Labor market rigidity and the transmission of business cycle shocks*

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Abstract

This paper provides a detailed analysis of labor market flows in Germany and compares them to the US. It documents that in Germany average hiring and firing rates are much lower but that the firing rate volatility is 2.5 times larger. This leads to a contribution of $60-70\%$ of firings to aggregate unemployment volatility, the opposite of what is found for the US. We document further that wage rigidity is not at the root of the large differences.

To explain these cross-country differences we develop a labor market search model with endogenous firings, quits on the job, and skill heterogeneity. We show theoretically that lower average transition rates imply a higher firing rate volatility and amplify the response of the economy to business cycle shocks. We calibrate the model to jointly match stylized labor market facts for the US and Germany. The impulse-response analysis of the model shows that the lower transition rates are also responsible for substantially higher persistence of the unemployment rate in Germany in response to shocks. Thereby, the paper establishes a theoretical link between the effect of labor market institutions and the reaction to business cycle shocks.

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1 Introduction

Compared to the US the German labor market is characterized by substantially lower average hiring and firing rates[1]. Institutional differences, in particular the employment protection legislation and the influence of unions in the wage setting process, have been pointed out as causal for the lower transition rates. Moreover, Petrongolo and Pissarides (2009) study empirically the contribution of hirings and firings to unemployment volatility and argue that in countries like France with stricter employment protection legislation *'it is not surprising that the employment-unemployment transition contributes less to cyclical volatility'* (pp.11). Similarly, though on theoretical grounds, Veracierto (2008) shows that within a model of job reallocation firing taxes *'lower the response of the economy to aggregate productivity changes'* (pp.3).
This paper studies empirically and theoretically whether low average hiring and firing rates can indeed be associated with a lower contribution of firings to unemployment volatility and a lower response of the unemployment rate to business cycle shocks. We document that the evidence for Germany and the US suggests the opposite relationship, namely that a more rigid labor market is associated with more fluctuations over the business cycle rather than less. In Germany, firing rates are compared to the US lower by a factor of 4 and hiring rates by a factor of 5, but the unemployment rate is 1.2 times, the firing rate 2.5 times, and the hiring rate as volatile as the respective US counterparts. These volatility differences translate for Germany into a 30% stronger reaction of unemployment rates to business cycle shocks of the same size and firings that contribute $60-70\%$ to unemployment volatlity whereas for the US the opposite is true and hirings account for $60-70\%$. A similar finding holds for earnings, where we show that, if anything, German earnings are more flexible than US earnings, and wage rigidity can therefore not account for the observed differences.
To explain these empirical facts, we develop an extended version of the standard search and matching model featuring endogenous firings, search on the job, and match heterogeneity. In this model, we show analytically that lower hiring and firing rates are in general inversely related to business cycle volatility. This means that labor market policies that induce a decline in transition rates increase unemployment volatility, yield a higher contribution of firings to unemployment volatility, and moreover, induce a substantial increase in the persistence of shocks. A calibrated version of our model generates a reaction of the unemployment rate to a business cycle shock that is five years after the shock still two times larger in Germany than in the US. This pattern is consistent with the empirical observation after the large oil price shocks in the eighties.
Thereby, our results add theoretical insights to the empirical discussion on *'shocks vs. institutions'* in Blanchard and Wolfers (2000). Our model shows how institutional difference leading to low transition rates do not only amplify the transmission of shocks but also increase the persistence of the reaction. It is exactly this interplay that makes rigid labor markets so vulnerable to business cycle shocks.

On empirical grounds, the paper fills a gap on the contribution of the *'ins'* and *'outs'* in Europe and provides a detailed analysis of labor market flows and earning dynamics for Germany.[2] We show that the stylized labor market facts as stated in Shimer (2005) for the US can also be found for Germany. However, two crucial differences arise. On the one hand, we observe

[1]We use the term *hiring* for unemployment-to-employment transitions and the term *firing* for employment-to-unemployment transitions.

[2]There are two other studies on worker flows in Germany. Bachmann (2005) uses a different concept to measure worker flows and focuses on the dynamics of annual transition rates. Some selected results are consistent with our findings. Gartner et al. (2009) consider quarterly transition rates and do not control for non-employment, tenure, and earnings. The aggregation to quarterly transition rates makes their results not comparable to our findings.

substantially lower transition rates, but on the other hand, a substantially higher firing rate volatility. Extending the methodology of Fujita and Ramey (2007) to a three state decomposition adding flows from and to non-employment, we show that in Germany firings are twice as important in explaining unemployment fluctuations than hirings.

A second empirical contribution of this paper is to uncover an important dimension of labor market heterogeneity. We show that the bulk of worker flows results from low tenured and badly paid matches. Good matches, i.e. matches that are long lasting and relatively better paid, are associated with lower firing and quitting rates. This match heterogeneity provides an empirical motivation for both search on the job and endogenous firings in labor market models. To complete the picture, we also look at differences in worker flows across education groups and sex.

Besides the employment protection legislation, unions or, more generally, the wage setting mechanism has been identified as a prime candidate in explaining the unemployment volatility puzzle originally recognized by Shimer (2005), Hall (2005) and Costain and Reiter (2005).[3] As a third empirical contribution we show that rigidity of this kind is likely not at the root of the cross-country differences, confirming results in Pissarides (2009) who finds that the co-movement of wages with the business cycle might even be higher in Europe than in the US. We provide strong support for this claim for Germany. We apply different approaches proposed in the literature to control for composition bias in wage dynamics but our robust finding across all methods is that German earnings are not rigid and have an elasticity between $0.6 - 0.8$ with respect to productivity for all types of workers.[4] A similar finding for the US has been established by Haefke et al. (2007).

The theoretical contribution of the paper is to account for the above stylized facts within the context of an extended version of the standard search and matching model, featuring endogenous firings, as suggested in den Haan et al. (2000), search on the job, as recently explored in Fujita and Ramey (2007), as well as heterogeneity across matches, as discussed in Menzio and Shi (2009). Our model allows us to provide a simple closed form solution up to a first order approximation for special cases.

We show that endogenous firings have compared to exogenous firings no impact on the hiring rate volatility and can therefore not resolve the basic volatility puzzle. However, the endogeneity of firings is crucial to explain the empirically observed large contribution of firings in the unemployment volatility. Adding search on the job does quantitatively not help in explaining a significant fraction of the unemployment volatility.[5] Yet, it helps to reconcile the model and the data by matching the *Beveridge curve* confirming numerical results in Ramey (2008). In contrast to the results in Pries (2008), we find that type differences and the associated composition effects across workers have only a weak impact on aggregate volatilities. However, the introduction of heterogeneity across job types generates positive incentives to search, accounts for observed type differences in average firing rates, and delivers a large average surplus of a match. Type differences paired with search on the job address therefore at least partly the critique raised to the small surplus calibration of Hagedorn and Manovskii (2008).

We show using a Kalman filtering strategy that once the model is calibrated at the right

[3] Resolutions typically rely on arguments that make wages react only weakly to aggregate conditions inducing a strong surplus for firms to hire in booms. The proposed changes to the benchmark Nash bargaining solution were to change the bargaining set as in Hall (2008), inducing countercyclical bargaining power (Shimer (2005)), using optimal contracts with risk averse agents (Rudanko (2009)), or using staggered wage contracts (Gertler and Trigari (2005)).

[4] Peng and Siebert (2007) using GSOEP data, though limited by the sample size, also provide evidence that wages appear to be fairly flexible in Germany.

[5] At least for Germany, though we find a mildly larger impact for the US.

macroeconomic elasticities, it predicts the entire time-series pattern of labor market dynamics in both countries very well. We perform an impulse-response analysis of the model and find that the implied persistence to shocks turns out to be dramatically different across countries. Five years after a shock hit the economy, the deviation of the unemployment rate from its long-run trend will still be twice as large in Germany as in the US. The large differences in the persistence of shocks do not stem from differences in the wage elasticity but can be traced to the different reaction of firings over the cycle. While a single labor market institution alone cannot be held responsible for all cross-country differences our findings suggest that in particular differences in the bargaining power and the hiring and firing costs across countries can explain the observed differences in the firing rate volatility, the low average transition rates, and the high unemployment persistence.

We proceed in 4 steps. Section 2 describes the data and documents stylized facts about labor market transitions, decomposes the unemployment volatility, examines the effect of tenure, and studies the cyclical behavior of earnings. Section 3 describes and solves an augmented search and matching model. In section 4, we provide a calibration for our model that jointly matches Germany and the US and perform the impulse-response analysis. Section 5 concludes. The appendix provides more detailed information on different subgroups males, females, education or other observable features of the data.

2 Data description and aggregate dynamics

Our dataset is the IAB employment panel that is a 2% representative subsample taken from the German social security and unemployment records for the period from $1975 - 2004$. The sample contains employees that are covered by the compulsory German social security system, it excludes self-employed and civil servants ('Beamte'). Still, it covers about 80% of Germany's labor force. Since the East German labor market was subject to additional regulations and restructuring after the reunification, we exclude all persons with employment spells in East Germany from our sample.[6] We observe the entire employment history of each worker on a daily basis. The income reported at one spell is the average daily income of an individual during the employment spell. We do not observe hours worked but observe whether the person is full-time, part-time, or from 1999 on in marginal employment.[7] We impute earnings above the social security threshold following Gartner (2005), adjust for the change in income reporting in 1983 following Fitzenberger (1999), and adjust the education variables following Fitzenberger et al. (2006). Our basic time-period will be one month. Other studies using the IAB-panel study transitions at lower frequency (see Gartner et al. (2009) and Bachmann (2005)). Using a monthly frequency allows us, among other things, to reduce the time-aggregation bias.

Aggregate data are taken from the statistic office ('Statistische Bundesamt'). We use nominal GDP and convert it to real GDP by the CPI deflator from the Bundesbank. We deflate nominal earnings in the IAB sample using again the same CPI deflator. After 1991, we only observe GDP for the unified Germany and we control for the structural break. Productivity measures are obtained by dividing through total employment or total hours worked, as is done by the statistical office. Further details are relegated to the appendix.

[6] We do a first step sample selection where we remove very few individuals with missing observations. Details can be found in the appendix.

[7] We control for transitions into part-time or from part-time to full-time. We mainly report aggregate statistics. All transitions into different subclasses are available upon request.

2.1 Basic Properties

The stylized labor market facts for Germany are highlighted in table 1 and refer to all workers. In the appendix, we give the flows separated by sex and education. For a better comparison we also present the corresponding US statistics in table 2.

Table 1: German GDP and productivity, employment, and labor market flows $Jan1980 - Sep2004$

	Mean	Std	Rel. Std	Corr (GDP)	Corr (GDP p. Emp.)	Autocorr
GDP		0.024	1	1	0.7809	0.9533
GDP per Emp.		0.0164	0.6836	0.7809	1	0.9246
GDP per Hour		0.0187	0.7808	0.7979	0.9534	0.9608
U-rate (official)	0.0837	0.1808	7.535	−0.7629	−0.4448	0.9794
Vacancies		0.3337	13.9	0.818	0.5556	0.9777
IAB median earnings		0.0168	0.6997	0.8447	0.6764	0.8605
IAB U-rate	0.0758	0.1694	7.059	−0.7222	−0.3231	0.9734
IAB E-rate	0.9242	0.0119	0.4969	0.6409	0.1319	0.9728
Firm exit	0.0239	0.0549	2.288	0.4719	0.2262	0.7532
Empl. exit	0.0152	0.0382	1.592	−0.4284	−0.2031	0.5096
EU	0.0053	0.1479	6.163	−0.8043	−0.501	0.9
EN	0.01	0.0633	2.637	0.5493	0.4008	0.7789
UE	0.0622	0.1034	4.31	0.4157	0.0728	0.7894
UN	0.0488	0.1024	4.268	0.4672	0.5309	0.7978
NE*	0.0649∗	0.178	7.418	0.326	−0.0558	0.8511
NU*	0.0234∗	0.1596	6.651	−0.2098	−0.1126	0.8984
Quits	0.0086	0.158	6.585	0.6528	0.327	0.9189

Notes: All data are in logs and are HP-filtered with $\lambda = 100,000$. GDP data is nominal GDP per capita from the statistic office deflated by the CPI, taken from the Bundesbank. Employment and total hours worked are also taken from the statistics office. IAB data are quarterly averages of monthly data. All IAB data are authors' calculations. Firm exit is defined as the sum of EU+EN+Quits. Employment exit is defined as EU+EN. Quits are defined as job-job transitions between two consecutive dates and a change in the firm counter as defined in the IAB-data. The star at the non-employment flows indicate that the denominator, that is the state of non-employed workers is measured with problems given that we do not have the corresponding universe of searching non-employed. We partially control for this by dropping early retired and only look at workers that eventually will return to the labor market in our sample period. The log volatility measures might be less affected by the problem.

We find cyclical patterns across the two countries that are similar along many dimensions. In particular, we find for Germany that while aggregate output is approximately as cyclical as in the US, aggregate unemployment rates and vacancy rates[8] are more volatile in Germany. Firing rates (EU) are highly countercyclical. Jobfinding rates (UE) are procyclical in both countries but are considerably more correlated with the cycle in the US than in Germany.[9] Quitting rates, defined as on the job transitions to a new establishment, are highly procyclical

[8]Our vacancy measure is fairly crude given that it includes only open positions reported to the Bundesagentur fuer Arbeit. Most job offers will go through internal firm markets as well as newspaper adds etc., so neither the scale nor the volatility should be over-interpreted. However, the correlation structure across the two countries is almost identical as well as the broad picture that vacancy are substantially more volatile than output.

[9]It is important to notice that the correlation structure in almost all labor market variables is considerably more pronounced when we look at a broad aggregate measure, GDP per capita, instead of a productivity measure like output per person or per hour. Productivity measured as output per employed or per hour will be a problematic concept in our framework when viewed, within the model, as an exogenous TFP shock. Productivity will suffer from the same composition effects Haefke et al. (2007) highlight for wages and which we will extensively discuss below. However, for Germany due to the reunification the bias might be particularly severe, and the HP-filter is particularly problematic. We will typically rely on a broader measure of economic activity like GDP per capita, which seems less affected.

Table 2: US GDP and productivity, employment, and labor market flows $Jan1980 - Sep2004$

	Mean	Std	Rel. Std	Corr (GDP)	Corr (GDP p. Emp.)	Autocorr
GDP		0.0263	1	1	0.4443	0.9309
GDP per Emp.		0.0140	0.5307	0.4443	1	0.8487
GDP per hour		0.0142	0.5385	0.1448	0.8883	0.8769
Earnings (BLS)		0.0177	0.6739	0.4231	0.6182	0.9427
U-rate	0.0626	0.1505	5.7224	−0.8904	−0.0272	0.9579
E-rate		0.0143	0.5420	0.8580	−0.0035	0.9576
Vacancies		0.2044	7.7719	0.8457	0.0553	0.9629
Empl. exit	0.0477	0.0372	1.4156	−0.2438	−0.1192	0.3425
EU	0.0203	0.0653	2.4818	−0.7166	−0.3759	0.5083
EN	0.0274	0.0458	1.7413	0.4420	0.2583	0.4418
UE	0.3069	0.1123	4.2705	0.8152	−0.0715	0.8943
UN	0.2658	0.0911	3.4629	0.7276	−0.0477	0.8756
NE	0.0424	0.0592	2.2512	0.6277	0.2285	0.5752
NU	0.0357	0.0713	2.7114	−0.5544	−0.1496	0.6997

Notes: US output data are taken from the NIPA and are deflated by the GDP deflator, productivity and unemployment rate data are taken from the BLS, vacancy postings are taken measured by the Help wanted index, and the labor market transition probabilities are taken from Shimer (2005). All data are in logs and are HP-filtererd with $\lambda = 100,000$.

in Germany. For the US, we do not have equivalent data, but the analysis in Nagypal (2005) suggests that this also holds for the US. Separation rates from the firm's perspective (the sum of quits, EN, and EU) are procyclical implying that the behavior of quits and separations into non-employment dominate the behavior of firings. Given that both rates have counteracting correlation signs overall separation is rather acyclical. We lack a precise counterpart of this variable for the US, given that we do not observe quits on the job directly. Employment exit rates (the sum of EU and EN) are countercyclical both in the US and in Germany. Employment to non-employment rates are procyclical in both countries and are mirroring the behavior of quits on the job, suggesting that, if anything, they reflect quitting behavior. Median earnings obtained from the IAB data are highly procyclical.

There are two fundamental differences across the two countries. First, average transition rates in Germany are substantially lower than in the US. The average jobfinding rate in Germany is smaller by a factor of 5 and the firing rate by a factor of 4. Second, firing rates are roughly 2.3 times as volatile in Germany as in the US. Relative to GDP firing rates are 2.5 times and the unemployment rate 1.2 times as volatile but hiring rates are equally volatile. These differences translate into the finding of the next section that German unemployment volatility is mainly driven by variations in firings, explaining between $60 - 70\%$ of the unemployment volatility while in the US unemployment volatility is dominated by the behavior of hirings and firings account only for $30 - 40\%$. We will now make this statement quantitatively precise.

2.2 Unemployment volatility decomposition

Petrongolo and Pissarides (2009) analyze the contribution of job in- and outflow rates to the fluctuations in unemployment for UK, France, and Spain. Fujita and Ramey (2007) do an analysis for the US. The analysis in both papers is based on a first-order approximation around trend unemployment but the detrending methods and the considered labor market flows differ. The analysis in Petrongolo and Pissarides (2009) is based on a first difference filter allowing for four aggregate transition rates whereas Fujita and Ramey (2007) use the HP-Filter and a two state decomposition. Fujita and Ramey show that the first difference filter is typically very sensitive to high-frequency fluctuations. To address the importance of firings and jobfindings in explaining unemployment volatility, we extend the methodology proposed in Fujita and Ramey (2007) but allow for a three states with six transition rates. We describe briefly the decomposition in Fujita and Ramey (2007) and our extension. An extensive sensitivity analysis with respect to different methods, time periods, and group selection can be found in the appendix. To derive the contribution rates we taken an approximation around trend unemployment

$$\begin{aligned}
u_t &\approx \frac{\Pi_{EU,t}}{\Pi_{EU,t}+\Pi_{UE,t}} \\
\log\left(\frac{u_t}{\bar{u}_t}\right) &= (1-\bar{u}_t)\log\left(\frac{\Pi_{UE,t}}{\bar{\Pi}_{UE,t}}\right) - (1-\bar{u}_t)\log\left(\frac{\Pi_{EU,t}}{\bar{\Pi}_{EU,t}}\right) + \epsilon_t \\
du_t &= dUE_t + dEU_t + \epsilon_t
\end{aligned}$$

where $\Pi_{EU,t}$ denotes the firing probability while $\Pi_{UE,t}$ is the hiring probability and a bar denotes the trend component of the respective variable. $\log(u_t/\bar{u}_t)$ measures the relative deviation of the unemployment rate from its trend. Fujita and Ramey (2007) show that the variance of $\ln(u_t/\bar{u}_t)$ can then be decomposed such that $1 = \beta_{\pi_{ue}} + \beta_{\pi_{eu}} + \beta_\epsilon$ where $\beta_x = \frac{cov(du_t, d\Pi_x)}{var(du_t)}$. The decomposition allows us to obtain two separate components (and an error term) for the importance of the respective series in explaining the cyclical variation of the unemployment rate. Using an equivalent steady state approximation for the three state case and defining weights $\alpha := \frac{\bar{\Pi}_{NU}}{\bar{\Pi}_{NE}+\bar{\Pi}_{NU}}$ and $\lambda_{ij} := (1-\bar{u})\frac{\bar{\Pi}_{ij}}{\bar{\Pi}_u}$, as well as the (weighted) average of separation and hiring rates $\bar{\Pi}_u := \bar{\Pi}_{EU} + \frac{\bar{\Pi}_{NU}}{\bar{\Pi}_{NE}+\bar{\Pi}_{NU}}\bar{\Pi}_{EN}$ and $\bar{\Pi}_e := \bar{\Pi}_{UE} + \frac{\bar{\Pi}_{UN}}{\bar{\Pi}_{NE}+\bar{\Pi}_{NU}}\bar{\Pi}_{NE}$, we obtain an extended decomposition

$$\begin{aligned}
\log\left(\frac{u_t}{\bar{u}}\right) &= \log\left(\frac{\Pi_{EU,t}}{\bar{\Pi}_{EU}}\right)\lambda_{EU} - \log\left(\frac{\Pi_{UE,t}}{\bar{\Pi}_{UE}}\right)\lambda_{UE} \\
&\quad + \log\left(\frac{\Pi_{EN,t}}{\bar{\Pi}_{EN}}\right)\alpha\lambda_{EN} - \log\left(\frac{\Pi_{NE,t}}{\bar{\Pi}_{NE}}\right)(1-\alpha)(\lambda_{UE}+\lambda_{UN}-\lambda_{EU}) \\
&\quad + \log\left(\frac{\Pi_{NU,t}}{\bar{\Pi}_{NU}}\right)\alpha(\lambda_{EU}+\lambda_{EN}-\lambda_{UE}) - \log\left(\frac{\Pi_{UN,t}}{\bar{\Pi}_{UN}}\right)(1-\alpha)\lambda_{UN} + \varepsilon_t \\
du_t &= dEU_t + dUE_t + dEN_t + dNE_t + dNU_t + dUN_t + \varepsilon_t
\end{aligned}$$

Using again $\beta_x = \frac{cov(du_t, d\Pi_x)}{var(du_t)}$ a similar covariance decomposition as in Fujita and Ramey (2007) of the form $1 = \sum_{i=1}^{n}\beta_i + \varepsilon_t$ applies.[10] Table 3 summarizes our finding based on the two-state and three state decomposition.

The way of detrending is not innocent for many datasets given that the steady state approximation is not necessarily very accurate during certain time periods. However, for Germany our results are not driven by the detrending method used. We obtain the same decomposition with a first difference filter.[11]

Based on a two state decomposition the contribution of firing rates account, depending on the sample periods used, for $60-70\%$ of the volatility while in the US it accounts for $30-40\%$. The robust finding, using a three state decomposition, indicates that German firing rates contribute

[10]The formula is similar to the first difference filter obtained in Petrongolo and Pissarides (2009), though they essentially lump the non-employment rates $dEN_t + dUN_t$ and the corresponding inflow rate into $dNE_t + dNU_t$ together. In fact the non-employment flows are hard to interpret in their decomposition. It is important to notice that the decomposition does not rely on knowing the state of non-employed workers, which is not available for Germany but only the (gross) flows are needed. A derivation is available upon request.

[11]The appendix provides a sensitivity check with respect to the first difference filter of Petrongolo and Pissarides (2009) and also gives the results for different education groups, different sample periods and separated by sex.

Table 3: Unemployment decomposition

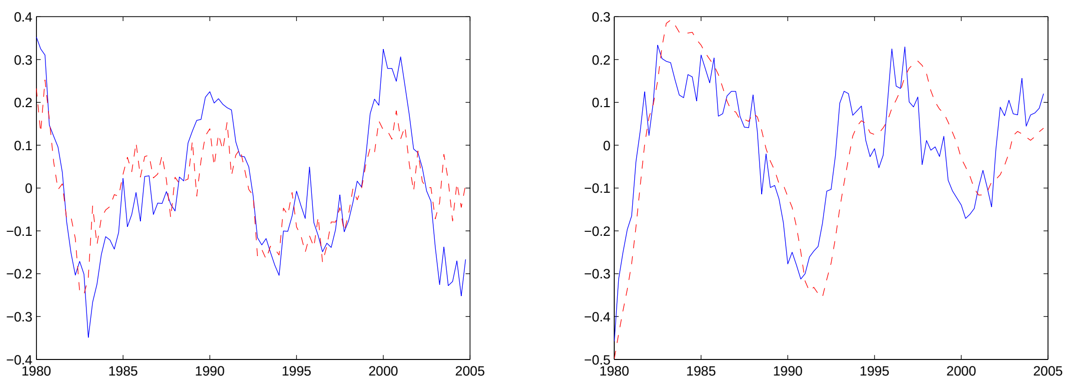
Country	Data	EU	UE	NE	EN	NU	UN	ε
Germany	IAB	0.6073	0.3898					0.0030
	IAB	0.4186	0.2498	0.2020	−0.0470	0.0678	0.1122	−0.0020
US	Shimer	0.3260	0.6763					−0.0022
	Fujita/Ramey	0.3837	0.6185					−0.0022
	Shimer	0.2013	0.4855	0.0884	−0.0378	0.1039	0.1516	0.0072

Notes: Data is HP-filtered ($\lambda = 100,000$) for the period $1980q1 - 2004q4$. For Germany the transition rates are for all male and female workers. The US data is obtained from Shimer (2005) and Fujita and Ramey (2007)

twice as much as jobfinding rates to the unemployment volatility while in the US the opposite is true. Firing and jobfinding rates taken together account in both countries for around 70% of the unemployment volatility possibly justifying the focus on a two-state decomposition. The left panel of figure 1 visualizes the tight connection of firings und unemployment in Germany by plotting the HP-filtered firing rate against the cyclical component of the unemployment rate. It is evident that firings lead the unemployment rate by one quarter but is otherwise almost perfectly correlated with the unemployment rate. The right panel shows the tight connection between quits on the job and hirings, suggesting a common matching market.

Figure 1: Labor market cyclicality

(a) Firing rate and unemployment rate (b) Quits and jobfinding rate



Notes: Left Panel: The blue solid line reports the HP-filtered firing rate. The red dotted line reports the HP-filtered unemployment rate. Right Panel: The blue solid line reports the HP-filtered quitting rate. The red dotted line reports the HP-filtered jobfinding rate.

So far, we have analyzed aggregate worker flows, however, the aggregate picture masks important differences in the characteristics of workers with respect to observable characteristics, in particular tenure on the job. We now turn to a discussion of these disaggregated facts.

2.3 Disaggregation of firings, quits, and jobfindings by tenure

The analysis of aggregate flows between employment, unemployment, and non-employment abstracted from heterogeneity within these flows and their composition. In the following analysis, we focus on one special dimension of heterogeneity by distinguishing labor market flows by the duration in the previous labor market state. For simplicity, we call this duration from now on *tenure*. We break the analysis further down and distinguish labor market flows also by sex and education. The analysis shows that tenure is not only a widely unexplored dimension of heterogeneity but also of primary importance when it comes to understanding labor market flows.

To document the important role of tenure for hiring, firing, and quitting rates, we construct four tenure cells and assign labor market flows to one of the cells according to the time spent in the initial state of the labor market flow. For transitions out of employment we only count the time with the current employer. In 1975, we do not observe tenure of a particular worker, and therefore, we start in 1980 to overcome the truncation problem. Given that our maximum tenure class is five years and above, we can assign from 1980 on the transition to the correct tenure cell.

Table 4: Tenure on the job

Quits	< 365 days	$365 - 730$ days	$730 - 1825$ days	> 1825 days	*overall* days
mean	0.0183	0.0110	0.0079	0.0036	0.0081
std	0.1193	0.1575	0.1749	0.1481	0.1620
rel. share	0.4165	0.1504	0.2175	0.2156	
rel. earnings	0.9018	0.9308	0.9248	0.9197	
corr (GDP)	0.5595	0.5568	0.6053	0.5149	0.6345
corr (Productivity)	0.2545	0.3261	0.3104	0.3580	0.3312
Firings	< 365 days	$365 - 730$ days	$730 - 1825$ days	> 1825 days	*overall* days
mean	0.0176	0.0066	0.0035	0.0015	0.0054
std	0.1936	0.1726	0.2283	0.2302	0.1500
rel. share	0.5860	0.1344	0.1454	0.1341	
rel. earnings	0.8549	0.8208	0.8046	0.8125	
corr (GDP)	-0.7727	-0.7308	-0.7195	-0.5574	-0.7616
corr (Productivity)	-0.4650	-0.4644	-0.4213	-0.2546	-0.4739
Jobfindings	< 180 days	$180 - 365$ days	$365 - 730$ days	> 730 days	*overall* days
mean	0.0934	0.0431	0.0301	0.0204	0.0614
std	0.1156	0.1122	0.1370	0.1730	0.1019
rel. share	0.7137	0.1480	0.0821	0.0562	
corr (GDP)	0.3442	0.0444	0.4166	0.4970	0.3919
corr (Productivity)	0.0532	-0.1251	0.1757	0.1249	0.0485

Notes: The data is for full-time employed males and females for the period $Jan1980 - Sep2004$. The columns contain the bounds of the different tenure groups. The tenure groups are formed for the labor market state before the transition and are given in days.
All statistics are computed conditional on being in the respective labor market state and tenure group. *mean* is the average transition probability of the respective labor market transition. *std* is the relative deviation of the transition rate over time. *rel. share* is the average share of transitions falling in this tenure group relative to all transitions. *rel. earnings* are the average relative earnings of all persons with a transition relative to the average earnings in the current labor market and tenure group. *corr* are the respective correlations of the transition rate with GDP per capita respectively per employed as our business cycle measures.

Table 4 reports the basic statistics for firing, quitting, and jobfinding rates of full-time employed workers disaggregated to the tenure cells. The table highlights the strong impact of tenure on mean transition rates. The firing risk drops by an order of magnitude from 1.8% for low tenured workers to 0.15% for high tenured workers. The quitting probability collapses by the same order of magnitude from 1.8% for low tenured workers to 0.36% for high tenured workers. The jobfinding probability shows the same pattern decreasing from 9.3% for short unemployment spells to only 2.0% for long unemployment spells.

The *relative share* in table 4 measures the part of the transitions that originates from the particular tenure cell. It shows the same pattern across tenure cells as the transition rates. We see that 70% of all firings and 57% of all quits fall into the class of workers having tenure of less than 2 years.[12] For jobfindings, we get that over 85% of all jobfindings accrue to persons that have been unemployed for less that one year, however, the major share of persons find a job already within six month (71%).

When it comes to cyclical fluctuations, we see that the correlation and the standard deviation are similar across tenure cells for all transitions.

Finally, to learn more about the job quality of destructed jobs, we look at the median earnings ratio of destructed to continued jobs (*relative earnings*). Our data shows that destructed jobs come from the lower end of the distribution. The discount is $15-20\%$ for jobs destructed due to firings and $7-10\%$ for jobs destructed due to quits.

Of course, the above measures might be affected by other composition effects. In the appendix, we report the same statistics for males and females and control for different education levels. Although the general pattern remains unchanged, some results are worthwhile to mention. First, jobfinding is substantially lower for low skilled compared to medium and high skilled workers. Second, differences in unemployment rates across medium and high-skilled workers are driven mainly by differences in average firing rates, not by differences in the jobfinding rates. The earnings discount, expressed relative to the peer tenure-education group, is particularly large for high skilled workers.

2.4 Earnings

In a recent survey article Pissarides (2009) discusses the empirical evidence on wage rigidity for the US and Europe. He concludes that the available evidence suggests a stronger co-movement of wages with the business cycle in Europe than in the US. We provide strong support for this claim for Germany, arguing that at least rigid earnings[13] are not at the root of the cross-country differences highlighted above.

Table 1 shows that German median earnings are tightly connected to aggregate productivity measures. However, the cyclicality of aggregate statistics can be substantially biased due to composition effects in the labor force as highlighted in Solon et al. (1994) and extensively discussed in Haefke et al. (2007).

Several approaches have been proposed to control for this composition bias. Solon et al. (1994) use a group selection procedure to fix the group of individuals to avoid changes in the composition over time. The long panel dimension and the high quality of our income data allows us to do the same, however, with a substantially larger cross-section. We identify in our dataset ongoing job relations that do not only exist on a year-to-year basis but over the whole sample period. This constitutes a particular homogeneous subpanel of workers, namely those who had a job in 1975 and were continuously full-time employed at the same firm until 2004. That is, for this non-representative group, we ensure that no quit and no firing happened during their entire work experience nor any non-employment spell.[14] For this group we only have earning information at annual frequency, and in contrast to part of the business cycle literature, we have to move to annual frequency. However, the annual frequency might actually be the more

[12] We do a sensitivity analysis with respect to very short spells in the appendix to rule out high frequency noise of unstable jobs. The results show that most jobs survive beyond the threshold of 6 month and results are robust.

[13] The IAB data, although superior to many other data sets for labor market transitions has the disadvantage of lacking information on hours worked. It only contains information on the employment status (full-time, part-time, marginal employment) of an individual. However, this limitation is not severe because hours worked per person employed does not vary much with the cycle. Other studies for the US have provided evidence that earnings and wage cyclicality are quantitatively close (see Haefke et al. (2007)). We will therefore in the following repeatedly refer to studies that considered wages instead of earnings.

[14] The group still consists of approximately 6,126 workers and is therefore large enough to provide reasonable estimates.

natural frequency given that bonus and special payments are typically not paid out quarterly. Given that, at least in models with risk-neutral agents, the precise timing of the payment is indetermined, we believe that an annual frequency offers some advantages over a quarterly analysis. Although the group of continuously employed workers is highly selective, it allows us to examine the earnings dynamics of very stable jobs. The selection procedure addresses therefore also concerns regarding job quality over the cycle raised by Gertler and Triagari (2005).

Starting with Bils (1985) researchers have estimated individual wage growth equations using first differences along the panel dimension to control for individual specific fixed effects. The approach might be restrictive if only a short panel dimension is available. In particular, last earnings of unemployed workers might not exist or are unobserved. For quitting workers this problem does not exist. Our long panel dimension allows us to keep track of last earnings of unemployed workers which we use as a proxy for unobserved earnings in the regressions. We construct a sample comprising all spells with certain labor market transitions, e.g. quits. For this sample we regress individual earnings growth on the particular labor market event on several individual control variables and the growth of the respective business cycle statistic. The labor market events are grouped by years and individual controls are a fourth order polynomial in potential labor market experience, dummies for sex, three education groups, and for foreigners. We also include a time-trend. Aggregating at annual frequency allows us to abstract from adjusting for seasonality in the data. We run ordinary least squares (OLS) and least absolute deviations (LAD) regressions to check the sensitivity of our results with respect to outliers. The estimates can be found in table 5.

Although, the panel dimension of our dataset allows us to overcome missing pre-employment earnings for jobfinder, there might still be concern regarding this approach. To overcome potential concerns, we follow Haefke et al. (2007) who propose a wage index construction. They propose to control for observable characteristics like age, sex, education, and experience and to focus on the behavior of the residual. We follow their procedure and construct earnings indices for jobfinder, quitter, persons who stayed at the same firm throughout the year (stayer), and for the group of continuously employed workers described above. We plot the cyclicality of the earnings index together with our business cycle measure in figure 2. Table 5 summarizes the estimation results. The details of the estimation procedures and an extensive sensitivity check can be found in the appendix.

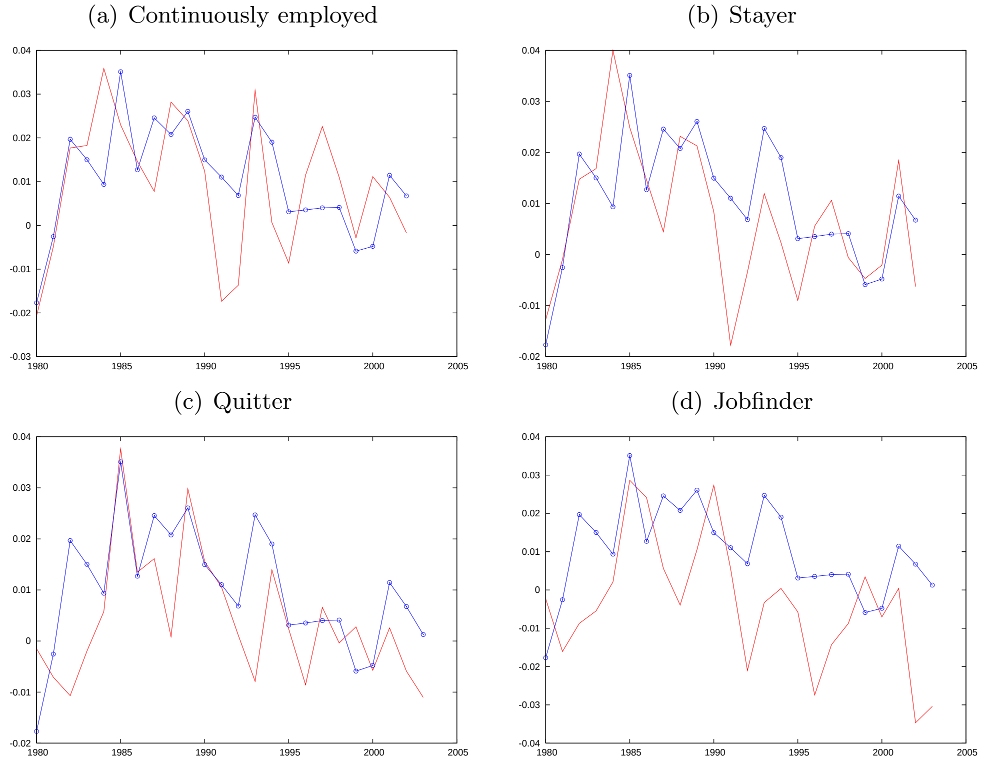
Table 5: Earnings elasticity

	Quitter	Jobfinder	Stayer	Cont. employed
Index	0.5909	0.6328	0.6651	0.7440
(Std. error)	(0.1353)	(0.1945)	(0.1502)	(0.1702)
Growth	0.3302	0.8089	0.6714	0.6214
(Std. error)	(0.1264)	(0.2493)	(0.1400)	(0.1629)
Correlation	0.5764	0.4651	0.5860	0.5811

Notes: Annual earnings cyclicality for full-time employed workers (male and female, all education groups). *Index* refers to the earnings index using the first difference filter. *Correlation* refers to the correlation coefficient of the earnings index and the business cycle measure. *Growth* refers to the estimation in first difference using OLS. The business cycle measure is GDP per employed.

We see that earnings and productivity are tightly connected. For continuously employed the correlation between the two series is around 0.6 and the elasticity estimate is beteen $0.62-0.74$. This finding is robust for all other groups and across methods. Jobfinder and quitter have an elasticity of 0.6 when we look at the earnings index. Using individual growth rates we find a higher elasticity of 0.8 for jobfinder, and a lower elasticity for quitter, likely due to outliers. Using

Figure 2: Earnings index cyclicality



Notes: Earnings index (blue dotted-line) cyclicality ($1st$ difference filter) for full-time workers (male and female), business cycle measure GDP per employed (red line). Time period is $Jan1980 - Sep2004$.

an LAD robustness check supports this view. There, we find an elasticity of around 0.5. The appendix provides detailed estimates for different education groups, sex, sample periods, and filtering methods all confirming that the earnings elasticity on productivity (or other aggregate measures) is between $0.6 - 0.8$.

3 Model

The empirical analysis has highlighted important features of the German labor market. Most importantly, (i) the cyclical variation in the firing rate, (ii) the importance of job-to-job transitions, and (iii) the heterogeneity of transition probabilities across tenure classes. To account for these empirical observations, we present a stylized search model featuring (i) endogenous firings, (ii) a basic search on the job mechanism, and (iii) we allow for type differences to capture heterogeneity in match quality. The model is simple enough to work out the basic mechanisms in closed form, yet rich enough to capture the essence of labor market fluctuations over the business cycle.

Setup : Time is discrete. There is a measure of size one of workers in society. Workers and firms are risk-neutral. Workers can be employed in two types of jobs $z \in [g, b]$, good or bad, or are unemployed. At the beginning of each period, the aggregate state of the economy is given by the triple $(a, l_b, l_g) = s \in S = A \times L \times L$. The first element is the aggregate exogenous productivity state $a \in A = \mathbb{R}$ following a Markov process. The second and third component $l_z \in L = [0, 1]$ denote the measure of workers that are employed in a good respectively bad job.

Letting u denote the measure of unemployed, we have the accounting identity $l_g + l_b + u = 1$. When firms open a position they randomly draw a job type. With probability π_g the new job is good and with probability $\pi_b = 1 - \pi_g$ it is bad. At the beginning of the period, workers who are currently in a match relation of a particular type bargain jointly and efficiently about the wage and the separation decision for next period. If the bargaining is successful, they produce output according to the linear production technology $y_z = AB_z$ where the aggregate technology A is assumed to evolve exogenously and common to all matches. The individual types are differentiated by the assumption that $B_g > B_b$.[15]

At the end of the period, after production has taken place, workers in bad matches might decide to search for a different job. The decision to search on the job is taken as exogenous and random, reflecting idiosyncratic utility attached to the particular match. However, the probability of receiving an offer is still endogenous and related to the aggregate matching function.[16] We assume that workers search with exogenous probability π_s and receive an outside offer from a competing firm with endogenous probability π_{ee}. They accept outside job offers for sure, given that they will obtain an expected wage gain. We assume that workers in good matches do not search for new jobs because their expected wage gain is zero.[17]

If, at the end of the period, the worker has decided not to search or has not received an offer, the firm receives an idiosyncratic cost shock ϵ_i, where ϵ_i is an i.i.d. random shock logistically distributed with mean zero and variance $\frac{\pi^2}{3}\psi_z^2$. The firm has to pay the costs only if it wishes to continue the production process. The costs are sunk after the current period and will not be relevant for any future decision. The assumption of a logistic distribution allows us to obtain closed form solutions and is done for convenience (see Jung (2008) for details). Let $\bar{\omega}$ denote the threshold for the continuation costs. The threshold level will be part of the bargaining set and will be efficiently bargained about by workers and firms. All matches with cost realizations above the threshold will decide to dissolve the match. If the match is dissolved, the firm has to pay a firing tax τ to the government[18] and the worker becomes unemployed. An unemployed worker searches for a job and is matched in a matching market governed by a standard Cobb-Douglas matching function. Unemployed workers are matched with probability π_{ue} and become employed, with probability $(1 - \pi_{ue})$ they remain unemployed and keep on searching. While unemployed they receive unemployment benefits $b < 1$.

Firm's surplus: Consider a worker-firm pair at the beginning of the period. The firm discounts the future, as does the agent, with a constant discount factor β. For given wages $w_z : S \to \mathbb{R}$ and cut-off strategies $\bar{\omega} : S \to \mathbb{R}$ the firm's surplus follows the recursive formulation

$$J(S, B_z) = AB_z - w_z(S) + (1 - \pi_{ee}(S)\pi_s)\Big((1 - \pi_{eu,z}(S))\beta\mathbb{E}\left[J(S, B_z)\right] - \pi_{eu,z}(S)\tau + \Psi_z(S)\Big)$$

The firing probability $\pi_{eu,z} : S \to \mathbb{R}$ and the option value[19] $\Psi_z : S \to \mathbb{R}$ follow directly from the

[15] We normalize such that $\frac{B_g + B_b}{2} = 1$.

[16] It is straightforward to make the search decision also a discrete choice and endogenous. Though it helps in making aggregate quits more volatile, we decided to keep it exogenous in this version for simplicity. An older working paper version had an endogenous search decision, also modeled as a discrete choice. The qualitative results are unaffected, but the derivations become more complex without adding new insights.

[17] Again, this assumption can be relaxed considerably without changing the main mechanism. See Menzio and Shi (2009) for a richer model along these lines.

[18] Note that τ is expressed as a firing tax, or a reorganization cost and does not include severance payments. In our framework, severance payments are efficiently bargained away and would have no effects on the equilibrium outcomes. The government transfers all income lump sum back to the worker, so under risk-neutrality, there is no need to specify formally governmental behavior.

[19] The term Ψ_z captures the option value of having the choice to continue the match and is always positive. The

assumption of a logistically distributed random variable

$$\begin{aligned}\Psi_z(S) &= -\psi_z\Big((1-\pi_{eu,z}(S))\log(1-\pi_{eu,z}(S)) + \pi_{eu,z}(S)\log(\pi_{eu,z}(S))\Big)\\ \pi_{eu,z}(S) &= \left(1+\exp\left(\frac{\bar{\omega}(S)}{\psi_z}\right)\right)^{-1}\end{aligned}$$

The quitting probability is given by $\pi_{ee}(S)\pi_s$ and is zero in the case of a good match ($z = g$).

Worker's surplus: The value flows of the different types of employed workers $V_{e,z} : S \to \mathbb{R}$ and unemployed workers $V_u : S \to \mathbb{R}$ are given by

$$\begin{aligned}V_{e,b}(S) &= w_b(S) + \pi_{eu,b}\beta\mathbb{E}\left[V_u(S')\right]\\ &\quad + (1-\pi_{eu,b})\left((1-\pi_{ee}(S)\pi_s)\beta\mathbb{E}\left[V_{e,b}(S')\right] + \pi_{ee}(S)\pi_s\left(\sum_z \pi_z\beta\mathbb{E}\left[V_{e,z}(S')\right]\right)\right)\\ V_{e,g}(S) &= w_g + (1-\pi_{eu,g}(S))\beta\mathbb{E}\left[V_{e,g}(S')\right] + \pi_{eu,g}\beta\mathbb{E}\left[V_u(S')\right]\\ V_u(S) &= b + \pi_{ue}(S)\left(\sum_z \pi_z\beta\mathbb{E}\left[V_{e,z}(S')\right]\right) + (1-\pi_{ue}(S))\beta\mathbb{E}\left[V_u(S')\right]\end{aligned}$$

and the worker's surplus becomes

$$\Delta_z = V_{e,z}(S) - V_u(S)$$

Matching: New matches are formed by a standard Cobb-Douglas matching technology that links the measure of searching workers to the measure of vacancies v. The measure of searching workers is the sum of unemployed workers and the fraction of workers searching on the job. We denote the resulting matches by m and $\varkappa$ denotes a scaling parameter of the matching function.

$$m = \varkappa v^{1-\varrho}(u + \pi_s l_b)^{\varrho}$$

Labor market tightness is given as the ratio of vacancies to searching workers $x := \frac{v}{u+\pi_s l_b}$. The probability of a searching worker to find a new job is

$$\pi_{ue} = \frac{m}{u + \pi_s l_b} = \varkappa x^{1-\varrho}$$

and the probability that a firm fills its vacancy is given by

$$\pi_{ve} = \frac{m}{v} = \varkappa x^{-\varrho}$$

Free entry: To determine the number of vacancies posted, we impose a standard free entry condition. In equilibrium, the cost to post a vacancy κ must equal the expected profits of a match

$$\kappa = \pi_{ve}\sum_z \pi_z\beta\mathbb{E}\left[J_z(S', B_z)\right]$$

reason is that although the idiosyncratic shock has an unconditional mean of zero the manager only continues if the continuation value is positive. The payoff resembles the payoff profile of an option and is therefore increasing in the variance ψ of the shock.

Bargaining: We assume standard Nash-bargaining jointly over wages and separation decisions. The outcome of the bargaining process is characterized by

$$(w_z, \bar{\omega}) \in \arg\max_{w_z, \bar{\omega}} \mu \log(\Delta_{z,t}) + (1-\mu)\log(J_z)$$

where μ denotes the bargaining power of the worker. First order conditions deliver

$$\begin{aligned}\bar{\omega}(S) &= \beta\mathbb{E}\left[\Delta_z(S') + J_z(S')\right] + \tau \\ \frac{\mu}{1-\mu} &= \frac{\Delta_z(S)}{J_z(S)}\end{aligned}$$

Law of Motion: The law of motion for the state variables is given by

$$\begin{aligned}l_g' &= l_g(1-\pi_{eu,g}) + l_b\pi_s\pi_{ee}\pi_g + u\pi_{ue}\pi_g \\ l_b' &= l_b(1-\pi_{eu,b} - \pi_s\pi_{ee}\pi_g) + u\pi_{ue}\pi_g \\ u' &= u(1-\pi_{ue}) + l_g\pi_{eu,g} + l_b(1-\pi_s\pi_{ee})\pi_{eu,b}\end{aligned}$$

Technology evolves exogenously according to

$$\begin{aligned}A &= \exp(a) \\ a' &= \rho a + \eta'\end{aligned}$$

where ρ denotes the autocorrelation coefficient.

3.1 Basic Results

To understand the basic mechanisms, we consider first the special case of homogenous types, i.e. $\pi_g = 0$. With homogeneous matches search on the job does not deliver a wage gain. If we set $\pi_s = 0$, the model nests the standard model without search on the job. All choices in the model are then functions of the total surplus $H := J + \Delta$. Proposition 1 summarizes the properties of the basic model up to a first order approximation around the deterministic steady state. We use $\bar{x}$ to denote the steady state of variable x and use $\hat{x}$ to denote the deviation from the steady state, i.e. $\hat{x} := x - \bar{x}$.

Proposition 1. *Up to a first order approximation, the dynamics of the model are only functions of the business cycle shock a*

$$\hat{H} \approx \sigma_H a \qquad \hat{\pi}_{eu} \approx \sigma_{eu} a \qquad \hat{x} \approx \sigma_x a \qquad \hat{\pi}_{ue} \approx \sigma_{ue} a \qquad \hat{w} \approx \sigma_w a$$

and coefficients are given by

Surplus:

$$\begin{aligned}\sigma_H = &\left(1 - \beta\rho(1 - \bar{\pi}_{ue} - \bar{\pi}_{eu} + \pi_s\bar{\pi}_{ue}\bar{\pi}_{eu}) + \bar{\pi}_{ue}\beta\rho\left(\frac{\mu - \varrho}{\varrho}\right)\right. \\ &\left. + \pi_s\bar{\pi}_{ue}\beta\rho\left(\frac{1-\mu}{\varrho} + \frac{1-\varrho}{\varrho}\psi\frac{\log(1-\bar{\pi}_{eu})}{\bar{H}}\right)\right)^{-1}\end{aligned} \tag{1}$$

Firing:

$$\frac{\sigma_{eu}}{\bar{\pi}_{eu}} = -(1-\bar{\pi}_{eu})\frac{\rho\beta}{\psi}\sigma_H \tag{2}$$

Tightness:

$$\frac{\sigma_x}{\bar{x}} = \frac{\rho}{\varrho}\frac{\sigma_H}{\bar{H}} \tag{3}$$

Jobfinding:

$$\frac{\sigma_{ue}}{\bar{\pi}_{ue}} = (1-\varrho)\frac{\sigma_x}{\bar{x}} \tag{4}$$

Wage setting:

$$\begin{aligned}\sigma_w &= \mu\sigma_H\Bigg(1 - \beta\rho(1-\bar{\pi}_{ue}-\bar{\pi}_{eu}+\pi_s\bar{\pi}_{ue}\bar{\pi}_{eu}) \\ &\quad + \beta\rho\bar{\pi}_{ue}(1-\pi_s\bar{\pi}_{eu})\frac{1-\varrho}{\varrho} - \bar{\pi}_{eu}(1-\bar{\pi}_{eu})(1-\pi_s\bar{\pi}_{ue})\beta\frac{\bar{H}}{\psi}\Bigg)\end{aligned} \tag{5}$$

Volatility of the unemployment rate:

$$\begin{aligned}var(\hat{u}) &= \frac{z_2^2}{1-z_1^2}\frac{1+\rho z_1}{1-\rho z_1}var(a) \\ z_1 &= 1-\bar{\pi}_{ue}-\bar{\pi}_{eu}+\pi_s\bar{\pi}_{ue}\bar{\pi}_{eu} \\ z_2 &= \sigma_{eu}(1-\pi_s\bar{\pi}_{ue})(1-\bar{u}) - \sigma_{ue}(\pi_s\bar{\pi}_{eu}+\bar{u}(1-\pi_s\bar{\pi}_{eu}))\end{aligned} \tag{6}$$

Beveridge curve:

$$\frac{Cov(\hat{v},\hat{u})}{\bar{v}\bar{u}} = \left(\frac{\sigma_x}{\bar{x}}\frac{\rho(1-z_1^2)}{z_2(1+\rho z_1)} + \frac{1-\pi_s}{\bar{u}(1-\pi_s)+\pi_s}\right)\frac{var(\hat{u})}{\bar{u}} \tag{7}$$

The proof is straightforward and therefore omitted. As the labelling suggests, the absolute values of the coefficients coincide with the standard deviation of the respective variable relative to the standard deviation of the productivity process. Throughout the paper, we focus on standard deviations of log rates rather than on the standard deviations of absolute rates, and to ease the exposition, we use $\tilde{\sigma}_x$ to denote the log standard deviation of variable x, i.e. we define

$$\tilde{\sigma}_x := \frac{\sigma_x}{\bar{x}}$$

3.2 Discussion

Proposition 1 provides analytic expressions for the firing and hiring volatility as well as the implied expressions for the unemployment rate volatility and the *Beveridge curve.* This allows us to discuss the effects of observed cross-country differences on differences in labor market volatilities and the implications of differences in labor market institutions. Within the model, we capture labor market institutions by six parameters summarizing in a reduced form important differences across countries. (*i*) The bargaining power μ captures the influence of unions in the wage setting process, (*ii*) vacancy posting costs κ relate to rigidities in the firm entry process, (*iii*) firing restrictions τ are used as a summary measure of employment protection, (*iv*) the contact rate π_s parameterizes the willingness of searching on the job, (*v*) the outside option b directly relates to the competitiveness of the labor market, and (*vi*) the idiosyncratic firm shock variance ψ measures wage compression by parameterizing the number of workers living around the cut-off value.

3.2.1 Firing Volatility

Formula (2) provides an expression for the firing volatility. To simplify the analysis, we drop quantitatively negligile terms and set $1-\bar{\pi}_{eu} \approx 1$, $\bar{\pi}_{eu}\pi_s \approx 0$, and $\beta\rho \approx 1$. Using this simplification, we derive the following expression

$$\begin{aligned}\frac{\tilde{\sigma}_{eu}^{Ger}}{\tilde{\sigma}_{eu}^{US}} &= \frac{\psi^{US}}{\psi^{Ger}}\,\frac{\sigma_H^{Ger}}{\sigma_H^{US}} \\ &= \frac{\psi^{US}}{\psi^{Ger}}\,\frac{\varrho\bar{\pi}_{eu}^{US}+(\mu^{US}+\pi_s(1-\mu^{US}))\bar{\pi}_{ue}^{US}}{\varrho\bar{\pi}_{eu}^{Ger}+(\mu^{Ger}+\pi_s(1-\mu^{Ger}))\bar{\pi}_{ue}^{Ger}}\end{aligned} \tag{8}$$

We see that if we ignore search on the job ($\pi_s = 0$) and assume that both countries face the same idiosyncratic productivity shock processes ($\psi^{US} = \psi^{Ger}$), then the countries can not operate at the efficiency point of the *Hosios condition* ($\varrho = \mu$) because this would imply

$$\frac{\tilde{\sigma}_{eu}^{Ger}}{\tilde{\sigma}_{eu}^{US}} = \frac{\bar{\pi}_{eu}^{US}+\bar{\pi}_{ue}^{US}}{\bar{\pi}_{eu}^{Ger}+\bar{\pi}_{ue}^{Ger}} \approx 5 > 2.5$$

However, equation (8) makes transparent that the differences in average transition rates map into substantial differences in firing volatilities across countries. The intuition for this result is simple: A business cycle shock of the same size affects the match surplus in Germany stronger than in the US ($\sigma_H^{Ger} > \sigma_H^{US}$). To see this, consider a positive shock in both countries and a currently unemployed worker. In Germany, it takes her —due to the lower jobfinding rate— much longer to find a new job. As a consequence, she benefits much later from the booming conditions. Relative to her an employed worker benefits immediately because she can demand an higher wage. This implies a stronger increase of the worker's surplus Δ in Germany relative to the US where the unemployed worker benefits much earlier from the booming conditions. Since worker's surplus enters total surplus H, the total surplus of a match increases and it increases more strongly in Germany. In return, firings will adjust more strongly in Germany and we see a higher firing rate volatility ($\tilde{\sigma}_{eu}^{Ger} > \tilde{\sigma}_{eu}^{US}$). This mechanism is generic for most simple search and matching frameworks and it establishes the inverse relationship between transition rates and volatilities that we document empirically in section 2.
In fact, lower hiring and firing rates alone would generate too much firing volatility and it must be the case that either the bargaining power in Germany is higher ($\mu^{Ger} > \mu^{US}$) to dampen the surplus reaction or the idiosyncratic shock variance in the US is lower ($\psi^{Ger} > \psi^{US}$). A higher bargaining power has some empirical support[20] while explanations relying on a shock variance is unattractive. In our model, the idiosyncratic shock variance would map into cross-sectional wage inequality. Recent country studies by Fuchs-Schündeln et al. (2009) and Heathcote et al. (2009) for the US and Germany provide cross-country comparable inequality measures that show that the US wage inequality exceeds German inequality by far.

3.2.2 Hiring Volatility

Using equation (4) and $1-\pi_{eu} \approx 1$, we can derive the following expression

$$\frac{\tilde{\sigma}_{ue}^{Ger}}{\tilde{\sigma}_{ue}^{Ger}} = \frac{\psi^{Ger}}{\psi^{US}}\,\frac{\bar{H}^{US}}{\bar{H}^{Ger}}\,\frac{\tilde{\sigma}_{eu}^{Ger}}{\tilde{\sigma}_{eu}^{US}}$$

[20] The *OECD Employment database* (see www.oecd.org for details) reports a union density, i.e. the share of workers affiliated to a trade union, for Germany of 35% in 1975 and 22% in 2004, whereas for the US the respective numbers are as low as 22% in 1975 and only 12% in 2004.

If we plug in the expression for the relationship between $\tilde{\sigma}_{eu}^{Ger}$ and $\tilde{\sigma}_{eu}^{US}$, we see that matching the cross country differences requires

$$\frac{\bar{H}^{Ger}}{\bar{H}^{US}} \approx 2.5\frac{\psi^{Ger}}{\psi^{US}}$$

Hence, to explain the equally volatile hiring rates in Germany and the US we either need a larger steady state surplus in Germany ($\bar{H}^{Ger} > \bar{H}^{US}$) or lower idiosyncratic volatilities in Germany ($\psi^{Ger} < \psi^{US}$). A higher surplus in Germany would, ceteris paribus, lead to the puzzling observation that one should expect higher mean jobfinding rates in Germany given that jobfinding rates are proportional to the surplus ($\bar{\pi}_{ue} \propto \bar{H}$). Looking at the data, we see that the average jobfinding rates in Germany are lower by a factor of 5. Hence, a lower idiosyncratic shock variance, i.e. higher wage compression, in Germany is likely the more relevant channel to align the model with the data. Empirically, the lower idiosyncratic shock variance in Germany receives support as discussed above.

Note, however, that we still need a small surplus for newly hired workers to match the hiring rate volatility. Neither of the newly introduced features alters the basic problem along this dimension. In particular, the surplus equation (1) shows that a model with endogenous firings generates an identical surplus response as a model with exogenous firings up to a first order approximation.

3.2.3 Unemployment volatility

Equation (6) delivers a model-based closed form approximation of the unemployment volatility which is exclusively based on the linearization of the unemployment flow equation around the steady state. The formula has the property shared by many simple search frameworks that the volatility of hirings and firings are only functions of the productivity state and perfectly negative correlated.[21] Furthermore, all empirical counterparts of the variables in this equation can be directly read off from tables 1 and 2 in section 2. We use this fact to identify the main drivers behind unemployment volatility by conducting a series of four comparative statics experiments. The first three experiments focus on the effect of hirings and firings, and the fourth experiment examines the effect of on the job search on the unemployment volatility. This analysis complements and extends the empirical decomposition of the unemployment volatility in section 2.2.

Table 6: Unemployment volatility in the benchmark model

	$\bar{\pi}_{eu}$	$\bar{\pi}_{ue}$	$\tilde{\sigma}_{eu}$	$\tilde{\sigma}_{ue}$	$\pi_s\bar{\pi}_{ee}$	$\bar{u}$	$\tilde{\sigma}_u$	$\tilde{s}_u$	$1-\tilde{\sigma}_u/\tilde{s}_u$
Germany	0.0053	0.062	−6.20	4.30	0	0.079	8.60	7.06	−22%
US	0.020	0.31	−2.48	4.27	0	0.062	6.18	5.72	−8%

Notes: The table reports in columns $1-5$ the data equivalents to the respective model variables, and column 6 gives the model prediction for the mean unemployment rate. Column 7 reports the relative standard deviation of the unemployment rate to the standard deviation of the productivity process in the model ($\tilde{\sigma}_u$). Column 8 reports the empirical counterpart of this number ($\tilde{s}_u$). The last column gives the residual unexplained volatility of the model relative to the data. We use an autocorrelation coefficient of $\rho = 0.975$ in line with our estimates.

Before turning to our experiments, we check the validity of the approximation. In table 6, we compare the model's prediction for the unemployment volatility to its empirical counterpart from tables 1 and 2. Although the model generates slightly too much unemployment volatility

[21]This property holds in much more general circumstances and is characterized formally in Menzio and Shi (2009) who use a substantially richer model of directed search on the job.

compared to the data, the fit is quite accurate. Hence, the model captures the main mechanisms behind the unemployment volatility in the data. We take this model as our benchmark to see how much of the benchmark volatility can be attributed to the different sources. We summarize the findings of the experiments in table 7.

Table 7: Model-based unemployment decomposition experiments

	$\bar{\pi}_{eu}$	$\bar{\pi}_{ue}$	$\tilde{\sigma}_{eu}$	$\tilde{\sigma}_{ue}$	$\pi_s \bar{\pi}_{ee}$	$\bar{u}$	$\tilde{\sigma}_u$	$\tilde{\sigma}_u^*$	$1 - \tilde{\sigma}_u / \tilde{\sigma}_u^*$
Experiment 1: *Role of separations*									
Germany	0.0053	0.062	**0**	4.30	0	0.079	3.40	8.60	60%
US	0.02	0.31	**0**	4.27	0	0.062	3.90	6.18	37%
Experiment 2: *Role of means*									
Germany	**0.02**	**0.31**	−6.20	4.08	0	**0.062**	10.03	8.60	−17%
US	**0.0053**	**0.062**	−2.48	4.27	0	**0.079**	5.33	6.18	14%
Experiment 3: *Role of standard deviations*									
Germany	0.0053	0.062	**−2.48**	**4.27**	0	0.079	5.33	8.60	38%
US	0.020	0.31	**−6.20**	**4.30**	0	0.062	9.96	6.18	−61%
Experiment 4: *Role of quits*									
Germany	0.0053	0.062	−6.20	4.30	**0.01**	0.079	9.01	8.60	−5%
US	0.02	0.31	−2.48	4.27	**0.01**	0.062	6.76	6.18	−9%
US	0.02	0.31	−2.48	4.27	**0.02**	0.062	7.32	6.18	−18%

Notes: The table reports in columns $1-5$ the data equivalents to the respective model variables, and column 6 gives the model prediction for the mean unemployment rate. Column 7 reports the relative standard deviation of the unemployment rate to the standard deviation of the productivity process after the comparative statics experiment ($\tilde{\sigma}_u$). Column 8 reports the equivalent of this number for the benchmark model ($\tilde{\sigma}_u^*$). The last column gives the residual unexplained volatility in the model relative to benchmark model.

In experiment 1, we reproduce —within the model— the empirical thought experiment by Shimer (2005). We set firing volatilities to zero and compare the predicted unemployment volatilities of the model with constant firing rates to our benchmark model. The results align very well with our empirical estimates from section 2.2. We find that for Germany firings are more important than hirings, and that quantitatively firing volatility explains around 60% of the unconditional standard deviation of the unemployment rate. For the US, we find that the firing volatility accounts for 37% of the benchmark unemployment volatility, a result that again aligns well with the empirical contribution rates derived before.

In experiment 2, we ask how much of the unemployment volatility can be attributed to differences in mean hiring and firing rates. For this experiment, we keep volatilities constant and exchange only the US and German mean rates. We see that the impact of the differences in the mean rates is around 15% in absolute value, and hence, rather small.

In experiment 3, we perform the same experiment for hiring and firing volatilities. This time, we hold mean rates constant and focus on the effect of differences in volatilities. We see that the sole impact of differences in volatilities is very large. For Germany, the model generates an unemployment volatility that falls 38% short of the benchmark economy, whereas for the US the unemployment volatility is 61% too high compared to the benchmark model.

It is important to recall that during these experiments we kept the volatilities constant while changing the means. However, we showed before that as soon as we impose equilibrium restrictions, this ceteris paribus assumption would clearly be violated.

Finally, experiment 4 examines how much the introduction of on the job search changes the unemployment volatility. For Germany, we use an average quit rate of 1%, in line with our empirical estimate. We find that the contribution of quits is very small, leading to a 5% higher unemployment volatility compared to the benchmark model. For the US, we lack an exact empirical counterpart for the quit rate, however, the impact might be considerably higher (18% increase) if we are willing to assume a monthly quitting probability of 2% which is in line with some estimates from the literature (see Nagypal (2005)). In our simulation experiments, we found that this effect enhances the ability of the model in generating more unemployment volatility, in line with findings of Menzio and Shi (2009), but it is quantitatively small.

3.2.4 Beveridge curve

Search on the job plays an important role (in both countries) in explaining within the model the *Beveridge curve*. With search on the job there are, as Equation (7) shows, two counteracting forces at work. The first term captures the negative covariance between unemployment and productivity (noticing that $z_2 < 0$). The second positive term captures the effect that in a recession many workers lose their jobs and increase the pool of searching workers. The increase in the search pool makes it relatively cheap for firms to find new workers given that their matching probability increases. They start to post more vacancies in times of high unemployment rates, inducing a positive correlation between vacancies and unemployment. This effect might well dominate and destroy the *Beveridge curve*. Search on the job can mitigate the problem. In the limit, if all workers are searching ($\pi_s = 1$), the positive term disappears completely. We find that, quantitatively, search on the job indeed restores the *Beveridge curve*.[22]

We showed how differences in mean transition rates and labor market institutions interact in explaining the observed cross-country differences in volatilities. In the next step, we calibrate our model including match heterogeneity and study the implications of the observed differences on the transmission of business cycle shocks to the labor market.

4 Calibration

Our basic time period is one month and we aggregate to quarterly rates when simulating the model. We target for both countries a discount rate of annualized 4% and set the matching elasticity to the linearity point ($\varrho = \frac{1}{2}$) in line with recent estimates by Petrongolo and Pissarides (2001).

Means: There are three differences in the average rates across countries we want to match. These are the average jobfinding rates that differ by a factor of 5, the average firing rates that differ by a factor of 4, and the average quit rates that differ by a factor of 2. This imposes the following cross-country restrictions

$$\frac{\bar{\pi}_{ue}^{US}}{\bar{\pi}_{ue}^{Ger}} \approx 5 \qquad \frac{\bar{\pi}_{eu}^{US}}{\bar{\pi}_{eu}^{Ger}} \approx 4 \qquad \frac{\pi_s^{US}\bar{\pi}_{ee}^{US}}{\pi_s^{Ger}\bar{\pi}_{ee}^{Ger}} \approx 2$$

Standard deviations: There are two facts about the second moments across countries we want to match. These are the standard deviation of the firing rate and the jobfinding rate. Relative to the business cycle, the standard deviation of firings differ by a factor of 2.5 but hirings are equally volatile across countries.

$$\frac{\tilde{\sigma}_{eu}^{Ger}}{\tilde{\sigma}_{eu}^{US}} \approx 2.5 \qquad \frac{\tilde{\sigma}_{ue}^{Ger}}{\tilde{\sigma}_{ue}^{US}} \approx 1$$

[22]See Ramey (2008) for a similar finding.

Wage elasticity: Finally, we want our model to be consistent with our estimates on the wage elasticities. We focus on a wage elasticity of $\tilde{\sigma}_w = 0.8$ for both countries. This number is in line with our upper bound estimates for Germany and the estimate of Haefke et al. (2007) for jobfinder in the US.[23] A common elasticity estimate implies that our findings will not be driven by differences in wage rigidity but can be traced to institutional differences.

The introduction of heterogenous types does not alter the main mechanisms outlined above. As explained in the empirical analysis, we target the differences in the mean firing rates across tenure groups as a proxy for match heterogeneity to pin down the additional parameters. For the US, we lack a precise empirical counterpart for the effect of tenure, however, results in Menzio and Shi (2009) suggest that a similar pattern as observed for Germany also holds for the US. In table 8, we summarize our numerical results and our calibration strategy, which is otherwise standard given the targets outlined above.

Table 8: Calibration

Parameter	*heterogeneous types*		*homogeneous types*		*Target (Ger,US)*	*Source*
	Germany	*US*	*Germany*	*US*		
β	0.997		0.997		Annual real rate of 4%	
$\varkappa$	0.198		0.198		Normalization	
ϱ	0.5		0.5		Matching elasticity	Petronglo
ρ	0.975		0.975		Kalman estimates	Solow Residual
B_b	0.975		1		Quit premium 5%	Data
B_g	1.025				Normalization	
π_g	0.12	0.03	0		$\bar{\pi}_{eu} = (0.017, 0.04)$	Data
π_s	0.58	0.14	0.128	0.065	Mean quits $(0.008, 0.02)$	Data
ψ_b	0.61	0.73	0.80	0.90	$\bar{\pi}_{eu} = (0.005, 0.02)$	Data
ψ_g	1.64	1.76			$\bar{\pi}_{eu,g} = (0.002, 0.002)$	Data
κ	0.23	0.03	0.27	0.05	$\bar{\pi}_{ue} = (0.0622, 0.3069)$	Data
τ	2.3	2.0	3.0	2.9	Rel. std π_{eu}	see table 7
b	0.96	0.93	0.95	0.94	Rel. std π_{ue}	see table 7
μ	0.68	0.47	0.63	0.38	Wage elasticity $(0.8, 0.8)$	Data

Notes: This table documents our chosen parameters. We allow six parameters to differ across countries to target the six differences identified in the main text. In the case of heterogenous agents, we allow for differences in π_g and ψ to additionally target the differences across tenure groups using information for Germany.

4.1 Results

There exist an equilibrium that matches jointly all targets in both countries. The model demands a small surplus from opening a position, implying a very high outside option b.[24] Yet, due to search on the job and the time it takes to find a good job, the average surplus in the society is substantial, and amounts to roughly 60% of annual income in Germany and 40% of annual income in the US. The surplus of a bad job is small and amounts to roughly one monthly income. An important difference across countries lies in the substantially higher bargaining power ($\mu^{Ger} > \mu^{US}$) and in the costs to open a position ($\kappa^{Ger} > \kappa^{US}$). Firing costs are calibrated to be higher in Germany ($\tau^{Ger} > \tau^{US}$). The exogenous search rate must be much higher in Germany given that Germans have to search considerably more often to find a better job due to the lower contact rates ($\pi_S^{Ger} > \pi_S^{US}$). Finally, idiosyncratic productivity risk is found to be higher in the US ($\psi^{US} > \psi^{Ger}$).

[23] It turns out, quantitatively, that the particular number chosen has almost no bearing on the results. With the exception that it has to be smaller one, of course.

[24] Hall and Milgrom (2007) provide a rational by reinterpreting the outside option.

Given that we used up the two volatilities in our calibration and therefore lost an important metric of success, we evaluate the performance of the model by studying its predictive power. To this end, we estimate for both countries the underlying TFP process using a Kalman filter on GDP growth. We feed the estimated process into the model and predict all endogenous variables applying an HP-filter ($\lambda = 100,000$) to the resulting time-series.[25] Figures 3 and 4 graphically illustrates the success of the model. Table 9 reports the standard deviations of the estimated series as well as the correlation between predicted and actual values as a measure of fit.[26]

Table 9: Summary Statistics

	Germany			US		
Name	Std (Data)	Std (Model)	Corr	Std (Data)	Std (Model)	Corr
URate	0.18	0.198	0.87	0.150	0.16	0.89
Productivity	0.016	0.014	0.47	0.014	0.02	0.48
Wage income	0.015	0.011	0.78	0.018*	0.017*	0.29*
Quits (NE)*	0.20	0.10	0.60	0.059*	0.127*	0.48*
Vacancies*	0.33	0.16*	0.46*	0.20	0.17	0.80
	calibrated moments					
Firings	**0.15**	**0.15**	0.71	**0.06**	**0.06**	0.71
Jobfinding	**0.10**	**0.10**	0.59	**0.11**	**0.11**	0.72

Notes: The table reports summary statistics for all endogenous variables predicted by the model and compares them to the data. Corr refers to the correlation between the actual and the predicted data. The star indicates that for quits in the US we do not have corresponding data and proxy by the NE flows (see Nagypal (2005)). However, the proxy might capture very distinct phenomena and should be interpreted with care. Calibrated moments are in bold.

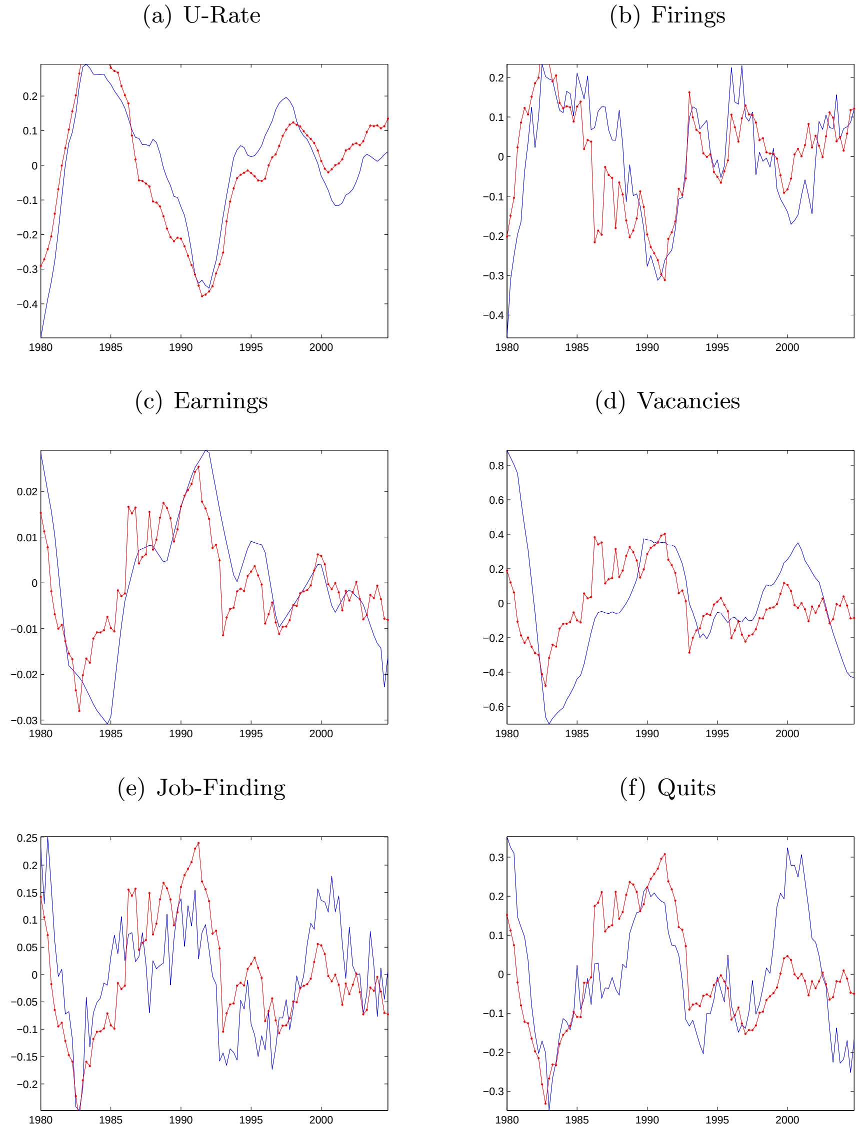
The model reproduces the time series pattern of the unemployment rate almost perfectly and captures firing dynamics very well in both countries. German median earnings obtained from the microdata are also fitted almost perfectly, while the model fails to match the BLS earnings series. Given that the aggregate earnings series for the US is not very reliable and faces the same composition effects as discussed in section 2.4, it is not clear whether the mismatch is exclusively a model problem or partly a data problem as well. The model captures the correlation structure of vacancies, quits, and jobfinding rates well but underestimates the volatility for the vacancy proxy in Germany. The data on open positions for Germany does only capture a small universe of all open positions, so clearly the model and data are measuring different things. The quit correlation is captured well, but the standard deviation is off considerably. An easy fix would be a procyclical search probability which would typically be the outcome of a model with endogenous search choice. The correlation between vacancies and unemployment for the US is -0.8 in the model, showing that quits on the job indeed help recovering the *Beveridge curve*. For Germany, we do slightly worse given that the correlation is -0.6, but we still reproduce the negative *Beveridge curve* relation fairly well.

The model is driven by one contemporaneous shock hitting the demand for labor while the data likely requires a richer shock structure to capture some of the autocorrelated deviations and measurement error. However, the basic model driven by one shock seems to capture the main forces in the labor market fairly well. Furthermore, the simple and stylized model can reconcile

[25]When applying a Bandpass-filter, the findings are very similar.

[26]We only report results for the heterogenous agent case, though the basic fit of the model is not much affected when focussing on the homogenous agent case.

Figure 3: Prediction for Germany



Notes: The figure plots the model predictions (red dotted lines) and the data (blue solid line). The prediction is based on a technology process obtained from a Kalman filter on GDP growth. Model and data are in logs and are HP-filtered with $\lambda = 100,000$. Earnings for Germany refer to median earnings obtained from the micro-data. Vacancies are open position obtained from the *Bundesagentur fuer Arbeit* and do not correspondent to the universe of all open positions.

labor market dynamics across countries relying only on differences in institutional parameters.

4.2 Transmission of shocks

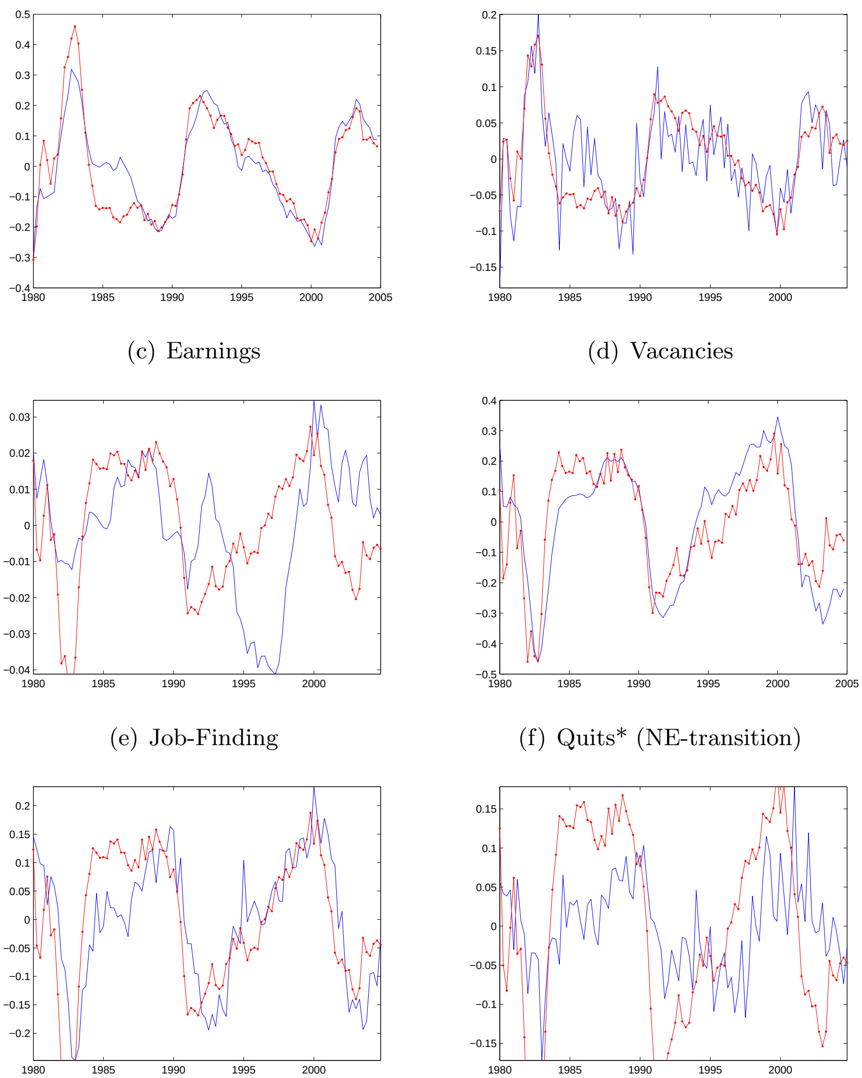
We have demonstrated that our model reproduces the right macro-elasticities with respect to aggregate shocks for important labor market dimensions. In this section, we use the model to inform us about the transmission of business cycle shocks into the labor market. In particular, we examine how the German labor market reacts to business cycle shocks compared to the US market. As Figure 5 makes clear, the impulse-response functions for a large shock (-5%) are substantially different across countries.

Figure 4: Prediction for the US

(a) U-Rate (b) Firings

(c) Earnings (d) Vacancies

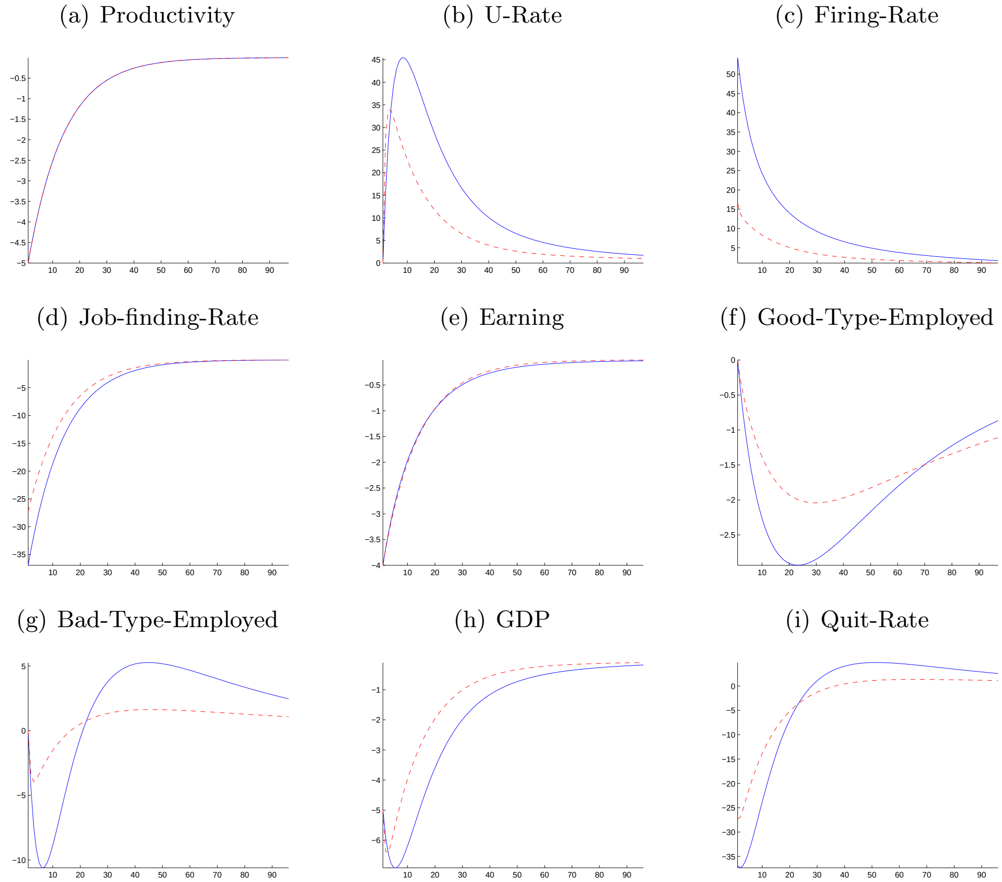
(e) Job-Finding (f) Quits* (NE-transition)



Notes: The figure plots the model predictions (red dotted lines) and the data (blue solid line). The prediction is based on a technology process obtained from a Kalman filter on GDP growth. Model and data are in logs and are HP-filtered with $\lambda = 100,000$. Earnings for the US are from the Bureau of Labor statistics. Labor market transitions are taken from Shimer (2005).

The model predicts, on impact, a stronger increase in unemployment rates measured in percentage deviation from the respective long-run rates in Germany. The differences are not generated by differences in the reaction of wages. Despite the lower bargaining power in the US the wage reaction was targeted to be the same across the two countries, and is confirmed in figure 5(e). The difference is also not due to the hiring margin, given that the job-finding rate reacts very similar (see figure 5(d)). The assumption of heterogenous job types does not drive the results either, in fact, we obtain the same picture for the aggregate rates when focussing on the homogenous agent case. The composition effects do not have a strong impact on the aggregate reaction, but interesting differences can be stated. At our calibrated parameters, more bad matches will be destroyed in Germany compared to the US. Over time (roughly after two years) there will be

Figure 5: Impulse response functions



Notes: The figure plots the impulse response functions for the US (red dotted lines) and Germany (blue solid line). Good type and bad type employed refer to the measure of good and bad matches.

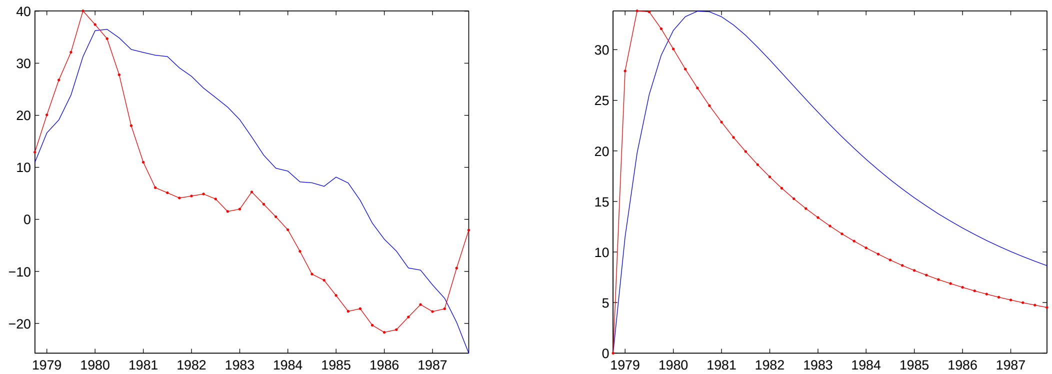
more workers in bad jobs compared to the long-run steady state in Germany. These workers will over time move into good jobs. However, this process takes time and the number of good jobs will be below the long-run average for a substantial amount of time. Correspondingly, there might be considerable risk involved for good workers when being fired, loosing a substantial fraction of their surplus during the periods of unemployment and search for a good job.

In fact, to have a similar response on impact the shock would have to be only 3.72% in Germany, implying an impact that is approximately 30% larger in Germany. The right panel of figure 6 shows the re-scaled impulse response function, where we scale the German shock such that both countries face the same peak unemployment rate. In the left panel of figure 6, we plot the behavior of the actual unemployment rate in Germany and the US after the large oil price shock at the beginning of the eighties.

The plots show that the striking difference across countries is the differences in the persistence of the shock. According to our model the US react without much delay but also recover fairly quickly, while Germany reacts slowly but likely suffers much longer. After 20 quarters (or five years) we see that the German unemployment rate will still be 25% away from its long-run average while the US is only 12% away. When we compare the model to the data, we observe the same pattern. Although Germany came from considerably lower unemployment level, it appears to be the case that the shock showed much more persistence in Germany while it

Figure 6: Rescaled impulse response functions

(a) Unemployment rate (data) - HP-detrended (b) Unemployment rate (model)



Notes: Right panel: Impulse response functions for unemployment rates in the US (red dotted lines) and Germany (blue solid line) rescaled to match the initial shock. The shock magnitude for the US is 5% and for Germany 3.72%. Left panel: The HP-filtered percentage deviation of the actual data. The red dotted line are the US, the blue solid line is Germany.

leveled off much more quickly in the US.

This experiment in our realistically calibrated model shows that shocks can be the driver of substantially higher unemployment rates for a long time but that the reason for the persistence is not the shock by itself but the interplay with the more rigid labor market institutions. It is the coexistence of low transition rates, high volatilities, and long persistence that makes rigid labor markets so vulnerable to business cycle shocks.

5 Conclusion

In this paper we document that the German and the US labor market share many similarities in their dynamics over the business cycle. We find that many of the stylized facts for the US as stated in Shimer (2005) do also hold for Germany, however, two crucial differences arise: (*i*) lower average transition rates and (*ii*) a higher firing volatility that constitutes the major driving force behind unemployment volatility.

We show that these differences matter in a quantitative sense. Shocks in Germany are considerably amplified (+30%) and are substantially more persistent than in the US (+25% after five years). The volatility differences are not rooted in different wage reactions across countries. If anything, the earnings elasticity in Germany is at least as high as in the US. Instead we find that differences in labor market institutions leading to lower average transition rates in Germany are responsible for the large amplification of business cycle shocks. Viewed through the lens of a search and matching framework, no mean-variance trade-off between higher unemployment rates on the one hand and lower business cycle volatility on the other hand exists. This raises fear for the future given the large shock currently hitting the labor market in both countries. The relatively modest effect on unemployment rates we witnessed so far in Germany might partly be due to a reaction of policy, substantially subsidizing layoffs and preventing a boost in firings. Whether this policy reaction is indeed an optimal choice will be studied in our future research.

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A Data

A.1 Data description

The data is taken from the IAB regional files that cover the period January 1975 to December 2004. The data consists of employment records of workers that have at least for one day been employed in a job under mandatory social security. The dataset comprises a 2% representative subsample of workers drawn from these records. Once an individual has been put into the sample, the full employment history of this individual during the sampling period is observed. The employment history consists of employment spells that are subject to mandatory social security and unemployment spells where social security benefits have been paid. The sample does therefore not contain spells in public service (*Beamte*), self-employment, and periods of non-employment. We describe below in detail how we control for these periods by constructing artifical spells. Still, the data covers about 80% of the German workforce.

A.2 Sampling period and sample selection

Due to measurement problems in unemployment during the years 1977 and 1978 we use the first 5 years ($1975 - 1979$) only as a pre-sample and start our main analysis in 1980.
In a first step sample selection, we drop all individuals where the East-West information is missing ($2,787$ individuals dropped) or information regarding the current job[27] ($14,490$ individuals dropped). Furthermore, we drop homeworkers ('Heimarbeiter') from the sample ($7,315$ individuals dropped). This results in a dropping rate of 1.81% for the whole sample, and leaves us with a sample of employment histories for $1,336,357$ individuals. After the German reunification the data contains employment histories with spells that are located in East Germany. Since the East German labor market was subject to additional regulations and restructuring after the reunification, we exclude in a second step all persons with employment spells in the East from our sample. This leaves us with a final sample of $1,087,555$ employment records. From these records we drop all marginal employment spells to avoid mismeasurement because marginal employment spells are only reported for the last five years of the sample period.

A.3 Construction of monthly employment histories

The employment history is given as a collection of employment spells on a daily basis. A new spell can either occur due to administrative reasons of the social security system or changes within a given firm, due to a quit to a new firm, the begin of an unemployment or a non-employment spell. Regularly, individuals have periods of parallel employment in the sample. This is reported as multiple spells. For every spell, we observe whether it is a full-time, part-time, or marginal employment.
If persons have parallel spells in their employment history, we consider only what we call *primary spells*. The idea is to consider the employment spell that generates the most income and occupies the most working time of an individual. To identify the *primary spell*, we apply a hierarchical selection procedure. If a person is at the same time full-time and part-time employed, we label him or her as full-time employed and drop the part-time spells, if a person has two part-time employments, we follow the ordering in the dataset that applies a hierarchical ordering based on income and part-time status over parallel spells, finally, if a person has employment and unemployment spells at the same time, we label the employment spells as primary to be

[27] stib information missing.

consistent with the procedure in the next step of determining the employment status.[28]
Our basic time-period will be one month. We adopt the ILO timing convention to measure the employment status of a person in a given month. For each month we determine the Monday of the second week in the month and take the week starting from this Monday as our reference week. We look at all spells that overlap with this week. If only one spell overlaps, then this spell determines the labor market status. If several spells overlap, we use a hierarchical ordering of spells where a full-time employment spell dominates part-time spells and any employment spell beats unemployment or non-employment spells. From this classification of monthly employment states, we construct time-series at monthly frequency. By tracking the employment histories through time, we can generate additional labor market statistics like tenure on the current job and can construct the sample of continuously employed workers. To check whether a person stays with the same employer, we use the establishment number of the employment spells. A transition of a person between establishments but within the same firm is then also counted as a quit. The definition of who is counted as unemployed follows from the content of the dataset. A person is unemployed if she receives unemployment benefits or other benefits on the basis of the Social Security Code III ('Sozialgestzbuch III'). We can not follow the ILO definition that is based on interview questions on job search because this is unobservable in our sample.
We label inactive employment that is reported in the dataset as non-employment. These spells are periods of sustained employment relationships but that are currently inactive, i.e. the worker does not work and no income is paid. Examples for these periods are maternity leave, long periods of illness, sabbaticals. We construct additional non-employment spells as residual spells in the dataset. The additional spells are included if a person is not observed in the sample for some time period between two spells. To deal with persons entering the sample or dropping out of the sample, we introduce additional labor market states that we label *labor market entry* and *retirement*. The labor market entry state is an artificial state that we add before the first employment state. The retirement state is an artificial state at the end of the labor market history. We assign it to persons that are of age 55 or older when they have their last observed spell. The retirement state is by construction an absorbing state. Persons that are below 55 and have no future spells in the sample are labeled as *other employment* and are no longer considered after the transition into this non-employment state, i.e. they do not generate transitions out of non-employment. Persons that are below 55 but have future spells are labelled as *out of the labor force*. The labor market entry, the reported spells of inactivity, and the *out of the labor force* spells constitute the pool from which all non-employment transitions originate. Table 10 gives an overview over the different non-employment states in our analysis

Table 10: Description of non-employment states

status	definition
retirement	age ≥ 55, no further spells
other employment	age < 55, no further spells
labor market entry	before 1^{st} spell of labor market history
out of the labor force	age < 55, further spells
inactive	in data

[28]This problem only arises with marginal employment and can therefore be disregarded for the analysis in this paper.

A.4 Measurement error

For variables regarding the job status, the income paid, or the duration of the job the data contains virtually no measurement error because it is taken from the social security and unemployment records that are used to determine social security contributions and benefits. The personal characteristics that we observe with every spell like year of birth, education, industry, and location of the employer may, however, contain measurement error. Fitzenberger et al. (2006) point out that the education variable may be subject to higher measurement error and provide imputation and correction rules for this variable. We adopt their imputation and correction procedure and determine the highest attained education level of an individual over the employment history to group persons into education classes.

A.5 Earnings

The income reported at one spell is the average daily income of an individual during the employment spell[29]. We do not observe hours worked but observe whether the person is full-time, part-time, or from 1999 on in marginal employment. We use income of the *primary spell* for the analysis in this paper.

A.6 Imputation and correction for structural breaks

Income in the sample is top-censored at the upper contribution limit ('Beitragsbemessungsgrenze') of the German social security system, and bottom censored at the marginal employment contribution level ('Geringfuegigkeitsgrenze'). For some of steps of the analysis we need an uncensored income distribution. For these steps we impute income above and below the two censoring points using the method proposed in Gartner (2005). The imputation uses a censored regression together with the log-normality assumption for income to impute the censored observations. For details see Gartner (2005).
Starting 1984 the income data also includes overtime and bonus payments. We correct for this structural break using the method proposed in Fitznberger (1999). His procedure leaves the median and all observations below the median unchanged and corrects income observations only above the median. The approach is based on measuring the excess growth of the upper income quantiles between 1983 and 1984. For details see Fitznberger (1999).

A.7 Aggregate data

Aggregate data are taken from the statistic office ('Statistische Bundesamt'). We use nominal GDP and convert it to real GDP by the CPI deflator from the Bundesbank. We deflate nominal income in the sample using the same CPI deflator. Productivity measures are obtained by dividing through total employment or total hours worked, as is done by the statistical office. This measure is rather noisy and does not correspond to the BLS productivity measure for the US that uses a more disaggregate procedure, but still suffers from aggregation problems highlighted when discussing the cyclical properties of income. After 1991, we only observe GDP for the unified Germany. We use the X-12 ARIMA method to align the series in the fourth quarter of the year 1991 to avoid jumping behavior of the series.

A.8 Seasonal adjustment

All data that is generated based on our own calculations is seasonally adjusted at monthy frequency using the X-12 ARIMA method. We also perform the default outlier correction

[29] The working period is not adjust for weekends or holidays.

implemented in X-12 ARIMA.

B Sensitivity

B.1 Transitions by education and sex for all workers

Table 11: Labor market flows $Jan1980 - Sep2004$ for workers by sex

	Mean	Std	Rel. Std	Corr (GDP)	Corr (GDP p. Emp.)	Autocorr
				Males		
Firm exit	0.0236	0.0561	2.34	0.3245	0.1559	0.6724
Empl. exit	0.0148	0.0517	2.154	−0.5201	−0.2935	0.6238
EU	0.0056	0.1812	7.553	−0.8073	−0.5159	0.9034
EN	0.0092	0.0743	3.095	0.5293	0.371	0.7894
UE	0.0679	0.1172	4.883	0.3615	0.0558	0.7273
UN	0.0444	0.1138	4.742	0.4964	0.5952	0.7937
NE*	0.0784	0.1762	7.342	0.3535	0.0081	0.8115
NU*	0.033	0.1552	6.468	−0.3826	−0.2136	0.8782
Quits	0.0087	0.1589	6.622	0.6118	0.3306	0.8931
				Females		
Firm exit	0.0243	0.0595	2.478	0.6099	0.3027	0.8287
Empl. exit	0.0158	0.0339	1.412	−0.0571	0.0899	0.3581
EU	0.0048	0.1024	4.266	−0.7474	−0.4361	0.8356
EN	0.011	0.0588	2.451	0.5065	0.4059	0.6953
UE	0.0542	0.1051	4.381	0.5897	0.2254	0.8364
UN	0.0556	0.0935	3.898	0.2948	0.3222	0.6992
NE*	0.0551	0.1846	7.694	0.2917	−0.1165	0.8724
NU*	0.0163	0.177	7.377	0.0147	0.0142	0.8845
Quits	0.0085	0.1601	6.671	0.6877	0.3126	0.9352

Notes: All data are in logs and are HP-filterer with $\lambda = 100,000$. The rates are quarterly averages of monthly data. Firm exit is defined as the sum of EU+EN+Quits. Employment exit is defined as EU+EN. Quits are defined as job-job transitions between two consecutive dates and a change in the firm counter as defined in the IAB-data. All IAB-rates are authors' calculations. The star at the non-employment flows indicate that the denominator, that is the state of non-employed workers is measured with problems given that we do not have the corresponding universe of searching non-employed. We partially control for this by dropping early retired and only look at workers that eventually will return to the labor market in our sample period. The log volatility measures might be less affected by the problem.

Table 12: Labor market flows $Jan1980 - Sep2004$ for workers by education

	Mean	Std	Rel. Std	Corr (GDP)	Corr (GDP p. Emp.)	Autocorr
	Low education					
Firm exit	0.0245	0.0761	3.172	0.3526	0.2753	0.7477
Empl. exit	0.0191	0.0692	2.884	0.0635	0.1612	0.7223
EU	0.0053	0.136	5.668	−0.5839	−0.2139	0.8261
EN	0.0138	0.0894	3.727	0.397	0.2962	0.7887
UE	0.034	0.1474	6.144	0.4107	0.1008	0.7695
UN	0.0524	0.1195	4.98	0.2481	0.4766	0.7164
NE*	0.0824	0.2267	9.449	0.3888	0.0036	0.8912
NU*	0.0325	0.1838	7.66	0.0781	0.1788	0.8856
Quits	0.0054	0.1963	8.181	0.5502	0.3009	0.8743
	Medium education					
Firm exit	0.0236	0.0521	2.173	0.4796	0.1997	0.75
Empl. exit	0.0147	0.0379	1.581	−0.5814	−0.3431	0.5495
EU	0.0054	0.1578	6.576	−0.8261	−0.538	0.9073
EN	0.0093	0.0617	2.57	0.6093	0.4296	0.7736
UE	0.0684	0.1012	4.219	0.4295	0.0814	0.7709
UN	0.0475	0.1049	4.37	0.515	0.5321	0.7967
NE	0.0637	0.1674	6.977	0.374	−0.0221	0.8495
NU	0.0248	0.157	6.545	−0.2729	−0.1626	0.8907
Quits	0.0089	0.1569	6.54	0.6681	0.3309	0.9165
	High education					
Firm exit	0.0262	0.0921	3.839	0.3217	0.2251	0.7204
Empl. exit	0.0154	0.0892	3.718	0.019	0.1454	0.4976
EU	0.004	0.1236	5.153	−0.527	−0.2329	0.7488
EN	0.0114	0.1266	5.274	0.1753	0.1889	0.5525
UE	0.0664	0.1201	5.006	0.5075	0.172	0.8066
UN	0.0544	0.0895	3.729	0.2258	0.279	0.5942
NE	0.0538	0.1917	7.99	0.1019	−0.1795	0.7512
NU	0.0105	0.1868	7.783	−0.1652	−0.1582	0.7272
Quits	0.0108	0.1438	5.992	0.5027	0.2486	0.8784

Notes: All data are in logs and are HP-filterer with $\lambda = 100,000$. The rates are quarterly averages of monthly data. Firm exit is defined as the sum of EU+EN+Quits. Employment exit is defined as EU+EN. Quits are defined as job-job transitions between two consecutive dates and a change in the firm counter as defined in the IAB-data. All IAB-rates are authors calculations. The star at the non-employment flows indicate that the denominator, that is the state of non-employed workers is measured with problems given that we do not have the corresponding universe of searching non-employed. We partially control for this by dropping early retired and only look at workers that eventually will return to the labor market in our sample period. The log volatility measures might be less affected by the problem.

B.2 Unemployment decomposition

We perform the unemployment decomposition for different subgroups. We use the decomposition based on the HP-Filter ($\lambda = 100,000$)
We perform the decomposition of unemployment fluctuations based on a first difference filter as derived in Petrongolo and Pissarides (2009). The first difference filter for the case including non-employment does not allow to separate the contributions of EN and NU flows and the contribution of UN and NE flows. The columns are therefore reordered in this table. We report the decomposition using the HP-filter ($\lambda = 100,000$) as given in the main text for comparison.

Table 13: Unemployment decomposition for different subgroups

Sample	Data	EU	UE	NE	EN	NU	UN	ε
Men	IAB	0.6391	0.3580					0.0029
	IAB	0.4517	0.2545	0.1707	−0.0433	0.0833	0.0851	−0.0010
Women	IAB	0.4831	0.5137					0.0032
	IAB	0.3261	0.2854	0.2573	−0.0460	0.0359	0.1449	−0.0037
Low education	IAB	0.4740	0.5244					0.0016
	IAB	0.2806	0.2719	0.3174	−0.0362	0.0810	0.0868	−0.0015
Medium education	IAB	0.6340	0.3627					0.0033
	IAB	0.4438	0.2422	0.1822	−0.0472	0.0720	0.1093	−0.0024
High education	IAB	0.5165	0.4830					0.0030
	IAB	0.3682	0.2652	0.2142	−0.0166	0.0654	0.1028	0.0008

Notes: Contribution of labor market transitions to unemployment fluctuations. Data is HP-filtered ($\lambda = 100,000$) for the period $1980q1 - 2004q3$. For Germany the transition rates are for all male and female workers. The US data is obtained from Shimer and Fujita/Ramey.

Table 14: Unemployment decomposition for different filters

Country	Data	EU	UE	EN	NU	UN	NE	ε
Germany	IAB (Δ)	0.6353	0.3647					0.0000
	IAB (Δ)	0.3610	0.2131	0.2625		0.1634		−0.0000
	IAB (HP)	0.4186	0.2498	−0.0469	0.0677	0.1122	0.2020	−0.0020
US	Shimer (Δ)	0.6434	0.3566					−0.0000
	Fujita/Ramey (Δ)	0.5174	0.4826					−0.0000
	Shimer (Δ)	0.4010	0.3054	0.1207		0.1729		−0.0000
	Shimer (HP)	0.2013	0.4855	−0.0378	0.1039	0.1516	0.0884	0.0072

Notes: Contribution of labor market transitions to unemployment fluctuations. Data is detrended by a first difference filter (Δ) for the period $1980q1 - 2004q3$. The row labelled (HP) contains the numbers for the decomposition using the HP-filter ($\lambda = 100,000$). For Germany the transition rates are for all male and female workers. The US data is obtained from Shimer and Fujita/Ramey.

Table 15: Unemployment decomposition for the period $1977 - 2004$

Country	Data	EU	UE	NE	EN	NU	UN	ε
Germany	IAB	0.6600	0.3371					0.0029
	IAB	0.4486	0.2014	0.1323	−0.0481	0.1423	0.1238	−0.0004
US	Shimer	0.3677	0.6361					−0.0038
	Fujita/Ramey	0.4054	0.5986					−0.0040
	Shimer	0.2316	0.4702	0.0853	−0.0403	0.0957	0.1499	0.0076

Notes: Contribution of labor market transitions to unemployment fluctuations. Data is HP-filtered ($\lambda = 100,000$) for the period $1977q1 - 2004q3$. For Germany the transition rates are for all male and female workers. The US data is obtained from Shimer and Fujita/Ramey.

Table 16: Unemployment decomposition before and after the German reunification

Period	Data	EU	UE	NE	EN	NU	UN	ε
$1980q1 - 1991q4$	IAB	0.6188	0.3766					0.0046
	IAB	0.4585	0.2403	0.2080	−0.0796	−0.0309	0.2066	−0.0029
$1992q1 - 2004q4$	IAB	0.5855	0.4116					0.0029
	IAB	0.3678	0.2374	0.1862	−0.0362	0.1825	0.0586	0.0036

Notes: Contribution of labor market transitions to unemployment fluctuations before and after the German reunification. Data is HP-filtered ($\lambda = 100,000$). The transition rates are for all male and female workers.

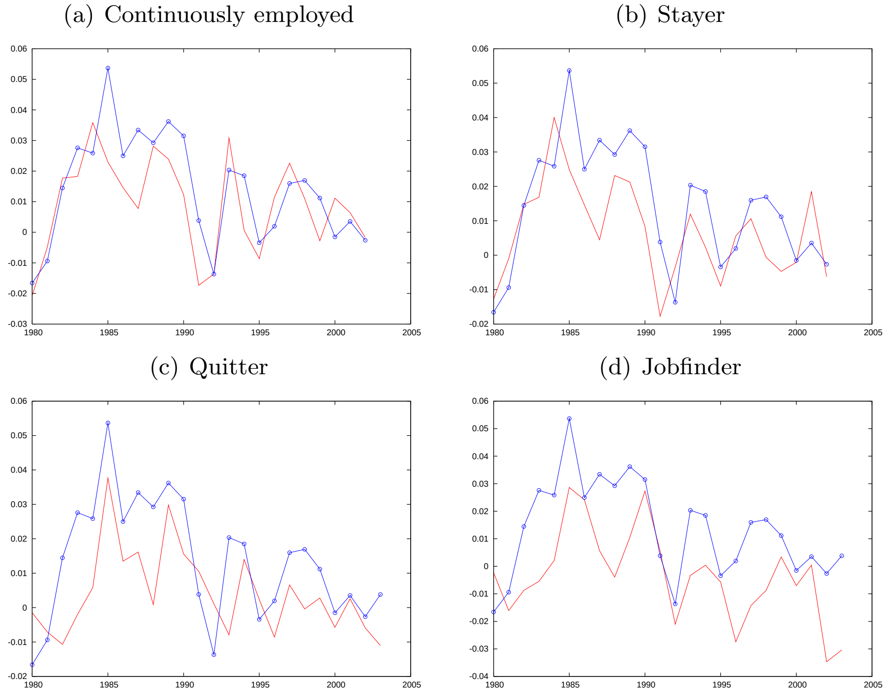
Table 17: Unemployment decomposition for full-time employed workers

Sample	Data	EU	UE	NE	EN	NU	UN	ε
Full-time	IAB	0.6073	0.3898					0.0030
	IAB	0.4181	0.2494	0.2018	-0.0469	0.0677	0.1120	-0.0020

Notes: Contribution of labor market transitions to unemployment fluctuations if only full-time employment is considered. Data is HP-filtered ($\lambda = 100,000$). The transition rates are for male and female workers.

B.3 Earnings

Figure 7: Earnings cyclicality and GDP per capita



Notes: Earnings index cyclicality ($1st$ difference filter) for full-time workers (male and female), business cycle measure GDP per capita. Time period is $Jan1980 - Sep2004$.

Table 18: Earnings cyclicality using GDP per capita

	Quitter	Jobfinder	Stayer	Cont. employed
Index	0.4841	0.6231	0.5414	0.6436
std error	(0.0854)	(0.1163)	(0.0943)	(0.1006)
Correlation	0.6874	0.6668	0.6982	0.7358
Growth	0.4588	0.8160	0.6759	0.6491
std error	(0.0534)	(0.1297)	(0.0817)	(0.0918)

Notes: Annual earnings cyclicality for full-time employed workers (male and female, all education groups). *Index* refers to the earnings index using the first difference filter. *Correlation* refers to the correlation coefficient of the earnings index and the business cycle measure. *Growth* refers to the estimation in first difference using OLS. standard errors are clustered by time periods. The business cycle measure is GDP per capita. Time period is $Jan1980 - Sep2004$.

Table 19: Earnings cyclicality for the period 1977 − 2004

	Quitter	Jobfinder	Stayer	Cont. employed
Index	0.6091	0.6111	0.7221	0.7478
std error	(0.1336)	(0.2060)	(0.1304)	(0.1497)
Correlation	0.5620	0.4045	0.6398	0.6005
Growth	0.3292	0.7854	0.8036	0.6858
std error	(0.1104)	(0.2251)	(0.1342)	(0.1373)

Notes: Annual earnings cyclicality for full-time employed workers (male and female, all education groups). *Index* refers to the earnings index using the first difference filter. *Correlation* refers to the correlation coefficient of the earnings index and the business cycle measure. *Growth* refers to the estimation in first difference using OLS. The business cycle measure is GDP per employed. Time period is $Jan1977 - Sep2004$.

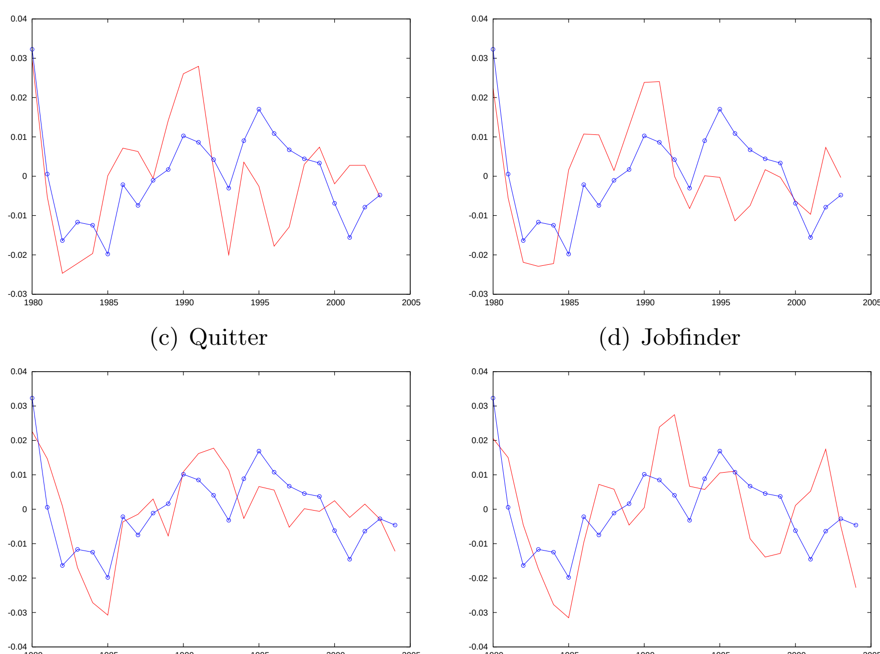
Table 20: Earnings cyclicality (HP filtered)

	Quitter	Jobfinder	Stayer	Cont. employed
Index(p.cap.)	0.5420	0.6101	0.5387	0.6416
std error	(0.0819)	(0.1147)	(0.0878)	(0.0911)
Correlation	0.8036	0.7357	0.7878	0.8264
Index(p.empl.)	0.7454	0.7244	0.6100	0.6633
std error	(0.1686)	(0.2369)	(0.1956)	(0.2259)
Correlation	0.6700	0.5295	0.5452	0.5221

Notes: Annual earnings cyclicality for full-time employed workers (male and female, all education groups). *Index p.cap.* refers to the earnings index using the HP-filter ($\lambda = 100,000$) and GDP per capita as business cycle measure and *Index p.empl.* refers to the earnings index using the HP-filter ($\lambda = 100,000$) and GDP per employed as business cycle measure. *Correlation* refers to the correlation coefficient of the earnings index and the business cycle measure. Time period is $Jan1980 - Sep2004$.

Figure 8: Earnings cyclicality (HP filtered) and GDP per employed

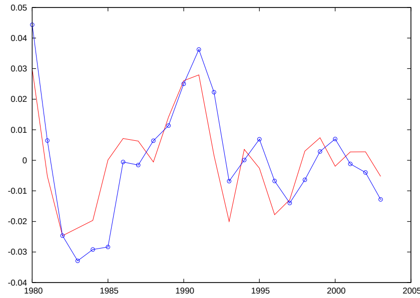
(a) Continuously employed (b) Stayer (c) Quitter (d) Jobfinder



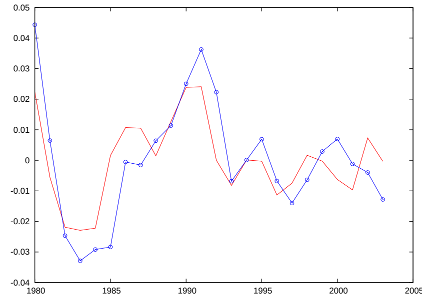
Notes: Earnings index cyclicality (HP filter, $\lambda = 100,000$) for full-time workers (male and female), business cycle measure GDP per employed. Time period is $Jan1980 - Sep2004$.

Figure 9: Earnings cyclicality (HP filtered) and GDP per capita

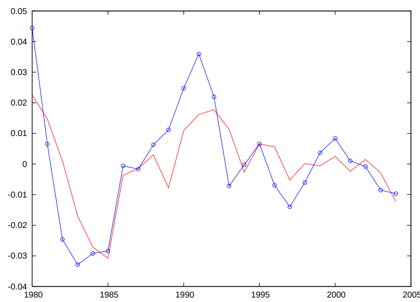
(a) Continuously employed



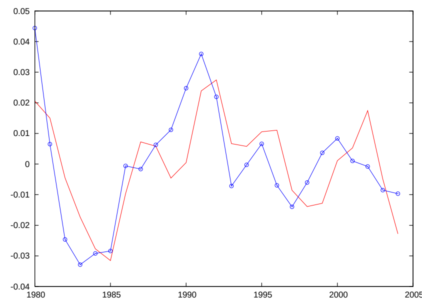
(b) Stayer



(c) Quitter



(d) Jobfinder



Notes: Earnings index cyclicality (HP filter, $\lambda = 100,000$) for full-time workers (male and female), business cycle measure GDP per capita. Time period is $Jan1980 - Sep2004$.

Table 21: Earnings cyclicality (LAD estimation)

	Quitter	Jobfinder	Stayer	Cont. employed
$Growth(p.cap.)$	0.5181	0.6455	0.5895	0.5702
std error	(0.0633)	(0.1452)	(0.0870)	(0.1097)
$Growth(p.empl.)$	0.4870	0.6751	0.6389	0.6056
std error	(0.1263)	(0.2446)	(0.1613)	(0.1840)

Notes: Annual earnings cyclicality for full-time employed workers (male and female, all education groups). *Growth p.cap.* refers to the estimation in first difference using a LAD regression and GDP per capita as business cycle measure. *Growth p.empl.* refers to the estimation in first difference using a LAD regression and GDP per employed as business cycle measure. Standard errors are bootstrapped with 100 repetitions and clustered by time periods. Time period is $Jan1980 - Sep2004$.

Table 22: Earnings cyclicality for full-time employed workers

	Quitter	Jobfinder
$Growth(p.cap.)$	0.5277	0.7709
std error	(0.0604)	(0.0928)
$Growth(p.empl.)$	0.3875	0.7164
std error	(0.1394)	(0.2125)

Notes: Annual earnings cyclicality for full-time employed workers (male and female, all education groups). Sample is restricted to unemployed that are unemployed less than 360 days and employed that are employed for at least 180 days.*Growth p.cap.* refers to the estimation in first difference using OLS and GDP per capita as business cycle measure. *Growth p.empl.* refers to the estimation in first difference using a OLS and GDP per employed as business cycle measure. Standard errors are clustered by time periods. Time period is $Jan1980 - Sep2004$.

B.4 Tenure

The table reports tenure transition rates for EN flows. The NE transition rates are not reported because of mismeasurement of the number of non-employmed workers.

Table 23: Tenure statistics for non-employment flows

EN	< 365 days	$365 - 730$ days	$730 - 1825$ days	> 1825 days	*overall* days
mean	0.0194	0.0058	0.0041	0.0018	0.0060
std	0.0996	0.1291	0.1511	0.2302	0.1334
rel. share	0.5959	0.1073	0.1539	0.1429	
rel. earnings	0.7224	0.7724	0.7769	0.8125	
corr (per capita)	0.2003	0.2022	0.2588		0.4464
corr (per empl.)	-0.4650	-0.4644	-0.4213	-0.2546	-0.4739
av. obs.	$1,202$	218	312	286	$2,017$

Notes: Tenure statistics for non-employment flows (*out of the labor force* state) for the period $Jan1980 - Sep2004$. The columns contain the bounds of the different tenure groups. The tenure groups are formed for the labor market state before the transition and are given in days. All statistics are computed conditional on being in the respective labor market state and tenure group. *mean* is the average transition probability of the respective labor market transition. *std* is the relative deviation of the transition rate over time. *rel. share* is the average share of transitions falling in this tenure group relative to all transitions. *rel. earnings* are the average relative earnings of all persons with a transition relative to the average earnings in the current labor market and tenure group. *corr* are the respective correlations of the transition rate with GDP per capita respectively per employed as our business cycle measures. *av. obs* are the average number of transitions per month from the respective labor market and tenure group.

Table 24: Sensitivity of the relative share with respect to short spells

Jobfindings

0	0.7137	0.148	0.0821	0.0562
15	0.6791	0.1658	0.092	0.0631
30	0.6447	0.1838	0.1018	0.0696

Quits

0	0.4165	0.1504	0.2175	0.2156
60	0.3432	0.1694	0.245	0.2424
90	0.3041	0.1796	0.2596	0.2567
100	0.2985	0.181	0.2617	0.2587
120	0.274	0.1874	0.2709	0.2677

Firings

0	0.586	0.1344	0.1454	0.1341
60	0.5257	0.154	0.1667	0.1537
90	0.4887	0.1661	0.1796	0.1657
100	0.4823	0.1681	0.1819	0.1677
120	0.4609	0.1751	0.1894	0.1746

Notes: The first column contains the minimum tenure in days in the initial state for the transition to be counted. The next four columns contain the share of transitions in the respective tenure class given the restriction. The first row contains the benchmark case without selection that is reported in the main part of the paper.

Table 25: Transition rates between labor market states for full-time employed workers (males and females, $Jan1980 - Sep2004$)

Low skilled					
Quits	< 365 days	$365 - 730$ days	$730 - 1825$ days	> 1825 days	*overall* days
mean	0.0126	0.0067	0.0043	0.0024	0.0048
std	0.1915	0.2428	0.2436	0.1976	0.1997
rel. share	0.4204	0.1227	0.1642	0.2927	
rel. earnings	0.8849	0.8689	0.9012	0.9217	
corr (per capita)	0.3803	0.2687	0.4351	0.2804	0.5170
corr (per empl.)	0.1286	0.2192	0.2383	0.2870	0.3142
av. obs.	72.9433	21.2435	28.0935	49.4463	171.7266
Jobfindings	< 180 days	$180 - 365$ days	$365 - 730$ days	> 730 days	*overall* days
mean	0.0557	0.0258	0.0175	0.0093	0.0335
std	0.1684	0.1836	0.2076	0.3042	0.1466
rel. share	0.6719	0.1616	0.0991	0.0674	
corr (per capita)	0.2697	0.3168	0.3168	0.4203	0.3734
corr (per empl.)	-0.0185	0.0745	0.0857	0.1339	0.0477
av. obs.	129.0431	30.7276	18.6991	12.8358	191.3055
Firings	< 365 days	$365 - 730$ days	$730 - 1825$ days	> 1825 days	*overall* days
mean	0.0207	0.0081	0.0035	0.0020	0.0057
std	0.1763	0.2121	0.2828	0.2815	0.1418
rel. share	0.5651	0.1205	0.1114	0.2030	
rel. earnings	0.9297	0.8349	0.8345	0.8568	
corr (per capita)	-0.6787	-0.5440	-0.5159	-0.3415	-0.5588
corr (per empl.)	-0.3776	-0.2961	-0.2626	-0.0555	-0.2500
av. obs.	115.9110	25.0279	24.0253	42.4594	207.4235
Medium skilled					
Quits	< 365 days	$365 - 730$ days	$730 - 1825$ days	> 1825 days	*overall* days
mean	0.0193	0.0112	0.0079	0.0037	0.0083
std	0.1214	0.1581	0.1750	0.1476	0.1612
rel. share	0.4238	0.1476	0.2137	0.2150	
rel. earnings	0.9068	0.9244	0.9045	0.9002	
corr (per capita)	0.5802	0.5916	0.6284	0.5321	0.6474
corr (per empl.)	0.2666	0.3502	0.3290	0.3634	0.3330
av. obs.	938.8651	327.4333	469.2897	471.4502	2207.0383
Jobfindings	< 180 days	$180 - 365$ days	$365 - 730$ days	> 730 days	*overall* days
mean	0.1009	0.0464	0.0325	0.0234	0.0674
std	0.1111	0.1098	0.1384	0.1792	0.0992
rel. share	0.7224	0.1451	0.0782	0.0543	
corr (per capita)	0.3694	-0.0064	0.4245	0.4965	0.4053
corr (per empl.)	0.0773	-0.1551	0.1915	0.1141	0.0572
av. obs.	1197.9836	243.3641	131.5879	89.4922	1662.4279
Firings	< 365 days	$365 - 730$ days	$730 - 1825$ days	> 1825 days	*overall* days
mean	0.0187	0.0068	0.0037	0.0015	0.0057
std	0.2015	0.1837	0.2367	0.2308	0.1598
rel. share	0.5947	0.1315	0.1466	0.1272	
rel. earnings	0.8736	0.8394	0.8134	0.8196	
corr (per capita)	-0.7845	-0.7386	-0.7437	-0.6018	-0.7830
corr (per empl.)	-0.4778	-0.4745	-0.4526	-0.3034	-0.5066
av. obs.	879.9904	194.8828	220.8215	190.2625	1485.9571
High skilled					
Quits	< 365 days	$365 - 730$ days	$730 - 1825$ days	> 1825 days	*overall* days
mean	0.0161	0.0125	0.0103	0.0051	0.0100
std	0.1070	0.1753	0.1664	0.1857	0.1432
rel. share	0.3651	0.1845	0.2666	0.1838	
rel. earnings	0.8356	0.9298	0.9516	0.9592	
corr (per capita)	0.3295	0.3083	0.3868	0.3862	0.4722
corr (per empl.)	0.1879	0.1406	0.1694	0.1981	0.2280
av. obs.	125.1352	65.1689	93.2625	65.7016	349.2682
Jobfindings	< 180 days	$180 - 365$ days	$365 - 730$ days	> 730 days	*overall* days
mean	0.0896	0.0501	0.0414	0.0368	0.0661
std	0.1268	0.1473	0.1881	0.3145	0.1194
rel. share	0.6664	0.1636	0.1056	0.0644	
corr (per capita)	0.4534	0.1301	0.2985	0.2938	0.4783
corr (per empl.)	0.1538	-0.0125	0.1278	0.1930	0.1536
av. obs.	94.1415	23.5517	15.4566	9.6481	142.7979
Firings	< 365 days	$365 - 730$ days	$730 - 1825$ days	> 1825 days	*overall* days
mean	0.0084	0.0046	0.0026	0.0010	0.0036
std	0.1743	0.1796	0.2375	0.2588	0.1252
rel. share	0.5236	0.1907	0.1867	0.0991	
rel. earnings	0.7190	0.7218	0.7013	0.7567	
corr (per capita)	-0.5051	-0.2938	-0.4658	-0.2228	-0.4523
corr (per empl.)	-0.2119	-0.1883	-0.2304	0.0583	-0.1883
av. obs.	62.2201	23.4874	22.9498	12.5574	121.2147

Notes: The data is for full-time employed males and females for the period $Jan1980 - Sep2004$. The columns contain the bounds of the different tenure groups. The tenure groups are formed for the labor market state before the transition and are given in days. All statistics are computed conditional on being in the respective labor market state and tenure group. *mean* is the average transition probability of the respective labor market transition. *std* is the relative deviation of the transition rate over time. *rel. share* is the average share of transitions falling in this tenure group relative to all transitions. *rel. earnings* are the average relative earnings of all persons with a transition relative to the average earnings in the current labor market and tenure group. *corr* are the respective correlations of the transition rate with GDP per capita respectively per employed as our business cycle measures. *av. obs* are the average number of transitions per month from the respective labor market and tenure group.

Table 26: Transition rates between labor market states for full-time employed workers (males, $Jan1980 - Sep2004$)

Low skilled					
Quits	< 365 days	$365 - 730$ days	$730 - 1825$ days	> 1825 days	*overall* days
mean	0.0139	0.0075	0.0048	0.0026	0.0052
std	0.2230	0.2662	0.2868	0.2192	0.2153
rel. share	0.4326	0.1202	0.1554	0.2918	
rel. earnings	0.8627	0.8543	0.9018	0.9221	
corr (per capita)	0.4247	0.2761	0.4030	0.2111	0.5237
corr (per empl.)	0.1791	0.2280	0.1978	0.2778	0.3490
av. obs.	47.8621	13.2773	16.9000	31.1387	109.1781
Jobfindings	< 180 days	$180 - 365$ days	$365 - 730$ days	> 730 days	*overall* days
mean	0.0649	0.0295	0.0199	0.0091	0.0383
std	0.1882	0.2355	0.2805	0.3561	0.1661
rel. share	0.6829	0.1516	0.1000	0.0655	
corr (per capita)	0.2663	0.3124	0.2151	0.2457	0.3633
corr (per empl.)	0.0185	0.0609	0.0248	0.0207	0.0839
av. obs.	81.1979	17.8317	11.7300	7.8381	118.5978
Firings	< 365 days	$365 - 730$ days	$730 - 1825$ days	> 1825 days	*overall* days
mean	0.0232	0.0087	0.0036	0.0018	0.0060
std	0.2073	0.2910	0.3765	0.3563	0.1703
rel. share	0.6016	0.1166	0.0974	0.1844	
rel. earnings	0.8874	0.8218	0.8465	0.8935	
corr (per capita)	-0.6882	-0.5508	-0.4234	-0.3514	-0.5984
corr (per empl.)	-0.4304	-0.3177	-0.1980	-0.0745	-0.2793
av. obs.	75.9306	15.0722	12.9324	23.4219	127.3572
Medium skilled					
Quits	< 365 days	$365 - 730$ days	$730 - 1825$ days	> 1825 days	*overall* days
mean	0.0208	0.0118	0.0079	0.0037	0.0085
std	0.1277	0.1580	0.1721	0.1471	0.1624
rel. share	0.4341	0.1418	0.1966	0.2274	
rel. earnings	0.8915	0.9170	0.9127	0.8974	
corr (per capita)	0.5791	0.5484	0.5665	0.4810	0.6018
corr (per empl.)	0.2781	0.3503	0.3167	0.3645	0.3256
av. obs.	647.1872	211.5719	290.4672	334.5967	1483.8230
Jobfindings	< 180 days	$180 - 365$ days	$365 - 730$ days	> 730 days	*overall* days
mean	0.1108	0.0495	0.0321	0.0219	0.0718
std	0.1306	0.1373	0.1658	0.1872	0.1111
rel. share	0.7372	0.1356	0.0752	0.0520	
corr (per capita)	0.3058	-0.0359	0.3567	0.4378	0.3410
corr (per empl.)	0.0518	-0.1899	0.0922	0.0681	0.0219
av. obs.	815.0900	151.7632	83.8491	56.4856	1107.1878
Firings	< 365 days	$365 - 730$ days	$730 - 1825$ days	> 1825 days	*overall* days
mean	0.0212	0.0072	0.0038	0.0014	0.0060
std	0.2211	0.3863	0.2747	0.2844	0.1877
rel. share	0.6192	0.1238	0.1345	0.1225	
rel. earnings	0.8590	0.8435	0.8277	0.8458	
corr (per capita)	-0.7940	-0.3993	-0.7192	-0.5472	-0.7833
corr (per empl.)	-0.5095	-0.2512	-0.4274	-0.2547	-0.5107
av. obs.	638.3019	127.5673	141.2551	127.5865	1034.7107
High skilled					
Quits	< 365 days	$365 - 730$ days	$730 - 1825$ days	> 1825 days	*overall* days
mean	0.0159	0.0128	0.0106	0.0052	0.0098
std	0.1123	0.1799	0.1600	0.1913	0.1392
rel. share	0.3342	0.1815	0.2753	0.2089	
rel. earnings	0.8508	0.9325	0.9434	0.9787	
corr (per capita)	0.1991	0.1808	0.3211	0.3557	0.3917
corr (per empl.)	0.1275	0.0630	0.1551	0.1953	0.1910
av. obs.	84.7555	47.5185	71.0302	55.1714	258.4756
Jobfindings	< 180 days	$180 - 365$ days	$365 - 730$ days	> 730 days	*overall* days
mean	0.0888	0.0483	0.0392	0.0324	0.0631
std	0.1495	0.1948	0.2171	0.3761	0.1323
rel. share	0.6627	0.1611	0.1115	0.0647	
corr (per capita)	0.3735	-0.0115	0.2979	0.2346	0.3769
corr (per empl.)	0.0640	-0.0862	0.1272	0.1934	0.0510
av. obs.	53.5241	13.2736	9.3044	5.5077	81.6099
Firings	< 365 days	$365 - 730$ days	$730 - 1825$ days	> 1825 days	*overall* days
mean	0.0075	0.0039	0.0023	0.0009	0.0030
std	0.2034	0.2056	0.2443	0.3211	0.1525
rel. share	0.5127	0.1793	0.1947	0.1133	
rel. earnings	0.7093	0.7202	0.7029	0.8008	
corr (per capita)	-0.4846	-0.2830	-0.3987	-0.2396	-0.4338
corr (per empl.)	-0.1894	-0.1144	-0.1618	0.0362	-0.1365
av. obs.	38.7696	14.1463	15.4448	9.3647	77.7254

Notes: The data is for full-time employed males for the period $Jan1980 - Sep2004$. The columns contain the bounds of the different tenure groups. The tenure groups are formed for the labor market state before the transition and are given in days. All statistics are computed conditional on being in the respective labor market state and tenure group. *mean* is the average transition probability of the respective labor market transition. *std* is the relative deviation of the transition rate over time. *rel. share* is the average share of transitions falling in this tenure group relative to all transitions. *rel. earnings* are the average relative earnings of all persons with a transition relative to the average earnings in the current labor market and tenure group. *corr* are the respective correlations of the transition rate with GDP per capita respectively per employed as our business cycle measures. *av. obs* are the average number of transitions per month from the respective labor market and tenure group.

Table 27: Transition rates between labor market states for full-time employed workers (females, $Jan1980 - Sep2004$)

Low skilled					
Quits	$<$ 365 days	365 − 730 days	730 − 1825 days	$>$ 1825 days	*overall* days
mean	0.0107	0.0057	0.0039	0.0022	0.0042
std	0.1949	0.2655	0.2885	0.2900	0.2055
rel. share	0.4014	0.1285	0.1802	0.2899	
rel. earnings	0.8930	0.8506	0.8737	0.9028	
corr (per capita)	0.1991	0.1295	0.3606	0.1867	0.4182
corr (per empl.)	-0.0023	0.0641	0.1960	0.1664	0.2088
av. obs.	25.3265	7.9807	11.3525	18.3500	63.0097
Jobfindings	$<$ 180 days	180 − 365 days	365 − 730 days	$>$ 730 days	*overall* days
mean	0.0449	0.0222	0.0149	0.0095	0.0281
std	0.1709	0.1942	0.2791	0.4515	0.1548
rel. share	0.6561	0.1770	0.0965	0.0704	
corr (per capita)	0.3515	0.2352	0.3170	0.3653	0.4123
corr (per empl.)	0.0183	0.0934	0.1340	0.1583	0.0570
av. obs.	48.3157	12.9190	6.9710	4.9977	73.2033
Firings	$<$ 365 days	365 − 730 days	730 − 1825 days	$>$ 1825 days	*overall* days
mean	0.0175	0.0073	0.0035	0.0021	0.0053
std	0.1629	0.2253	0.2794	0.2450	0.1211
rel. share	0.5124	0.1260	0.1309	0.2307	
rel. earnings	0.9668	0.8552	0.8356	0.8552	
corr (per capita)	-0.5042	-0.2932	-0.4202	-0.2790	-0.3822
corr (per empl.)	-0.2191	-0.1159	-0.2179	-0.0456	-0.1681
av. obs.	40.3859	9.9306	11.1931	19.1049	80.6144
Medium skilled					
Quits	$<$ 365 days	365 − 730 days	730 − 1825 days	$>$ 1825 days	*overall* days
mean	0.0167	0.0102	0.0078	0.0036	0.0081
std	0.1163	0.1701	0.1879	0.1674	0.1673
rel. share	0.4033	0.1591	0.2500	0.1876	
rel. earnings	0.9145	0.8986	0.8612	0.8651	
corr (per capita)	0.5771	0.6228	0.6710	0.5760	0.7008
corr (per empl.)	0.2204	0.3345	0.3129	0.3307	0.3266
av. obs.	291.4141	115.1827	178.2881	134.6110	719.4960
Jobfindings	$<$ 180 days	180 − 365 days	365 − 730 days	$>$ 730 days	*overall* days
mean	0.0847	0.0421	0.0331	0.0268	0.0598
std	0.1039	0.1041	0.1352	0.2025	0.1002
rel. share	0.6937	0.1641	0.0838	0.0584	
corr (per capita)	0.6008	0.1807	0.4064	0.5198	0.5895
corr (per empl.)	0.2369	0.0628	0.3134	0.2044	0.2252
av. obs.	384.7245	91.7228	47.7336	33.0633	557.2441
Firings	$<$ 365 days	365 − 730 days	730 − 1825 days	$>$ 1825 days	*overall* days
mean	0.0142	0.0061	0.0034	0.0017	0.0051
std	0.1565	0.1479	0.1903	0.1505	0.1079
rel. share	0.5383	0.1491	0.1738	0.1388	
rel. earnings	0.8704	0.8024	0.7703	0.7456	
corr (per capita)	-0.7070	-0.6740	-0.7305	-0.6986	-0.7345
corr (per empl.)	-0.3471	-0.4101	-0.4497	-0.4517	-0.4614
av. obs.	241.6299	67.2226	79.0972	62.7242	450.6738
High skilled					
Quits	$<$ 365 days	365 − 730 days	730 − 1825 days	$>$ 1825 days	*overall* days
mean	0.0165	0.0117	0.0095	0.0046	0.0107
std	0.1420	0.2098	0.2537	0.2998	0.1742
rel. share	0.4611	0.1936	0.2402	0.1051	
rel. earnings	0.8632	0.9171	0.9504	0.8436	
corr (per capita)	0.4274	0.5563	0.4946	0.3078	0.5874
corr (per empl.)	0.2204	0.3195	0.2462	0.1641	0.2764
av. obs.	40.0849	17.8844	22.5298	10.5418	91.0409
Jobfindings	$<$ 180 days	180 − 365 days	365 − 730 days	$>$ 730 days	*overall* days
mean	0.0907	0.0528	0.0453	0.0487	0.0707
std	0.1353	0.1999	0.2507	0.6424	0.1278
rel. share	0.6726	0.1663	0.0973	0.0637	
corr (per capita)	0.4734	0.2526	0.0969	0.1539	0.5210
corr (per empl.)	0.2738	0.1177	0.0325	0.0811	0.2913
av. obs.	40.5999	10.2701	6.1552	4.1436	61.1688
Firings	$<$ 365 days	365 − 730 days	730 − 1825 days	$>$ 1825 days	*overall* days
mean	0.0103	0.0065	0.0034	0.0015	0.0055
std	0.1733	0.2257	0.2826	0.3652	0.1306
rel. share	0.5454	0.2121	0.1720	0.0705	
rel. earnings	0.8114	0.8240	0.7712	0.6307	
corr (per capita)	-0.4134	-0.2501	-0.4152	-0.0378	-0.3596
corr (per empl.)	-0.2082	-0.2540	-0.2747	0.0312	-0.2780
av. obs.	23.5057	9.3485	7.5014	3.1862	43.5418

Notes: The data is for full-time employed females for the period $Jan1980 - Sep2004$. The columns contain the bounds of the different tenure groups. The tenure groups are formed for the labor market state before the transition and are given in days. All statistics are computed conditional on being in the respective labor market state and tenure group. *mean* is the average transition probability of the respective labor market transition. *std* is the relative deviation of the transition rate over time. *rel. share* is the average share of transitions falling in this tenure group relative to all transitions. *rel. earnings* are the average relative earnings of all persons with a transition relative to the average earnings in the current labor market and tenure group. *corr* are the respective correlations of the transition rate with GDP per capita respectively per employed as our business cycle measures. *av. obs* are the average number of transitions per month from the respective labor market and tenure group.