The Era of the U.S.-Europe Labor Market Divide: What can we learn?

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Abstract

Comparing labor markets in the United States and Germany as Europe's largest economy over the period from $1980-2004$ uncovers three stylized differences: (1) Germany's mean transition rates from unemployment to employment (UE) were lower by a factor of 5 and transition rates from employment to unemployment (EU) were lower by a factor of 4. (2) The volatility of the UE rate was equal in both countries, but the EU rate was 2.3 times more volatile in Germany. (3) In Germany EU flows contributed $60-70\%$ to unemployment volatility, whereas in the U.S. they contributed only $30-40\%$. Using a search and matching model we show theoretically that the joint analysis of first and second moments offers general identification restrictions on the underlying causes for these differences. We find that a lower efficiency in the matching process can consistently explain the facts while alternative explanations such as employment protection, the benefit system, union power, or rigid earnings can not. We document that a lower matching efficiency due to lower occupational and regional mobility in Germany finds strong support in the data. Finally, we show that the highlighted matching friction leads in the model calibrated to the German economy to a substantial amplification and propagation of shocks.

JEL: E02, E24, E32

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Over the last decades a large literature has studied the differences in average unemployment rates between Europe and the United States. Only recently a new empirical literature has emerged that starts to document differences in the behavior of business cycle fluctuations across countries (see Elsby et al. (2010b) and the survey by Pissarides (2009)) but so far very little is known about the underlying causes for the cross-country differences in the reaction to business cycle shocks.

In this paper we explain the cross-country differences in the first and second moments of the data jointly within a common structural framework. We use the identification restrictions resulting from the joint considerations of the long run average labor market transition rates and the business cycle dynamics to differentiate between various alternatives proposed in the literature to rationalize the rigid labor markets in Europe compared to the U.S. Our findings suggest that the usual 'suspects' of the transatlantic labor market division like firing protection, the unemployment benefit system or unions are not fully consistent with the flow view of the labor market at least viewed through the lens of a fairly standard search and matching model. Instead, we argue that the technological microstructure in the matching process itself is a prime candidate in explaining the cross-country differences.

We consider two labor market prototypes: On the one hand, Germany as Europe's largest labor market and a prime example of a typical rigid labor market, and on the other hand the United States with its flexible labor market. Using micro data for the period from 1980 to 2004 we provide in a first step a comprehensive empirical analysis of Germany's labor market. We document three stylized cross-country differences in labor market flows: First, German transition rates from unemployment to employment (UE rate) are lower by a factor of 5, and inflow rates from employment to unemployment (EU rate) are lower by a factor of 4. Second, while (log) UE rates are equally volatile for Germany and the U.S., the volatility of the (log) EU rate is 2.3 times larger in Germany compared to the U.S. Third, if we decompose the unemployment rate volatility into contributions of EU and UE flows, we find that in Germany, the EU flows are dominant and account for $60-70\%$ of the unemployment volatility, whereas in the U.S., they account for only $30-40\%$.

In a second step we adapt a search and matching model with endogenous separation similar to den Haan et al. (2000) to uncover the causes underlying these differences. We derive simple closed-form solutions for the second moments so that we can analytically characterize the implications of institutional changes for the reaction to business cycle shocks. In extensions, we allow for worker- and firm-specific human capital accumulation, persistent idiosyncratic shocks and tenure-dependent firing taxes. Using the calibrated model we find that a lower efficiency in matching unemployed workers to open positions in Germany is the key barrier to faster labor reallocation and can by itself account for 60% of the documented cross-country differences.

Our findings are consistent with the view that the strongly credential-based occupational structure and the resulting low regional and occupational mobility rates in Germany (Gangl, 2004) compared to the large occupational mobility rates in the U.S. (Kambourov and Manovskii, 2008) prevents a faster labor reallocation process. We suggest that German worker searching for a job sample from a narrower occupational offer distribution which would imply a lower matching efficiency on the aggregate level. We provide evidence for this viewpoint by documenting that during our sample period occupational mobility rates were substantially lower in Germany compared to the U.S.

Our argument why the matching technology is the crucial friction in the German labor reallocation process works as follows: a lower efficiency in the matching process leads to a decline in the frequency of unemployment-to-employment transitions in Germany. Being unemployed in Germany consequently becomes less attractive due to the longer search duration, so the average match surplus *increases*. This increase makes it less likely that an idiosyncratic shock hitting a particular match leads to a separation. The frequency of transitions from employment into unemployment declines. This explains the mean differences across countries. However, differences in matching efficiency do not only influence average transition rates. The increase in the average surplus also makes German workers more sensitive to business cycle shocks. To see this consider a German worker after a positive business cycle shock. If she separates, she has to search longer to find a new match than a U.S. worker. Since aggregate conditions are currently good, she would miss a larger fraction of the most profitable time of being employed, whereas the U.S. worker would more quickly find a job and profit from the good economic conditions. This difference makes employed workers in Germany more reluctant to separate after a positive business cycle shock. Similarly, after a negative business cycle shock the German worker is more willing to separate because she will only miss the least profitable time of being employed while searching for a job. As a result, the German EU rate decreases, in percentage terms, more strongly after positive shocks and increases more strongly after negative shocks. Hence, the EU rate is more volatile in Germany.

We show analytically that the EU rate volatility is a function of the absolute change of the match surplus. In contrast, the UE rate volatility, in percentage terms, is driven by the relative change of the surplus as long as firms can freely enter the market with open positions. Intuitively, every change in the surplus for given vacancy posting costs has to be balanced by a proportional change in the probability of finding a worker. A lower matching efficiency leaves the cyclical pattern in the relative surplus largely unaffected due to the simultaneous increase in the average surplus and the increase in the sensitivity of the surplus reaction to shocks. An increased EU rate volatility, together with an unchanged UE rate volatility, leads to an increase in the contribution of the inflows in the unemployment volatility decomposition. Taken together, a lower matching efficiency in Germany provides a unified explanation for all three empirical differences.

It is the simultaneous decline in the average UE rate and increase in the average surplus of the match that sets our explanations apart from three prominent alternatives proposed in the literature that are based on institutional differences: The first alternative argues that the lower UE rates in Europe are caused by a combination of a more benevolent unemployment insurance system and stricter employment protection that may affect the human capital accumulation process (Ljungqvist and Sargent, 2008; Wasmer, 2006). However, this explanation lowers the average match surplus in Germany and increases the UE rate volatility by more than the EU rate volatility. The second alternative argues for a stronger bargaining position of the worker/union in Germany induced by the employment protection legislation (Blanchard and Portugal, 2001). We show that an increase in bargaining power typically lowers the average surplus and the EU rate volatility. In fact, as we point out if the bargaining power happens to equal the match elasticity (Hosios, 1990) both the average surplus and the EU rate volatility are minimized. A deviation from the Hosios condition is quantitatively too small to account for the empirical differences. As a third alternative, we study differences in firing taxes between low and high tenured workers or the presence of short term employment contracts (Bentolila et al., 2010; Costain et al., 2010). Firing taxes lower the match surplus and increase the UE rate volatility by more than the EU rate volatility. Moreover, differences in firing taxes lead to inconsistencies in the tenure pattern over transition rates, which we document empirically.

We use our model to show that a lower efficiency in the matching process can also explain the stronger propagation of business cycle shocks in Germany. In our quantitative model, which is calibrated to reproduce the empirical differences across both labor markets, an adverse shock hitting the U.S. economy leads to a peak in the unemployment rate after 3 quarters and levels off fairly quickly afterwards. In contrast, the German unemployment rate peaks 9 quarters after the initial shock, and even five years later, the deviation of the unemployment rate from its long-run trend is still twice as large in Germany relative to the U.S.

Our paper relates to a large empirical literature that has pointed towards matching efficiency as an explanation for the frictional labor reallocation process observed in Europe (Schioppa (1991), Franz (2009) and the references therein). Recently, occupational and regional mismatch as an explanation for a lower matching efficiency has also attracted increased attention in connection with the labor market dynamics in the U.S. in the course of the financial crisis, e.g. Barnichon and Figura (2011) and Sahin et al. (2011). The large differences in occupational and regional mobility that hinder efficient labor reallocation have been documented in cross-country comparisons by Gangl (2004) and Molloy et al. (2011) and are consistent with our findings that occupational mobility rates are 50% lower compared to the U.S rates obtained from Kambourov and Manovskii (2008).

Our empirical work adds to the growing literature that documents the 'ins and outs' of unemployment (Shimer (2007)) by providing a detailed account for Germany.[1] On theoretical grounds, our paper is, to the best of our knowledge, the first to explain the cross-country differences in labor market flows in terms of both the mean rates and the business cycle dynamics in a common framework.

The remainder of the paper is organized as follows: Section 1 documents labor market facts for

[1]A large amount of literature examines worker flows in the U.S., for example Fallick and Fleischman (2004), Fujita and Ramey (2009), Elsby et al. (2009). A number of papers have started to document similar facts on the 'ins and outs' of European unemployment, as discussed by Petrongolo and Pissarides (2008) and Pissarides (2009) based on micro-data and by Burda and Wyplosz (1994) and Elsby et al. (2010b) who use aggregate data. For Germany there are studies by Bachmann (2005) and very recently by Gartner et al. (2010).

Germany, section 2 develops the model, section 3 characterizes the results, extensions are in section 4 and section 5 concludes. We provide robustness to the potential presence of rigid wages in appendix C and offer additional cross-country evidence in appendix D. An online appendix accompanying the paper provides more details on the 'ins and outs' of unemployment for Germany.

1 Data

1.1 Data description

Our dataset is the IAB employment panel, which comprises a 2% representative sample taken from the German social security and unemployment records for the period of $1980 - 2004$. The sample contains employees covered by the compulsory German social security system, and excludes the self-employed and civil servants ('Beamte'). It covers about 80% of Germany's labor force. Because the East German labor market was subject to additional regulations and restructuring after reunification, we exclude all persons with employment spells in East Germany from our sample. The data are available at a daily frequency, but we construct monthly employment histories using one fixed week within each month to yield data comparable to the U.S. CPS data, which comes at a monthly frequency. In the appendix, we provide additional information on the data set, and sample selection and explain how we construct monthly employment histories from the daily data. For the U.S., we take labor market transition rates based on the CPS from Shimer (2007) and from Fallick and Fleischman (2004) for employer-to-employer transitions.

1.2 Labor market flows

Table 1 summarizes our results on labor market transition rates for Germany and presents a cross-country comparison along three dimensions: aggregate business cycle fluctuations, mean labor market transition rates, and volatilities of the transition rates.[2]

[2]In the online appendix, we provide transition rates by sex and education to show that results are not driven by a particular labor market group. We also provide a sensitivity analysis with respect to the smoothing parameter of the HP filter to show that the stylized differences are robust to the choice of this parameter. We do not report NU and NE transition rates in table 1 because we do not observe the universe of all non-employed individuals, so the transition rates can not be computed. The online appendix reports the correlations and volatilities for these flows.

Table 1: GDP, unemployment rates, and transition rates over the business cycle

	Series	mean	std	corr	Transition rate	mean	std	corr
Germany	GDP		2.4	1	EU	0.5	15.1	-0.81
U.S.			2.6	1		2.0	6.5	-0.72
Germany	Productivity		1.6	0.77	UE	6.2	10.4	0.40
U.S.			1.4	0.44		30.7	11.2	0.82
Germany	Earnings		1.7	0.84	EE	0.9	15.6	0.65
U.S.			1.8	0.42		2.6	6.3	0.65
Germany	Vacancies		33.4	0.82	EN	1.0	6.2	0.53
U.S.			20.4	0.85		2.7	4.6	0.44
Germany	Urate	8.4	18.1	-0.76	UN	4.9	10.3	0.45
U.S.		6.3	15.0	-0.89		26.6	9.1	0.73

Notes: Data series are quarterly or quarterly averages of monthly data for the period 1980q1 - 2004q3. Standard deviations (STD) are given as percentage deviations from an HP-filtered trend ($\lambda = 100,000$) in logs. Correlations (CORR) give the correlation coefficient with GDP. Our productivity measure is GDP per employed. Aggregate data for Germany are from the German statistical office ('Statistische Bundesamt') and the German Employment Agency ('Bundesagentur für Arbeit') and for the U.S. from the BLS. U.S. transition rates are taken from Shimer (2007) and Fallick and Fleischman (2004) for the EE rates that start in 1994. German transition rates are authors' own calculations based on IAB data.

The aggregate measures of the labor market are slightly more volatile in Germany compared to the U.S. The unemployment rate is 1.2 times as volatile, and vacancies[3] are 1.6 times as volatile. Correlations with GDP have the same sign and similar magnitudes across the two countries. Additionally, the Beveridge curve, depicting the correlation between unemployment rates and vacancies, is strongly negative in both Germany (correlation -0.85) and the U.S. (correlation -0.91).

Average labor market transition rates are substantially lower in Germany. The EU rate is lower by a factor of 4, and the UE rate is lower by a factor of 5. Transition rates to a new employer (EE) and the employment-to-inactivity (EN) rates differ by a factor of approximately 3.[4] The opposite picture arises for the volatilities. Although the UE rates in both countries are equally volatile, the German EU rate is 2.3 times more volatile than the U.S. rate. Figure 1(a) visualizes the close connection of the cyclical component of the EU rate and the unemployment rate in Germany; the link is present but not as close in the U.S. (Figure 1(b)).

[3] We use the help wanted index for the U.S. and open positions registered at the job centers for Germany. It must be noted that open positions at the job centers for Germany do not constitute the whole universe of open positions. Indeed, a comparison of recent firm survey data with the data on registered vacancies suggests that about 1/3 of all open positions are announced to job centers. We therefore take registered vacancies only as an indicator.

[4] These lower rates can be observed throughout the sample period and are not an artifact of the developments in the 1990ss. In 1980, the average UE rate in Germany is 10.9% declining over time to 4.7% in the mid 1990ss (1995). During the same time period the EU rate increases from 0.4% to 0.5%.

(a) Germany (b) United States

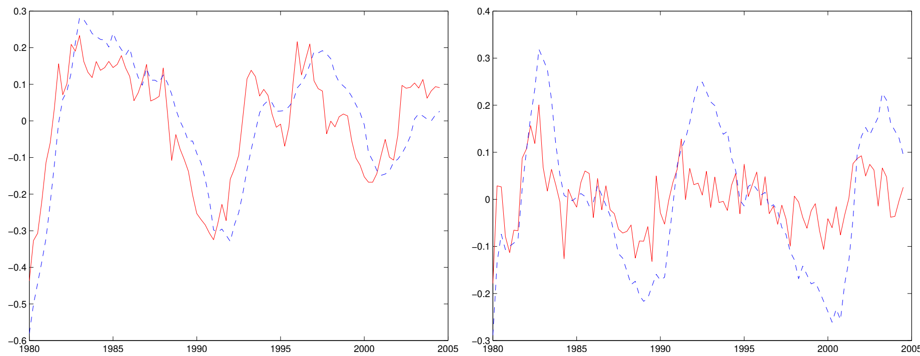

Figure 1: Cyclical component of EU rate and unemployment rate

Notes: The figure shows the cyclical component of the EU rate and the official unemployment rate based on an HP-filter ($\lambda = 100,000$). The red solid line is the EU rate and the blue dashed line is the unemployment rate.

1.3 Unemployment decomposition

To address the importance of EU and UE flows in explaining unemployment volatility, we use the methodology proposed in Fujita and Ramey (2009) and develop an extended decomposition with three states and six transition rates to control for flows into inactivity.[5] Table 2 summarizes our findings based on the two-state and three-state decompositions, where the numbers represent the shares of unemployment volatility attributed to the corresponding labor market transition rates.

Table 2: Unemployment Volatility Decomposition

Country	Data	# of states	EU	UE	NE	EN	NU	UN	ε
Germany	IAB	2	61.1	38.6					0.3
	IAB	3	42.5	24.6	20.0	−4.5	6.6	11.0	−0.3
U.S.	Shimer	2	32.6	67.6					−0.2
	Fujita/Ramey	2	38.4	61.9					−0.2
	Shimer	3	20.1	48.6	8.8	−3.8	10.4	15.2	0.7

Notes: Data is HP-filtered ($\lambda = 100,000$) for the period $1980q1-2004q4$. For Germany the transition rates are authors' own calculations. The U.S. data is obtained from Shimer (2007) and Fujita and Ramey (2009). Contribution shares of flows are given in the corresponding column and are given as percentage numbers. The third column reports the number of states considered in the decomposition. Source: Authors' own calculations based on the data source given in column 2.

Based on a two-state decomposition, EU rates account for more than 60% of the volatility in unemployment whereas in the U.S. they account for $30 - 40\%$.[6] The three-state decomposition

[5]Details on the volatility decomposition of Fujita and Ramey (2009) and our extension can be found in Appendix B.

[6]For the U.S. Hall (2005) and Shimer (2007) emphasize the importance of the UE flows in understanding labor market dynamics whereas Fujita and Ramey (2009) and Elsby et al. (2009) focus more on the EU flows. Our estimates

indicates that German EU rates contribute about twice as much to the unemployment volatility as UE rates do, while in the U.S. the opposite is true. In the next section we present a structural search and matching model of the labor market to explore how technological and institutional differences on the labor market can explain the empirical differences.

2 Model

There is a continuum of workers with measure one. Workers and firms are risk neutral. Workers can be either employed or unemployed, denoted by $l \in \{e, u\}$. The aggregate technology state A is random and follows a Markov process. Additionally, there is an idiosyncratic state attached to each worker denoted by $x \in \mathbb{X}$. The state x follows a discrete Markov process. We allow this process to depend on the labor market transition from the current labor market state l to the next period's state l' to model, for example, the loss of firm-specific human capital after an EU transition. Thus, the model has different conditional distributions over tomorrow's idiosyncratic state depending on current and future employment status. We denote these distributions by $p_{ee}(x'|x)$, $p_{eu}(x'|x)$, $p_{ue}(x'|x)$, and $p_{uu}(x'|x)$ depending on whether the agent stays employed, moves into unemployment, moves out of unemployment or stays unemployed, respectively.

The measure of unemployed workers in the different idiosyncratic states is denoted by $u(x)$ and for employed workers by $e(x)$. The joint distribution over employment states l and idiosyncratic states x is $\lambda : \{e, u\} \times \mathbb{X} \to [0, 1]$, and Λ denotes the set of possible joint distributions.

Time is discrete. At the beginning of the period, workers who are matched with a firm bargain jointly and efficiently over the wage and the separation decision for the current period. If the bargaining is successful, they produce output according to the production technology $Ag(x)$, where the aggregate technology A evolves exogenously and common to all matches, and $g(x)$ summarizes the individual productivity for a worker of type x. The individual productivity $g(x)$ is assumed to be large enough that production is efficient. At the end of the period, but before the realization of tomorrow states, the firm receives an idiosyncratic cost shock ε. We assume that ε is i.i.d. across

are at the upper end of estimates by Shimer (2007) and the lower end of Fujita and Ramey (2009). In the online appendix, we provide a sensitivity analysis with respect to filtering and decomposition methods.

firms and over time and logistically distributed with mean zero and variance $\frac{\pi^2}{3}\psi^2$. The assumption of a logistic distribution allows us to obtain closed-form solutions and is done for convenience. The firm has to pay the costs ε only if it wishes to continue the production process. The costs are sunk after the period and will not affect any future decision. At the bargaining stage, the firm and the worker agree upon a threshold value $\bar{\omega}$ for the continuation costs ε. The bargained cut-off value $\bar{\omega}$ represents a quantile of the cost shock distribution. If the realized continuation costs ε are larger than this threshold value, the match dissolves, the firm has to pay a state dependent firing tax $\tau(x)$ to the government and the worker becomes unemployed. The transition probability for the individual state in this case is $p_{eu}(x'|x)$. If the costs ε are less than the cut-off value, then the firm pays the continuation costs and continues the match. In this case, the worker transits to a new idiosyncratic state with probability $p_{ee}(x'|x)$. This structure for the optimal decision allows us to cast the separation decision solely in terms of cut-off values.

An unemployed worker searches for a job and is matched in a matching market governed by a standard Cobb-Douglas matching function. Search is random, so unemployed workers receive job offers from firms with probability π_{ue}. Together with the offer, there is a realized idiosyncratic productivity component. The probability distribution for the idiosyncratic state is $p_{ue}(x'|x)$. In case the worker does not receive an offer, a new idiosyncratic state is drawn according to $p_{uu}(x'|x)$. While unemployed, a worker has a utility flow b.

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 β. For given wages $w : \mathbb{R}_+ \times \mathbb{X} \times \Lambda \to \mathbb{R}_+$ and cut-off strategies $\bar{\omega} : \mathbb{R}_+ \times \mathbb{X} \times \Lambda \to \mathbb{R}$, the firm's surplus is:

$$\begin{aligned} J(A, x, \lambda) &= Ag(x) - w(A, x, \lambda) \\ &\quad + \int_{-\infty}^{\bar{\omega}} \left(\beta \mathbb{E} \left[\sum_{x'} p_{ee}(x'|x) J(A', x', \lambda') \right] - \varepsilon \right) df(\varepsilon) - \int_{\bar{\omega}}^{\infty} \tau(x) df(\varepsilon). \end{aligned} \tag{1}$$

The separation probability[7] π_{eu} is

$$\pi_{eu}(A,x,\lambda) = 1 - Prob(\varepsilon < \bar{\omega}) = \left(1 + \exp\left(\frac{\bar{\omega}(A,x,\lambda)}{\psi}\right)\right)^{-1}.$$

The value functions for employed workers $V_e : \mathbb{R}_+ \times \mathbb{X} \times \Lambda \to \mathbb{R}$ and unemployed workers $V_u : \mathbb{R}_+ \times \mathbb{X} \times \Lambda \to \mathbb{R}$ are given by

$$\begin{aligned} V_e(A,x,\lambda) &= w(A,x,\lambda) + (1-\pi_{eu}(A,x,\lambda))\beta\mathbb{E}\left[\sum_{x'} p_{ee}(x'|x)V_e(A',x',\lambda')\right] \\ &\quad + \pi_{eu}(A,x,\lambda)\beta\mathbb{E}\left[\sum_{x'} p_{eu}(x'|x)V_u(A',x',\lambda')\right] \qquad (2) \\ V_u(A,x,\lambda) &= b + (1-\pi_{ue}(A,\lambda))\beta\mathbb{E}\left[\sum_{x''} p_{uu}(x''|x)V_u(A',x'',\lambda')\right] \\ &\quad + \pi_{ue}(A,\lambda)\beta\mathbb{E}\left[\sum_{x'} p_{ue}(x'|x)V_e(A',x',\lambda')\right]. \qquad (3) \end{aligned}$$

We denote the worker's surplus by $\Delta(A,x,\lambda) = V_e(A,x,\lambda) - V_u(A,x,\lambda)$ and the match surplus as $S(A,x,\lambda) = J(A,x,\lambda) + \Delta(A,x,\lambda)$. New matches are formed by a standard Cobb-Douglas matching technology that links searching workers to vacancies:

$$m = \varkappa v^{1-\varrho} u^{\varrho} \quad \text{with} \quad u = \sum_{x\in\mathbb{X}} u(x).$$

The measure of unemployed workers is denoted by u, the posted vacancies by v, the resulting matches by m and ϱ denotes the matching elasticity. Labor market tightness is defined as the ratio of vacancies to searching workers $\theta := \frac{v}{u}$. The probability that a searching worker will meet a firm

[7] Solving the conditional expectation for $\pi_{eu}(A,x)$, the firm's profit is:

$$J(A,x,\lambda) = Ag(x) - w(A,x,\lambda) + (1-\pi_{eu}(A,x,\lambda))\beta\mathbb{E}\left[\sum_{x'} p_{ee}(x'|x)J(A',x',\lambda')\right] - \pi_{eu}(A,x,\lambda)\tau(x) + \Psi(A,x,\lambda).$$

The option value Ψ follows directly from the assumption of a logistically distributed cost shock. It captures the value of having a choice to continue the match and is always positive:

$$\Psi(A,x) = -\psi_{\varepsilon}\Big((1-\pi_{eu}(A,x,\lambda))\log(1-\pi_{eu}(A,x,\lambda)) + \pi_{eu}(A,x,\lambda)\log(\pi_{eu}(A,x,\lambda))\Big).$$

is $\pi_{ue} = \frac{m}{u} = \varkappa\theta^{1-\varrho}$ and the probability that a firm posting a vacancy will meet some worker is given by $\pi_{ve} = \frac{m}{v} = \varkappa\theta^{-\varrho}$. To determine the number of vacancies posted, we impose a standard free entry condition:

$$\kappa = \pi_{ve} \sum_{x \in \mathbb{X}} \frac{u(x)}{u} \beta \mathbb{E}\left[\sum_{x'} J(A', x', \lambda') p_{ue}(x'|x)\right]$$

where κ denotes the vacancy posting costs per period. The probability of meeting a specific worker with characteristics x is $\frac{u(x)}{u}$. We assume Nash bargaining jointly over wages and cut-off values. The outcome of the bargaining process is characterized by

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

where μ denotes the bargaining power of the worker.[8]

Technology evolves exogenously according to

$$A = \exp(a) \qquad a' = \rho a + \eta'$$

where ρ denotes the auto-correlation coefficient and innovations η are normally distributed. The laws of motion for $e(x)$ and $u(x)$ are

$$\begin{aligned}
e'(x') &= \sum_x (1 - \pi_{eu}(A, x, \lambda)) p_{ee}(x'|x) e(x) + \sum_x \pi_{ue}(A, \lambda) p_{ue}(x'|x) u(x) \\
u'(x') &= \sum_x \pi_{eu}(A, x, \lambda) p_{eu}(x'|x) e(x) + \sum_x (1 - \pi_{ue}(A, \lambda)) p_{uu}(x'|x) u(x) \\
1 &= \sum_x u(x) + \sum_x e(x).
\end{aligned}$$

[8] First order conditions show that the cut-off value $\bar{\omega}$ is proportional to the match surplus

$$\bar{\omega}(A, x, \lambda) = \beta \mathbb{E}\left[\sum_{x'} p_{ee}(x'|x)(J(A', x', \lambda') + V_e(A', x', \lambda')) - \sum_{x'} p_{eu}(x'|x) V_u(A', x', \lambda')\right] + \tau(x)$$

3 Results

In this section, we specialize to the homogeneous worker case by abstracting from idiosyncratic states, i.e., we set $x = 1$, so that all policy rules are functions of the aggregate state only.[9] The baseline version allows us to derive an analytic characterization of the model. In section 3.1 we use this closed form solution to characterize the basic mechanism that links lower mean UE rates to higher EU volatilities and a higher contribution of the EU rate in the unemployment decomposition. In section 3.2 we provide a mapping to the underlying institutional factors, section 3.3 determines the quantitative importance of the differences in labor market parameters and section 3.4 shows that the differences matter for the propagation of aggregate shocks. Section 3.5 offers micro-evidence for a lower matching efficiency in Germany that we identify as the main channel to explain the observed differences.

3.1 Basic Mechanism

Table 3 reports in the first column analytical expressions for the steady state and for the second moments based on a first-order approximation. To ease the discussion we also report a simple approximation to the resulting expressions in the second column. The steady state of a variable y is denoted by $\bar{y}$ and the coefficient of the first-order approximation by σ_y. If productivity deviates by $\hat{a}$ from its steady state, then it holds that $y = \bar{y} + \sigma_y \hat{a}$. Furthermore, we use $\tilde{\sigma}_y := \frac{\sigma_y}{\bar{y}}$ to denote percentage deviations from steady state. The absolute value of $\tilde{\sigma}_y$ coincides with the log standard deviation of a variable y relative to the standard deviation of productivity.

The two bottom rows of table 3 uncover the decisive difference in the reaction of EU and the UE rate to business cycle shocks. The EU rate volatility ($|\tilde{\sigma}_{eu}|$) is proportional to the *absolute* surplus reaction σ_S scaled by the standard deviation ψ of the cost shock.[10] In contrast, the UE rate volatility ($|\tilde{\sigma}_{ue}|$) is proportional to the *relative* surplus volatility $\frac{\sigma_S}{S}$. Using the approximation

[9]In the absence of idiosyncratic states x, the model is block-recursive in the sense of Menzio and Shi (2009), so the employment measure does not enter the policy functions.

[10]This is the standard logic of generating countercyclical EU rates in models with endogenous destruction and also applies to models using log-normal multiplicative shocks. Intuitively, less dispersed idiosyncratic cost shocks have more mass around the cut-off value $\bar{\omega}$. For a given shock distribution, a decline in the surplus due to a negative shock will lead to more firms that draw cost shocks below the cut-off value and to more separation. At the aggregate level the EU rate increases and is countercyclical.

Table 3: Analytical Expressions for the First and Second Moments

$\bar{S}$	$\frac{\bar{A}-b-\psi\log(1-\bar{\pi}_{eu})}{1-\beta(1-\bar{\pi}_{ue}\mu)}$	$\frac{\bar{A}-b}{\bar{\pi}_{ue}\mu}$
$\bar{\pi}_{ue}$	$\varkappa\left(\frac{(1-\mu)\varkappa\beta\bar{S}}{\kappa}\right)^{\frac{1-\varrho}{\varrho}}$	$\varkappa\left(\frac{1-\mu}{\mu}\frac{\bar{A}-b}{\kappa}\right)^{1-\varrho}$
$\bar{\pi}_{eu}$	$\left(1+\exp\left(\frac{\beta\bar{S}+\tau}{\psi}\right)\right)^{-1}$	$\left(1+\exp\left(\frac{\bar{A}-b}{\bar{\pi}_{ue}\mu\psi}+\frac{\tau}{\psi}\right)\right)^{-1}$
σ_S	$\left(1-\beta\rho\left(1-\bar{\pi}_{eu}\right)+\beta\rho\bar{\pi}_{ue}\frac{\mu}{\varrho}\right)^{-1}$	$\frac{\varrho}{\bar{A}-b}\bar{S}$
$\tilde{\sigma}_{ue}$	$(1-\varrho)\frac{\rho}{\varrho}\frac{\sigma_S}{\bar{S}}$	$\frac{1-\varrho}{\bar{A}-b}$
$\tilde{\sigma}_{eu}$	$-(1-\bar{\pi}_{eu})\frac{\rho\beta}{\psi}\sigma_S$	$-\frac{\varrho}{\bar{A}-b}\frac{\bar{S}}{\psi}$

Notes: Analytic expressions for the first order approximations are in the first column. In the second column additional approximations utilize $\beta \approx 1$, $\rho \approx 1$, and $\pi_{eu} \approx 0$. The coefficients capturing second moments σ result from a first-order approximation around the steady state.

from the second column we obtain

$$\tilde{\sigma}_{ue} = \frac{1-\varrho}{A-b} \qquad \tilde{\sigma}_{eu} = \frac{\varrho}{\mu\psi}\bar{\pi}_{ue}^{-1}$$

and it becomes evident that the UE volatility is a direct function of the outside option b, a fact that has been discussed in the recent literature (see Shimer (2005) and Hagedorn and Manovskii (2008)). Furthermore, we see that the EU rate volatility is inversely related to the average UE rate. Hence, the model predicts the observed empirical relationship between low mean UE rates and high EU volatilities.[11]

The contribution of the EU rate to the unemployment volatility is determined by the ratio of $|\tilde{\sigma}_{eu}|$ to $|\tilde{\sigma}_{ue}|$.[12] It follows from the approximation in table 3 that the contribution of the EU rate to the unemployment volatility is proportional to the average surplus $\frac{|\tilde{\sigma}_{eu}|}{|\tilde{\sigma}_{ue}|} = \frac{\varrho}{1-\varrho}\frac{\bar{S}}{\psi}$. Hence, as a first result, we note that to explain a higher contribution of EU transitions to the volatility of

[11] In appendix D we investigate this relationship further and find that it holds when we consider a large set of OECD countries using the data series on worker flows constructed from aggregate data by Elsby et al. (2010b).

[12] To see this note that the unemployment rate volatility is given by

$$\begin{aligned} |\tilde{\sigma}_u| &= \frac{|\sigma_{eu}(1-\bar{u})-\sigma_{ue}\bar{u}|}{\bar{u}\sqrt{1-(1-\bar{\pi}_{ue}-\bar{\pi}_{eu})^2}}\sqrt{\frac{1+\rho(1-\bar{\pi}_{ue}-\bar{\pi}_{eu})}{1-\rho(1-\bar{\pi}_{ue}-\bar{\pi}_{eu})}} \\ &\approx (|\tilde{\sigma}_{eu}|+|\tilde{\sigma}_{ue}|)(1-\bar{u}) \end{aligned}$$

unemployment rate, the average surplus has to be larger in Germany.

The intuition for this finding has its seeds in the reemployment prospects of workers after separation. The recursive formula of the surplus obtained from equations (1), (2) and (3), where we set $\psi \log(1-\pi_{eu}) \approx 0$ for simplicity, is

$$S \approx A - b + \beta \mathbb{E}\left[S'\right] - \pi_{UE}\mathbb{E}\left[\Delta'\right].$$

We see that the current surplus is the discounted surplus of the current match $A - b + \beta\mathbb{E}[S']$ net of the worker's expected reemployment gain $\pi_{UE}\mathbb{E}[\Delta']$.

Consider now how a positive business cycle shock affects these two values. The surplus of the current match increases, so the EU rate falls. The increase in the surplus of the current match is dampened by the reaction of the expected reemployment gain, which enters negatively into the total surplus. After a positive business cycle shock the expected reemployment gain rises because π_{ue} and Δ increase. However, the strength of the dampening effect differs across countries because Germany has lower steady state level of the UE rate. After a positive business cycle shock the opportunity costs of separation are therefore larger in Germany than in the U.S. so the German worker is more reluctant to separate. The lower average reemployment probability in Germany amplifies the surplus reaction and consequently the EU rate reaction and explains the inverse relation between the average UE rates and the EU rate volatility.[13]

3.2 Structural parameters

What structural or institutional differences can explain the observed differences in labor market flows between the U.S. and Germany? Table 4 reports the analytic elasticities of average transition rates and volatilities with respect to a change in the underlying parameter. They can be used to sign the impact of each of the structural parameters on the four endogenous dimensions considered in this paper.[14]

We start our analysis from the steady state formulas in table 3 to show that there are essentially

[13] A symmetric argument applies to a negative shock.

[14] To obtain the elasticities we implicitly differentiate the system of steady state equations and the analytical expressions for the volatilities. To improve readability, we use some simple approximations. The exact elasticities are available upon request.

Table 4: Analytic approximations of steady state elasticities

p	Parameter	$\frac{p}{\pi_{ue}}\frac{d\pi_{ue}}{dp}$	$\frac{p}{\pi_{eu}}\frac{d\pi_{eu}}{dp}$	$\frac{p}{\lvert\tilde{\sigma}_{eu}\rvert}\frac{d\lvert\tilde{\sigma}_{eu}\rvert}{dp}$	$\frac{p}{\tilde{\sigma}_{ue}}\frac{d\tilde{\sigma}_{ue}}{dp}$
$\varkappa$	Matching Efficiency	$\frac{\varrho}{1-\varrho}$	$\frac{\varrho}{1-\varrho}\frac{\bar{S}}{\psi}$	$-\frac{\varrho}{1-\varrho}$	0
μ	Bargaining Power	$-\frac{1-\varrho}{1-\mu}$	$-\frac{\mu-\varrho}{1-\mu}\frac{\bar{S}}{\psi}$	$\frac{\mu-\varrho}{1-\mu}$	0
b	Outside Option	$-\frac{(1-\varrho)b}{A-b}$	$\frac{\varrho b}{\mu\psi\bar{\pi}_{ue}}$	$(1-\varrho)\frac{b}{A-b}$	$\frac{b}{A-b}$
τ	Firing Tax	$-\frac{(1-\varrho)\tau\bar{\pi}_{eu}}{A-b}$	$-(1-\frac{\varrho\bar{\pi}_{eu}}{\mu\bar{\pi}_{ue}})\frac{\tau}{\psi}$	$(1-\varrho)\frac{\tau\bar{\pi}_{eu}}{A-b}$	$\frac{\tau\bar{\pi}_{eu}}{A-b}$
ψ	Idiosyncratic risk	$-\frac{\bar{\Psi}(1-\varrho)}{A-b}$	$\frac{\tau+\bar{S}}{\psi}+\frac{\bar{\Psi}\varrho}{\psi\mu\bar{\pi}_{ue}}$	$-\left(1-\frac{\bar{\Psi}(1-\varrho)}{A-b}\right)$	$\frac{\bar{\Psi}}{A-b}$

Notes: Approximation to the steady state elasticities. Rows give the parameters and columns the variables to which the elasticities apply. $\bar{\Psi}$ is the steady state value of the option value from the separation decision. The approximation uses $\beta \approx 1$, $\rho \approx 1$, and $\pi_{eu} + \frac{\mu}{\varrho}\pi_{ue} \approx \frac{\mu}{\varrho}\pi_{ue}$.

three options to generate lower average UE rates in Germany. First, a lower *efficiency of the matching function* $\varkappa$ directly lowers the average UE rate (table 3, row 2), in turn the surplus of the match increase and lowers the average EU rate (table 3, rows 1 and 3). The UE volatility remains unchanged because the increase in the surplus is accompanied by a stronger surplus reaction to business cycle shocks, keeping the percentage change in the surplus largely unaffected (table 4, row 1). The EU rate volatility increases by the same factor as the average UE rate declines (table 4, row 1) matching therefore all of our stylized facts qualitatively.

Second, a *higher outside option* b as argued for in Ljungqvist and Sargent (2008) lowers the surplus of the match, profits, and the average UE rate (table 3, rows 1 and 2). The lower surplus would lead to a counterfactual increase in the average EU rate, so this option has to rely on additional firing taxes τ to jointly explain the mean rate differences across countries (table 3). Still, the mechanism will be inconsistent with the second moments of the data. The third row in table 4 shows that the reaction of the EU rate volatility ($|\tilde{\sigma}_{eu}|$) is always lower by a factor of $1-\varrho$ compared to the reaction of the UE rate volatility ($|\tilde{\sigma}_{ue}|$). Therefore, a decline in the surplus unambiguously decreases the contribution of inflows relative to outflows in the unemployment volatility decomposition and is inconsistent with our empirical evidence. A similar argument can be made for higher firing taxes alone (table 4, fourth row).

Third, a higher *bargaining power* of the worker μ in Germany lowers the share of the surplus accruing to the firm. This in turn lowers the incentives to create jobs and thereby the average UE rate (table 4, row 2). This mechanism is used for example in Blanchard and Portugal (2001) to argue that employment protection legislation implicitly increases the threat point of the worker, thereby raising the worker's bargaining power. The effect of a greater bargaining power on the average surplus is ambiguous and depends on the distance to the Hosios point of efficiency (table 4, second row).

Two counteracting forces are at work: A higher bargaining power lowers the UE rate which tends to increase the average surplus. At the same time, the gain from reemployment in an alternative match increases, which tends to lower the surplus. The surplus is minimized exactly at the Hosios condition[15], when the bargaining power of the worker μ is equal to the matching elasticity ϱ. To see this, we implicitly differentiate the steady state surplus with respect to the bargaining power:

$$\frac{\partial S}{\partial \mu} = \frac{\mu - \varrho}{1-\mu} \frac{\beta \bar{S} \bar{\pi}_{ue}}{\varrho\left(1-\beta+\beta\left(\bar{\pi}_{eu}+\frac{\mu}{\varrho}\bar{\pi}_{eu}\right)\right)}.$$

It can be immediately verified that the surplus has its minimum at the Hosios condition.[16] Intuitively, in the benchmark scenario of a perfectly competitive market without search and matching friction the surplus would be competed to zero, making all workers employed, and force wages to be equal to productivity. The matching friction imposes a deviation from this benchmark leading to a positive surplus. Given all other parameters, the social planner minimizes this deviation by setting the economy at the Hosios condition. As a result, the EU rate volatility is also minimized. Due to the sign switch in the elasticity of $|\tilde{\sigma}_{eu}|$ at the Hosios condition (table 4, second row), a cross-country change in the bargaining power can increase or decrease the EU rate volatility depending on the initial conditions. To the extend that the change in the bargaining power is large enough, the channel works similarly to a change in the matching efficiency. It lowers the gains from posting a vacancy and simultaneously increases the surplus of the match. However, as we show in our calibrated model in the next section, quantitatively the effect is too weak.

[15] Despite our endogenous destruction mechanism, showing that the Hosios condition still holds in our framework is straightforward, conditional on interpreting the outside option as at home-production or the value of leisure, not as a choice of the government.

[16] The second term is always positive, so the extremum must be a minimum.

Table 4 shows that larger firing taxes τ or differences in the standard deviation of the cost shock ψ also affect the average UE rate but this effect occurs only through the impact of τ and ψ on the average EU rate, so their impact turns out to be quantitatively too small to explain the large UE rate differences.

3.3 Quantitative Results

The theory guides us which parameters have the potential to account for the cross country differences. In this section we investigate whether the identified channel also work quantitatively.

3.3.1 Calibration

To calibrate the model, we harmonize four parameters to be equal across countries and allow five parameters to vary. The model is at monthly frequency. Data moments and estimated parameters are given in Table 5. We set the autocorrelation of the aggregate shock to $\rho = 0.975$ implying a standard estimate of 0.95 on a quarterly base, and normalize the volatility of productivity to 1.4% for both countries in line with our empirical findings for the U.S. We set the discount factor $\beta = 0.996$ implying an annual interest rate of 4% and the matching elasticity $\varrho = 0.5$ in line with estimates reported in Petrongolo and Pissarides (2001). We normalize vacancy posting costs to $\kappa = 0.38$ to obtain a probability of filling a vacancy of 90% per month for the U.S.[17] We assume these four parameters to be equal across countries.

The remaining parameters b, ψ, τ, and $\varkappa$ are chosen to exactly match the two average rates $\bar{\pi}_{eu}$ and $\bar{\pi}_{ue}$ and the volatilities $\tilde{\sigma}_{eu}$ and $\tilde{\sigma}_{ue}$. Additionally, we follow ideas in Hagedorn and Manovskii (2008) and choose the bargaining power μ to match the wage elasticity $|\sigma_w|$.[18] Haefke et al. (2007)

[17] The model dynamics depend only on the ratio $\frac{\varkappa}{\kappa}$, so our discussion would also apply to a change in vacancy posting costs. However, an increase in vacancy posting costs κ increases the probability of finding a worker π_{ve} from the firm's perspective, while a lower matching efficiency $\varkappa$ lowers the probability. Evidence on open positions shows that firms search considerably longer in Germany, in line with a decline in the average matching efficiency. Evidence for the U.S. on this point is presented in Davis et al. (2009) and can be compared to establishment level data on open positions for Germany ('IAB Erhebung des gesamtwirtschaftlichen Stellenangebots'). We discuss this point in detail below. The calibration targets are derived using this evidence.

[18] The first-order approximation for the wage elasticity is

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

report estimates for the U.S. of around 0.8 for newly employed workers, whereas they report wage elasticities for job-stayers of 0.4. For Germany, we find estimates for newly employed workers of $0.55-0.85$ and for job-stayers in the range of $0.6-0.8$, depending on how we control for selection.[19] We target $\sigma_w = 0.8$ in both countries, which is at the upper range of the estimates, to allow for fairly flexible wages. In appendix C we show that our results do not depend on the small surplus calibration but that the findings are robust with respect to stronger versions of wage rigidities and a large surplus calibration following ideas of Blanchard and Gali (2010).

Table 5: Calibration

Parameter	$\varkappa$	μ	ψ	b/w	τ
U.S.	0.52	0.27	0.98	0.95	3.23
Germany	0.2	0.55	0.9	0.95	3.38
Data target	$\bar{\pi}_{ue}$	$\bar{\pi}_{eu}$	$\lvert\tilde{\sigma}_{eu}\rvert$	$\tilde{\sigma}_{ue}$	$\tilde{\sigma}_w$
U.S.	30.6	2.0	6.5	11.2	0.8
Germany	6.2	0.53	15.1	10.4	0.8

Notes: Data targets and calibrated parameters.

3.3.2 Quantitative Investigation

In a first experiment we start from the calibrated U.S. economy and change one parameter at a time. We choose the parameter to match one target of the German economy (bold number). In the second experiment we change step by step parameters from their calibrated U.S. values to the calibrated values for Germany to decompose the contribution of each single parameter in accounting for the cross country difference. Table 6 reports the results for the first experiment where we report in the first column the parameter that has been changed relative to the calibrated U.S. economy and the corresponding value. The cases $\mu = 0.5$ (Hosios condition) and $\mu = 0.73$ (volatilities identical to the U.S. benchmark) are included to highlight the changing effect of the bargaining power on $|\tilde{\sigma}_{eu}|$.

(1) A decline in the efficiency of the matching process $\varkappa$ can qualitatively and largely quantitatively account for the cross country differences in means and volatilities. The EU rate volatility is slightly

[19] The estimation results can be found in an earlier working paper that can be downloaded from the authors' webpage.

Table 6: Parameter experiments

		$\bar{\pi}_{ue}$	$\bar{\pi}_{eu}$	$\lvert\tilde{\sigma}_{eu}\rvert$	$\lvert\tilde{\sigma}_{ue}\rvert$	$\lvert\tilde{\sigma}_{w}\rvert$	$\frac{\lvert\tilde{\sigma}_{eu}\rvert}{\lvert\tilde{\sigma}_{eu}\rvert+\lvert\tilde{\sigma}_{ue}\rvert}$
	U.S. (data)	30.6	2.0	6.5	11.2	0.8	32.6
	Germany (data)	6.8	0.5	15.1	10.4	0.8	61.1
(1)	$\varkappa = 0.14$	**6.2**	0.6	20.3	11.5	0.6	63.8
	$\mu = 0.5$	19.0	2.1	5.9	11.2	0.85	34.5
(2)	$\mu = 0.73$	11.2	2.0	6.5	11.2	0.9	36.7
	$\mu = 0.89$	**6.2**	1.6	8.9	11.3	0.9	44.0
(3)	$b/w = 0.99$	**6.2**	3.2	14.5	121	0.5	10.7
(4)	$\tau = 4.6$	26	**0.5**	8.1	16.5	0.85	32.9
(5)	$\psi = 0.7$	25	**0.5**	11.6	17.3	0.85	40.1
	U.S. calibration	$\varkappa = 0.52$	$\mu = 0.27$	$b/w = 0.95$	$\tau = 3.23$	$\psi = 0.98$	

Notes: The second column gives the parameter that has been changed relative to the calibrated U.S. economy and the corresponding value. The bold number shows the targeted data point. The parameters of the calibrated U.S. economy are given in the last line. The two cases where no data point is targeted examine the non-monotonic effect of μ on $\tilde{\sigma}_{ue}$.

too high whereas the wage elasticity is too low. An increase in the bargaining power dampens both effects and allows us to align model and data (see Tables 4 and 5). This can be seen when looking first at the U.S. with a calibrated bargaining power below the Hosios condition. Starting from there we observe a decline in the EU rate volatility until $\mu = 0.73$, so our final parameter choice $\mu^{GER} = 0.52$ dampens the EU rate volatility.[20] (2) An increase in the bargaining power alone would qualitatively move the economy in the right direction, but leaves us quantitatively substantially away from the observed differences. The changes in both the average EU rate and the EU rate volatility are too small. (3) An increase in the outside option b increases the UE rate volatility substantially while the EU rate volatility increases only slightly.[21] (4) An increase in firing taxes lowers the average EU rate but it has only a very modest impact on the average UE rate and almost no impact on the EU volatility while increasing the UE volatility. (5) The variance of the idiosyncratic shock process ψ lowers the average EU rate, but increases both the EU and UE volatilities, leaving the contribution rates in the decomposition of the unemployment volatility unaffected.

Our experiments show that differences in the matching efficiency can explain qualitatively and

[20]We consider $\mu = 0.73$ in particular because there it holds that $\mu = \varrho + 0.23$ and we have $\mu^{US} = \varrho - 0.23$.

[21]We show in appendix C that this effect is not an artifact of the small surplus calibration but also holds more broadly in a *'large surplus'* calibration with rigid wages.

quantitatively the empirical cross-country differences. To make this statement quantitatively precise we use the sum of squared distances of the targeted moments and see how much of the distance each of the calibrated parameter can account for. To control for the differences in levels and measurement we weight the differences by the inverse of the variance-covariance matrix that we bootstrap from the data. The decomposition is shown in table 7.[22]

Table 7: Decomposition experiment

$\varkappa$	0.52	0.20					58.40 %
ψ	0.98	0.98	0.90				20.05 %
μ	0.27	0.27	0.27	0.55			7.57 %
τ	3.23	3.23	3.23	3.23	3.38		7.36 %
b/w	0.95	0.95	0.95	0.95	0.95	0.95	6.62 %
		58.72 %	78.45 %	86.02 %	93.38 %	100.0 %	

Notes: The columns show the different parameterization. The first column shows the U.S. calibration. Starting from there one parameter is changed with every column to the German value. The last column gives the contribution of every parameter in explaining the cross country differences. The last row gives the share explained by the current parameterization. The difference to be explained is the total sum of squared deviations and we weight the difference by the inverse of the variance covariance matrix of the targets that we bootstrap from the German data. (5,000 repetitions)

The table shows that the matching efficiency accounts for 60% of the cross-country differences, more than all other parameters taken together. Wage inequality related to the variance of the idiosyncratic shock accounts for another 20%. The institutional differences pick up only the remaining 20%.

3.4 Transmission of Shocks

Do the documented differences matter for the transmission of shocks? We first show that the simple shock structure imposed in this model still captures important aspects of the data. We then report impulse response functions to highlight differences in the propagation of shocks. We find that the lower matching efficiency induces a significant propagation to shocks in Germany. Our mechanism

[22]The decomposition is done by changing one by one parameters from the calibrated U.S. value to the German value. Once a parameter has been changed, we keep it at the German target so that after the last parameter change the steady state of the German economy is reached. For each step we measure the change in the distance between the targets under the current calibration and see how much the economy has moved. We do the order of changes by the shares in the decomposition. We tried other orders but the decomposition shares do change only very little.

provides therefore a rational for Germany's observed sluggish recovery in the aftermath of the oil price shocks during the 1980s.

For both countries, we estimate the underlying shock processes using a Kalman filter on GDP growth. We feed the estimated processes into the model using the estimated parameters of table 5 and predict all endogenous variables, applying an HP-filter ($\lambda = 100,000$) to the resulting time-series. Figure 2 illustrates the success of the simple model. The time series pattern of the

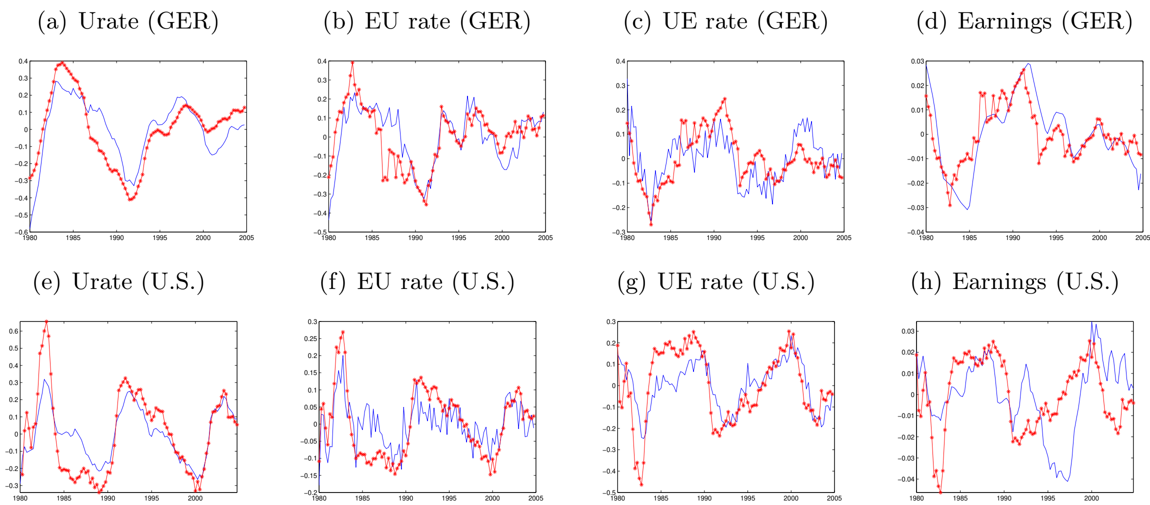

Figure 2: Data and predicted series

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 $\lambda = 100,000$.

unemployment rate are predicted well, and the model captures both the EU and UE rate dynamics in both countries. The model reproduces the time series pattern of earnings in Germany very well, yet it fails to predict the earnings in the 1990s for the U.S. Overall, the success for both countries lends credibility to the underlying mechanism explored in this paper.

Figure 3 shows impulse-response functions for the calibrated economies after a large negative shock of 4% that roughly matches the increase in the unemployment rate at the beginning of the major recession in Germany in the 1980s after the second oil crisis. The impulse-responses reveal the key cross-country difference in the reactions to a productivity shock. In the U.S. the unemployment rate peaks three quarters after the initial shock, whereas in Germany it peaks after nine quarters, demonstrating a substantial propagation to shocks. Afterwards, the German recovery is very slug-

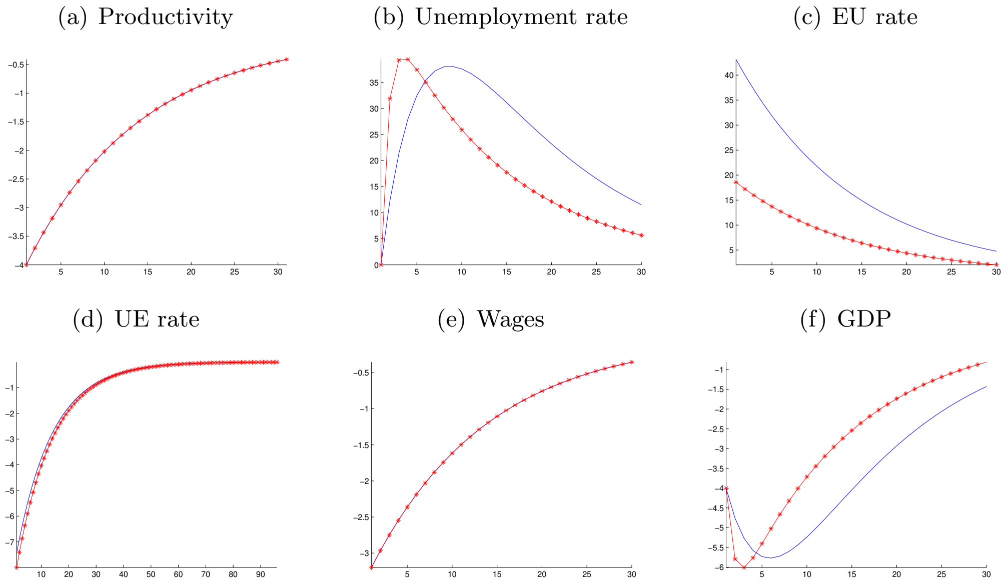

Figure 3: Impulse response functions

Notes: The figure plots the impulse response functions for the U.S. (red dotted lines) and Germany (blue solid line) on a quarterly scale. The initial productivity shock is -4%.

gish. In fact, five years after the shock hit the economy, the German unemployment rate is still 23% away from its long-run average, while the U.S. rate is only 12% above its steady state value. Peak unemployment is similar across the two countries, but the unconditional standard deviation of the unemployment rate for Germany is still 29% larger than it is for the U.S., consistent with our empirical findings.

Figures 3(d) and 3(e) show that the different reactions of the unemployment rate to shocks are not generated by differences in the reaction of UE rates or wages.[23] The sluggish response in Germany is caused by an interplay of the strong reaction in the EU rate causing a strong rise in unemployment (figure 3(c)) and low reemployment probabilities due to the lower average UE rate. Furthermore, the model generates positive output growth in Germany after 6 quarters that is accompanied by unemployment rates that continue to increase for an additional $3-4$ quarters.

[23] Recall that the wage reaction is calibrated to be the same across the two countries.

3.5 Empirical evidence

Our quantitative findings suggest that the microstructure of matching unemployed workers to open positions plays an important role in explaining the cross-country differences both in mean rates as well as in volatilities. We first present direct evidence for a lower matching efficiency in Germany and then offer a more detailed explanation based on occupational and regional mobility rates.

Direct evidence on a lower matching efficiency in Germany is provided by Burgess and Mawson (2003) who estimate a substantially lower matching efficiency for Germany than for the United States over the period $1967-1997$. Indirect evidence is widespread and unambiguously supports a lower matching efficiency in Germany. First, looking at the firm's side of the match: Davis et al. (2009) estimate using JOLTS data an average daily job filling of 5% and a corresponding average vacancy duration of 16.25 working days for the period $2001-2006$ for the U.S. Adding in weekends and holidays this period increases to $19-29$ calender days. For Germany the most comparable search duration is from the beginning of search to signing the contract.[24] For the period from $2001-2006$ the average vacancy duration for Germany has been 42 calender days slightly lower than the long-run average for $1989-2006$ of 46 calender days. An average duration of 42 days corresponds after controlling for weekends and holidays to a daily job filling rate of 2.9%.[25] This shows that German firms face more problems in filling their vacancies than their U.S. counterparts. On the worker's side the explanation that the lower matching efficiency in Germany is responsible for the low transition rates and the sluggish labor market response has been very prominent since the 1980s, when the empirical literature documented a strong outward shift of the Beveridge curve for Germany, e.g. Gross (1993) and Schettkat (1992). Franz (2009) provides a detailed survey of this literature. More recently, the outward shift of the Beveridge curve in the U.S. during the current crisis has also been discussed as a consequence of a decrease in the matching efficiency (Elsby et al. (2010a), Kocherlakota (2010)). In Germany the Hartz reforms starting at the end of our sample period have been precisely aimed at increasing the overall matching efficiency, possibly

[24]The IAB collects since 1989 establishment level data on open positions (*'IAB Erhebnung des gesamtwirtschaftlichen Stellenangebots'*). The data for Germany has been kindly provided by the IAB and comes from this survey.

[25]If instead of the time from opening the position to signing the contract the period from opening the position to the actual begin of working is considered the average vacancy duration increases for $2001-2006$ to 67 calender days again slightly below the long-run average of 72 days.

explaining the quicker recovery we witnessed in the current crisis.[26]

The aggregate picture just outlined is commonly attributed to the particular 'credential-based occupational structure' of the German labor market (Diprete et al. (1997), p.325)[27]. If workers and firms meet randomly in the market and face the same contact rate in Germany and the U.S. but more workers or jobs are rejected either due to missing occupational credentials or for example due to larger moving cost[28] the resulting matching efficiency parameter $\varkappa$ is estimated to be lower in Germany. In this case, the range of offers considered by a worker and the range of worker types considered by a firm shrinks which would then lead to a lower aggregate matching efficiency.[29] In the empirical literature this channel has been held responsible for the low matching efficiency in Germany (cp. Schioppa (1991), Franz (2009)).

The most closely related empirical study[30] along this dimension offering micro-evidence is Gangl (2004) who provides a direct comparison of German and U.S. occupational mobility rates using the same IAB data source for Germany. He contrasts occupational mobility in Germany with U.S. data from the Survey of Income and Program Participation (SIPP) over the period from $1984 - 1995$ covering partly our sample period. He finds that occupational mobility out of unemployment is about 40% higher in the U.S. Diprete et al. (1997) document gross flow rates across industries in the U.S. and in Germany. They also find that the gross flow rates for the U.S. are substantially higher. The high mobility rates for the U.S. have also been documented in Kambourov and Manovskii (2008) and Moscarini and Thomsson (2007) and evidence on low occupational mobility for Germany can be found in Franz (2009) and Hecker (2000).[31]

[26]The reaction to the financial crises shock in Germany is beyond the scope of this paper. The data currently available to us suggest though that a structural change has occurred possibly due to the large Hartz reforms that have been undertaken in the years 2001-2004.

[27]Soskice (1994) provides an excellent and comprehensive overview of the German apprenticeship system that underlies this 'credential-based occupational structure'.

[28]Molloy et al. (2011) document substantially higher regional mobility rates for the U.S. in comparison to Germany for 2005.

[29]From an earlier IAB survey on vacancies (Cramer (1990)) it can be seen that occupational barriers might play an important role. In 1989 firms report that 21% of applicants are not considered for a position because of missing or too few occupational training.

[30]Kambourov and Manovskii (2009) provide a micro-founded theoretical model for occupational mobility.

[31]The study by Hecker (2000) shows further that holding an occupational degree reduces occupational mobility significantly. She reports for 1999 that 53% of workers without occupational degree report at least one occupational change in their career (18% report more than one change) while for workers with occupational degree only 26% report an occupational change (6% report more than one change). Hecker documents that the occupational mobility in Germany has been stable since the beginning of the 1980s with a decrease at the end of the 1970s that marks the

The upper part of figure 4 uses data from Gangl (2004) to visualize low occupational mobility in Germany. It shows the relative differences for job-to-job transitions to occur within occupational classes vis-a-vis between occupational classes[32] for the years $1984-1995$ and 12 broadly defined occupational classes. The dark area along the diagonal and the fast transition to bright areas off the diagonal visualize that German workers are essentially attached to their occupations while the much more dispersed dark areas and the slow transition towards brighter areas visualize that U.S. workers more likely switch occupational classes.

In the lower part of figure 4 we compare mobility rates in Germany to the mobility rates reported in Kambourov and Manovskii (2008) for the U.S.[33] We see that the mobility rates in Germany have been fairly stable over time and are roughly 50% lower compared to U.S. data taken from Kambourov and Manovskii (2008) (industry mobility, 1-digit level).

Taken together the theoretical analysis and the presented evidence show that the microstructure of the German labor market likely differs substantially from the one of the United States. The presented evidence suggests that German workers sample from a more narrowly defined offer distribution so that the resulting matching rate of open positions to unemployed workers is lower. Besides its empirical support, the lower matching efficiency simultaneously explains, unlike arguments relying on institutional differences, both the lower average transition rates and the larger EU rate volatilities in Germany. We show in the next section that this result still holds in our model with heterogeneous worker types and refined explanations to account for the cross-country differences.

beginning of our sample period.

[32]Gangl (2004) discusses that similar results apply to UE transitions.

[33]Kambourov and Manovskii estimate a linear probability model to get the industry mobility rates shown in figure 4. This is necessary because they show that the PSID data they use for the U.S. suffers from misclassification in industry and occupation codes. They argue that this is due to missing information of the worker's employment history at the initial coding stage and they use the regression model to correct for this misclassification. In the German data industry information is coded by employers and it can be expected that this leads to less misspecification over time especially for workers that stay with their employer and who comprise the majority of our sample. To construct comparable mobility rates for Germany we take industry information of all employed workers in July of each year and compare it to the previous year. In case of unemployment we take the industry code of the last employment spell.

(a) United States (b) Germany

(c) United States (d) Germany

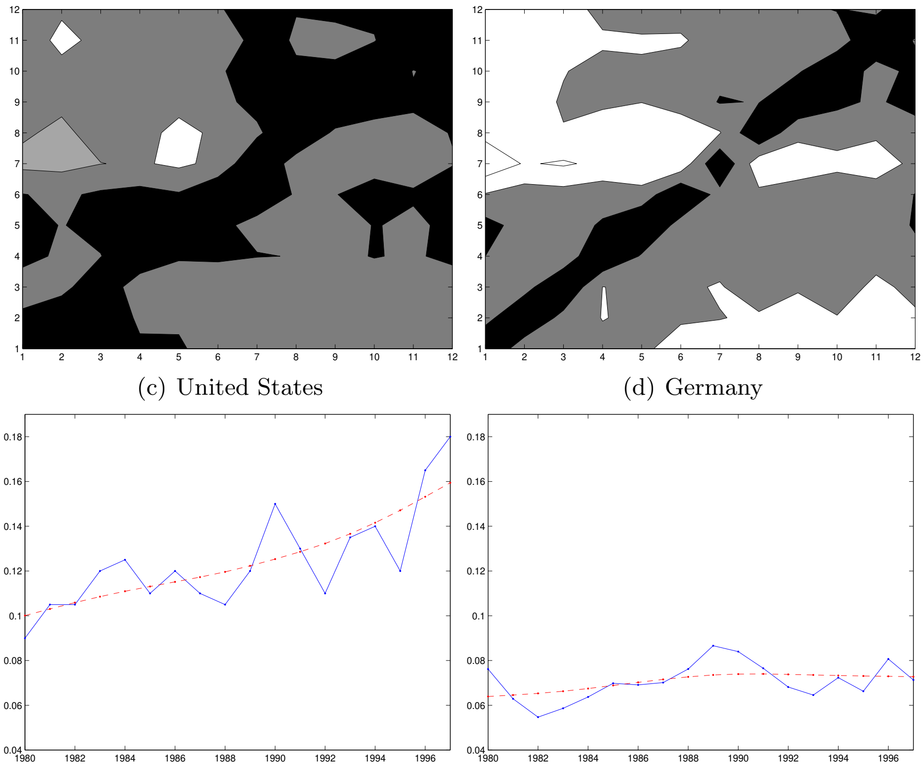

Figure 4: Occupational mobility

Notes: Top panel: The figures shows logit scores (λ) for mobility rates of job-to-job transitions for 12 broad occupational classes. The destination sector is given on the horizontal axis and the origin sector on the vertical axis. The logit score measures the transition probability from origin i to destination j relative to the probability of remaining at the origin i ($\pi_{ij} = \exp(\lambda)\pi_{ii}$). The darker shaded an area is the more intense are mobility flows. The three contour borders for logit scores (λ) are at -2, -4, and -6. The data has been kindly provided by Markus Gangl (see Gangl (2004) for further details). The sectors are Managerial and executive (1), Professional specialty (2), Technicians and related (3), Trade and sales (4), Administrative support (5), Services (6), Agriculture (7), Mechanics and related (8), Crafts and construction (9), Operators and assemblers (10), Transportation (11), Elementary (12). Bottom panel: The data for the U.S. has been taken from Kambourov and Manovskii (2008) for industry mobility at the one digit level. The data for Germany are authors' calculations. The blue solid line shows the raw data and the red dashed line a smoothed profile.

4 Extensions and Sensitivity

A large body of literature has argued that institutional differences related to the employment protection legislation might be an important source for the cross-country differences in average transition rates. Ljungqvist and Sargent (2008) propose that a combination of higher benefits, larger firing taxes and micro-economic turbulence can explain differences in mean rates between the U.S. and Europe. Moreover, the employment protection legislation might shield high-tenured and low-tenured workers differentially. This effect might give firms incentives to circumvent firing taxes for low tenured workers using for example short-term employment contracts (Costain et al. (2010), Bentolila et al. (2010)).

Our study so far has abstracted from worker heterogeneity to highlight the main channel. We now extend the baseline version of the model to account for heterogeneity effects. We first present some additional empirical results for the labor market dynamics in Germany and the U.S controlling for tenure. Then, we offer a theoretical exploration allowing for worker heterogeneity that uses our empirical findings to discriminate between the outlined explanations and our own channel.

4.1 Tenure - Data

To examine the role of skill accumulation and employment protection empirically, we construct transition rates conditioning on tenure for four tenure classes. For Germany, these data can be constructed from employment histories. For the U.S., we rely on irregular supplements to the CPS that report information on tenure with the current employer.[34]

Table 8 shows that both countries have a strongly declining pattern of transition rates with tenure. In Germany the average rates are substantially below the U.S. rates in all tenure classes, but the relative decline across tenure groups is similar. In both countries the shares in all transitions decline with tenure. For Germany we can also look at the volatilities of transition rates across tenure classes.[35] The EU rate volatility is very large for all tenure classes and is, if anything,

[34] Additional details on flows into inactivity and transitions to other firms can be found in the appendix.

[35] Because we only have information at a limited set of points in time for the U.S., we can not calculate reasonable volatilities for the different tenure classes there.

Table 8: EU transition rates by tenure classes

	Statistic	< 1	$1-2$	$2-5$	> 5
Germany	MEAN	1.8	0.7	0.4	0.2
	SHARE	58.5	13.5	14.6	13.5
	STD	19.6	17.4	23.0	23.4
	CORR	-0.77	-0.74	-0.73	-0.57
U.S.	MEAN	4.7	2.4	1.6	0.8
	SHARE	48.4	11.3	18.9	18.3

Notes: Tenure categories are given in years. All transition rates (MEAN) are given as percentages of the workers in the respective tenure group. SHARE gives the percentage share of all transitions that originate from this tenure class. For Germany STD gives that standard deviation of the log transition rate after the trend has been removed using a HP-Filter ($\lambda = 100,000$). CORR gives the correlation with GDP. Data for Germany are quarterly averages of monthly rates for full-time employed workers. For the U.S. averages of all available monthly rates are taken. Source: All rates are authors' calculations.

increasing over tenure.[36] The correlation is strongly negative but slightly decreasing across tenure classes.

4.2 Augmented Model

To investigate whether different human capital accumulation processes between the two countries are potentially a driver of the labor market differences pointed out in section 1 we augment the benchmark model by worker and match-specific human capital. To economize on the state space, we assume that employed workers can be in three tenure states, low, medium and high (L, M, H). We assume that workers stochastically gain match-specific skills by staying at their firm, i.e. accumulating tenure. We normalize the initial state and set match specific productivity in the lowest tenure state to $s_L = 1$. The worker needs on average 2 years to transit to tenure level M, and another three years to transit to the final tenure state H. Workers with $2-5$ years of tenure (state M) have a skill level $s_M = (1+g_M)$ and workers with 5 years or more of tenure (state H) have skill level $s_H = (1 + g_H)$. Upon separation the worker loses tenure. We target g_M and g_H to reproduce the declining EU transition rates in the U.S. We find $g_M = 0.034$ and $g_H = 0.067$ so the yearly increase of skills in tenure is roughly 1.3%.[37].

[36] The uniformly larger volatilities across tenure classes compared to the unconditional transition rate can be shown to result from composition effects.

[37] Altonji and Williams (2005) reports gains to tenure of 11% for ten years for the U.S., roughly in line with these numbers. Dustmann and Meghir (2005) report returns to tenure for skilled German workers of $1.7 - 2.4\%$.

To study skill losses, we additionally assume that the worker can be in one of three worker-specific skill states, namely, bad, normal, or good with productivity denoted by z_B, z_N, and z_G, respectively, so that the total number of idiosyncratic productivity states is nine. We assume that the skill process attached to the worker z_i is given by a discrete approximation to an AR(1) process with three states.[38] We set the autocorrelation coefficient at 0.98 on a monthly basis to generate a persistent process as in Costain et al. (2010) and set the standard deviation to match a shock size of 10% in our discrete approximation, normalizing $z_N = 1$.[39] During unemployment, the worker also switches states according to this AR(1) process.

Worker and match-specific states follow independent stochastic processes, so we calculate the appropriate transitions functions p_{ee}, p_{eu},p_{ue} and p_{uu} on the stacked vector of idiosyncratic states as the convolution of the two processes and assume that a particular individual state is the product of the two processes.[40] We aggregate over the worker-specific states and report the average for each tenure class.

We recalibrate the remaining parameters to match the same aggregate statistics as in the benchmark case.[41] The upper part of Table 9 reports the calibrated U.S. economy together with the empirical targets. The last line in the upper part reports the data targets for Germany. In the lower part of the table we perform four experiments similar to those in table 6. Again, we change parameters (first column) starting from the calibrated U.S. economy to match a German data target (bold number).[42]

[38]We use the method of Kopecky and Suen (2010) to obtain the conditional Markov transition kernel numerically.

[39]In contrast to standard models with endogenous destruction the variance of the worker specific shock process is less important for the business cycle dynamics given that separation rates are still governed by idiosyncratic match-specific shocks with variance proportional to ψ. We again calibrate these shocks to reproduce the aggregate EU rate volatility of the U.S. Varying the standard deviation between $5-20\%$ and recalibrating ψ does not affect the results.

[40]That is the first state is $x_1 = s_L z_B, x_2 = s_L z_N, \ldots, x_9 = s_H z_G$. The resulting transition matrix $p_{ue}(x, x\prime)$, for example, captures the fact that unemployed workers can only switch to low tenured jobs.

[41]We additionally introduce a stochastic probability of retiring to allow for exogenous separations for high tenured workers. We set the work-life to 30 years as in Costain et al. (2010), and assume that newly born workers are born with skill levels according to the invariant distribution of the Markov transition. We adjust the model equations accordingly. We see that heterogeneity lowers the average net replacement rate but only very modestly. All other parameters are very similar to the benchmark case.

[42]We rely throughout on a first order approximation, given that the state space has to include all employment states by skill, implying 18 state variables in the model.

Table 9: Experiments

		$\pi_{eu,L}$	$\pi_{eu,M}$	$\pi_{eu,H}$	π_{ue}	$\lvert\tilde{\sigma}_{ue}\rvert$	$\lvert\tilde{\sigma}_{eu,L}\rvert$	$\lvert\tilde{\sigma}_{eu,M}\rvert$	$\lvert\tilde{\sigma}_{eu,H}\rvert$	σ_w
	U.S. (Data)	3.6	1.7	0.8	30.6	11.2		*6.5		0.8
	U.S. (Model)	3.6	1.7	0.8	30.6	11.2	4.6	5.8	6.7	0.8
	GER (Data)	1.3	0.4	0.2	6.2	10.5	18.4	23.0	23.4	0.8
(1)	$\varkappa = 0.12$	1.4	0.5	0.2	**6.2**	10.1	14.6	16.8	19.1	0.7
(2)	$\tau_M, \tau_H = 4.9$	3.7	**0.4**	**0.2**	28.9	14.3	5.2	9.0	10.0	0.8
(3)	$\tau_M, \tau_H = 4.5$ $\mu = 0.92$	2.9	**0.4**	**0.2**	**6.2**	12	8.0	12.6	14.5	0.9
(4)	*Turbulence*	2.6	0.9	0.4	21.5	19	6.4	9.1	12.3	0.9
U.S. calibration		$\varkappa = 0.52$		$\mu = 0.35$		$b/w = 0.93$	$\tau = 3.05$		$\psi = 1.08$	$\kappa = 0.26$

Notes: The upper part reports the data. The value on the EU rate volatility for the U.S. marked by * is the average over all tenure classes due to data limitations. The lower part reports the experiments. $\pi_{eu,L}$, $\pi_{eu,M}$ and $\pi_{eu,H}$ denote the EU rate for low, medium, and high tenured workers averaged over all idiosyncratic skill levels. The same applies for $|\tilde{\sigma}_{eu}|$. The second column gives the parameter that has been changed relative to the U.S. calibration and the corresponding value. The calibration for the baseline U.S. economy is given in the last line.

4.2.1 Matching Efficiency

The first experiment decreases the matching efficiency $\varkappa$ to show that the identified mechanism from the previous section still works in the extended model. The average EU rate falls in each tenure class because accumulated skills become more valuable and the surplus increases. Upon separation high tenured workers lose tenure. Due to the long search duration it takes longer to accumulate human capital in a new match which makes German workers more reluctant to separate. The average EU rates fall in a way consistent with the observed tenure pattern. Moreover, due to the larger surplus in each tenure class the EU rate volatilities increase.

4.2.2 Differential Firing Taxes

In experiments 2 and 3, we introduce different firing taxes for low and high tenured workers. We keep τ_L at its U.S. value and increase τ_M and τ_H to target the observed EU rates in Germany. In experiment 2, the presence of tenure-dependent firing taxes leads to a decline in the EU rates for protected workers and to an increase for unprotected workers. Due to a larger surplus, the EU rate volatility modestly increases for workers with higher tenure and remains largely unchanged for low-tenured worker. The unemployment volatility is amplified because both the UE rate and the EU rate volatility increase. In the decomposition, the contribution of the EU rate falls because the increase in the UE rate volatility dominates.

A firing tax by itself has only a very small impact on the average UE rate. If firing taxes additionally affect the threat point of the bargaining, the implicit bargaining power increases. Therefore, the third experiment jointly varies the firing taxes as well as workers bargaining power. As analyzed before, a substantial increase in the bargaining power will raise the surplus, if the deviation from the Hosios condition is large enough ($\mu = 0.92$). Again, we see a larger decline in the EU rates for high tenured workers, a counterfactually high average EU rate for low tenured workers and a counterfactually low EU rate volatility. Moreover, the surplus of low-tenured workers declines, which increases the UE rate volatility.

4.2.3 Human Capital Accumulation and Turbulence

The final experiment considers a version of *turbulence* along the lines of Ljungqvist and Sargent (2008) and similarly Wasmer (2006) to study the role of worker and firm specific human capital. We assume that skills are firm specific in Germany and are lost after a separation. Concretely, we assume that highly skilled workers (good types) lose their skills and become a normal type upon separation, while workers with normal skill levels become bad types. That is, a large fraction of the people in the work force lose 10% of their skill levels upon separation. This assumption transforms skills that are attached to the worker in the U.S. to skills that are more firm-specific in Germany.[43] The higher risk of losing skills increases the surplus for medium- and high-skilled workers in Germany. As a result the average EU rates decline for these groups. For low-tenured workers, the decline is not as pronounced as observed in the data. Two effects are at work. Making skills more match-specific in Germany tends to increase the average surplus and therefore the average UE rate because it is more attractive for firms to post vacancies. However, the composition of the unemployment pool changes, too. There are more bad types in the search pool. This effect tends to make it less attractive to post vacancies. In our calibration, there are 44% bad types in the unemployment pool for the U.S., while in Germany, due to the skill losses, the number increases

[43] We choose this calibration that is at the upper end of previously reported empirical values (Fujita (2008), Burda and Mertens (2001)) to get the largest effects from our experiment. The flexible specification of the transition matrices would also allow for specifications where only a fraction of the skills are lost, but such specification would yield smaller effects.

to 75%. If differences in the skill processes are the main driving force in explaining the empirical labor market differences across countries, the deterioration in the skills of the unemployed has to dominate to explain the lower UE rates in Germany. This is the case in our calibration. However, the resulting decline in the expected surplus from creating an open position then increases the UE rate volatility, and the contribution to unemployment volatility of the EU flows, relative to the UE flows, declines.

Our experiments show that the behavior of the transition rates by tenure is potentially informative for further discriminating between the different explanations studied in the literature. Differential firing taxes do not explain the low average transition rates of low-tenured workers in Germany. Differences in the idiosyncratic skill processes depending on the strength of the composition effect in the unemployment pool, increases either the average UE rate or the contribution of the UE rate volatility. Both implications are counterfactual. To explain the data, one needs a mechanism that jointly increases the surplus and lowers the average UE rate.

5 Conclusions

In this paper, we document large differences in the average transition rates and in the behavior of the EU rate volatility in Germany in comparison to the U.S. We show analytically that in a fairly standard search and matching model the second moments of the data offer identification restrictions that help to disentangle different explanations for the large cross-country differences in first moments. We also show that some of the usual 'suspects' for the transatlantic division, such as employment protection, union bargaining and the benefit system are likely not the main driving forces of the observed differences. Instead, we identify a lower matching efficiency as an alternative explanation and show that roughly 60% of the observed differences between Germany and the U.S. can be explained by inefficiencies in the matching process. We discuss widespread empirical evidence that supports a lower matching efficiency in Germany. We suggest that barriers to switch occupations are an important source for these matching imperfection and largely responsible for the propagation of shocks in Germany. While the crucial step taken in this paper is to show how to discriminate between alternative explanations for differences in labor market dynamics, it will be the subject of future research to understand the details of the identified labor market friction in a more micro-founded way. In particular, the large labor market reforms associated with the 'Hartz' legislation were explicitly directed to increase the efficiency in the matching process in Germany and might explain the altered transmission mechanism we observed during the Great Recession. We plan to explore the identified low matching efficiency in Germany in the light of these structural changes in our future research.

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A Data

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). The data consists of daily 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 inactivity. 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.1 Sampling period and sample selection

Due to problems in measuring 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 ($2,787$ individuals dropped) or information regarding the current job is missing[44] ($14,490$ individuals dropped). Furthermore, we drop homemakers ('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 German reunification, the data contain employment histories with spells that are located in East Germany. Because 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 $1,087,555$ individuals. 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.

To construct employment spells, we need the person's age from time to time. We use year of birth and the date of the spell to construct age. However, the variable year of birth is censored for all observations in the employment history, if a person is at least at one spell below 16 or older than 62. Due to the sample length both cases can not occur simultaneously. In the first case, we set year of birth as if the person is 15 at the first spell and in the second case as if the person is 63

[44] stib information missing.

at the last spell. We recover age at all spells consistently. For variables regarding the job status, earnings, or the duration of the job the data contains virtually no measurement error because it is taken from the social security records that are used to determine social security contributions and benefits.

A.2 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 for administrative reasons of the social security system or change within a given firm. Importantly for our analysis, every change of employers or the beginning of an unemployment or an inactivity spell is recorded in the data. Individuals in the sample regularly have periods of parallel employment which are reported as multiple spells. For every spell, we observe whether it is full-time, part-time, or starting in 1999 marginal employment. We apply a hierarchical ordering to classify these spells.[45]

Our basic time-period is one month. We adopt a CPS like timing convention to measure the employment status of a person in a given month. For each month we identify the date of 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 in the current month. If several spells overlap, we again use a hierarchical ordering of spells[46] From this classification of monthly employment states, we construct monthly time-series. To check whether a person stays with the same employer, we use the establishment number of employment spells. Thus, the transition of a person between establishments but within the same firm is counted as a job-to-job transition. The definition of

[45]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 of an individual's working time. 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 jobs, we follow the ordering in the dataset, which applies a hierarchical ordering based on income and part-time status over parallel spells. Finally, if a person has simultaneous 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. This problem only arises with marginal employment and can be disregarded for the analysis in this paper.

[46]A full-time employment spell dominates part-time spells and any employment spell trumps unemployment or inactivity spells.

who is counted as unemployed follows from the content of the dataset. A person is unemployed if she receives unemployment benefits or other benefits on the basis of the Social Security Code III ('Sozialgestzbuch III'). We can not follow the CPS definition that is based on interview questions about an unemployed individual's job search and willingness to take up employment, because this information is unobservable in our sample.

Intervals during which an individual in the dataset is not working are labeled as inactive employment periods. These spells are periods of sustained employment relationships that are currently inactive, i.e., the worker does not work and no income is paid. Examples of these periods are maternity leave, long periods of illness, and sabbaticals. We construct additional inactivity 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 or dropping out of the sample, we introduce additional labor market states that we label *labor market entry* and *retirement*.[47]

A.3 Aggregate data

Our GDP measure for Germany is GDP per capita. We use GDP per capita because of the large inflows to West Germany after the fall of the Berlin Wall but before the official reunification. To obtain productivity, we divide by the number of employed persons. The time series for West Germany at quarterly frequency are only available until 1992Q4 afterwards only GDP series for Germany are available at a quarterly frequency. We merge the two series in 1992Q4 and run an ARIMA X-12 outlier correction on the combined series. The outlier correction controls for additive outlier, temporary, and permanent shifts in the data. The earnings series for Germany are median earnings of full-time employed workers from our dataset[48]. We deflate all series using the CPI. The unemployment rates for Germany are available at monthly frequency for West Germany and

[47]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 who are 55 years or older when they have their last observed spell. The retirement state is, by construction, an absorbing state and persons that enter will be dropped from the analysis one month later. 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 inactivity state, i.e. they do not generate transitions out of inactivity. Persons who are younger than 55 but have future spells are labeled as *out of the labor force*. The *labor market entry* state, the reported spells of inactivity, and the *out of the labor force* spells constitute the pool from which all inactivity transitions originate.

[48]Details on earnings can be found in the online appendix.

we aggregate to quarterly frequency by taking quarterly averages of monthly rates. GDP, GDP per employed (productivity), earnings, and unemployment rates for the U.S. are obtained from the Bureau of Labor Statistics (BLS). Except for the EE rates obtained from Fallick and Fleischman (2004) all data on transition rates are obtained from Shimer (2007). The transition rates by tenure groups for the U.S. are the authors' calculations. We rely on irregular supplements to the CPS that report information on tenure with the current employer. These are the *Occupational Mobility and Job Tenure* supplements for the years 1983, 1987, 1991, 1996, 1998, 2000, 2002, 2004, and 2006. We link the supplement information to the basic monthly data files as described in Shimer (2007). Using the linked monthly files, we construct gross flow rates by tenure for the nine months for which tenure information is available. The reported transition rates are time averages. Due to the rotation of the panel and the point in time information on tenure in the CPS, we report only transition rates in the month where tenure is available. U.S. transition rates are adjusted for seasonal effects and time aggregation to match their unconditional averages. The transition rates by tenure for Germany are constructed using the employment histories of full-time employed workers from the IAB panel. All data are generated based on our own calculations are seasonally adjusted at a monthly frequency using the X-12 ARIMA method.

B Unemployment decomposition

We describe here the decomposition proposed in Fujita and Ramey (2009) and our extension. The decomposition of Fujita and Ramey is a two-state decomposition with two-transition rates. The idea of the decomposition of the unemployment volatility into contribution rates from EU and UE flows is to take an approximation around trend unemployment

$$\begin{aligned} u_t &\approx \frac{\pi_{eu,t}}{\pi_{eu,t} + \pi_{ue,t}} \\ \log\left(\frac{u_t}{\bar{u}_t}\right) &= (1-\bar{u}_t)\log\left(\frac{\pi_{ue,t}}{\bar{\pi}_{ue,t}}\right) - (1-\bar{u}_t)\log\left(\frac{\pi_{eu,t}}{\bar{\pi}_{eu,t}}\right) + \epsilon_t \\ du_t &= dUE_t + dEU_t + \epsilon_t \end{aligned}$$

where $\pi_{eu,t}$ denotes the EU rate and $\pi_{ue,t}$ the UE rate. A bar denotes the trend component of the respective variable. $\log(u_t/\bar{u}_t)$ measures the relative deviation of the unemployment rate from its trend.

Fujita and Ramey 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 contribution of the corresponding series in explaining the cyclical variation of the unemployment rate. Using an equivalent steady state approximation for the three state case and defining weights $\alpha := \frac{\bar{\pi}_{nu}}{\bar{\pi}_{ne}+\bar{\pi}_{nu}}$ and $\lambda_{ij} := (1-\bar{u})\frac{\bar{\pi}_{ij}}{\bar{\pi}_u}$, as well as the (weighted) average of separation and hiring rates $\bar{\pi}_u := \bar{\pi}_{eu} + \frac{\bar{\pi}_{nu}}{\bar{\pi}_{ne}+\bar{\pi}_{nu}}\bar{\pi}_{en}$ and $\bar{\pi}_e := \bar{\pi}_{ue} + \frac{\bar{\pi}_{un}}{\bar{\pi}_{ne}+\bar{\pi}_{nu}}\bar{\pi}_{ne}$, we obtain an extended decomposition

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

Again using $\beta_x = \frac{cov(du_t, d\pi_x)}{var(du_t)}$ a similar covariance decomposition as in Fujita and Ramey (2009) of the form $1 = \sum_{i=1}^n \beta_i + \varepsilon_t$ applies. The formula is similar to the first difference filter obtained in Petrongolo and Pissarides (2008), although they essentially lump together the rates $dEN_t + dUN_t$ and the corresponding inflow rate into $dNE_t + dNU_t$. In fact, the inactivity 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 only the (gross) flows are needed. A detailed derivation is available upon request.

C Robustness

Our quantitative results use a 'small surplus' calibration, as proposed in Hagedorn and Manovskii (2008), to generate the UE rate volatility observed in the data. The recent literature has stressed versions of wage rigidities as an alternative explanation for the large UE rate volatilities.[49] Although the micro-foundations of the form of wage rigidities differ substantially across papers, the basic mechanism is similar: Making wages rigid over the cycle increases firm profits more than proportionally in a boom, so the percentage change in firm profits is amplified, and in turn, the UE rate volatility increases.

We capture this effect by introducing a countercyclical outside option $\tilde{b} = b \exp(\varphi(x)a)$. If we set $\varphi(x) = 1$, we obtain an outside option indexed to the average wage over the cycle and a wage elasticity of 1; if $\varphi(x) = 0$ we obtain our benchmark model typically used in the literature; and if $\varphi(x) < 0$ we can make wages more rigid. Conditioning on tenure status, we can make wages for different subgroups, i.e., newly employed workers or continuously employed workers, rigid to different degrees. This capability allows us to study the impact of wage rigidities on our findings.

We use the same calibration strategy as before, with the exception that we now target a replacement rate of 80%, which we call a 'large surplus' calibration.[50] We use $\varphi = -2.9$ to generate the UE volatility observed in the data. We still target a wage elasticity of 0.8 initially, so the bargaining power for the U.S. has to increase substantially. Compared to the benchmark calibration, the total surplus of a match increases but average profits accruing to firms remain small due to the high bargaining power of workers. Together with the countercyclical reaction of the outside option the model generates large UE rate volatilities.

Table 10 shows the results for the calibrated U.S. economy in the upper part together with the data targets for the U.S. and Germany. The lower part comprises the parameter experiments.

The first experiment reproduces the outcomes for a change in the matching efficiency. We see the same picture emerging as in the main part of the paper verifying that our results are not driven by the small surplus calibration. The second experiment shows a change in the outside option consistent with a decline in the average UE rate. If a larger outside option were the main driver of the average UE rate differences, we would need a large increase in the outside option. At the

[49] Hall and Milgrom (2008), Shimer (2005), Rudanko (2009) and Elsby and Michaels (2010), among others, propose different rationales and/or micro-foundations for these wage rigidities.

[50] The number is taken from Elsby and Michaels (2010) who generate this outside option endogenously in a model with decreasing returns to scale, endogenous separation and a wage bargaining mechanism that differentiates the marginal wage and the average wage paid. Hall and Milgrom (2008) argue for a similar number.

Table 10: Experiments

		$\pi_{eu,L}$	$\pi_{eu,M}$	$\pi_{eu,H}$	π_{ue}	$\lvert\tilde{\sigma}_{ue}\rvert$	$\lvert\tilde{\sigma}_{eu,L}\rvert$	$\lvert\tilde{\sigma}_{eu,M}\rvert$	$\lvert\tilde{\sigma}_{eu,H}\rvert$	σ_w
	U.S. (Data)	3.6	1.7	0.8	30.6	11.2		*6.5		0.8
	U.S. (Model)	3.6	1.7	0.8	30.6	11.2	4.4	6.3	7.7	0.8
	GER (Data)	1.3	0.4	0.2	6.2	10.5	18.4	23.0	23.4	0.8
(1)	$\varkappa = 0.11$	1.0	0.35	0.15	**6.2**	11.5	19.3	22.3	24.1	0.8
(2)	$b/w = 0.97$	4.8	2.5	1.3	**6.2**	146	12.0	13.4	17.2	0.8
(3)	$\varphi = -14.5$	3.6	1.7	0.8	30.6	38.6	14.9	19.4	**22.5**	0.5
(4)	$\varphi = -1.45$	3.6	1.7	0.8	30.6	7.3	2.9	4.3	5.6	0.9
(5)	$\varphi_L = -13.6$ $(\varphi_M, \varphi_H) = -2.9$	3.6	1.7	0.8	30.6	46.2	**18.1**	3.6	4.7	0.8
(6)	$\varphi_L = -2.9$ $(\varphi_M, \varphi_H) = -13.6$	3.6	1.7	0.8	30.6	9.2	3.4	20.5	**23.7**	0.5
U.S. calibration		$\varkappa = 0.52$		$\mu = 0.91$		$b/w = 0.8$	$\tau = 5.15$		$\psi = 1.8$	$\kappa = 0.06$

Notes: The upper part reports the data. The value on the EU rate volatility for the U.S. marked by * is the average over all tenure classes due to data limitations. The lower part reports the experiments. $\pi_{eu,L}$, $\pi_{eu,M}$, and $\pi_{eu,H}$ denote the EU rate for low, medium, and high tenured workers averaged over all idiosyncratic skill levels. The same applies for $|\tilde{\sigma}_{eu}|$. The second column gives the parameter that has been changed relative to the U.S. calibration and the corresponding value. The calibration for the baseline U.S. economy is given in the last line.

same time, the impact on the volatilities is comparable to the baseline model. A similar argument applies to all other parameters.

Intuitively, a larger surplus calibration only changes the strength of the underlying steady state elasticities Costain and Reiter (2008). What matters for our argument, and what is not driven by a larger surplus calibration, is the joint impact of a change in the parameter on the steady states and the volatilities.

To show the impact of wage rigidities on our results, we make wages more (less) rigid in the third (fourth) experiment. This change increases (decreases) both the UE and the EU rate volatilities in our model and leaves the ratio and the decomposition of the unemployment volatility almost unaffected.

The fifth experiment looks at versions of wage rigidities that only affect newly employed workers, i.e. we make wages for low-tenured jobs more rigid. We see that this channel will increase the EU rate volatility for low-tenured workers and also the UE rate volatility. However, the EU rate volatility is reduced for high-tenured workers, which is counterfactual. The last experiment reverses the argument and makes wages for medium- and high-tenured workers more rigid, while leaving the wage rigidity for low-tenured workers at its U.S. value. Although the EU rate volatility increases for high-tenured workers, the EU rate volatility for low-tenured workers is much too low.

Our findings imply that there is a tight connection between rigid wages and the EU rate volatility. Subgroups of workers, e.g. newly employed workers, who might have a different wage elasticity, also experience a different behavior of the separation decision in our model compared to workers who are continuously employed. However, our data on the uniform increase in the EU rate volatility by tenure suggest that differences in wage rigidities are likely not the main driving force for the differences in the second moments between the U.S. and Germany.

D International evidence

The mechanism described in this paper links the mean UE rate to the volatility of the EU rate. To provide some additional evidence that this relationship holds across a broader set of countries we run a regression of the log EU rate volatility on the log average UE rate using a sample from the data collected by Elsby et al. (2010b).[51] The estimated relation is shown in figure 5.

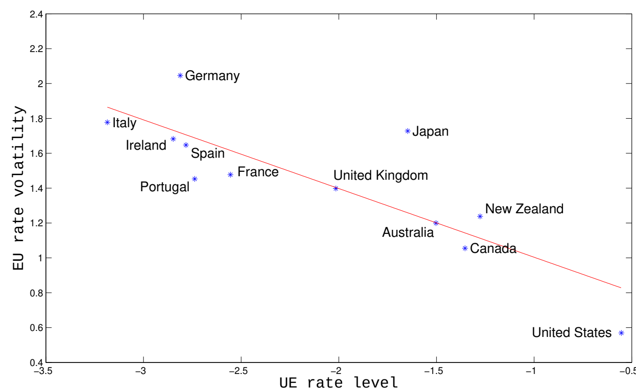

Figure 5: Regression fit

Notes: The figure shows the data and the fitted regression line from a linear regression of the log EU rate volatility on the log UE rate. The countries used in the regression are indicated next to the corresponding data points.

[51] Aggregate data might be more open to measurement problems so the available evidence does not always correspond to available micro-evidence for some of the countries.

We see that the estimated regression line reproduces the inverse relation between mean UE rates and EU rate volatilities. The alignment of countries other than the United States and Germany shows that the inverse relation between low average UE rates and large EU rate volatilities as discussed in this paper is also present if we consider a much wider set of countries.

Online Appendix
Not for Publication

This online appendix accompanies the paper *'The Era of the U.S.-Europe Labor Market Divide: What can we learn?'*. It comprises three parts. Part I presents a comprehensive picture on worker flows in Germany. Part II provides a sensitivity analysis for the sensitivity of the our empirical facts with respect to the choice of the smoothing parameter of the HP filter and part III presents a sensitivity analysis to the volatility decomposition of the unemployment rate with respect to both methods and data.

I Worker flows

In the analysis we distinguish labor market groups by sex and education. The sex information is taken directly from the data because measurement error is unlikely. To form education groups, we do not use the information on education directly from the data because Fitzenberger et al. (2006) point out that the education variable may be subject to higher measurement error. They provide imputation and correction rules for this variable. We use their imputed and corrected data and determine the highest attained education level of an individual over the employment history to group persons into education groups. The lowest education group comprises all individuals with no vocational training, the medium education group all individuals with vocational training or high-school ('Abitur') but no vocational training, and high-school and vocational training, and the highest education group all individuals with technical college degree or university degree.
Table A gives an overview over transition rates in the German labor market from $1980-2004$. Table B distinguishes transition rates for males and female workers. Table C distinguishes transition rates by education levels. Table D gives the cyclical properties of employment outflow rates for different tenure classes in Germany.

Table A: German transition rates over the business cycle

Transition rate	Mean	Std	Corr	Transition rate	Mean	Std	Corr
EU	0.5	15.1	-0.81	NE	(6.5)	17.6	0.33
UE	6.2	10.4	0.40	NU	(2.3)	16.2	-0.21
EE	0.9	15.6	0.65	EU + EN	1.5	3.8	-0.47
EN	1.0	6.2	0.53	EU + EN + EE	2.4	5.3	0.46
UN	4.9	10.3	0.45	UE + UN	11.1	8.7	0.49

Notes: Data series are quarterly averages of monthly data for the period 1980q1 - 2004q3. Standard deviations (STD) are given as percentage deviations from an HP-filtered trend ($\lambda = 100,000$) in logs. Correlations (CORR) give the correlation coefficient with GDP. Mean transition rates for NU and NE flows are given in brackets because the pool of inactive workers is not observed in the dataset. Transition rates are authors' own calculations based on IAB data.

Table B: Labor market transition rates by sex

	SEX	MEAN	STD	CORR
EU	Males	0.6	18.5	-0.81
	Females	0.5	10.5	-0.76
EN	Males	0.9	7.3	0.52
	Females	1.1	5.9	0.48
UE	Males	6.8	11.7	0.36
	Females	5.4	10.4	0.59
UN	Males	4.4	11.4	0.48
	Females	5.6	9.5	0.28
EE	Males	0.9	15.6	0.61
	Females	0.9	16.1	0.68

Notes: Data series are quarterly averages of monthly data for the period 1980q1 - 2004q3. Standard deviations (STD) are given as percentage deviations from an HP-filtered trend ($\lambda = 100,000$) in logs. Correlations (CORR) give the correlation coefficient with GDP. Transition rates are authors' own calculations based on IAB data.

Table C: Labor market transition rates by education

	EDUCATION	MEAN	STD	CORR
	low	0.5	13.8	−0.60
EU	medium	0.5	16.2	−0.83
	high	0.4	12.5	−0.53
	low	1.4	9.0	0.37
EN	medium	0.9	6.1	0.59
	high	1.1	12.6	0.17
	low	3.4	14.5	0.42
UE	medium	6.8	10.2	0.41
	high	6.6	11.7	0.52
	low	5.2	12.0	0.23
UN	medium	4.8	10.5	0.50
	high	5.5	9.2	0.23
	low	0.5	19.4	0.56
EE	medium	0.9	15.5	0.67
	high	1.1	14.1	0.50

Notes: Data series are quarterly averages of monthly data for the period 1980q1 - 2004q3. Standard deviations (STD) are given as percentage deviations from an HP-filtered trend ($\lambda = 100,000$) in logs. Correlations (CORR) give the correlation coefficient with GDP. Transition rates are authors' own calculations based on IAB data.

Table D: Transition rates by tenure over the business cycle over the period $1980 - 2004$

TENURE IN YEARS	< 1	$1 - 2$	$2 - 5$	> 5
	EU			
MEAN	1.8	0.7	0.4	0.2
STD	19.6	17.4	23.0	23.4
REL. SHARE	58.5	13.5	14.6	13.5
CORR	−0.77	−0.74	−0.73	−0.57
	EE			
MEAN	1.8	1.1	0.8	0.4
STD	12.0	15.9	17.4	14.6
REL. SHARE	41.7	15.1	21.8	21.5
CORR	0.58	0.58	0.61	0.51
	EN			
MEAN	1.9	0.6	0.4	0.2
STD	11.4	13.5	15.6	17.2
REL. SHARE	59.4	10.7	15.3	14.7
CORR	0.20	0.20	0.29	0.27

Notes: Tenure categories are given in years. All transition rates are given as percentages of the workers in the respective tenure group and are averages over time. Only workers in full-time employment are considered. Standard deviations are given as percentage deviations from trend of the rates (in logs). Correlations give the correlation coefficient with GDP.

II HP-Filter choice

As a sensitivity check with respect to the filter choice ($\lambda = 100,000$), we provide in table E the results for the HP filter is $\lambda = 1,600$. In table F we present the decomposition of the unemployment volatility for the HP Filter with $\lambda = 1,600$.

Table E: GDP, unemployment rates, and transition rates over the business cycle

	Statistic	mean	std	corr	Transition rate	mean	std	corr
Germany	GDP		1.1	1	EU	0.5	8.7	-0.69
U.S.			1.7	1		2.0	5.6	-0.68
Germany	Productivity		0.7	0.70	UE	6.2	7.2	0.53
U.S.			1.1	0.68		30.7	7.2	0.71
Germany	Earnings		0.9	0.45	EE	0.9	9.0	0.66
U.S.			1.0	0.37		2.6	5.4	0.58
Germany	Vacancies		15.4	0.74	EN	1.0	3.6	0.31
U.S.			11.8	0.91		2.7	3.9	0.34
Germany	Urate	8.4	7.8	-0.75	UN	4.9	6.5	0.46
U.S.		6.3	9.2	-0.85		26.6	6.3	0.68

Notes: Data series are quarterly or quarterly averages of monthly data for the period $1980q1$ - $2004q3$. Standard deviations (STD) are given as percentage deviations from an HP-filtered trend ($\lambda = 1,600$) in logs. Correlations (CORR) give the correlation coefficient with GDP. Our productivity measure is GDP per employed. Aggregate data for Germany are from the German statistical office ('Statistische Bundesamt') and the German Employment Agency ('Bundesagentur für Arbeit') and for the U.S. from the BLS. U.S. transition rates are taken from Shimer (2007) and Fallick and Fleischman (2004) for the EE rates that start in 1994. German transition rates are authors' own calculations based on IAB data.

Table F: Unemployment Volatility Decomposition

Country	Data	# of states	EU	UE	NE	EN	NU	UN	ε
Germany	IAB	2	57.7	42.4					0.1
	IAB	3	36.8	24.3	20.8	-1.1	7.2	12.3	-0.4
U.S.	Shimer	2	40.1	60.2					-0.3
	Fujita/Ramey	2	40.3	60.0					-0.3
	Shimer	3	25.2	45.6	8.6	-4.3	8.6	15.6	0.8

Notes: Data is HP-filtered ($\lambda = 1,600$) for the period $1980q1 - 2004q4$. For Germany the transition rates are authors' own calculations. The U.S. data is obtained from Shimer (2007) and Fujita and Ramey (2009). Contribution shares of flows are given in the corresponding column and are given as percentage numbers. The third column reports the number of states considered in the decomposition. Source: Authors' own calculations based on the data source given in column 2.

III Unemployment decomposition

For comparison table G presents the unemployment decomposition as given in the main paper. Table H uses the same data but the decomposition as proposed in Petrongolo and Pissarides (2008). This decomposition includes transitions from and to inactivity (not in the labor force). The trend component is derived using first differences so that the contributions of EN and NU flows can not be seperately identified from the contribution of UN and NE flows. Table I uses data for different subgroups and uses the same decomposition as in the main paper.

Table G: Unemployment Volatility Decomposition

Country	Data	# of states	EU	UE	NE	EN	NU	UN	ε
Germany	IAB	2	61.1	38.6					0.3
	IAB	3	42.5	24.6	20.0	−4.5	6.6	11.0	−0.3
U.S.	Shimer	2	32.6	67.6					−0.2
	Fujita/Ramey	2	38.4	61.9					−0.2
	Shimer	3	20.1	48.6	8.8	−3.8	10.4	15.2	0.7

Notes: Data is HP-filtered ($\lambda = 100,000$) for the period 1980q1−2004q4. For Germany the transition rates are authors' own calculations. The U.S. data is obtained from Shimer (2007) and Fujita and Ramey (2009). Contribution shares of flows are given in the corresponding column and are given as percentage numbers. The third column reports the number of states considered in the decomposition. Source: Authors' own calculations based on the data source given in column 2.

Table H: Unemployment decomposition sensitivity to filter choice

Country	Data	# of states	EU	UE	NU + EN	UN + NE	ε
Germany	IAB (Δ)	2	49.0	51.0			0
	IAB (Δ)	3	34.6	28.4	20.6	16.4	0.0
	IAB (HP)	3	42.5	24.6	−2.7	31.0	−0.3
U.S.	Shimer (Δ)	2	64.3	35.7			0.0
	Fujita/Ramey (Δ)	2	51.7	48.3			0.0
	Shimer (Δ)	3	40.1	30.5	12.1	17.3	0.0
	Shimer (HP)	3	20.1	48.6	6.6	24.0	0.7

Notes: Data period $1980q1 - 2004q4$. For Germany the transition rates are for all workers. The U.S. data is obtained from Shimer (2007) and Fujita and Ramey (2009). Contribution shares are given as percentage numbers. (Δ) denotes the cases where a 1st difference filter has been used. HP refers to the cases where a HP-Filter ($\lambda = 100,000$) has been used. For the 1st difference Filter NU and EN contributions and UN and NE contributions can not be separately identified. For the HP Filter these rates are summed and treated as one transition rate.

Table I: Unemployment decomposition for different subgroups in Germany

Sample	EU	UE	NE	EN	NU	UN	ε
males	64.3	35.4					0.3
	45.7	24.9	16.9	−4.1	8.3	8.4	−0.1
females	49.4	50.3					0.3
	33.5	28.0	25.4	−4.6	3.7	14.5	−0.3
low skilled	48.0	51.9					0.1
	29.2	26.8	31.6	−3.2	7.9	7.9	−0.2
medium skilled	63.7	35.9					0.3
	45.0	23.8	18.1	−4.5	7.1	10.8	−0.2
high skilled	51.7	48.2					0.1
	36.5	26.2	20.9	−1.0	6.7	10.3	0.4

Notes: Contribution of labor market transitions to unemployment fluctuations. Data is detrended using the HP-filter ($\lambda = 100,000$) for the period $1980q1 - 2004q3$. Transition rates are authors' own calculations based on IAB data.