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# Labor Market Rigidity and Business Cycle Volatility

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# Labor Market Rigidity and Business Cycle Volatility

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**Abstract**

In this paper we show empirically and theoretically that institutions which lead to a low average hiring rate simultaneously induce a large volatility in the firing rate. A large volatility in the firing rate translates into more volatility of the unemployment rate, and finally, into an increased vulnerability of the economy to business cycle shocks.
We document empirically that compared to the U.S. hiring rates in Germany are a quarter the size while the firing rate volatility is 2.5 times larger. Firings contribute to 70% of the aggregate unemployment volatility in Germany while in the U.S. hirings explain the bulk of the unemployment volatility. Neither wage rigidities nor employment protection legislation explain these large differences.
We show theoretically within a search and matching model featuring endogenous firings and efficient bargaining that these results are to be expected. Our model is well able to reproduce the time series pattern of labor market variables for both countries. The highlighted mechanism leads to a substantial amplification and propagation effect of business cycle shocks.

JEL: E24, E32

Keywords: Business Cycle Fluctuations, Wages, Unemployment, Endogenous Firing

Are countries with rigid labor markets more or less affected by business cycle shocks? This paper shows, using a search and matching framework, that labor market institutions which lead to low average hiring rates simultaneously generate a large response of the firing rate to business cycle shocks. This inverse relationship constitutes an amplification and propagation mechanism that makes rigid labor markets more vulnerable to the business cycle. Our theoretical mechanism accounts qualitatively and quantitatively for the new empirical finding of this paper that the German unemployment volatility is mainly driven by firings and not by hirings as in the U.S.. We show that alternative explanations relying on rigidity in the wage-setting process or frictions in the firing process are at odds with the empirical evidence.

On empirical grounds the paper contributes to the growing literature on the *'ins'* and *'outs'* in Europe (Petrongolo and Pissarides (2008)) and provides a detailed analysis of labor market flows and earning dynamics for Germany.[1] Compared to the stylized U.S. labor market facts, as stated for example in Shimer (2005), two crucial differences arise for Germany. We observe

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[1]There are two other studies on worker flows in Germany that show a limited amount of overlap with our results. Bachmann (2005) uses a slightly different concept to measure worker flows. He measures worker flows on a monthly frequency but focuses for the dynamics at an annual frequency. However, his results regarding

substantially lower transition rates and a substantially higher firing rate volatility. In Germany firing rates (EU-rates) are lower by a factor of 4 and hiring rates (UE-rates) by a factor of 5. When we look at volatilities, we find the inverse relationship to be true. The German unemployment rate is 1.2 times, the firing rate 2.5 times, and the hiring rate equally as volatile as their U.S. counterparts.

Extending the methodology developed in Fujita and Ramey (2007) and Petrongolo and Pissarides (2008), we document that these volatility differences translate into the surprising result that in Germany, firings contribute to $60-70\%$ of the unemployment volatility, whereas in the U.S. the opposite is true and hirings account for $60-70\%$ of its unemployment volatility. The basic picture does not change even when we control for non-employment flows, education, sex or tenure.

Rigidities in the wage-setting process[2] are not likely to be at the root of these large cross-country differences. In a robust finding using a variety of empirical approaches to control for composition effects[3], we show that German earnings are not rigid and have an elasticity between $0.6-0.8$[4] with respect to productivity both for workers who stay on their jobs as well as for newly employed workers. Our results for Germany are similar to the findings of Haefke et al. (2007) for the U.S. and confirm results in Pissarides (2009) which finds that the co-movement of wages with the business cycle might even be higher in some European countries than in the U.S..

The theoretical contribution of this paper is the linking of empirical cross-country facts to institutional differences within a search and matching framework with endogenous firings similar to Ramey's (2008) and admitting to a closed form solution as in Jung (2008) .

We show theoretically that with endogenous firings the inverse relationship between low average hiring rates and large firing rate volatilities is a general feature of the model. In this model a worker and firm separate if the total surplus of the match becomes negative. Over the business cycle two effects related to labor market institutions govern the reaction of the separation probability to shocks: The first effect is related to institutions that affect the average hiring rate in the economy. A low average hiring rate prevents unemployed workers from quickly participating in boom conditions after a positive business cycle shock. This delayed reaction amplifies the wedge between employed and unemployed workers' job valuation, in addition to amplifying the surplus reaction and therefore tends to increase the reaction of the firing rate to business cycle shocks. The second effect, related to wage-setting institutions, dampens or reinforces the first effect depending on the strength of the bargaining power relative to the match elasticity (*Hosios condition*). The value of having a worker employed compared to the implicit costs of hiring a new worker increases with the bargaining strength of the firm. Over the cycle countries which have a higher bargaining power of firms tend to fire less in booms and more in recessions, making firings become more cyclical. We show that at the efficiency point

average transition rates are consistent with our findings. Gartner et al. (2009) use different definitions for labor market states, for example they do not control for non-employment, so that their results are not comparable to our findings. Most importantly, abstracting from non-employment flows does change the cyclical characteristics of transition rates, as we highlight below.

[2]There is a large body of literature on resolutions of the unemployment volatility puzzle originally recognized by Shimer (2005), Hall (2005) and Costain and Reiter (2005) which relies on arguments of wage rigidities. 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 (2009)).

[3]The importance of composition effects has been documented in Solon et al. (1994) and is extensively discussed in Haefke et al. (2007). We follow the proposed approaches in these papers and the estimation in first differences following Bils (1985) to control for composition effects.

[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.

of the *Hosios condition* the second effect is zero.

Quantitatively we use a method of moment procedure to show that the model is able to reproduce the empirically documented stylized facts for both countries jointly. Once it has been calibrated to match the right macroeconomic elasticities for both countries the model predicts the entire time-series pattern of labor market dynamics in both countries very well. This independent success allows us to identify, based on the structural model, two main labor market institutions likely driving the large cross-country differences: market entry costs and match efficiency.[5] Two other institutions that have been used to explain labor market volatilities within a country, namely the (unionized) wage bargaining mechanism (Shimer (2005)) and the employment protection legislation (Veracierto (2008)) are not likely to be the driving factors behind the empirically observed cross-country volatility differences.

The highlighted differences matter in a quantitative sense. We show that the implied persistence of shocks across the two countries turns out to be substantially different. Five years after a shock hit the economy, the deviation of the unemployment rate from its long-run trend is still twice as large in Germany as in the U.S.. This large difference in the persistence of shocks does not stem from differences in the wage elasticity (which is estimated to be almost identical), but can be traced to the different firing reactions over the cycle. The same institutional difference leading to a large amplification of firings therefore directly translates into a large propagation of shocks. It is this joined amplification and propagation of endogenous firings that makes rigid labor markets much more vulnerable to business cycle shocks.

We proceed in four steps. Section 1 describes the data and documents stylized facts about labor market transitions, studies the cyclical behavior of earnings, and decomposes the unemployment volatility. Section 2 describes and solves our model. In section 3, we provide a calibration for our model that jointly matches Germany and the U.S. and perform the impulse-response analysis. Section 4 concludes the paper. The appendix provides more detailed empirical information on three different subgroups males, females, and education.

# 1 Empirical Facts

We now turn to our discussion of the empirical labor market facts for Germany in comparison to the U.S..

## 1.1 Data description

Our dataset is the IAB employment panel[6] that comprises a 2% representative subsample taken from the German social security and unemployment records for the period from $1980 - 2004$. The sample contains employees that are covered by the compulsory German social security system, and excludes self-employed and civil servants ('Beamte'). It nevertheless 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.[7] We observe the entire employment history of each worker (social security status) on a daily basis. We account explicitly for periods of non-employment and transitions out of the labor force, e.g. (early) retirement or maternity leave. The income reported during one spell of employment is the average daily income of an individual

[5]We measure match efficiency as the deviation of the bargaining power from the *Hosios condition*.

[6]This study uses the factually anonymous BA-Employment Panel (Years $1975 - 2004$). Data access was provided via a Scientific Use File supplied by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB).

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

during the employment spell. We do not observe hours worked, but do observe whether the person is full-time, part-time, or from 1999 on in marginal employment.[8] 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. Using monthly transition rates 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 the same CPI deflator. After 1991, we only observe GDP for unified Germany and we control for the structural break. Productivity measures are obtained by dividing by total employment or total hours worked, as is done by the statistical office. Further details are relegated to the appendix.

## 1.2 Labor market flows

The stylized labor market facts for Germany are highlighted in Table 1 and refer to all workers. In the appendix, we present the flows separated by sex and education. For a better comparison we also present the corresponding U.S. 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 asterix at the non-employment flows indicates that the denominator, which 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 across many dimensions. In particular, firing rates (EU) are highly countercyclical. Hiring rates (UE) are procyclical in

[8] 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.

Table 2: U.S. 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: U.S. 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 $\lambda = 100,000$.

both countries but are considerably more correlated with the cycle in the U.S. than in Germany.[9] Quitting rates, defined as on the job transitions to a new establishment, are highly procyclical in Germany. Employment to non-employment transition rates (EN) are procyclical in both countries and are mirroring the behavior of quits on the job, suggesting that, if anything, they reflect quitting behavior. For the U.S., we do not have equivalent data for quits, but the analysis in Nagypal (2005) suggests that the results for Germany also hold for the U.S.. To illustrate the comovement of quits and EN rates, we plot their cyclical component in figure 0(a). 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. However, the fast that firing rates have a counteracting correlation indicate that quits and EN rates when separated become significantly more acyclical. Lumping all *firm exit* flows into one separation rate leads to the impression that the separation decision is rather acyclical although the underlying economic decisions are in fact different. This becomes apparent when looking at their considerably different cyclical properties. We lack a precise counterpart of the *firm exit* rate for the U.S., given that we do not directly observe quits on the job. If we disregard quits, then *employment exit* rates (the sum of EU and EN) become countercyclical again both in the U.S. and in Germany, although EU and EN rates have opposite correlation signs. Finally, looking at the relative standard deviations, we find for Germany that aggregate output is approximately as cyclical as it is in the U.S..

Despite all of the similarities across countries in the cyclical behavior of labor market transitions, the data shows two fundamental differences between the two countries. First, average transition rates in Germany are substantially lower than in the U.S.. The average hiring rate in Germany is smaller by a factor of 5 and the firing rate by a factor of 4. Second, firing rates

[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.


Figure 1: Labor market cyclicality

Notes: Left panel: The green line denotes the HP-filtered quitting rate and the red line denotes the HP-filtered EN transition rate. Right panel: The green line denotes the HP-filtered unemployment rate and the red line reports the HP-filtered firing rate.

Figure 2: Labor market cyclicality

relative to GDP are 2.5 times and the unemployment rate 1.2 times as volatile as in the U.S. but hiring rates are equally as volatile. At first glance, this observation is puzzling given that there is no direct link between lower mean rates and higher volatilities. We show below that these differences translate into a further surprising finding, which is that German unemployment volatility is mainly driven by variations in firings, explaining between $60-70\%$ of the unemployment volatility, while in the U.S. unemployment volatility is dominated by the behavior of hirings and firings account for only $30-40\%$. Again, this seems puzzling at first glance, given that one probably expected that German employers adjust their labor force by adjusting hirings rather than by adjusting firings over the business cycle.

### 1.3 Unemployment volatility decomposition

Petrongolo and Pissarides (2008) analyze the contribution of job in- and outflow rates to the fluctuations in unemployment for the UK, France, and Spain. Fujita and Ramey (2009) do an analysis for the U.S.. 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 (2008) is based on a first difference filter allowing for four aggregate transition rates whereas Fujita and Ramey (2009) 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 hirings in explaining unemployment volatility, we use the methodology proposed in Fujita and Ramey (2009) but allow for three states with six transition rates. We describe briefly the decomposition in Fujita and Ramey 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 take an approximation made around trend unemployment

$$u_t \approx \frac{\pi_{eu,t}}{\pi_{eu,t}+\pi_{ue,t}} \tag{1}$$

$$\log\left(\frac{u_t}{\bar{u}_t}\right) = (1-\bar{u}_t)\log\left(\frac{\pi_{ue,t}}{\bar{\pi}_{ue,t}}\right) - (1-\bar{u}_t)\log\left(\frac{\pi_{eu,t}}{\bar{\pi}_{eu,t}}\right) + \epsilon_t \tag{2}$$

$$du_t = dUE_t + dEU_t + \epsilon_t \tag{3}$$

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. The decomposition is in terms of relative deviations justifing our focus on relative deviations above.

Fujita and Ramey (2009) 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 $\beta_x = \frac{cov(du_t, d\pi_x)}{var(du_t)}$. Their 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

$$\begin{aligned}
\log\left(\frac{u_t}{\bar{u}}\right) &= \log\left(\frac{\pi_{eu,t}}{\bar{\pi}_{eu}}\right)\lambda_{eu} - \log\left(\frac{\pi_{ue,t}}{\bar{\pi}_{ue}}\right)\lambda_{ue} && (4)\\
&+ \log\left(\frac{\pi_{en,t}}{\bar{\pi}_{en}}\right)\alpha\lambda_{en} - \log\left(\frac{\pi_{ne,t}}{\bar{\pi}_{ne}}\right)(1-\alpha)(\lambda_{ue}+\lambda_{un}-\lambda_{eu})\\
&+ \log\left(\frac{\pi_{nu,t}}{\bar{\pi}_{nu}}\right)\alpha(\lambda_{eu}+\lambda_{en}-\lambda_{ue}) - \log\left(\frac{\pi_{un,t}}{\bar{\pi}_{un}}\right)(1-\alpha)\lambda_{un} + \varepsilon_t\\
du_t &= dEU_t + dUE_t + dEN_t + dNE_t + dNU_t + dUN_t + \varepsilon_t && (5)
\end{aligned}$$

Using again $\beta_x = \frac{cov(du_t, d\pi_x)}{var(du_t)}$ a similar covariance decomposition as in Fujita and Ramey (2009) 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.

Table 3: Unemployment decomposition

| Country | Data | EU | UE | NE | EN | NU | UN | $\varepsilon$ |
|---|---|---|---|---|---|---|---|---|
| Germany | IAB | 0.6073 | 0.3898 | | | | | 0.0030 |
| | IAB | 0.4186 | 0.2498 | 0.2020 | −0.0470 | 0.0678 | 0.1122 | −0.0020 |
| U.S. | 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 (2009)

Based on a two state decomposition the contribution of firing rates account for 60−70% of the volatility, depending on the sample periods used, while in the U.S. it accounts for 30−40%. The robust finding, using a three state decomposition, indicates that German firing rates contribute twice as much to the unemployment volatility as do hiring rates, while in the U.S. the opposite is true. Firing and hiring rates taken together account in both countries for around 70% of the unemployment volatility possibly justifying the focus on a two-state decomposition. Figure 0(b) visualizes the close connection between firings und unemployment in Germany by plotting the HP-filtered firing rate against the cyclical component of the unemployment rate. It is evident that the firing rate leads the unemployment rate by one quarter but is otherwise almost perfectly correlated with the unemployment rate.

[10] The formula is similar to the first difference filter obtained in Petrongolo and Pissarides (2008), 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 note that the decomposition does not rely on knowing the state of non-employed workers, which is not available for Germany but that only the (gross) flows are needed. A derivation is available upon request.

For some datasets the way of detrending is not innocent 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. The appendix provides a sensitivity check with respect to the first difference filter of Petrongolo and Pissarides (2008) and also gives the results for different education groups, different sample periods and separated by sex. The contribution rates are very stable across groups with a lower bound on the contribution of firings in Germany of 47% for low educated workers.

### 1.4 Earnings

We have shown that the Germany labor market has a lot of cyclical variation in some cases even more than in the U.S.. To generate labor market cyclicality in search and matching models, the rigidity of wages has been identified as an important margin to amplify the reaction of labor market variables to business cycle shocks. This section provides evidence that earnings in Germany are clearly not sticky when compared to available evidence for the U.S..[11] From our empirical estimates we conclude that the observed differences in labor market volatilities can not be attributed to a lower wage/earnings elasticity in Germany. This finding is in line with a recent survey by Pissarides (2009) for other European countries.

Table 1 shows that German median earnings are already tightly connected to aggregate productivity measures. However, the cyclicality of aggregate statistics can be substantially biased due to composition effects in the labor force over the business cycle 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 in order 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. In our dataset we identify ongoing job relations that exist not just on a year-to-year basis but over the whole sample period. This constitutes a particularly homogeneous subpanel of workers, namely those who had a job in 1975 and were continuously employed full-time at the same firm until 2004. In other words, for this non-representative group, we ensure that no quit and no firing happened during their entire work experience or in any non-employment spell.[12] For this group we only have earnings information at annual frequency, and in contrast to some of the business cycle literature, we have to move to annual frequency. However, the annual frequency might actually be the more natural frequency given that bonuses and special payments are not typically paid out quarterly, and that, at least in models with risk-neutral agents, the precise timing of the payment is undetermined. 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, concerns regarding job quality over the cycle raised by Gertler and Triagari (2009).

As a second correctional approach, we follow Bils (1985) and estimate individual wage growth equations using first differences to control for individual specific fixed effects. This

[11] 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 the hours worked per person employed do not vary much with the cycle. Other studies for the U.S. have provided evidence that earnings and wage cyclicality are quantitatively close (see Haefke et al. (2007)). We will therefore in the following discussion repeatedly refer to studies that consider wages instead of earnings.

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

approach might be restrictive if only a short panel dimension is available. In particular, we do not observe the last earnings of unemployed workers are unobserved. We overcome this problem by exploiting our long panel dimension. We keep track of last earnings of unemployed workers and use them 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 for 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. The estimates can be found in Table 4.

Although, the panel dimension of our dataset allows us to overcome missing pre-employment earnings for jobfinder, there might still be concerns 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 3. Table 4 summarizes the estimation results. The details of the estimation procedures and an extensive sensitivity check can be found in the appendix.


Figure 3: 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 $Jan1980 - Sep2004$.

From Table 4 we see that earnings and productivity are tightly connected. For continuously employed workers, the elasticity estimate is between $0.62 - 0.74$. 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 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

Table 4: 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.

confirming that the earnings elasticity on productivity (or other aggregate measures) is between $0.6 - 0.8$. In the model, we calibrate to the upper bound of the estimated elasticities for both countries. For the U.S., we take estimates from Haefke et al. (2007). They report estimates for earnings elasticities in the range of $0.4 - 0.8$.

### 1.5 Tenure

Stronger employment protection in Germany compared to the U.S. is commonly offered as an explanation for the substantially lower average firing rates. The high employment protection in Germany is fairly uncontroversial and can for example be read off the employment protection index by Allard (2005). Higher employment protection increases adjustment costs for firms, and we might therefore expect that firms would abstain from using firings when it comes to adjusting their workforce. Hence, if differences in employment protection were the explanation for the empirical differences between Germany and the U.S., then we should find a contribution of firings to unemployment volatility that is lower in Germany than in the U.S.. However, this is contradicted by to the empirical evidence. The decomposition analysis above shows that firings are more important when explaining the unemployment volatility in Germany. Thereby, this finding provides a first piece of evidence that employment protection is not likely to be at the root of the cross-country differences. However, the employment protection legislation could also induce a nonlinear composition effect forcing firms to adjust by firing only low tenured workers. Although the majority of firings is indeed for low tenured workers, we show that the business cycle behavior seems to be uniform across all tenure groups. In Table 5, we distinguish labor market flows by tenure[13]. The table shows that most firings occur for low tenured workers (*rel. share*). This finding is in line with less employment protection for low tenured workers and aligns with the firing probability for low tenured workers, which is 12 times higher than for high tenured workers. However, if we look at the volatilities, we find them to be increasing with tenure, so that high tenured workers have a 1.2 times more volatile firing rate. Higher employment protection for these workers suggests the opposite relationship. Hence, both statistics show that employment protection is likely to not be at the root of the cross-country differences.

The lower part of Table 5 reports the results for quits on the job and EN transitions. We see the same overall pattern for mean transition rates, but more importantly the transition rates are always positively correlated with the business cycle, showing that we are not misspecifying some firings as quits or EN transitions, which might be of particular concern for short employment spells.

[13] For this analysis, we focus only on full-time employed workers.

Table 5: Tenure on the job

| Firings | $< 365$ days | $365-730$ days | $730-1825$ days | $> 1825$ days | overall |
|---|---|---|---|---|---|
| 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 | |
| corr (GDP) | -0.7727 | -0.7308 | -0.7195 | -0.5574 | -0.7616 |
| corr (Productivity) | -0.4650 | -0.4644 | -0.4213 | -0.2546 | -0.4739 |
| Quits | $< 365$ days | $365-730$ days | $730-1825$ days | $> 1825$ days | overall |
| 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 | |
| corr (GDP) | 0.5595 | 0.5568 | 0.6053 | 0.5149 | 0.6345 |
| corr (Productivity) | 0.2545 | 0.3261 | 0.3104 | 0.3580 | 0.3312 |
| EN | $< 365$ days | $365-730$ days | $730-1825$ days | $> 1825$ days | overall |
| mean | 0.0246 | 0.0088 | 0.0066 | 0.0046 | 0.0092 |
| std | 0.0572 | 0.0760 | 0.0744 | 0.0648 | 0.0675 |
| rel. share | 0.5138 | 0.1040 | 0.1537 | 0.2285 | |
| corr (GDP) | 0.2980 | 0.1853 | 0.2898 | 0.0437 | 0.6017 |
| corr (Productivity) | 0.1238 | 0.4771 | 0.5224 | 0.2798 | 0.4676 |

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. *corr* are the respective correlations of the transition rate with GDP per capita respectively per employee as our business cycle measures.

# 2 Model

The empirical analysis has highlighted important features of the German labor market, most importantly, the cyclical variation in the firing rate and the large contribution to the dynamics of the unemployment rate. To account for these empirical observations within a stylized labor market model, we present a simple search model that features endogenous firings. The model is simple enough to derive the business cycle dynamics in closed form, yet rich enough to work out the basic mechanism that links mean hiring rates to firing rate volatilities.

**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 or are unemployed. At the beginning of each period, the aggregate state of the economy is given by the current technology state $A \in \mathbb{R}_+$ following a Markov process. Workers who are currently in a match relation bargain jointly and efficiently over the wage and the separation decision for the next period. If the bargaining is successful, they produce output according to the linear production technology $y = A$ where the aggregate technology $A$ is assumed to evolve exogenously and common to all matches.

At the end of the period, the firm receives an idiosyncratic cost shock $\varepsilon$ where $\varepsilon$ is an i.i.d. random shock logistically distributed with mean zero and variance $\frac{\pi^2}{3}\psi^2$. The firm has to pay the costs only if it wishes to continue the production process. The costs are sunk after the 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 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 $\tau$

to the government[14] 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 a probability of $\pi_{ue}$ and become employed, with probability of $(1-\pi_{ue})$ they remain unemployed and keep on searching. While unemployed they receive unemployment benefits $b$.

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

$$J(A) = A - w(A) + \Big((1 - \pi_{eu}(A))\beta\mathbb{E}\left[J(A')\right] - \pi_{eu}(A)\tau + \Psi(A)\Big) \tag{6}$$

The firing probability $\pi_{eu} : \mathbb{R}_+ \to [0,1]$ and the option value[15] $\Psi : \mathbb{R}_+ \to \mathbb{R}_+$ follow directly from the assumption of a logistically distributed random variable

$$\Psi(A) = -\psi\Big((1 - \pi_{eu}(A))\log(1 - \pi_{eu}(A)) + \pi_{eu}(A)\log(\pi_{eu}(A))\Big) \tag{7}$$

$$\pi_{eu}(A) = \left(1 + \exp\left(\frac{\bar{\omega}(A)}{\psi}\right)\right)^{-1} \tag{8}$$

**Worker's surplus:** The value flows of employed workers $V_e : \mathbb{R}_+ \to \mathbb{R}$ and unemployed workers $V_u : \mathbb{R}_+ \to \mathbb{R}$ are given by

$$V_e(A) = w + (1 - \pi_{eu}(A))\beta\mathbb{E}\left[V_e(A')\right] + \pi_{eu}\beta\mathbb{E}\left[V_u(A')\right] \tag{9}$$

$$V_u(A) = b + \pi_{ue}(A)\beta\mathbb{E}\left[V_e(A')\right] + (1 - \pi_{ue}(A))\beta\mathbb{E}\left[V_u(A')\right] \tag{10}$$

and the worker's surplus becomes

$$\Delta(A) = V_e(A) - V_u(A) \tag{11}$$

**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 unemployed workers is denoted by $u$ and the resulting matches by $m$. $\varkappa$ denotes a scaling parameter of the matching function.

$$m = \varkappa v^{1-\varrho} u^{\varrho} \tag{12}$$

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

$$\pi_{ue} = \frac{m}{u} = \varkappa x^{1-\varrho} \tag{13}$$

[14] Note that $\tau$ 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 formally specify governmental behavior.

[15] The term $\Psi$ captures the option value of having the choice to continue the match and is always positive. The reason is that although the idiosyncratic shock has an unconditional mean of zero the manager will only continue if the continuation value is positive. The payoff resembles the payoff profile of an option and therefore increases in the variance $\psi$ of the shock.

and the probability that a firm will fill its vacancy is given by

$$\pi_{ve} = \frac{m}{v} = \varkappa x^{-\varrho} \tag{14}$$

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

$$\kappa = \pi_{ve}\beta\mathbb{E}\left[J(A')\right] \tag{15}$$

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

$$(w, \bar{\omega}) = \arg\max_{w,\bar{\omega}} \mu \log\left(\Delta(A)\right) + (1-\mu)\log(J(A)) \tag{16}$$

where $\mu$ denotes the bargaining power of the worker. First order conditions deliver

$$\begin{aligned} \bar{\omega}(A) &= \beta\mathbb{E}\left[\Delta(A') + J(A')\right] + \tau \\ \frac{\mu}{1-\mu} &= \frac{\Delta(A)}{J(A)} \end{aligned} \tag{17}$$

**Law of Motion:** Technology evolves exogenously according to

$$A = \exp(a) \tag{18}$$
$$a' = \rho a + \eta' \tag{19}$$

where $\rho$ denotes the autocorrelation coefficient.

## 2.1 Basic results

All choices in the model are 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:***

$$\sigma_H = \left(1 - \beta\rho(1 - \bar{\pi}_{ue} - \bar{\pi}_{eu}) + \bar{\pi}_{ue}\beta\rho\left(\frac{\mu - \varrho}{\varrho}\right)\right)^{-1} \tag{20}$$

***Firing:***

$$\frac{\sigma_{eu}}{\bar{\pi}_{eu}} = -(1 - \bar{\pi}_{eu})\frac{\rho\beta}{\psi}\sigma_H \tag{21}$$

***Tightness:***

$$\frac{\sigma_x}{\bar{x}} = \frac{\rho}{\varrho}\frac{\sigma_H}{\bar{H}} \tag{22}$$

***Hiring:***

$$\frac{\sigma_{ue}}{\bar{\pi}_{ue}} = (1 - \varrho)\frac{\sigma_x}{\bar{x}} \tag{23}$$

***Wage setting:***

$$\sigma_w = \mu\sigma_H \left(1 - \beta\rho(1 - \bar{\pi}_{ue} - \bar{\pi}_{eu}) + \beta\rho\bar{\pi}_{ue}\frac{1-\varrho}{\varrho} - \bar{\pi}_{eu}(1 - \bar{\pi}_{eu})\beta\frac{\bar{H}}{\psi}\right) \tag{24}$$

***Volatility of the unemployment rate:***

$$\begin{aligned} var(\hat{u}) &= \frac{z_2^2}{1-z_1^2}\,\frac{1+\rho z_1}{1-\rho z_1} var(a) \\ z_1 &= 1 - \bar{\pi}_{ue} - \bar{\pi}_{eu} \\ z_2 &= \sigma_{eu}(1-\bar{u}) - \sigma_{ue}\bar{u} \end{aligned} \tag{25}$$

The proof is straightforward and therefore omitted. As the labelling suggests, the absolute value 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

$$\tilde{\sigma}_x := \frac{\sigma_x}{\bar{x}} \tag{26}$$

## 2.2 Discussion

Proposition 1 provides analytic expressions for the firing and hiring volatility as well as the implied expression for the unemployment rate volatility. This allows us to discuss the effects of observed mean differences on differences in labor market volatilities.

### 2.2.1 Unemployment volatility

Equation (25) 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.[16] If we approximate $\rho \approx 1$, then we obtain a formula for the reaction of the unemployment rate to business cycle shocks

$$\tilde{\sigma}_u = (1-\bar{u})\left(\tilde{\sigma}_{eu} - \tilde{\sigma}_{ue}\right) \tag{27}$$

The formula makes clear that one should compare the variances[17] of the log-rates, not the variances of the rates itself. To demonstrate this, consider two countries facing the same mean unemployment rate, but whose hiring and firing rates are scaled by a fixed factor in one of the countries. If these countries share the same firing and hiring rate volatilities measured in percentage deviations, then their unemployment dynamics (either in logs or in levels) over the cycle will be identical given that they have the same steady state unemployment rate. Furthermore the contributions of hirings and firings to unemployment dynamics would be identical across countries. However, if both countries would share the same volatilities in absolute terms, then

[16] 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.

[17] Remember, that we have to take the absolute value of the coefficients to obtain the standard deviation of unemployment relative to GDP, i.e.

$$|\tilde{\sigma}_u| = (1-\bar{u})\left(|\tilde{\sigma}_{eu}| + |\tilde{\sigma}_{ue}|\right)$$

The formula has an upward bias because we set $\rho \approx 1$.

the unemployment dynamics would be substantially different, given that the mean rates differ by a fixed factor. Analyzing the dynamics in relative terms avoids, therefore, having our results be mechanically driven by lower transition rates in Germany.

All empirical counterparts of the variables in equation (25) can be directly read off of Tables 1 and 2. We use this fact to identify the main drivers behind unemployment volatility by conducting a series of three comparative statics experiments. This analysis complements the empirical decomposition of the unemployment volatility by demonstrating that it is indeed the higher firing rate volatility rather than the lower mean rates that explains the large contribution of firings to the dynamics of unemployment.

Table 6: Unemployment volatility in the benchmark model

| | $\bar{\pi}_{eu}$ | $\bar{\pi}_{ue}$ | $\tilde{\sigma}_{eu}$ | $\tilde{\sigma}_{ue}$ | $\bar{u}$ | $\tilde{\sigma}_u$ | $\tilde{s}_u$ | $1 - \tilde{\sigma}_u/\tilde{s}_u$ |
|---|---|---|---|---|---|---|---|---|
| Germany | 0.0053 | 0.062 | $-6.20$ | 4.30 | 0.079 | 8.25 | 7.06 | $-16\%$ |
| US | 0.020 | 0.31 | $-2.48$ | 4.27 | 0.062 | 6.12 | 5.72 | $-7\%$ |

Notes: In columns $1-4$ the table reports the data equivalents to the respective model variables, and column 5 gives the model prediction for the mean unemployment rate. Column 6 reports the relative standard deviation of the unemployment rate to the standard deviation of the productivity process in the model ($\tilde{\sigma}_u$). Column 7 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 compared to the data, the fit is quite accurate. This shows that 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

| | $\bar{\pi}_{eu}$ | $\bar{\pi}_{ue}$ | $\tilde{\sigma}_{eu}$ | $\tilde{\sigma}_{ue}$ | $\bar{u}$ | $\tilde{\sigma}_u$ | $\tilde{\sigma}_u^*$ | $1 - \tilde{\sigma}_u/\tilde{\sigma}_u^*$ |
|---|---|---|---|---|---|---|---|---|
| Experiment 1: *Role of separations* | | | | | | | | |
| Germany | 0.0053 | 0.062 | **0** | 4.30 | 0.079 | 3.40 | 8.25 | 60% |
| US | 0.02 | 0.31 | **0** | 4.27 | 0.062 | 3.90 | 6.12 | 37% |
| Experiment 2: *Role of means* | | | | | | | | |
| Germany | **0.02** | **0.31** | $-6.20$ | 4.08 | **0.062** | 9.51 | 8.25 | $-15\%$ |
| US | **0.0053** | **0.062** | $-2.48$ | 4.27 | **0.079** | 5.31 | 6.12 | 14% |
| Experiment 3: *Role of standard deviations* | | | | | | | | |
| Germany | 0.0053 | 0.062 | $\mathbf{-2.48}$ | **4.27** | 0.079 | 5.31 | 8.25 | 35% |
| US | 0.020 | 0.31 | $\mathbf{-6.20}$ | **4.30** | 0.062 | 9.51 | 6.12 | $-55\%$ |

Notes: In columns $1-4$ the table reports the data equivalents to the respective model variables, and column 5 gives the model prediction for the mean unemployment rate. Column 6 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 7 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 conducted by Shimer (2005). We set firing volatilities to zero and compare the predicted unemployment volatilities of the model with the constant firing rates to our benchmark model. The results align very well with our empirical estimates from section 1.3. We find that for Germany, firings are more important than hirings, and that firing volatility quantitatively explains around 60% of the unconditional standard deviation of the unemployment rate. For the U.S., 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 U.S. 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.

Finally 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 35% short of the benchmark economy, whereas for the U.S. the unemployment volatility is 55% too high compared to the benchmark model. Hence, the fact that mean rates, and therefore, steady states across countries are substantially different can not explain the differences in the unemployment reaction, but instead it is the differences in the volatilities that explain these observed differences.

It is important to recall that during these experiments we kept the volatilities constant while changing the means. However, we show in the next section that as soon as we impose equilibrium restrictions, this ceteris paribus assumption is violated.

### 2.2.2 Firing volatility

Formula (21) provides an expression for the firing volatility. To simplify the analysis, we drop quantitatively negligible 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

$$\begin{aligned} \frac{\tilde{\sigma}_{eu}^{Ger}}{\tilde{\sigma}_{eu}^{US}} &= \frac{\psi^{US}}{\psi^{Ger}} \frac{\sigma_H^{Ger}}{\sigma_H^{US}} \\ &= \frac{\psi^{US}}{\psi^{Ger}} \frac{\bar{\pi}_{eu}^{US} + \bar{\pi}_{ue}^{US} + \bar{\pi}_{ue}^{US}\left(\frac{\mu^{US}-\varrho}{\varrho}\right)}{\bar{\pi}_{eu}^{Ger} + \bar{\pi}_{ue}^{Ger} + \bar{\pi}_{ue}^{Ger}\left(\frac{\mu^{Ger}-\varrho}{\varrho}\right)} \end{aligned} \tag{28}$$

We see that if we 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

$$\frac{\tilde{\sigma}_{eu}^{Ger}}{\tilde{\sigma}_{eu}^{US}} = \frac{\bar{\pi}_{eu}^{US} + \bar{\pi}_{ue}^{US}}{\bar{\pi}_{eu}^{Ger} + \bar{\pi}_{ue}^{Ger}} \approx \frac{\bar{\pi}_{ue}^{US}}{\bar{\pi}_{ue}^{Ger}} \approx 5 \tag{29}$$

However, equation (28) uncovers the basic mechanism that maps differences in average hiring rates[18] into differences in firing volatilities across countries. The intuition for the link is straightforward: A business cycle shock of the same size affects the match surplus in Germany more than in the U.S. ($\sigma_H^{Ger} > \sigma_H^{US}$). To understand this, consider a positive shock in both countries and a currently unemployed worker. In Germany, it takes her —due to the lower hiring rate— much longer to find a new job. As a consequence, she benefits much later from booming conditions. Relative to her an employed worker benefits immediately because she can demand a higher wage. This implies a stronger increase of the worker's surplus $\Delta$ in Germany relative to the U.S. where the unemployed worker benefits much earlier from the booming conditions. Since the worker's surplus enters total surplus $H$, the total surplus of a match increases and it

[18]Note that average firing rates are a factor of 15 smaller than average hiring rates and their impact on the ratio is negligible, so we can focus in our discussion on differences in the average hiring rates.

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 a large class of models with search frictions, which explains the inverse relationship between transition rates and volatilities that we document empirically in section 1.

In fact, lower hiring rates alone would generate too much firing volatility. But as expression (28) makes clear, the difference of the bargaining power from the efficiency point of the *Hosios condition* can dampen the reaction of the mean-volatility channel. If the bargaining power of the worker is larger than the match elasticity, the value of having a filled position increases and the firm is more reluctant to fire. This second effect —related to the firm's bargaining power— counteracts the first effect. It is zero at the *Hosios condition*.

Formula (28) together with the joined differences in average hiring rates and volatilities in firing rates uncover also a first institutional difference across the U.S. and Germany. To align the difference in the hiring rates with the difference in the volatilities, the bargaining power of the worker must be lower in the U.S. ($\mu^{US} < \mu^{Ger}$). Other labor market institutions do not enter the formula directly but only trough their effect on the mean rates. Hence, through this channel any labor market policy that affects mean hiring rates will affect the firing rate volatility and ultimately translate into higher unemployment volatility as can be seen from equation (25).

### 2.2.3 Hiring volatility

Using equation (23) and $1 - \pi_{eu} \approx 1$, we can derive the following expression for the ratio of cross-country hiring volatilities

$$\frac{\tilde{\sigma}_{ue}^{Ger}}{\tilde{\sigma}_{ue}^{Ger}} = \frac{\psi^{Ger}}{\psi^{US}} \frac{\bar{H}^{US}}{\bar{H}^{Ger}} \frac{\tilde{\sigma}_{eu}^{Ger}}{\tilde{\sigma}_{eu}^{US}} \tag{30}$$

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

$$\frac{\bar{H}^{Ger}}{\bar{H}^{US}} \approx 2.5 \frac{\psi^{Ger}}{\psi^{US}} \tag{31}$$

The cross-country difference reveals that if there is not much difference in the variance of the idiosyncratic shocks, then the average surplus in Germany must be substantially higher than in the U.S.. However, this would lead to the counterfactual result that average hiring rates —being proportional to the surplus via the free entry condition— would be higher in Germany, not lower by a factor of 4. To reconcile the model with the data, entry costs in Germany must be substantially higher. Thereby, the cross-country moment restriction uncovers a key institutional difference between the U.S. and Germany.

Finally note, that the model still demands a small surplus for newly hired workers to match the hiring rate volatility within a country. In particular, the surplus equation (20) shows that a model with endogenous firings generates an identical surplus response as does a model with exogenous firings up to a first order approximation, so the endogeneity of firings itself has no bearing on the resolution of the basic hiring rate volatility puzzle discussed between Shimer (2005) and Hagedorn and Manovskii (2008), yet it is an indispensable mechanism in explaining unemployment volatilities at least for Germany.

## 3 Calibration

Our basic time period is one month and we aggregate to quarterly rates when simulating the model. For both countries we target 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 two stylized differences in average rates across countries we want to match. These are the average hiring rates that differ by a factor of 5 and the average firing rates that differ by a factor of 4. This imposes the following cross-country restrictions

$$\frac{\bar{\pi}_{ue}^{US}}{\bar{\pi}_{ue}^{Ger}} \approx 5 \qquad \frac{\bar{\pi}_{eu}^{US}}{\bar{\pi}_{eu}^{Ger}} \approx 4 \tag{32}$$

**Standard deviations:** There are two stylized facts about the second moments across countries that we want to match. These are the standard deviation of the firing rate and the hiring 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.

$$\frac{\tilde{\sigma}_{eu}^{Ger}}{\tilde{\sigma}_{eu}^{US}} \approx 2.5 \qquad \frac{\tilde{\sigma}_{ue}^{Ger}}{\tilde{\sigma}_{ue}^{US}} \approx 1 \tag{33}$$

**Wage elasticity:** Finally, we calibrate to an equal wage elasticity across countries that we set to $\tilde{\sigma}_w = 0.8$. A common elasticity estimate implies that our findings will not be driven by differences in wage rigidity. This number is in line with our estimates for Germany and the estimate of Haefke et al. (2007) for the U.S..[19]

Table 8: Calibration

| *Parameter* | *homogeneous types* *Germany* | *US* | *Target (Ger,US)* | *Source* |
|---|---|---|---|---|
| $\beta$ | 0.997 | | Annual real rate of 4% | |
| $\varkappa$ | 0.2 | | Normalization | |
| $\varrho$ | 0.5 | | Matching elasticity | Petrongolo |
| $\rho$ | 0.975 | | Kalman estimates | Solow Residual |
| $\psi$ | 0.92 | 1.06 | $\bar{\pi}_{eu} = (0.0053, 0.02)$ | Data |
| $\kappa$ | 0.38 | 0.06 | $\bar{\pi}_{ue} = (0.0622, 0.3069)$ | Data |
| $\tau$ | 3.52 | 3.4 | Rel. std $\pi_{eu}$ | see table 7 |
| $b$ | 0.96 | 0.96 | Rel. std $\pi_{ue}$ | see table 7 |
| $\mu$ | 0.54 | 0.27 | Wage elasticity (0.8, 0.8) | Data |

Notes: This table documents our chosen parameters. We allow five parameters to differ across countries to target the five differences identified in the main text.

## 3.1 Results

There exists an equilibrium that jointly matches all targets in both countries. Table (8) shows our chosen parameters and the matched moments. The model demands a small surplus from opening a position, implying a very high outside option $b$ for both countries which is almost identical. Note that $b$ should not be interpreted as unemployment benefits, but as the average drop in consumption between employment and unemployment.[20] The calibration yields a reasonable institutional mix to explain the cross-country differences. We get a substantially higher bargaining power ($\mu^{Ger} > \mu^{US}$) and higher costs to open a position ($\kappa^{Ger} > \kappa^{US}$). Firing costs are calibrated to be slightly higher in Germany ($\tau^{Ger} > \tau^{US}$) and amount to an average of 3.5

[19]It turns out, quantitatively, that the particular number chosen has almost no bearing on the results, with the condition that it naturally has to be smaller one.

[20]Hall and Milgrom (2008) provide a different rational by reinterpreting the outside option.

monthly wage payments but are overall rather similar. The idiosyncratic productivity risk is higher in the U.S. ($\psi^{US} > \psi^{Ger}$). The discussion above and the calibrated parameters uncover that the main difference across countries must be due to differences in entry costs and in the efficiency position measured as deviation from the *Hosios condition*. Note that in our formulation $\kappa$ captures vacancy posting cost. However, all differences in fixed costs across countries, such as for example training costs, bureaucratic costs in the hiring process or administrative costs, could be summarized in this number.

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.[21] Figures 4 and 5 graphically illustrates the success of the model.

(a) Unemployment rate (b) Firings (c) Earnings (d) Hirings

Figure 4: 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.

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 U.S. is not very reliable and faces the same composition effects as discussed in section 1.4, it is not clear whether the mismatch is exclusively a model problem or partly a data problem as 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.

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

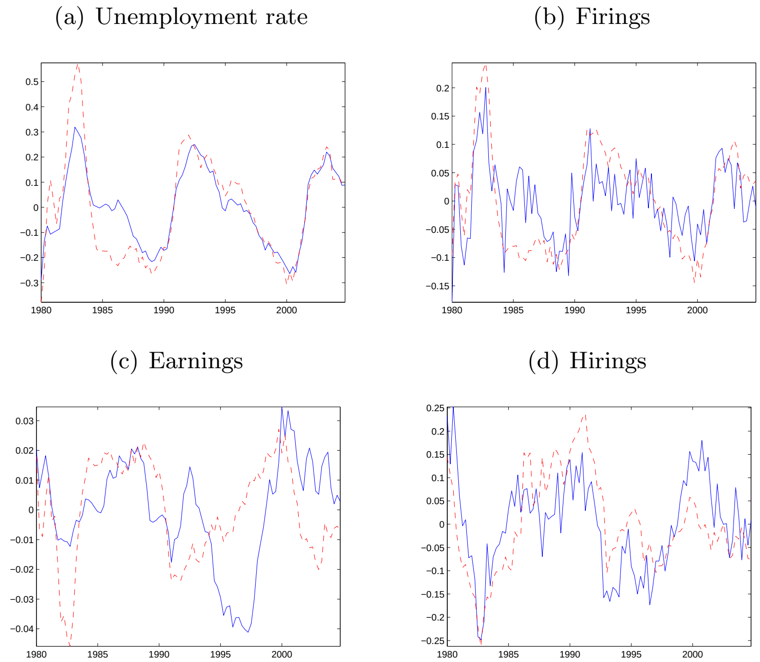


Figure 5: Prediction for the U.S.

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 U.S. are from the Bureau of Labor statistics. Labor market transitions are taken from Shimer (2005).

The correlation between vacancies and unemployment becomes counterfactually positive in the model. If a bad shock hits the economy, the unemployment pool suddenly becomes large and it is attractive to post vacancies. This effect induces a positive correlation between vacancies and unemployment. As a consequence the *Beveridge curve* gets destroyed. In an earlier working paper version, we showed that quits on the job can easily resolve the problem due to the fact that the pool of searching workers remains large.[22] However, the main channel we wish to stress in this paper is unaffected by the introduction of quits on the job.[23]

## 3.2 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 ourselves about the transmission of business cycle shocks into the labor market. As Figure 6 makes clear, the impulse-response functions for the unemployment rate after a large shock ($-5\%$) are substantially different between Germany and the U.S..

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 U.S. 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 hiring rate reacts very similarly (see figure 5(d)). The margin that explains the large differences is firings.

[22] This point was noticed and discussed extensively by Ramey (2008).

[23] Results for a version of the model with heterogeneous types of workers and quits on the job are available upon request.

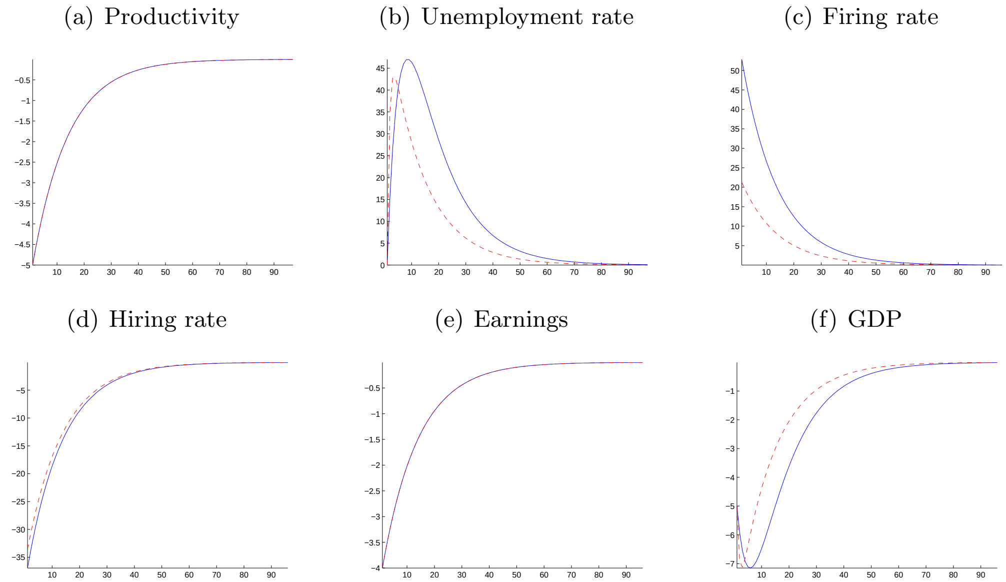


Figure 6: Impulse response functions

Notes: The figure plots the impulse response functions for the U.S. (red dotted lines) and Germany (blue solid line).

We see that the firing rate reacts significantly more strongly in Germany than in the U.S. after the shock. The amplification effect of the firing volatility increases the initial impact of the shock in Germany. If we want the same unemployment response on impact in both countries, we have to scale down the business cycle shock in Germany by 12%.

Figure 5(b) highlights the propagation effect of endogenous firings. We see the striking difference in the persistence of the unemployment rate after a business cycle shock. According to our model, the U.S. reacts without much delay but also recovers fairly quickly, while Germany reacts slowly but is likely to suffer 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 U.S. is only 12% away[24]. This is a pattern that can also be found in the data after the large oil price shocks at the beginning of the 1980s.

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 itself but the interplay with the more rigid labor market. From this finding, we conclude that it is the coexistence of low transition rates, high volatilities, and long persistence that makes rigid labor markets so vulnerable to business cycle shocks.

# 4 Conclusion

In this paper, we document that the U.S. and the German labor market share many similarities in their dynamics over the business cycle. We find that many of the stylized facts for the U.S. also hold for Germany; however, two crucial differences arise: (*i*) lower average hiring rates and (*ii*) a higher firing volatility that constitutes the major driving force behind unemployment volatility. We show that there exists an equilibrium relation between the two facts. Institutions that lower average hiring rates induce an increase in the firing and also the unemployment rate

[24]Note that due to amplification, the initial difference was less than 5%. The propagation effect is at the same order of magnitude if we control for the amplification effect in Germany and rescale the initial shock.

volatility.

We show that the cross country differences matter in a quantitative sense. Shocks in Germany are considerably amplified (+12%) and are substantially more persistent than in the U.S. (twice as large 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 U.S.. Viewed through the lens of a search and matching framework, there exists no mean-variance trade-off between average hiring rates on the one hand and business cycle vulnerability on the other.

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# A Data

## A.1 Data description

The data is taken from the IAB regional files that cover the period of January 1975 to December 2004. The data consists of employment records of workers that have been employed for at least one day 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 therefore does 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 five 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[25] ($14,490$ 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, either due to a quit and a move to a new firm, or the beginning 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 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 simultaneously employed full-time and part-time, 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 simultaneously employment and unemployment spells, we label the employment spells as primary to be consistent with the procedure in the next step of determining the employment status.[26]

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 trumps 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

[25] stib information missing.

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

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 the 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 which 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, or 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 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 9 gives an overview of the different non-employment states in our analysis.

Table 9: Description of non-employment states

| status | definition |
|---|---|
| retirement | age $\geq$ 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 |

## 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, such as 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[27]. 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.

[27]The working period is not adjusted for weekends or holidays.

### 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 the 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 in 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 U.S. 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 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 a monthy frequency using the X-12 ARIMA method. We also perform the default outlier correction implemented in X-12 ARIMA.

## B Sensitivity

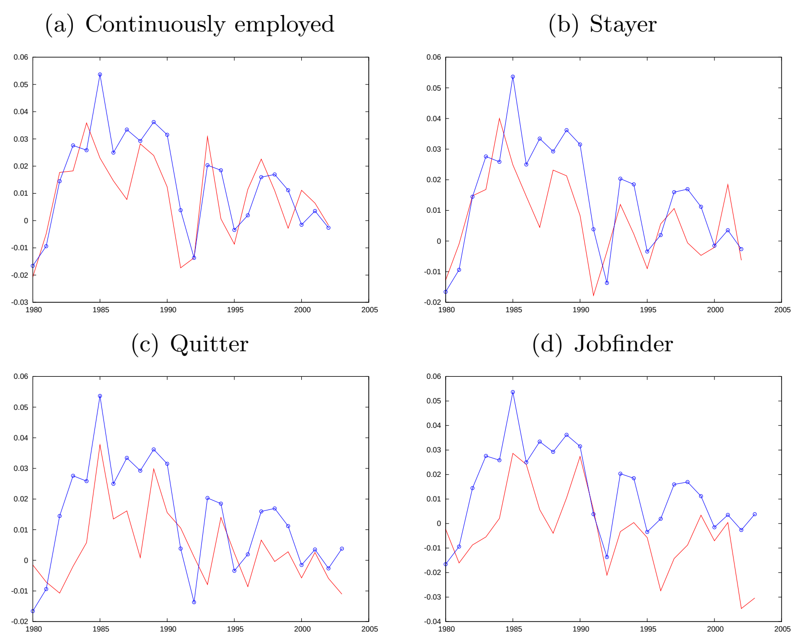
We provide labor market transition rates by sex and education groups and earnings cyclicality measures for different subgroups and time periods. For the unemployment fluctuations we perform the decomposition based on a first difference filter as derived in Petrongolo and Pissarides (2008). The first difference filter for the case including non-employment does not allow the separation of the contributions of EN and NU flows from 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 10: 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-filtered 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, or the state of non-employed workers is problematically measured given that we do not have the corresponding universe of those non-employed workers who are searching. We partially control for this by dropping early retired workers and only look at workers who will eventually return to the labor market in our sample period. The log volatility measures might be less affected by this problem.

Figure 7: Earnings cyclicality and GDP per capita




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

Table 11: 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 have been calculated by the authors. The asterix at the non-employment flows indicate that the denominator, or the state of non-employed workers has been problematically measured given that we do not have the corresponding universe of searching non-employed. We partially control for this by dropping those who have retired early and only look at workers that will eventually return to the labor market in our sample period. The log volatility measures might be less affected by this problem.

Table 12: 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) |

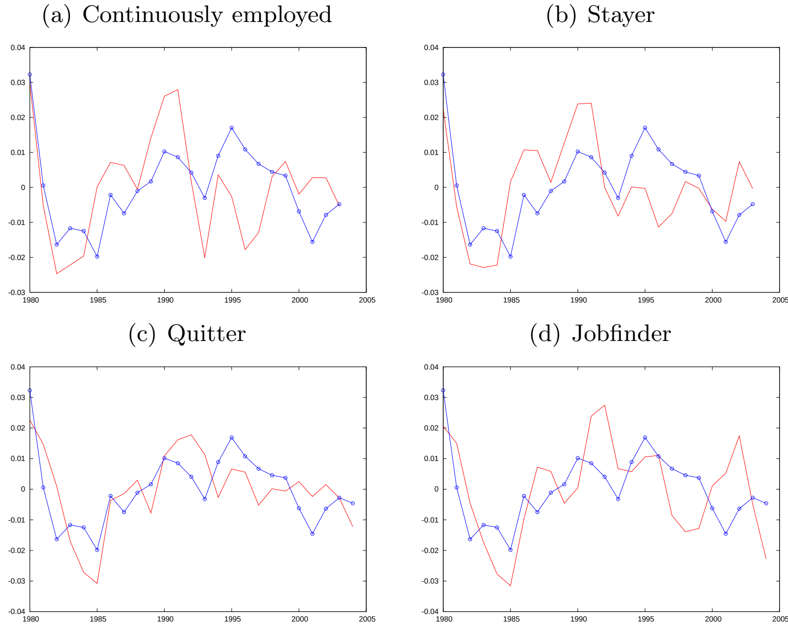
Notes: Annual earnings cyclicality for full-time employed workers (male and female, all education groups). *Index* refers to the earnings index using the first difference filter. *Correlation* refers to the correlation coefficient of the earnings index and the business cycle measure. *Growth* refers 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 13: 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 employee. Time period is $Jan1977 - Sep2004$.

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



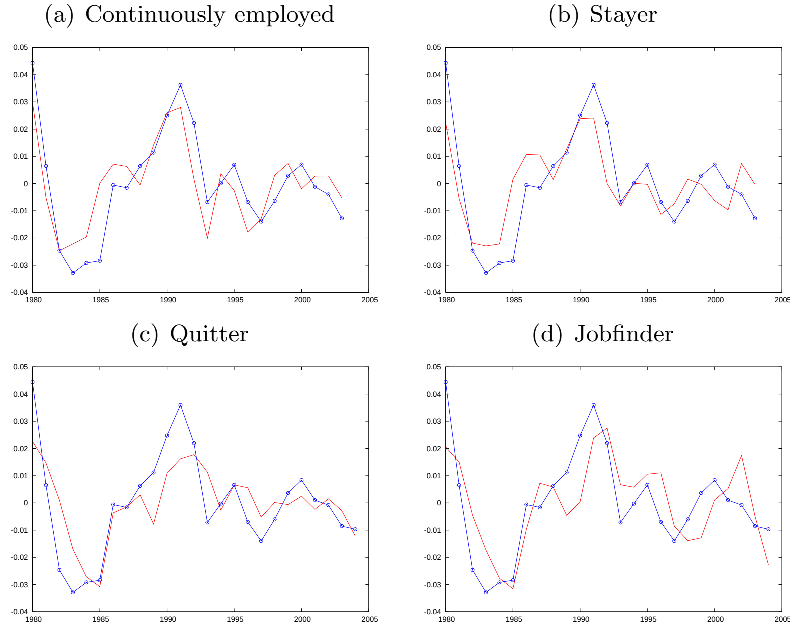

Notes: Earnings index cyclicality (HP filter, $\lambda = 100,000$) for full-time workers (male and female), business cycle measure GDP per employed. Time period is $Jan1980 - Sep2004$.

Table 14: 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 ($\lambda = 100,000$), *Index p.empl.* refers to the earnings index using the HP-filter ($\lambda = 100,000$) and GDP per employee is used as the business cycle measure. *Correlation* refers to the correlation coefficient of the earnings index and the business cycle measure. Time period is $Jan1980 - Sep2004$.

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




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 15: 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 employee as business cycle measure. Standard errors are bootstrapped with 100 repetitions and clustered by time periods. Time period is $Jan1980 - Sep2004$.

Table 16: 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 who have been unemployed for less than 360 days and have been 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 $Jan1980 - Sep2004$.

Table 17: Unemployment decomposition for different subgroups

| Sample | Data | EU | UE | NE | EN | NU | UN | $\varepsilon$ |
|---|---|---|---|---|---|---|---|---|
| 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 U.S. data is obtained from Shimer and Fujita/Ramey.

Table 18: Unemployment decomposition for different filters

| Country | Data | EU | UE | EN | NU | UN | NE | $\varepsilon$ |
|---|---|---|---|---|---|---|---|---|
| Germany | IAB ($\Delta$) | 0.6353 | 0.3647 | | | | | 0.0000 |
| | IAB ($\Delta$) | 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 |
| U.S. | Shimer ($\Delta$) | 0.6434 | 0.3566 | | | | | −0.0000 |
| | Fujita/Ramey ($\Delta$) | 0.5174 | 0.4826 | | | | | −0.0000 |
| | Shimer ($\Delta$) | 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 ($\Delta$) 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 U.S. data is obtained from Shimer and Fujita/Ramey.

Table 19: Unemployment decomposition for the period $1977 - 2004$

| Country | Data | EU | UE | NE | EN | NU | UN | $\varepsilon$ |
|---|---|---|---|---|---|---|---|---|
| Germany | IAB | 0.6600 | 0.3371 | | | | | 0.0029 |
| | IAB | 0.4486 | 0.2014 | 0.1323 | −0.0481 | 0.1423 | 0.1238 | −0.0004 |
| U.S. | 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 U.S. data is obtained from Shimer and Fujita/Ramey.

Table 20: Unemployment decomposition before and after the German reunification

| Period | Data | EU | UE | NE | EN | NU | UN | $\varepsilon$ |
|---|---|---|---|---|---|---|---|---|
| $1980q1 - 1991q4$ | 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.