA (3.17%) than in Continental Europe (0.76%). In the United Kingdom, the average job finding probability (8.24%) somewhat higher than in Continental Europe. The job exit probability of the United Kingdom is lower (0.58%) than the average Continental European one (0.74%), but higher than the German one (0.52%).

It can be seen that the variation of job exit probabilities over the business cycle across Europe (between 0.07% and 0.1%) does not differ much from the American one (0.12%). The standard deviations of the cyclical components of the job finding probabilities are not homogenous. France and Spain show relatively low variation of the job finding probability over the business cycle (0.65% and 0.58%, respectively). The United State's job finding variation is highest, while the German and the United Kingdom standard deviation of the job finding probability lie in between (1.1% and 1.22%, respectively). On the one hand, one can discern big differences in the variability of job finding rates between Europe and the United States. On the other hand, the differences in the variability of the separation rates is small between Europe and the United States. This is an indication that the job separations play a relatively more important role in explaining unemployment fluctuations in Europe than in the United States. This topic will be investigated in Section 5.2.1.

Two sources are consulted to check the robustness of our findings in Table 4.1: First, as it can be seen in Table 4.2, Azmat, Güell and Manning (2006) derived similar results for transition probabilities for men and women by estimating transition probabilities from ECHP data with binomial models.

	Average		*Standard Deviation*	
	$U \rightarrow E$	$E \rightarrow U$	$U \rightarrow E$	$E \rightarrow U$
France	6.71%	0.78%	0.65%	0.08%
Germany	5.58%	0.52%	1.1%	0.1%
Spain	6.1%	0.98%	0.58%	0.09%
United Kingdom	8.24%	0.58%	1.22%	0.07%
United States	44.67%	3.17%	2.33%	0.12%

Table 4.1: Average monthly job finding and job exit probabilities and standard deviations for the cyclical components of the transition probabilities

Notes: The standard deviations were derived from quarterly averages of the monthly figures. The cyclical components were calculated by taking the difference between a respective transition probability and its HP trend. The standard smoothing parameter of 1600 was applied.

The transition probabilities are averages from the first six waves of the ECHP (1994-1999). Our results for the job finding probabilities are in between male and female job finding probabilities. Comparing the job exit probabilities, only the probability of the United Kingdom lies in between the male and female job exit probabilities. The French and German probabilities are close, though.[1]

Second, Elsby, Hobijn and Sahin (2008) calculate transition rates from yearly OECD data for fourteen countries. They modify the approach proposed by Shimer (2007), and assume that transition rates are constant within years, in particular. A part of the data which Elsby, Hobijn and Sahin (2008) used were taken to assess the data quality of the short-term unemployment rate series in Section 3. As one can see in Table 4.3, the results for Germany and Spain are very similar, and the French averages differ only marginally. The average transition rates for the United Kingdom differ considerably, however. The difference in the transition rates is exactly in the order of the difference in the short-term unemployment rates (see Section 3).

As for now, the comparison of the transition probabilities shows that the transition rates are broadly consistent except for the United Kingdom. What strengthens our result is that is that Azmat, Güell and Manning (2006) check their results derived from ECHP data for the United Kingdom and Spain using labor force surveys from the respective countries. The results are "very similar" according to the authors (Azmat, Güell and Manning 2006:7).[2]

During the observation period, the unemployment rates of France, Spain, the United Kingdom, and until 2000 also of the United States show declining

[1] The discrepancy remains when we average our data from 1994 to 1999.

[2] Azmat, Güell and Manning (2006) mention that one general downside of ECHP data is that due to the retrospective design of the ECHP, European transitions are likely to be underestimated since interviewees tend to forget transitions in the course of one year.

	$U \rightarrow E$		$E \rightarrow U$	
	Men	*Women*	*Men*	*Women*
France	8.43%	6.29%	0.61%	0.76%
Germany	7.42%	5.03%	0.57%	0.61%
Spain	7.43%	5.62%	1.5%	1.9%
United Kingdom	7.7%	10.27%	0.61%	0.39%

Table 4.2: Average monthly job finding and job exit probabilities 1994–1999 (data by Azmat, Güell and Manning, 2006)

	Start year	$U \rightarrow E$	$E \rightarrow U$
France	1975	7.5%	0.8%
Germany	1983	5.8%	0.5%
Spain	1977	6.0%	1.0%
United Kingdom	1983	12.45%	1.0%
United States	1968	43.73%	3.54%

Table 4.3: Average monthly transition probabilities measured on a yearly basis (data by Elsby, Hobijn and Sahin, 2008)

Notes: All samples end in 2007.

unemployment rates, which is formed by increasing job finding rates and a more or less pronounced reduction in the job separation rate. Germany shows a hump in the unemployment rate. In remainder of this thesis, the transition rates are assessed in their cyclical behavior, and their contributions to unemployment variability are quantified. In that, we follow Shimer (2007) and Fujita and Ramey (2007, 2009).

5 The cyclicality of transition rates and their contributions to unemployment variability

5.1 Measuring contributions of transition rates: the approach of Shimer

In this subsection, our aim is to quantify the contributions of the job finding and employment exit probabilities to the fluctuations of the unemployment rate according to the method proposed by Shimer (2007). In his paper, he carries out the following steps, which will be replicated mechanically for the European data as well:

- Shimer (2007) finds that the stochastic steady state unemployment rate in month t is a good indicator for the actual unemployment rate in $t+1$. The correlation for the US data from 1994 to 2001 between $\frac{U_{t+1}}{L_{t+1}}$ and $\frac{x_t}{x_t+f_t}$ is 0.98.

- In order to remove measurement errors, quarterly averages of the unemployment rate $\frac{U_{t+1}}{L_{t+1}}$, the job finding rate f_t and the job exit rate x_t are calculated. The steady state unemployment rate is delayed by one month, as explained in Item 1.

- To quantify the contribution of the job finding rate and the job separation rate to the variability of the steady state unemployment rate, Shimer (2007) constructs counterfactual steady state unemployment rates, which he calls hypothetical unemployment rates. The hypothetical unemployment rate with variation in f_t is denoted as $\frac{\overline{x}}{\overline{x}+f_t}$, the one with variation in x_t, $\frac{x_t}{x_t+\overline{f}}$. $\overline{f}$ and $\overline{x}$ are the average values of f_t and x_t over the sample period. f_t and x_t denote quarterly values.

- The quarterly averages are detrended using a HP filter with a smoothing parameter 10^5. Shimer (2007) justifies this exceptionally high value with his observation that "a standard filter seems to remove much of the cyclical volatility in the variable of interest" (Shimer, 2007:8).

	Correlation	Coefficients	
		$\frac{\overline{x}}{\overline{x}+f_t}$	$\frac{x_t}{x_t+\overline{f}}$
France	0.87	-0.2	1.22*
Germany	0.58	0.34	0.76
Spain	0.95	1.05*	-0.3
United Kingdom	0.92	0.6	1.44*
United States	0.99	0.88*	0.25*

Table 5.1: "Contributions" of the job finding and job separation rate to unemployment variability (1).

Notes: The correlations are calculated from the quarterly values of the steady state unemployment rate and the actual quarterly unemployment rate. The coefficients stem from a regression of $\frac{\overline{x}}{\overline{x}+f_t}$ on $\frac{U_{t+1}}{L_{t+1}}$ and of $\frac{x_t}{x_t+\overline{f}}$ on $\frac{U_{t+1}}{L_{t+1}}$, respectively. The coefficients labeled with * are significantly different from zero on a 5% level. The betas do not add up to one in general since the method proposed by Shimer (2007) is no exact decomposition.

- Shimer (2007) regresses the actual unemployment rate on the so obtained hypothetical unemployment rates.

The results for all countries are listed in Table 5.1.

Apart from the fact that only the French job exit rate, the Spanish job finding rate, and the job exit rate from the United Kingdom are significantly different from zero on a 5% level, the method of Shimer (2007) does not yield economically reasonable contribution-values for the European countries. So, for example the coefficient of France would say that when the job finding probability goes up (which means that the hypothetical unemployment quote goes down), the actual unemployment rate goes up, which is counterintuitive. A similar argument goes for the Spanish contribution of the job separation rate. What comes more, the coefficients do not add up to (approximately) one in Germany, Spain, and the United Kingdom, so that it is difficult to interpret the coefficients as contributions of the transition rates to fluctuations in the unemployment rate. Anyway, coefficients which are not significantly different from zero are not interpretable.

The justification for the weak results is found rapidly: The United States have an average $x_t + f_t$ that amounts 0.64 from 1994 to 2001, so the half life of a deviation from steady state unemployment calculated from average values is just about 20 days. In European countries, the half life of a deviation is substantially higher and amounts to about seven months in the United Kingdom and to almost eleven months in Germany. Hence, the approximation of the unemployment rate with the steady state unemployment rate delivers bad results when assuming the same relationship as in the United States between the steady state unemployment rate and the actual unemployment rate. The less distinct labor market dynamics in Europe requires an approach that ac-

	Lag	Correlation	Coefficients	
			$\frac{\overline{x}}{\overline{x}+f_t}$	$\frac{x_t}{x_t+\overline{f}}$
France	$i=2$	0.94	0.24	1.14*
Germany	$i=3$	0.84	0.78	0.85
Spain	$i=2$	0.97	1.41*	-0.34
United Kingdom	$i=1$	0.93	1.23	0.93

Table 5.2: "Contributions" of the job finding and job separation rate to unemployment variability (2).

Notes: The hypothetical unemployment rates lag the actual unemployment rate i quarters. The number of lags was determined by the maximal correlation between the actual unemployment rate and the lagged steady state unemployment rate (which is shown in column 3). The coefficients stem from a regression of $\frac{\overline{x}}{\overline{x}+f_t}$ on $\frac{U_{t+q}}{L_{t+q}}$ and of $\frac{x_t}{x_t+\overline{f}}$ on $\frac{U_{t+q}}{L_{t+q}}$, respectively. The coefficients labeled with * are significantly different from zero on a 5% level.

counts for this fact. Therefore, we search for correlations between the steady state unemployment rate and the actual unemployment rate between different quarters in Europe, not between months as in the United States. For this purpose, we first take quarterly averages of the two variables, where the steady state unemployment rate does *not* serve as a monthly leading indicator (the monthly figures are taken at the same month t). Then, we search for the highest correlations between the steady state unemployment rate and the actual unemployment rate varying the number of quarters the steady state unemployment rate lags the actual unemployment rate, and repeat the method of Shimer (2007) with the same smoothing parameter 10^5.[1] The results can be drawn from Table 5.2.

The results have by no means improved. Now, only the coefficients for the French job exit rate, and the Spanish job finding rate are significantly different from zero. These coefficients cannot really be interpreted as contributions, since they are both bigger than one.

The approach proposed by Shimer (2007) is fundamentally problematic for European data, as it can be seen in Figure 4. Let us first have a look at the US data: As it can be observed, the steady state unemployment rate is very close to the actual unemployment rate. This has been pointed out above already. What can be seen additionally is that the hypothetical unemployment rate with variation in f_t only co-moves closely and with no lag to the actual unemployment rate while the hypothetical unemployment rate with variation in x_t, approximately remains on the same level over our observation period. The graphical analysis shows that the job finding rate must have greater ex-

[1] The correlations were calculated with the standard smoothing parameter of 1600 for quarterly data as well. The correlations were lower generally, so that the "contributions" were calculated with a smoothing parameter 10^5 only.

planatory power for the variation in the actual unemployment rate than the separation rate.

When looking at the European data in Figure 4, notably France and Germany have highly visible spikes in the steady state unemployment rates. Generally, all countries have a steady state unemployment rate that is much more volatile than the actual unemployment rate and hence does not represent the actual unemployment rate well. This missing coherence in the data multiplies when calculating the hypothetical unemployment rates for European countries. Consequently, hypothetical unemployment rates perform poorly as an explanation for the variation in the actual unemployment rate. This is the link to the next section, where firstly, the approach of Shimer is criticized, and secondly, alternative ways to quantify the cyclicality of job finding and job exit rates are applied.

5.2 Measuring cyclicality and contributions of transition rates: the approach of Fujita and Ramey

In this subsection, we rely on approaches proposed by Fujita and Ramey (2007, 2009) to measure contributions and cyclicality of respective transition rates. They brought forward two fundamental points of criticism, based on which a further analysis of the transition rates is conducted in this section. Firstly, as Fujita and Ramey (2007) rightly argue, Shimer (2007) does not evaluate cyclicality of the transition rates systematically. Cyclicality does have no clear meaning in Shimer's paper since co-movements of the transition rates with business cycle indicators such as GDP or unemployment rates are not examined. Shimer simply concludes that because the employment exit probability cannot explain much unemployment variability at business cycle frequencies, it is "comparatively acyclic" in the United States (Shimer, 2007:1). This is why in the last section, cyclicality was not discussed. Secondly, the hypothetical unemployment rates cannot decompose the unemployment variability rigorously since the sum of both hypothetical unemployment rates does not add up to the steady state unemployment rate, generally. The aim of this section is to clarify on these points.

5.2.1 Cyclicality

Our first aim is to analyze the cyclicality of transition rates from 1994 to 2001 more systematically. This is done by taking correlations of respective transition rates and business cycle indicators – the unemployment rate and GDP – at various leads and lags. The correlations are measured at business cycle frequencies.[2] This approach allows a more systematic decomposition of the cyclical behavior of the transition rates than the approach in Section 4.

Several approaches which are not discussed in this thesis, were tested to assess the robustness of the findings discussed below: Beside HP filtering, first differences were taken. The dynamic pattern of the correlations are similar but less pronounced in general. Hence, these series are left out of the analysis. Afterwards, the unemployment rate and the GDP are taken as business cycle indicators. We also took GDP growth and labor productivity as business cycle indicators. The results did not differ much to the results obtained with GDP, so they are not discussed.

We first take a look at the co-movement of transition rates and the unemployment rate. As it can be seen in Figure 5, the job finding rate in the USA is highly procyclical and symmetric around lag zero. The peak correlation between the job finding rate and the unemployment rate is more than -0.8 at lag zero. So by the time the business cycle reaches its top (bottom), the job finding rate in the USA is highest (lowest) in tendency. In the European countries, the job finding rates tend to lead the cycle and hence influence future unemployment, not predominantly actual unemployment as in the United States. In Germany, the correlation approaches zero two quarters prior the peak of the business cycle, whereas in Spain it is three quarters after the peak. So the job finding rates tend to diminish during downturns but do not show a clear trend as the economy recovers. In France and the United Kingdom, the correlation reverts around lag zero and peaks to approximately 0.5 after two quarters in France and one quarter in the United Kingdom. So in tendency, people seem to find a job more quickly after an economic downturn in the two countries or in other words, the hiring activity of firms tends to increase quickly as the economy recovers. Conversely, the job finding rate tends to diminish quickly after a boom in those countries.

Turning to Figure 6, correlations between job exit rates and the unemployment rates are depicted. Separation rates in all countries seem to be countercyclical. France, Spain, and the United States have correlations which are approximately symmetric around lag zero. The United Kingdom data show symmetry between lag zero and one. The German separation rate seems to peak about two to one quarter prior the peak of the business cycle. So the trend of the separation rate faces downward prior the bottom of the business

[2] The business cycle is measured by taking the difference between the log of the original series and the log of the HP filtered series with the standard smoothing parameter of 1600. Fujita and Ramey (2006) argue that CPS data contain a lot of high frequency noise, which is treated inadequately by a smoothing parameter 10^5. This is probably true for ECHP data as well. The results with the smoothing parameter 10^5 in the figures that follow are depicted for completeness.

cycle. Its correlation with the unemployment rate is still above 0.4 at lag zero, though. The cyclical behavior of the separation rate is least pronounced in Spain, with a peak correlation at lag zero below 0.3. Also United States data do not show a very pronounced correlation between the separation rate and the unemployment rate. Instead, its correlation remains positive over a comparatively long period. Primarily in Spain and the United Kingdom, the business cycle seems to have a comparatively short impact on the separation rate. But also French and German data show briefer relations with the cycle. The trend reverses after four quarters in France, two quarters in Germany and Spain, three quarters in the United Kingdom and six quarters in the United States. So after an economic downturn, separation rates tend to decrease, or conversely, to increase after a boom. This adjustment is slowest in the United States.

The analysis shows that neither for US data nor for European data, the separation rate is "comparatively acyclic" (Shimer, 2007:1). It is true that for US data, the peak correlation for the separation rate is less pronounced than the peak correlation for the job finding rate, so perhaps the job finding rate shows more cyclicality than the separation rate. This is probably true for Spain, too, but here the job finding rate leads the cycle. The data suggest that in France and the United Kingdom, the labor market turnover shortly after the economy starts to recover tends to be high. This is because both the job finding rate and the job separation rate tend to be high (and vice versa for after a boom).

As a second indicator for the business cycle, we take GDP.[3] In Figure 7, one can see the dynamic relations between the job finding rate and GDP. What stands out is that German data do not show a strong relationship between the business cycle and the job finding rate. In France and the United Kingdom, a similar pattern between the job finding rate and GDP can be observed as between the job finding rate and the unemployment rate. Again, the job finding rate in those countries tends to lead the cycle and reverses around lag zero or one. In Spain, the job finding rate is procyclical over a comparatively long period. It reverses after lead five or six, similar to the United States data. Again, the United States data show a very pronounced correlation between the job finding rate and GDP and symmetry around lag zero.

When turning to Figure 8, one can see that French and the United States

[3] All original series are quarterly, seasonally adjusted, in constant prices and provided by the OECD. The French, German, United Kingdom and United States series were downloaded from the "Main Economic Indicators" database. The Spanish series were downloaded from the "Quarterly National Accounts" database. The Spanish series are in 1995 prices and the United Kingdom series in 2003 prices. All other series are in 2000 prices.

separation rates are clearly countercyclical. Spanish and German data only show a weak relationship, but the data show slight countercyclicality as well, with the separation rate as a leading indicator again. United Kingdom data show a somewhat curious relationship. Here, the separation rate seems to be procyclical and to lead the cycle. After a peak of a cycle, no clear relationship can be observed. In that sense, the separation rate in the United Kingdom shows the same dynamics as the job finding rate.

Fujita and Ramey (2007, 2009) obtained similar results in the business cycle analysis for the United States. The cyclicality of the job finding rate shows about the same properties. However, the dynamics of the separation rate shows much more cyclicality when compared to the unemployment rate, and it leads the cycle by about one quarter. With that observation, they conclude that "declines in the job finding rate tend to be preceded by increases in the separation rate" (Fujita and Ramey, 2009:420). In general, it is reassuring that first, Fujita and Ramey (2007, 2009) show that the assessment of the cyclicality leads to similar results for both their series as well as for the Shimer-series, and secondly, that our US results for the comparatively short period are broadly consistent with the results obtained by Fujita and Ramey (2007, 2009).

The analysis in this section showed that the interpretations for both business cycle indicators are broadly congruent.[4] It can be concluded that both the job separation rate and the job finding rate influence fluctuations in unemployment in both Europe and the United States. In Europe, the job finding rate tends to be procyclical, and precede the business cycle while the job separation tends to be anticyclical and symmetric around lag zero. During a recovery, the job finding rates seem to rise in France and the United Kingdom, but not in Germany and the Spain. The separation rates tend to decrease during recovery. The analysis indicates that both the job finding rate and the separation rates are important in accounting for unemployment variability. Hence, the assumption of a constant separation rate seems implausible from an empirical point of view for Europe as well as for the United States. In the next subsection, the contributions of the transition rates to unemployment variability as proposed by Fujita and Ramey (2009) and Petrongolo and Pissarides (2008) are measured to get a more exact view on the relative importance of the two transition rates.

Although not a topic of this subsection, the similarities of labor market dynamics between France and the United Kingdom, and between Germany and Spain is apparent. This, however, does not fit into the picture of highly regu-

[4]The most prominent contradicting conclusions can be drawn when German job finding rates are compared, and when job separation rates of the United Kingdom are compared.

lated labor markets in Continental Europe on the one hand and a rather lowly regulated labor market in the United Kingdom on the other hand. Specifically, the dynamics of the job finding rate of France would be expected to resemble the Continental European. This topic will be addressed in the next subsection again.

5.2.2 Contributions

Fujita and Ramey (2009) and Petrongolo and Pissarides (2008) propose an exact way to quantify contributions of the transition rates to unemployment variability. Thereby, the contemporaneous unemployment variation is decomposed into contributions of the contemporaneous (logarithmic) variation in the job separation rate and the job finding rate. The starting point is the steady state unemployment rate,

$$u_t^{ss} \equiv \frac{x_t}{x_t + f_t} \approx u_t, \tag{5.1}$$

which can also be expressed by the trend components of the respective variables. The trend components obtained by a HP filter are denoted as $\overline{u}_t$, $\overline{s}_t$, and $\overline{f}_t$. Fujita and Ramey (2009) log-linearize around the trend to get following decomposition:

$$\ln\left(\frac{u_t^{ss}}{\overline{u}_t^{ss}}\right) = (1 - \overline{u}_t^{ss}) \ln\left(\frac{s_t}{\overline{s}_t}\right) - (1 - \overline{u}_t^{ss}) \ln\left(\frac{f_t}{\overline{\overline{f}}_t}\right) + \epsilon_t \tag{5.2}$$

Alternatively, first differences instead of HP trends can be implemented. This results in:

$$\Delta \ln u_t^{ss} = (1 - u_{t-1}^{ss}) \Delta \ln s_t - (1 - u_{t-1}^{ss}) \Delta \ln f_t + \epsilon_t \tag{5.3}$$

Equation (5.3) is labeled 'First differencing (1)'. Petrongolo and Pissarides (2008) propose a slight modification for the decomposition of unemployment variability. The subsequent equation is called 'First differencing (2)':

$$\Delta u_t^{ss} = (1 - u_t^{ss}) u_{t-1}^{ss} \frac{\Delta s_t}{s_{t-1}} - u_t^{ss}(1 - u_{t-1}^{ss}) \frac{\Delta f_t}{f_{t-1}} \tag{5.4}$$

Equations (5.2), (5.3), and (5.4) show that the deviations of job finding and job exit rates from trend contribute separately to deviations of the unemployment rate from trend. For convenience, the three equations are expressed as

$$d\,u_t^{ss} = d\,u_t^{x} + d\,u_t^{f} + \epsilon_t \tag{5.5}$$

subsequently.

As Fujita and Ramey (2009) point out, the linear decomposition makes it possible to assess the effects of the respective transition rates on unemployment variability quantitatively and exactly. They show that contributions can be expressed through

$$\beta^f = \frac{\mathrm{Cov}(d\,u_t^{ss}, d\,u_t^f)}{\mathrm{Var}(d\,u_t^{ss})}, \ \beta^x = \frac{\mathrm{Cov}(d\,u_t^{ss}, d\,u_t^x)}{\mathrm{Var}(d\,u_t^{ss})}, \text{ and } \beta^\epsilon = \frac{\mathrm{Cov}(d\,u_t^{ss}, \epsilon_t)}{\mathrm{Var}(d\,u_t^{ss})}, \quad (5.6)$$

and that $\beta^f + \beta^x + \beta^\epsilon = 1$. β^f is equivalent to the coefficient in a linear regression of $d\,u_t^f$ on $d\,u_t^{ss}$, which holds analogously for the other betas. Subsequently, the coefficients are interpreted as the contribution of the job finding and job exit rate rate to total unemployment variability.

Petrongolo and Pissarides (2008) adopt the same methodology to measure contributions of the transition rates to unemployment variability. As is has been shown in Section 5.1, the steady state unemployment rate is no good approximation for the actual unemployment rate in part, though. For this reason, Petrongolo and Pissarides (2008:259) remove "periods for which the difference between the change in steady state unemployment and the change in actual unemployment was more than 10% of actual unemployment", and calculate the betas with the outliers excluded.[5]

In Table 5.3, the results are presented for all three decompositions and for the full and reduced the data set. They are discussed subsequently and compared to the contribution values obtained by Petrongolo and Pissarides (2008).

When taking a first look at Table 5.3, it stands out that the coefficients do not provide a consistent picture. The coefficients for a respective country are variable and do not even show a clear trend, i.e. it depends on the data set and the method whether β^f or β^x is higher. The standard deviation of $d\,u^f$ under the full sample and HP filtering is always higher than $d\,u^x$, while under the reduced sample it is reversed.[6] This is reflected in the beta coefficients for HP filtering. The other methods do not show such sensitivity to outliers. On the other hand, for both first differencing methods, there are contributions values that exceed one and have negative counterparts, in turn. Furthermore, less coefficients for the first differencing methods are significantly different from zero. These are the main downsides of the first differencing methods. Looking at the β^f and β^x together, the sum of the coefficients for the full data set of Germany and the are far from one. Both first differencing methods do not

[5] With outliers excluded, the method of Shimer (2007) to calculate the contribution values, was repeated. The results do not improve and are not discussed here.

[6] The figures are not listed in this thesis.

		HP filter Equation (5.2)		First difference (1) Equation (5.3)		First difference (2) Equation (5.4)	
		full	reduced	full	reduced	full	reduced
France	β^f	*0.61**	0.37*	0.82*	0.64	0.87*	0.7
	β^x	*0.39**	0.63*	0.18	0.33	0.12	0.26
Germany	β^f	*0.55**	0.35	1.12*	0.33	1.11*	-0.01
	β^x	0.33	0.63	-0.38	0.67	-0.37	1.02
Spain	β^f	*0.52**	*0.47**	0.65*	0.91*	0.67*	1.06*
	β^x	*0.45**	*0.49**	0.32	0.06	0.31	-0.1
United Kingdom	β^f	*0.68**	0.25	*0.79**	0.93	*0.76**	0.61
	β^x	0.2	0.72	0.04	0.1	0.06	0.43
United States	β^f	*0.76**	–	0.46*	–	0.54*	–
	β^x	*0.23**	–	0.21	–	0.16	–

Table 5.3: Contribution of the job finding and job separation rate to unemployment variability (3)

Notes: The coefficients are obtained by regressing du_t^f on du_t^{ss}, and du_t^x on du_t^{ss}, respectively. The coefficients labeled with * are significantly different from zero on a 5% level. 3 outliers were excluded for France, 9 for Germany, 6 for Spain, and 18 for the United Kingdom. For the United States, no outliers were detected. For the definition of an outlier, see text.

		β^x	
	Period	full	reduced
France	$1997Q1 - 2001Q2$	0.449	–
Spain	$1994Q2 - 2006Q4$	0.392	0.461
United Kingdom	$1993Q2 - 2007Q2$	0.25	0.202

Table 5.4: Contribution of the job separation rate to unemployment variability (data by Petrongolo and Pissarides, 2008)

Notes: Petrongolo and Pissarides (2008) only reported contributions of job exit rates in their paper. The betas were calculated on the basis of equation (5.4) with an equivalent methodology as in this thesis. The full data set uses all observations while the reduced data set excludes observations according to the same algorithm that was used in this thesis. For France, no outliers were detected. Data sources and the calculation of the transition rates are described in Petrongolo and Pissarides (2008).

deliver appropriate results for the United States, either. In general, the first differencing (2) method performs poorly on our data and is not taken into account for further analysis.[7]

Turning to the coefficients that allow for a consistent interpretation, the Spanish contributions for the HP filtering method are quite close to the data obtained by Petrongolo and Pissarides (2008), although the latter used first differencing (2) for their calculation. Our results suggest a slightly higher importance of the separation rate for unemployment variability.

Although the German coefficients have defects in general, the contribution of the job finding rate with the full data set under HP filtering seems to be plausible for one reason: Germany and Spain show similar labor market dynamics,[8] so it is likely that their contribution values are close. Hence, the contribution of the job separation rate to unemployment variability could possibly be around 0.45 in Germany.

For France, Petrongolo and Pissarides (2008) provide a contribution value for the separation rate of 0.449 for the period $1997Q1 - 2001Q2$. The results from our data for the same period and method (first differencing (2)) are $\beta^x = 0.2$ and $\beta^f = 0.81$, which is far from what Petrongolo and Pissarides (2008)

[7]The United States data do not deliver consistent results in the sample from 1994 to 2001. It is possible that the reason lies in the characteristics job separation rate for this time period. As it can be seen in Section 5.2.1, the dynamics of the job separation rate are not as pronounced as the dynamics of the job finding rate. In the full sample from $1951Q1$ to $2005Q1$, however, the correlation between the cyclical components of the job finding rate and the unemployment rate is approximately 0.9 with lead one, and between the separation rate and the unemployment rate 0.7 with lead/lag zero. The betas under the full sample sum up to approximately one for each method. The contributions of the job finding rate lie in between $0.6 < \beta^f < 0.72$. The lowest value is obtained by the first differencing (1) method, and the highest value by the HP filtering method.

[8]This has been shown by two facts: Firstly, the transition probabilities are close for the two countries (Section 4) and secondly, the labor market dynamics show strong similarities (Section 5.2.1).

obtained. Again, the HP filtering method leads to results very close to the results obtained by Petrongolo and Pissarides (2008) with $\beta^x = 0.43$ and $\beta^f = 0.57$.[9] The betas obtained with the full sample and the HP filtering method are similar to the subsample $1997Q1 - 2001Q2$ and the results by Petrongolo and Pissarides (2008). Hence, they seem to be most reliable compared to the other results.

For the United Kingdom, the data quality in general seems to be poor, since 18 of 32 data points are classified as outliers according to the algorithm proposed by Petrongolo and Pissarides (2008). This basic problem leads to incoherent coefficients for the United Kingdom. However the contributions of the job finding rates of the full data sample are significantly different from zero and are in a similar range (from 0.68 to 0.79). This would suggest that the contribution of the job separation rate would be between 0.21 and 0.32 for the United Kingdom, which would be in line with the results obtained by Petrongolo and Pissarides (2008).

Fujita and Ramey (2007, 2009) argue that Shimer (2007) understates the importance of the job separation rate for unemployment variability with his method discussed in Section 5.1. For the sample from 1994 to 2001, however, the contribution of the job separation rate to total unemployment variability is almost the same under the HP filtering method and the method proposed by Shimer (2007).

As it has been shown in this thesis, the European steady state unemployment rates are bad approximations for the actual unemployment rates in part. This is why Elsby, Hobijn and Sahin (2008) modify the measurement of contributions. Their method allows for the deviation of the actual unemployment rate from steady state. Further, they show that current variation in unemployment can be decomposed into contributions due to current *and* past changes in the inflow and outflow rates. With that method, one gets a third beta-term, called β^0, which gives the contribution of the initial deviation from steady state to unemployment variability at $t = 0$. The effect is that the residual term approximates zero. In Table 5.5, β-estimations by Elsby, Hobijn ans Sahin (2008) with and without deviations from steady state are listed. Their results are taken as a robustness check for our findings.

It can be seen that the betas for the contributions with deviations from steady state converge to the betas without deviation from steady state, the higher $x_t + f_t$ is. This is apparent for the United States data, where labor market dynamics are by far highest. The steady state decompositions work poorly for European labor markets with the annual data of Elsby, Hobijn and

[9] There is only one set of coefficients because there are no outliers in the subsample.

	Steady state decomposition		Non-steady state decomposition		
	β^f	β^x	β^f	β^x	β^0
France	0.61	0.59	0.49	0.48	0.04
Germany	0.76	0.82	0.45	0.6	−0.04
Spain	0.81	0.4	0.62	0.36	0.02
United Kingdom	0.54	0.58	0.57	0.42	0.01
United States	0.82	0.18	0.82	0.18	0.0

Table 5.5: Contributions of transition rates to unemployment variability without and with deviations from steady state (data by Elsby, Hobijn and Sahin, 2008)

Year	94	95	96	97	98	99	00	01
France	3	3	3	3	3	3	3	3
Germany	2.6	2.6	2.6	2	2	2.1	2.1	2.1
Spain	3	2.4	2.4	2.4	2.3	2.3	2.3	2.3
United Kingdom	1.3	1.3	1.3	1.3	1.3	1.4	1.4	1.4
United States	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6

Table 5.6: Employment protection legislation index (data by Allard, 2005)

Notes: The employment protection legislation index ranges from zero to five. The higher the score, the higher job security is. For details on the construction of the index, see Allard (2005).

Sahin (2008). The contributions which allow for deviations from steady state are much better in terms of summing up to one. Although our β^fs differ by around 0.1 points with the non-steady state-β^f, the results are roughly consistent with a $\frac{\beta^f}{\beta^x}$ approximating $\frac{1}{1}$ among Continental European countries. This is what Elsby, Hobijn and Sahin (2008) find for all Continental European countries assessed. In the United States and the United Kingdom, $\frac{\beta^f}{\beta^x}$ equals $\frac{3}{1}$, roughly. The discussion of the results shows that our results are consistent with the results of Elsby, Hobijn and Sahin (2008).

All contribution values that seem to be plausible as argued above are written in italics in Table 5.3. Now, those contributions and the general labor market dynamics are related to employment protection legislation. The amount of regulation is measured from an index by Allard (2005) whose values are reported in Table 5.6 for the relevant countries and time period. High values are equivalent to high employment protection and thus high job security.

In order to find out how the relation between the contributions of the job finding and the job separation rate to unemployment variability behaves from a theoretical point of view, we consider different states of the business cycle.

Let us assume that legislation makes it hardly possible to lay off workers for a firm. In such a country, the job separation rate must be lower than in countries with little employment protection. Hence, the level of job finding rate is also lower than in countries with little legislation because firms are more reluctant to hire workers when it is difficult to lay them off in times of economic distress. These characteristics have been shown in Table 4.1. One can see that the level of the job finding rate is lower in Europe, where labor market regulation is stricter than in the United States (see Table 5.6).

Another effect shows up when comparing rising and falling unemployment and the contribution coefficients of the transition rates. In Germany, the unemployment rate rises from 7.79% to 9.36% in the period from 1995$Q1$ to 1997$Q4$ and returns to 7.34% in 2000$Q4$. In the first period with rising unemployment, the ratio of $\frac{\beta^f}{\beta^x}$ is $\frac{1}{1}$ approximately. In the subsequent period of falling unemployment, the ratio lowers to about $\frac{\beta^f}{\beta^x} = \frac{1}{2}$. Non of the betas obtained is significantly different from zero, however. So, the relation could be random. Petrongolo and Pissarides (2008) can confirm the relationship with their figures, though: For France, which has stricter labor market regulation than Germany (see Table 5.6), they compute the betas for two periods where unemployment remains approximately unaltered (1991$Q2-$1996$Q4$ and 2001$Q3-$2007$Q3$). The ratios for those periods are between $\frac{10}{1} < \frac{\beta^f}{\beta^x} < \frac{18}{1}$. In the period from 1997$Q1-$2001$Q2$, when unemployment falls from 11.55% to 8.27%, the ratio drops to approximately $\frac{1.2}{1}$.[10] Hence, the relative importance of the job separation rate increases when unemployment is falling.

Apparently, the importance of the job separation rate increases in times of declining unemployment in highly regulated labor markets. This leads to the following hypothesis: In a labor market with high job security, firms do not hire new workers before they are sure that the filling of the jobs pay off over a relatively long period since it cannot immediately lay off the workers in times of economic distress. This leads to a relatively low and less volatile outflow of unemployment.[11] Now, in times of declining unemployment, the contribution of the job separation rate must increase when the outflow does not alter much. This means that unemployment declines mainly because companies lay off less people.

Table 5.7 shows the contribution of the transition rates to unemployment variability for periods of rising and declining unemployment for the United States. It is apparent that from the 1980s, the job finding rate increases its

[10] With our data, the beta ratio is about the same for the period of falling unemployment, as shown above.

[11] Table 4.1 confirms that the volatility in the job finding rate is smaller in Europe than in the United States.

Period	Movement	β^f	β^x	Ratio
$1973Q3 - 1975Q4$	rise	0.59*	0.39*	9/6
$1975Q4 - 1979Q2$	decline	0.56*	0.41*	8/6
$1979Q2 - 1982Q4$	rise	0.50*	0.51*	6/6
$1982Q4 - 1989Q1$	decline	0.67*	0.33*	12/6
$1989Q1 - 1992Q2$	rise	0.58*	0.43	8/6
$1992Q2 - 2000Q1$	decline	0.79*	0.22	24/6
$2000Q1 - 2003Q2$	rise	0.61*	0.39*	9/6

Table 5.7: Contributions of the job finding and the job separation rate to unemployment variability in the United States for rising and declining unemployment

Notes: The column "Movement" indicates the direction of the unemployment's evolution. The numbers in the column "Ratio" approximate $\frac{\beta^f}{\beta^x}$. The coefficient labeled with * are significantly different from zero on a 5% level.

relative importance in times of declining unemployment. This is contrary to the findings for France and Germany, and it confirms the hypothesis since the United State's job security is low. Furthermore, the contribution of the job finding rate does not sink below 0.5 in any of the periods. So in any time of the business cycle, the job finding rate is more important in explaining unemployment variability. Additionally, the importance of the job finding probability as an explanation for deviations of the actual unemployment from the trend increases over time. In that respect, the results of Shimer (2007) – that the job separation rate has a smaller impact on unemployment fluctuations than the job finding rate – can be confirmed. But, the influence of the job finding rate on unemployment variability is much smaller with our approach: Shimer (2007) claims that the contribution of the job finding rate to unemployment variability amounts 0.95 from 1987 to 2007. With the HP filtering method, it is 0.79 at maximum.

Although Spain has got an approximately equally high regulated labor market as Germany, the hypothesis expressed above is not supported. From $1990Q4$ to $1994Q1$, when Spanish unemployment was rising, the contribution of the job separation rate was more than 0.6 according to Petrongolo and Pissarides (2008). Afterwards, in the period of declining unemployment from $1994Q2$ to $2006Q4$, the contribution declines to about 0.4 (as discussed above). Hence, the relative importance of the contribution of the job separation rate falls in periods of declining unemployment. This however, can be justified by the introduction of fixed-term contracts with a maximum duration of three years after the mid 1980s. "By the early 1990s, as much as 90% of new job creation and 30% of employment was with fixed-term contracts. [...] Virtually all job separations during this period [1990-1994] were due to expiring fixed-term contracts." (Petrongolo and Pissarides, 2008:261).

In France, Spain, the United Kingdom and the United States, falling unemployment rates in the period from $1994Q1 - 2001Q4$ can be observed. For those countries, the relative importance of the job separation rate increases the higher the job security is. For the United States with virtually no warranted job security, the job finding rate has got much more influence than the job separation rate, whereas in Continental Europe, both rates seem to influence the decline in unemployment equally. In that respect, the labor market dynamics of the United Kingdom resemble those of the United States, and the similarities with the French labor market dynamics that were found in Section 5.2.1 disappear. The presumption expressed in Section 4 that the job separation rate is likely to have a greater impact on unemployment variation in Europe than in the United States can be confirmed, at least what concerns Continental Europe.

6 Conclusion and discussion

In this thesis, job finding and job exit probabilities of France, Germany, Spain, and the United Kingdom were calculated from ECHP data for the period from 1994 to 2001. The United States data were taken from Shimer (2007). The transition rates were calculated with a two state model (employment-unemployment) proposed by Shimer (2007). We found out that labor market dynamics in European countries is much smaller than in the United States. Further, the transition rates and their contributions to unemployment variability react sensitively to the business cycle.[1] Both the procyclicality of the outflow rate and the countercyclicality in the inflow rate play an important role in cyclical unemployment. In Europe, while the job finding rate is procyclical and leads the cycle, the job separation rate is anticyclical and broadly symmetric around zero. The results for Continental Europe suggest that the contributions of the inflow and outflow rates to unemployment variability are equally important, whereas in the United Kingdom and the United States, the $\frac{\beta^f}{\beta^x}$-ratio is about $\frac{3}{1}$. Further, while in Continental Europe, the reduction in the job separation rate is important for a reduction in the unemployment rate, in the United States, it is the increase in the job finding rate.

This thesis suggests that standard job matching models with constant separation rates cannot account for the cyclicality of neither European nor American unemployment.[2] The job separation rates are highly cyclical, and at least in Europe, possibly even show more distinct cyclical behavior than the job finding rate. This has broad impacts on the job finding rate, which inevitably gets dependent on the job separation rate. This can be illustrated by the following example: Imagine being in steady state and having a fixed *number* of unemployed finding a job every month. Now, if the job separation rate increases, more people flow into the unemployment pool. Hence, the job finding rate decreases if the number of workers flowing out of unemployment does not change. In these circumstances, the job finding rate decreases *because* of in-

[1] For the assessment, we relied on approaches by Fujita and Ramey (2007, 2009). The Shimer (2007) approach performed poorly.

[2] This conclusion is supported by Elsby, Michaels and Solon (2009), Fujita and Ramey (2007, 2009) for United States data and by Elsby, Hobijn and Sahin (2008) for the OECD countries they assessed, among others.

flows to unemployment. Fujita and Ramey point out this fact for the United States, claiming that "since declines in the job finding rate tend to be preceded by increases in the separation rate, abstracting from cyclical adjustment in the separation rate may distort the analysis of unemployment dynamics in important ways" (Fujita and Ramey, 2009:429). To what extent this is valid for European countries is not straightforward from our data since the job finding rate leads the cycle while the job separation rate is symmetric around zero, generally. This point directly leads to further topics to be investigated on worker flows based on ECHP data.[3]

In order to investigate this point, one must look at the number of people flowing between unemployment and employment. For the United States, Elsby, Michaels and Solon (2009), and Fujita, and Ramey (2006) find that during recessions, total job loss, total hiring, and the job separation rate rise, while the job finding rate falls sharply. Elsby, Hobijn and Sahin (2008:23) find that "changes in inflows tend to lead changes in the unemployment rate in the annual data we use. What emerges from our results on worker flows is that, even though the OECD economies have very different levels of flows, the cyclical behavior of worker flows across countries is very similar." This approach could also clarify on the hypothesis that unemployment in Europe declines because firms lay off less people, contrary to the United States, where unemployment declines because of the increased hiring activity by firms.

Secondly, Elsby, Hobijn and Sahin (2008) present a method to assess contributions of transition rates to unemployment variability which allows for the deviation of the actual unemployment rate from steady state. Further, the contributions account for current and past changes in the inflow and outflow rates. As it has been shown, and as Elsby, Hobijn and Sahin (2008) point out, deviations from steady state should be considered, and past transitions seem to play an important role in explaining unemployment fluctuations. Their method would certainly lead to a clearer picture in contributions of transition rates to unemployment fluctuations.[4]

Thirdly, the data can be classified into subgroups to get a clearer picture on European transition rates. Two ideas can be pursued: Firstly, take a look at the difference between young and prime-age workers, and also con-

[3]Elsby, Michaels and Solon (2009) stress the importance of understanding the economic determinants of both the cyclical, see "Summary and Discussion" for a discussion of this topic.

[4]However, Elsby, Hobijn and Sahin (2008) reckon that monthly estimates of the job finding probability with the method of Shimer (2007) can be substantially noisy for countries with low job finding probabilities such as Continental Europe: "The simple reason is that low outflow rates imply that very few unemployed workers at a point in time are in their first month of unemployment, which increases the sampling variance of the estimate of $u^{<1}_{t+1}$ [short-term unemployment], and in turn leads to noisy estimates of f_t" (Elsby, Hobijn and Sahin, 2008:9).

sider prime-age men only, as it is done in many papers. Secondly, the fact of structural unemployment – predominantly in Europe – probably distorts labor market turnover (notably the job finding rate) significantly without affecting the dynamics of the labor market. Hence, the structurally unemployed could be taken out before transition rates are calculated. Alternatively, one could explicitly account for duration dependence of the job finding probability and the heterogeneity of workers in the model to calculate transition probabilities.[5]

Fourthly, as Section 3 made apparent, the missing at random approach seems to be insufficient for the ECHP data. There seems to be a lot of noise in the series constructed from the data set. So, it should be tested whether the missing at random approach is sufficient. If not, a more careful analysis of the raw data would certainly reduce volatility in the number of short-term unemployed people and therefore increase the reliability of the ECHP data.[6] Fujita and Ramey (2006) propose a method in which missing observations would not be regarded as random. Two approaches could then be used to test the robustness of the transition rates calculated: On the one hand, the two state model of Fujita and Ramey (2006) could be used, and on the other hand, the three state model proposed by Shimer (2007) with economic inactivity included could be be taken.

[5]See Shimer (2007), Section 3.

[6]However, the basic problem mentioned in Section 6, Footnote 4, remains.

Derivation of equations (2.3) and (2.6)

Given $U_t^s(0) = 0$, one can show that (2.4) is the solution to (2.3).

$$
\begin{aligned}
\dot{U}_{t+\tau} + U_{t+\tau} f_t &= \dot{U}_t^s + U_t^s(\tau) f_t \\
\int_0^1 \dot{U}_{t+\tau} + U_{t+\tau} f_t \, d\tau &= \int_0^1 \dot{U}_t^s + U_t^s(\tau) f_t \, d\tau \\
U_{t+\tau} e^{f_t \tau} \Big|_0^1 &= U_t^s(\tau) e^{f_t \tau} \Big|_0^1 \\
U_{t+1} e^{f_t} - U_t &= U^s(1) e^{f_t}
\end{aligned}
$$

With $1 - F_t = e^{-f_t}$ one gets

$$
U_{t+1} = (1 - F_t) U_t + U_{t+1}^s
$$

Derivation of equation (2.6).

$$
\begin{aligned}
\dot{U} &= E_{t+\tau} x_t - U_{t+\tau} f_t \\
\dot{U}_{t+\tau} + U_{t+\tau}(f_t + x_t) &= x_t L_t \\
\int_0^1 [\dot{U}_{t+\tau} + U_{t+\tau}(f_t + x_t)] e^{(f_t + x_t)\tau} \, d\tau &= \int_0^1 x_t L_t e^{(f_t + x_t)\tau} \, d\tau \\
U_{t+\tau} e^{(f_t + x_t)\tau} \Big|_0^1 &= \frac{1}{f_t + x_t} x_t L_t e^{(f_t + x_t)\tau} \Big|_0^1 \\
U_{t+1} &= \frac{(1 - e^{-f_t - x_t}) x_t}{f_t + x_t} L_t + e^{-f_t - x_t} U_t
\end{aligned}
$$

Pseudo code

Data generation from ECHP raw data

The following pseudo code is representative for one country and one year from 1995 onward. The data generation for 1994 works equally, except that there are no references to the previous year.

1. Import a country file of a specific year with all lines and the columns specified.
2. Generate a matrix with the monthly activity status. If status is either 1, 2, 3, or 4, assign "e", if status is 6, assign "u", otherwise, assign "x".[7]
3. Transpose the vector with the Personal Identification Numbers.
4. Transpose the vector with the Personal Weight, the Household Identification Number, the year of birth, age, and sex.
5. Join 2, 3, and 4.
6. Extract the observations of 5 that contain observations which were part of the last year's interview (the values not being part of the last years interview are assigned with "Null").
7. Delete all "Null" in the matrix of 6.
8. Give the positions of the Personal Identification Numbers from 7 in the matrix of the previous year.
9. Extract all observations which are part of 6 if the Household Identification Number, the year of birth, and sex are the same, and if the age of the observations is greater or equal the age of last year (for this, 8 is needed).
10. Delete all positions with "Null" in the matrix of 9.
11. Delete all positions in 8 that are not part of the sample generated in 9.

[7] "e" stands for employed, "u" for unemployed, and "x" for inactive/exclude.

Count the all who stayed in their job for the last and this month and all job to job transitions

12. Make a list and extract the personal weight of all "e" if "e" was assigned the previous month from February to December for all observations from the matrix in 2.

13. Replace all "Null" with "0" and partition the list from 12 into groups of 11 (so the list gets a matrix again).

14. Sum up all columns from 13.

15. Make a list of the Personal Weights for all observations that were assigned with "e" in 10, if they were assigned with an "e" in the last year (for this, 11 is needed).

16. Replace all "Null" with "zero".

17. Sum up 16.

18. Make a list of 12 and 16.

Count all transitions from unemployment to employment

Repeat the same procedure as in the previous section except that you count all "e", if the previous month it was assigned "u".

Count all short-term unemployed

Repeat the same procedure as in the previous section except that you count all "u", if the previous month it was assigned "e".

Count all long-term unemployed

Repeat the same procedure as in the previous section except that you count all "u", if the previous month it was assigned "u".

Unemployment rate and the short-term unemployment rate

19. Calculate the monthly unemployment rate.

20. Calculate the monthly short-term unemployment rate.

Join all series

21. Join the monthly short-term unemployment rate for all years.

22. Join the monthly unemployment rate for all years.

Combine and Export

23. Make a table of years.

24. Make a table of months.

25. Export time series.

Calculation of transition rates, business cycle analysis, and contributions of transition rates to unemployment variability

Up to Subsection "Export graphs", the program provided by Shimer[8] was used and adapted to our data. Then, the code was written autonomously.

Define HP Filter

1. Define a function that calculates the HP trend.

2. Define a function that calculates log cyclical components.

3. Set directory where inputs are retrieved and outputs filed.

Set the smoothing parameter of the HP filter to 10^5

Set start year to 1994

Import monthly data on unemployment, employment and the monthly of short-term unemployment rate

4. Import monthly unemployment data.

5. Print the first line of the imported file.

6. Drop the first line of the file.

7. Import monthly employment data.

8. Print the first line of the imported file.

9. Drop the first line of the file.

10. Import the share of short-term unemployment data, delete the first two lines of the list and delete the first row.

11. Quantify the minimal length of the lists imported by "available".

[8] `http://robert.shimer.googlepages.com/flows`

12. Calculate the level of short-term unemployment by multiplying the share of short-term unemployed with the level of unemployment. Take the last "available" elements of the lists to construct the level of short-term unemployment.

Define grids for monthly and quarterly data

13. Define grid for monthly data.
14. Define grid for quarterly data.
15. Define grid for yearly data.

Construct the unemployment rate

16. Calculate the monthly unemployment rate.
17. Calculate the monthly unemployment rate, led by on period.

Construct the job finding probability F according to Shimer (2007), equation 2.5

18. Calculate the monthly job finding probability.
19. Calculate the monthly job finding rate.

Calculate the job separation rate according to equation 2.6

20. Define a start value for t; define the empty list "sepM".
21. Find a numerical solution for the job separation rate for a start value of $t = 1$. Start searching by assuming a start value of zero for the separation rate s. Add the solution to the list "sepM", raise t by one and repeat the process. This loop is repeated as long as t is smaller than the length of the "UnempM" list.
22. Calculate the job separation probability.

Compute quarterly averages

23. Compute the quarterly average of the job finding rate.
24. Compute the quarterly average of the job separation rate.
25. Compute the quarterly average of the job finding probability.
26. Compute the quarterly average of the job separation probability.
27. Compute the quarterly average of the job unemployment rate, led by one period.

28. Compute the quarterly average of the unemployment rate.
29. Compute the quarterly average of the unemployment level.
30. Compute the quarterly average of the employment level.

Export data for Excel

Export quarterly and monthly series previously calculated.

Make tables of correlations between the actual unemployment rate and the steady state unemployment rate

31. Chose a subsample of the unemployment rate that goes from the second to the second last element.
32. Make a list of correlations between the detrended monthly steady state unemployment rate and the detrended actual unemployment rate from lead one to lag three.
33. Make a list of correlations between the detrended quarterly steady state unemployment rate and the detrended actual unemployment rate from lead one to lag three.

Print the output of a regression of "hypothetical" unemployment rates (only changes in f or only changes in s) on the actual unemployment rate (Shimer, 2007)

34. Print a regression of the detrended hypothetical unemployment rate with variation in f_t only on the detrended unemployment rate.
35. Print a regression of the detrended hypothetical unemployment rate with variation in x_t only on the detrended unemployment rate.

Do the same, lag z quarters

Repeat the regressions, but lag the hypothetical unemployment rates z quarters.

Export graphs

36. Set directory for outputs.
37. Import the seasonally adjusted unemployment rates from ECHP.
38. Import the short-term unemployment rates from ECHP and OECD.
39. Generate and export a monthly and quarterly graph of the official unemployment rate and the ECHP unemployment rate.

40. Generate and export a graph of the ECHP and OECD short-term unemployment rate.

41. Generate and export graphs of the actual unemployment rates, hypothetical unemployment rates, and the steady state unemployment rates.

Business cycle co-movement and contributions to unemployment variability (Fujita and Ramey, 2006, 2007)

42. Import GDP of all countries.

43. Import GDP growth of all countries.

44. Chose GDP for specific country.

45. Chose GDP growth for specific country.

46. Calculate labor productivity.

47. Calculate the correlations between the detrended separation rate and the detrended unemployment rate from lag 8 to lead 8 with a smoothing parameter of 1600.

48. Repeat 47 between the job finding rate and the unemployment rate.

49. Repeat 47 between the job separation rate and the GDP.

50. Repeat 47 between the job finding rate and the GDP.

51. Repeat 47 between the job separation rate and the productivity.

52. Repeat 47 between the job finding rate and the productivity.

53. Repeat 47 between the job separation rate and the GDP growth.

54. Repeat 47 between the job finding rate and the GDP growth.

55. Repeat 47 between the job separation rate and the job finding rate.

56. Repeat all the calculations with a smoothing parameter of 10^5.

57. Define grid for the x-axes of the subsequent graphs.

58. Generate graphs for all the correlations calculated above.

Do the same, take first differences instead of a HP Filter

All the calculations and generations of graphs from above are repeated, but with first differenced instead of HP filtering.

Contributions of transition rates to unemployment variability (Fujita and Ramey, 2009)

59. Calculate the monthly steady state unemployment rate.
60. Calculate the quarterly steady state unemployment rate.
61. Calculate the trend component of the steady state unemployment rate
62. Calculate the trend component of the separation rate.
63. Calculate the trend component of the job finding rate.
64. Calculate du_t^{ss} under HP filtering.
65. Calculate du_t^{x} under HP filtering.
66. Calculate du_t^{f} under HP filtering.
67. Calculate du_t^{ss} under first differencing (1).
68. Calculate du_t^{x} under first differencing (1).
69. Calculate du_t^{f} under first differencing (1).

Contributions of transition rates to unemployment variability (Pissarides, 2008)

70. Calculate du_t^{ss} under first differencing (2).
71. Calculate du_t^{x} under first differencing (2).
72. Calculate du_t^{f} under first differencing (2).

Print Regressions of du_t^{f} on du_t^{ss}, and du_t^{x} on du_t^{ss}

73. Regress du_t^{f} on du_t^{ss} under HP filtering.
74. Regress du_t^{x} on du_t^{ss} under HP filtering.
75. Repeat the regressions for first differencing (1) and first differencing (2).

Do the same, exclude outliers

76. Calculate the difference between the change in steady state unemployment and the change in actual unemployment.
77. Calculate the periods for which 76 is more than 10%.
78. List positions for which 77 is true.
79. Delete the positions from 78 in du_t^{ss} under HP filtering.

80. Delete the positions from 78 in du_t^f under HP filtering.
81. Delete the positions from 78 in du_t^x under HP filtering.
82. Repeat the same for first differencing (1) and (2).
83. Repeat all regressions with the outliers excluded.

Repeat the method of Shimer (2007) with outliers excluded

84. Delete outliers in the hypothetical unemployment rates.
85. Delete outliers in the actual unemployment rates.
86. Repeat regressions with outliers excluded.

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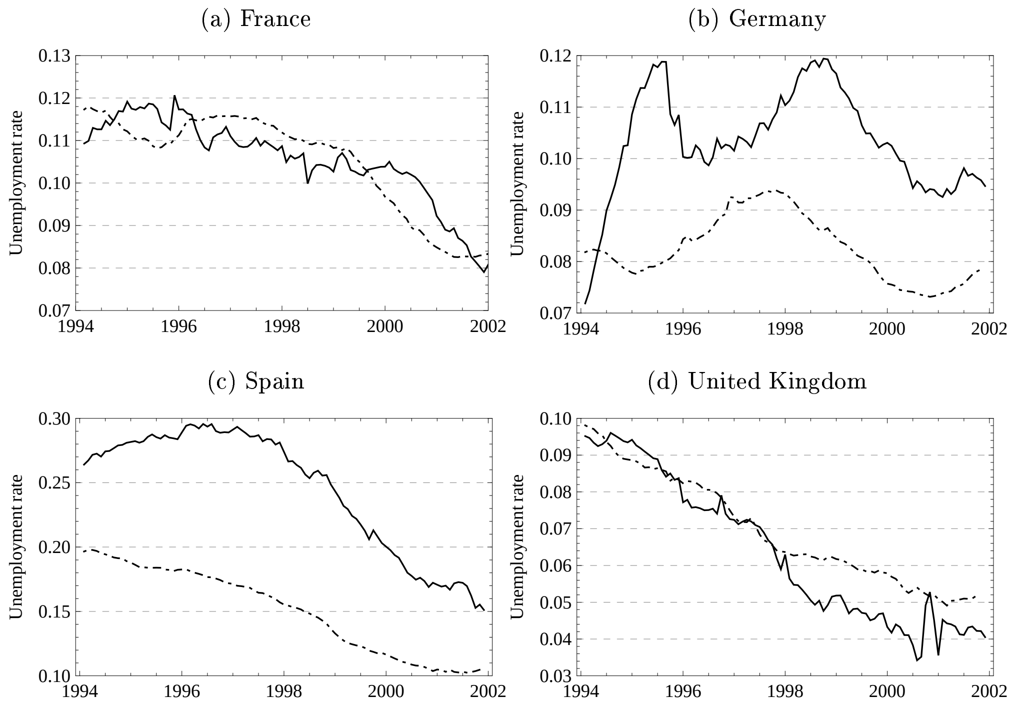
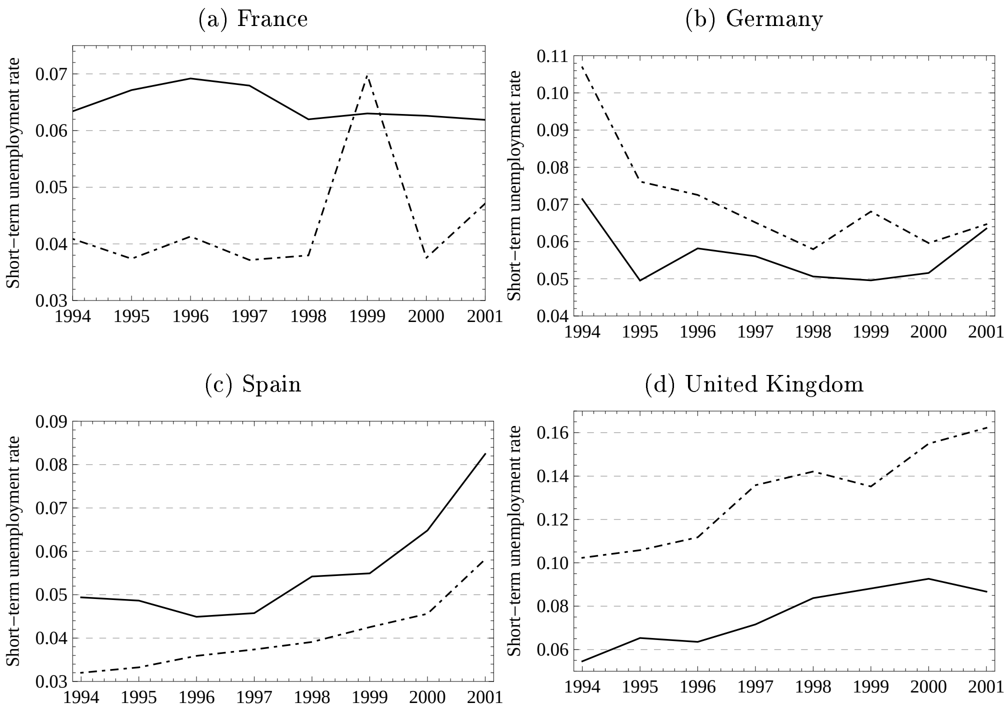
Figure 1: Monthly unemployment rates in comparison



Notes: The ECHP data are represented by the black line, the actual unemployment rate by the dot-dashed line. The unemployment rate is calculated from $u_t = \frac{U_t}{U_t + E_t}$. The number of employed E_t and unemployed U_t are monthly, seasonally adjusted series (see Section 3.2 for details). ECHP data with obvious recording errors were removed before the series were seasonally adjusted with TRAMO/SEATS (see Section 3.1 for details).

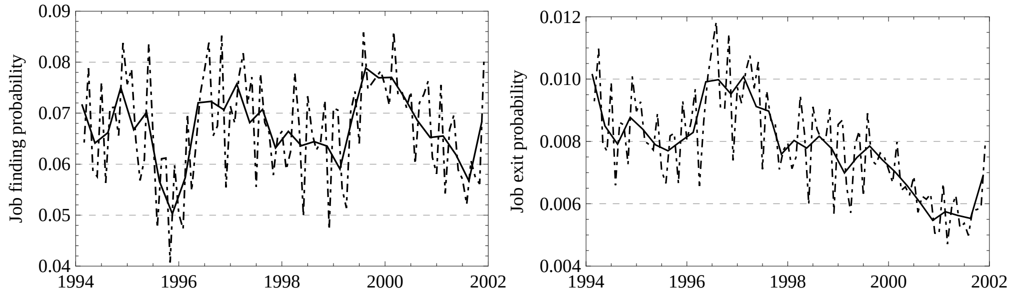
Figure 2: Short-term unemployment rates in comparison



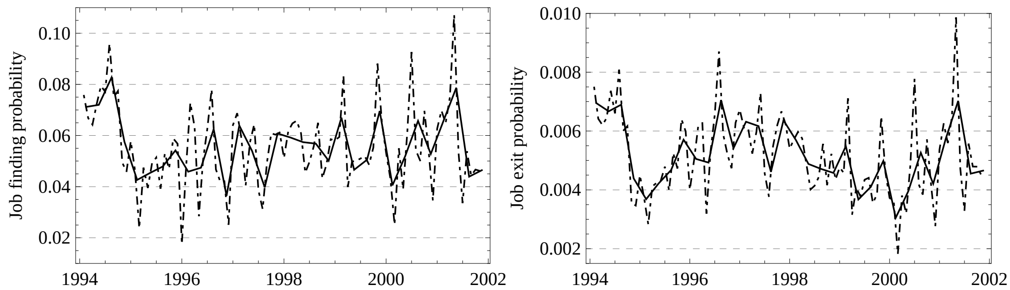
Notes: The ECHP data are represented by the black line, the OECD data by the dot-dashed line. The yearly figures for the ECHP series were obtained by averaging monthly values of the short-term unemployment rate. The OECD data were downloaded from `http://stats.oecd.org`.

Figure 3: Quarterly and monthly job finding and job exit probabilities from 1994 to 2001

(a) France



(b) Germany



(c) Spain

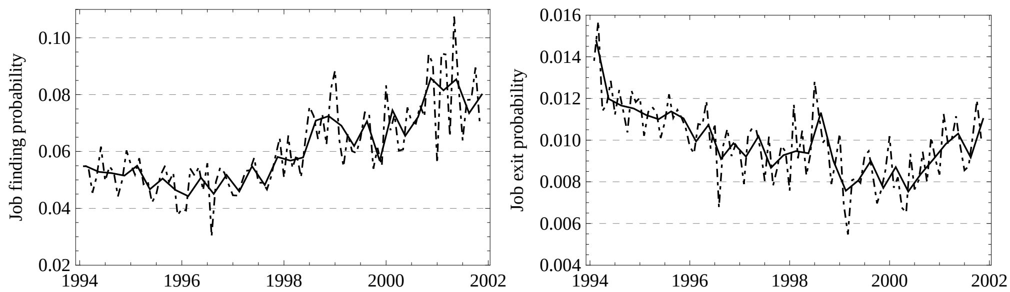
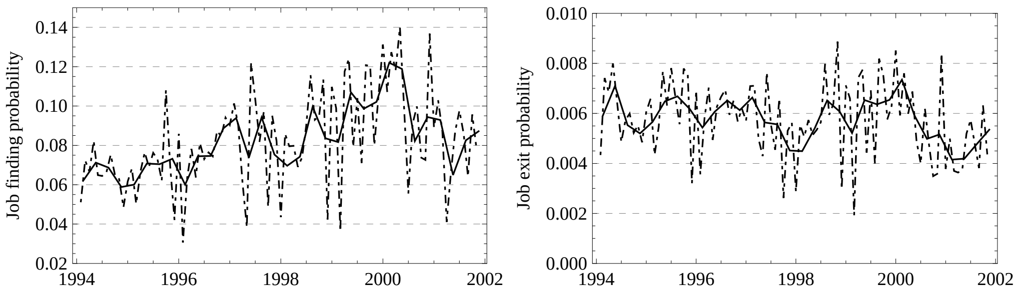
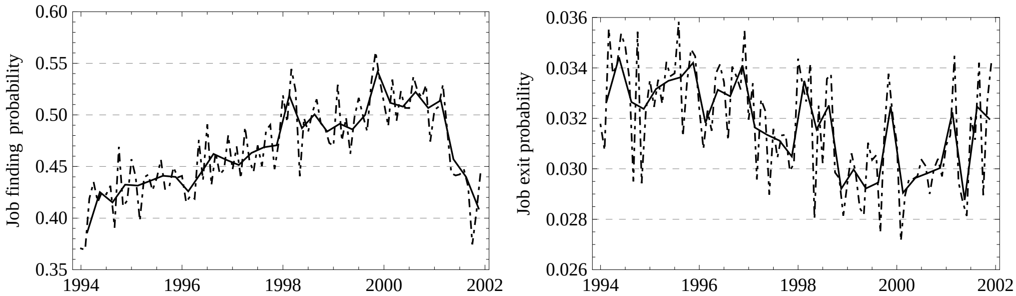


Figure 3: Quarterly and monthly job finding and job exit probabilities from 1994 to 2001

(d) United Kingdom



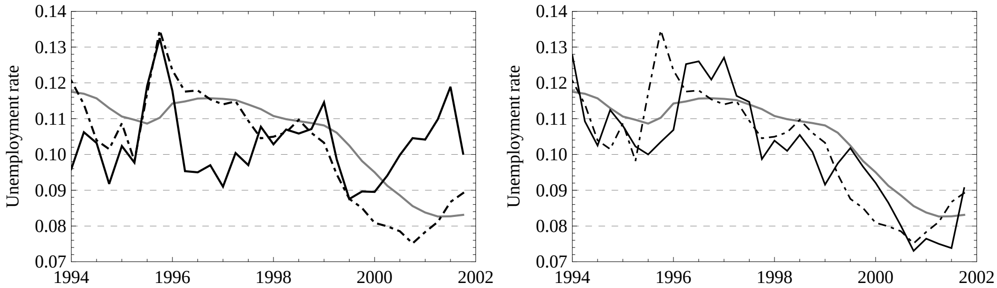
(e) United States



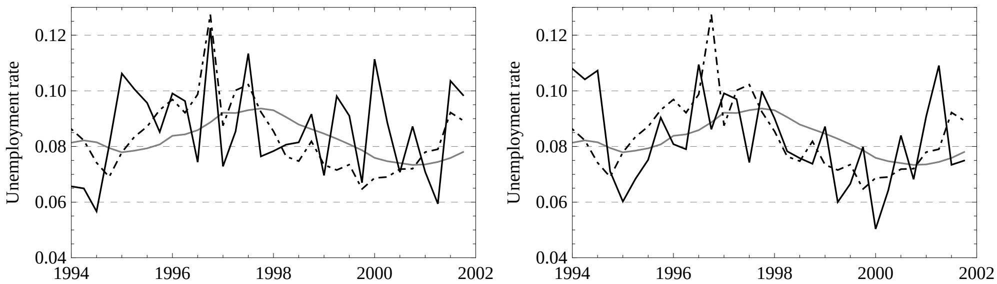
Notes: The quarterly averaged transition probabilities are represented by the black line, the monthly transition rates by the dot-dashed line.

Figure 4: Hypothetical and steady state unemployment rates (quarterly series)

(a) France



(b) Germany



(c) Spain

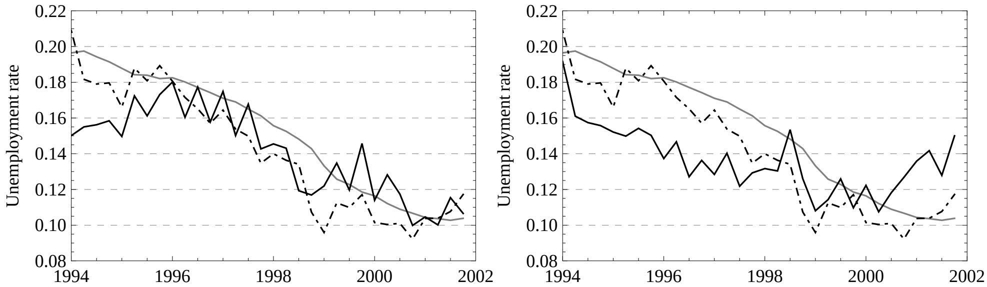
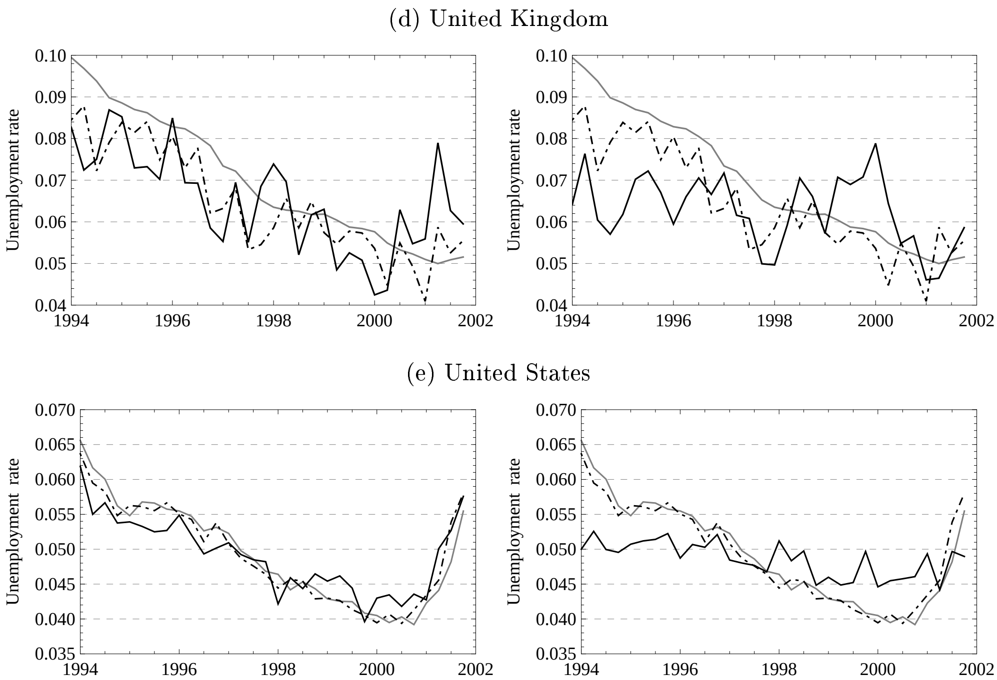


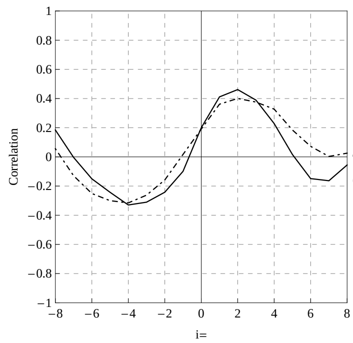
Figure 4: Hypothetical and steady state unemployment rates (quarterly series)



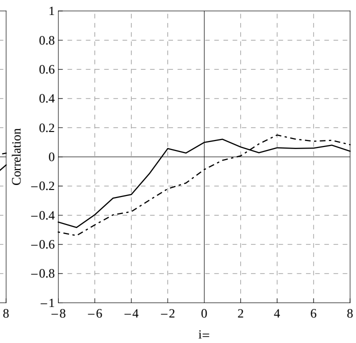
Notes: The actual unemployment rate is represented by the gray line. The steady state unemployment rate is represented by the dot-dashed line. In the left column, black line represents the hypothetical unemployment rate with variation in f_t. In the right column, black line represents the hypothetical unemployment rate with variation in x_t. For details on their calculation, see Section 5.1. The quarterly series are derived from monthly data. All data necessary was taken from the same month t, i.e. no lag was integrated.

Figure 5: Correlation between the cyclical components of the unemployment rate at t and the job finding rate at $t+i$

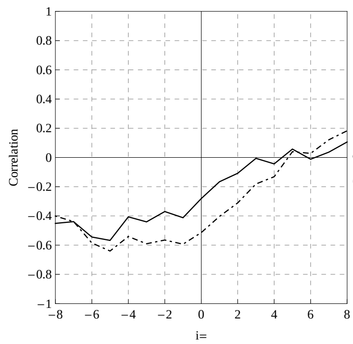
(a) France



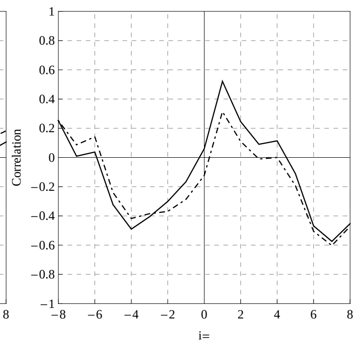
(b) Germany



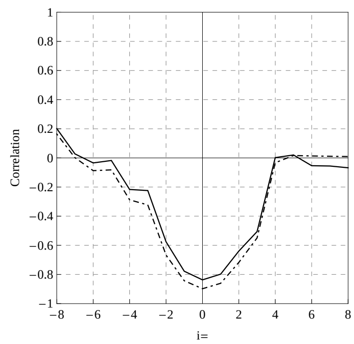
(c) Spain



(d) United Kingdom

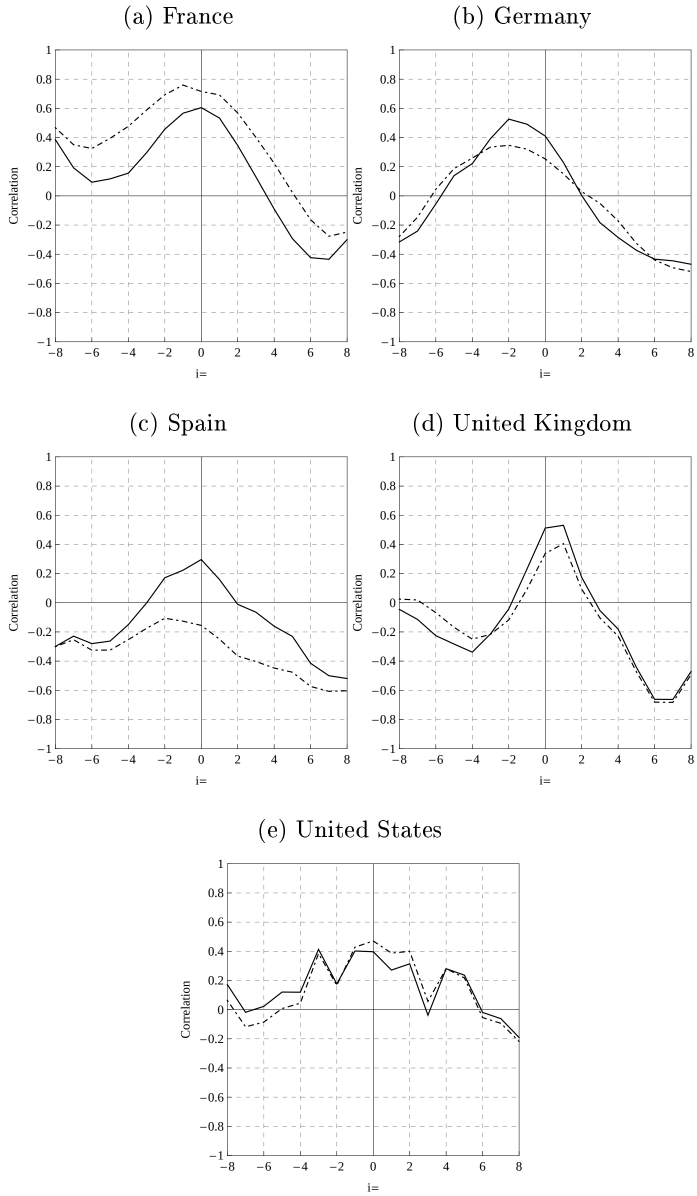


(e) United States



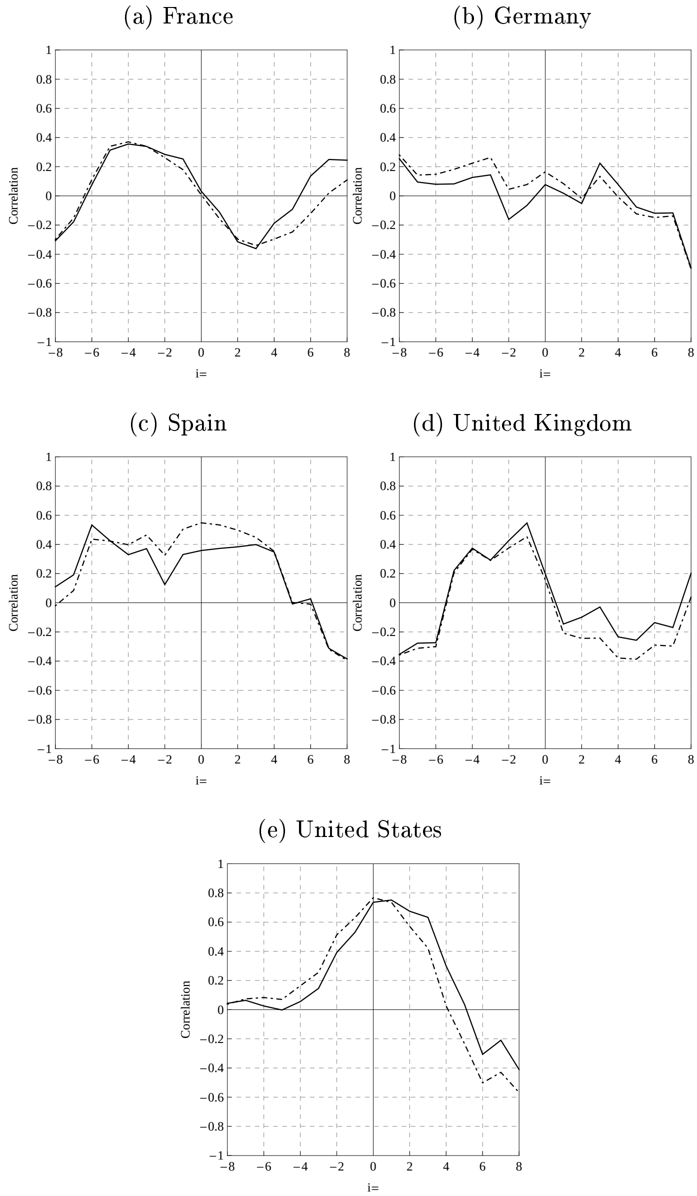
Notes: The continuous line represents results obtained with a HP filter with a smoothing parameter of 1600, the dot-dashed line results with a smoothing parameter of 10^5.

Figure 6: Correlation between the cyclical components of the unemployment rate at t and the job separation rate at $t+i$



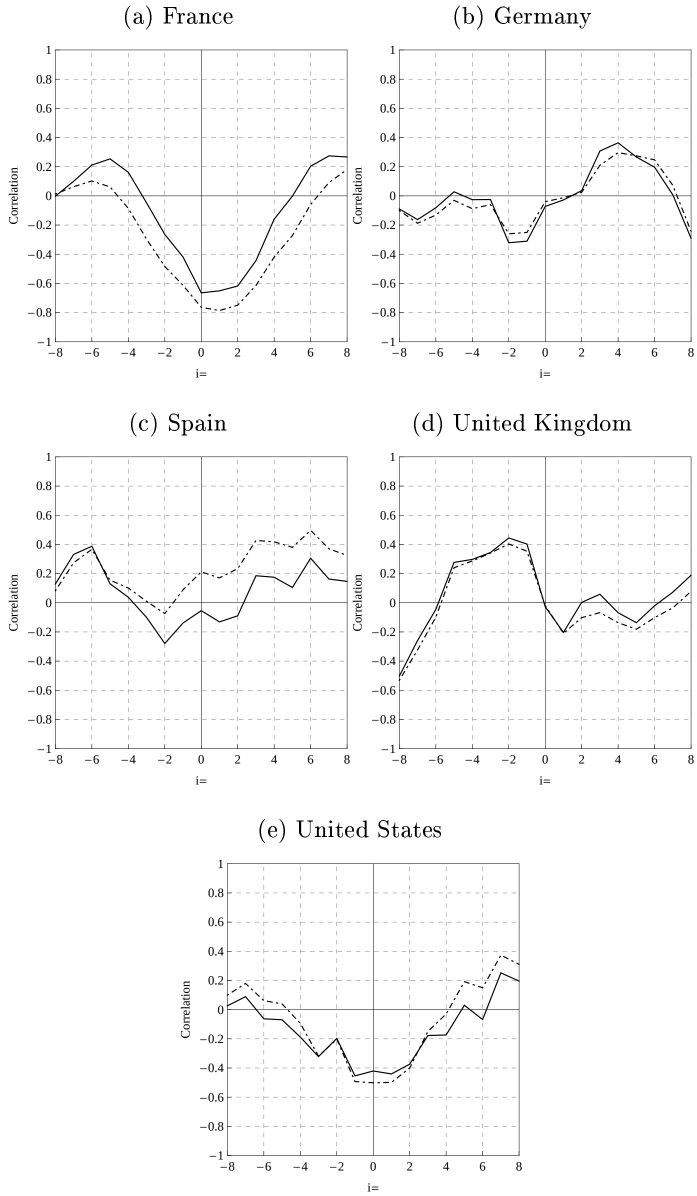
Notes: The continuous line represents results obtained with a HP filter with a smoothing parameter of 1600, the dot-dashed line results with a smoothing parameter of 10^5.

Figure 7: Correlation between the cyclical components of GDP at t and the job finding rate at $t+i$



Notes: The continuous line represents results obtained with a HP filter with a smoothing parameter of 1600, the dot-dashed line results with a smoothing parameter of 10^5.

Figure 8: Correlation between the cyclical components of GDP at t and the job separation rate at $t+i$



Notes: The continuous line represents results obtained with a HP filter with a smoothing parameter of 1600, the dot-dashed line results with a smoothing parameter of 10^5.