Explaining cross-country labor market cyclicality: U.S. vs. Germany

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Abstract

This paper studies cross country differences in labor market dynamics over the business cycle between Germany and the U.S.. We provide new empirical evidence for Germany using the IAB employment panel from 1975 - 2004. We document the importance of firings in Germany, explaining 80% of the unemployment volatility. When we control for tenure, we find that 75% of all firings (and quits) come from matches with tenure less than 2 years. We document that the firing and quitting probabilities as well as the sensitivity to the business cycle strongly decrease with tenure. Turning to the wage dynamics over the cycle we show that, in contrast to the U.S., German wages of workers in ongoing job relationships move almost one-to-one with the business cycle. Wages of job-finder and quitter are found to be mildly more rigid. To explain the observed differences we provide a labor market search model with endogenous firings, quits on the job, and skill heterogeneity. Allowing for institutional differences across countries the model is able to replicate jointly the observed labor market dynamics in Germany and the U.S. We find an important role for differences in the bargaining power potentially associated with the influence of unions across countries. The model with skill heterogeneity is furthermore able to generate a large average surplus.

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1 Introduction

A growing body of empirical research has recently started to look at cross-country evidence with respect to labor market dynamics over the cycle, see e.g. Petrongolo and Pissarides (2009). Cross-country comparisons is an important instrument to disentangle the role of institutions on observed labor market outcomes. This paper contributes to the literature by comparing the German and the U.S. labor market using the IAB employment panel from $1975 - 2004$.

The debate has evolved around two important margins, the quantitative importance of the inflows vs. the outflows into unemployment and the behavior of wages over the cycle. Using a monthly disaggregation of our panel dataset we disentangle the distinct contributions of quits, firings and flows into non-employment. The main finding is that unemployment volatility is driven to 80% by firings, not hirings. The consensus view for the U.S. seems to converge to 50%. Given that German employment protection ranks high on many measures, this finding seems surprising. To explain this finding, we distinguish job flows by controlling for tenure. We show that 50(75)% of all firings are by matches with tenure less than one (two) years pointing towards an important role of match specific heterogeneity. The firing probability drops from 1.6% for workers with tenure below a year to 0.15% for workers with tenure above five years. A similar behavior is documented for quits and other flows.

Turning to wages, we confirm the view of Pissarides (2009) that wages might be even more volatile in Europe than in the U.S.. We use the panel dimension of the data to document that the cohort of workers that was continuously employed *at the same firm* over their entire observed employment life without any intervening firing, quit or non-employment spell, moves one to one with the cycle. By disentangling the behavior of newly employed worker, that is quitter or job-finder, from workers in ongoing jobs, we show that both groups substantially co-move with the cycle, though newly employed workers have an elasticity around .45, while workers in ongoing jobs have an elasticity of around .7. The results suggest that wages are not, or only mildly, rigid.

The second contribution of the paper is to develop a labor market search model with endogenous firing, quits on the job and match heterogeneity, delivering simple closed form solutions for all second moments. The model generates, due to match specific productivity levels and search on the job, a large average surplus. We use the prediction of the model based on an estimated TFP process to evaluate the fit for Germany and the U.S.. We show that the model can predict most labor flows for both countries well. We argue that cross-country cyclical facts pose substantial structure on the parameters of labor market models currently used and explore this implication quantitatively.

With respect to data-treatment a distinct contribution of this paper relative to other studies using the IAB panel for Germany, see among others Gartner, Merkl, and Rothe (2009) or Bachmann (2005), is the disaggregation to a monthly frequency, controlling for age, sex, education as well as part-time and full-time measures and a partial control for retirement. Retirement cannot be directly identified, but by controlling for age above 55 (early retirement) and 60 (retirement) we will likely capture most of these transitions.[1] This allows us to obtain a cleaner picture of the different rates into unemployment (E-U rates), into non-employment (E-N rates) and quits on the job (E-E rates). We show that non-employment flows behave similar to quits, both are pro-cyclical and are correlated with job-findings suggesting a common or correlated matching function. However, E-N flows react to a weaker extend to aggregate shocks. Aggregating these flows into a single separation decision leads to a reduction of the volatility and to biased estimates on the true contribution of firings for unemployment volatility. This is particularly true when looking at E-U flows by tenure classes. Across all tenure classes E-U rates show a pronounced negative correlation with the cycle and substantial volatility. We use the wage behavior of quitter and job-finder to further disentangle these flows, showing that quitter receive a wage-growth premium relative to job-finders on average. By looking at the joint behavior of wages and quits across tenure classes we show that lower skilled within each tenure group (earning on average 12% less than their peer group) face a higher probability of getting fired. A similar pattern emerges for quits on the job where roughly 60% occur for workers with tenure below 2 years and again their average wage is 10% below their tenure-peer group. Our findings therefore suggest an important role for heterogeneity across matches. The importance of heterogeneity has also been suggested for Germany using information on employer-employee data by Bachmann and David (2009), who disentangles flows by looking at different firm size.

The second institution that has been pointed out as an important difference between the German and the U.S. labor market is the influence of trade unions[2]. This is especially important since unions might be able to influence the wage setting mechanism that was at the focus of recent attempts to resolve the unemployment volatility puzzle originally recognized by Shimer (2005), Hall (2005) and Costain and Reiter (2005). The proposed resolutions typically rely on arguments that make wages react only weakly to aggregate conditions inducing a strong surplus for firms to hire in booms. The proposed changes to the benchmark Nash bargaining solution were to change the bargaining set as in Hall (2008), inducing counter-cyclical bargaining power (Shimer (2005)), using optimal contracts with risk-averse agents (Rudanko (2009)), or using staggered wage contracts, see Gertler and Trigari (2005). All these attempts share the implication of a weak reaction of wages to productivity. However, Pissarides (2009) has recently surveyed the empirical evidence on wages and concludes that wage rigidity can not be used to resolve the unemployment volatility puzzle because of the empirical co-movement of individual wages with the business cycle. Pissarides (2009) also suggest that the co-movement of wages with the business

[1] Though time-aggregation is not a substantial problem in Germany given that labor market turnover is weaker, the disentangling of the different separation flows to non-employment, unemployment and to different firms will still be affected quite a bit. Results derived in other studies might differ due to the data-treatment or to different definitions of the respective flows, typically looking only at aggregate separations. However, the broad picture along dimensions that are in common across studies point in the same direction.

[2] The OECD reports a union density, i.e. the share of workers affiliated to a trade union, for Germany of $\sim 35\%$ in 1975 falling to $\sim 22\%$ in 2004 and for the U.S. $\sim 22\%$ in 1975 falling to $\sim 12\%$ in 2004.

cycle might even be higher in Europe than in the U.S.. Many studies find that wages are more rigid for workers in ongoing jobs, see Devereux and Hart (2006) and Haefke, Sonntag, and vanRens (2007) than for newly employed workers. Haefke, Sonntag, and vanRens (2007) document that for the U.S. wages of newly employed workers have an elasticity estimate close to one. They point out that wage rigidity in ongoing relations is irrelevant in the basic workhorse matching model given that only the profits of newly hired worker matters in the hiring decision. The irrelevance no longer holds once endogenous destruction is introduced. Here wage rigidity, influencing the surplus over the cycle, will influence job destruction.

In contrast to the results for the U.S., we find that wages in ongoing jobs have an even stronger co-movement with the business cycle than wages for newly hired workers.[3] We document this effect following three different routes to control for the composition bias that has been pointed out in Haefke, Sonntag, and vanRens (2007) and the literature referenced there. All different approaches point to a common result.

We first use the panel dimension of our data-set and construct a sub-sample of workers that were continuously full time employed *at the same firm* during their entire observed working life from 1975 to 2004. These workers never got fired, nor became non-employed or have quitted their jobs. We still have a sample size of more than $12,000$ individual observations that allows us to obtain reasonably precise estimates. Fixing this group, we show that their yearly labor income[4] moves essentially one to one with aggregate business cycle measures. Similarly looking at wages for workers that have been continuously employed for a given year we show that their wage react strongly to the cycle, though less volatile, pointing towards a composition effect.

In a second step, to make results comparable, we construct the wage index as proposed in Haefke, Sonntag, and vanRens (2007). The index is based on the idea to regress out effects of age, education, sex and experience and to look at the business cycle behavior of the residuals as a new measure of adjusted wages. The residual can then be separately considered for job-stayers, job-switchers (quitter), and job-finders. We show that wages of stayer react strongest, having an elasticity of around .7, while wages for job-finder and quitter also react strongly to the cycle, having an elasticity of around .5. Essentially, quitter and job-finder wages lag the cycle, leading to a mildly weaker response. The results suggest that wage rigidity is at best modest.

In a third step, we use information on individual growth rates, removing potential fixed effects of a particular worker by taking first differences. For job-finders, we exploit the panel dimension of our data and use the last employment wage to calculate the growth rates. This is not possible in CPS data, given that the information is typically not available. For on the job quitters the wage is of course available directly. The wage index as well as the individual growth rate share similar trends and behave very

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

[4] Our data are spell based and for continuously employed workers we only have yearly information. For job-finder and quitter we do observe wages before and after the transitions on a daily base.

similarly over the cycle suggesting that both methods capture the essence of the composition effect. We find also for this measure that the above picture holds.

The second contribution of the paper is to explain these findings within the context of an extended version of the standard search and matching model, featuring endogenous firings, as suggested first in den Haan, Ramey, and Watson (2000), search on the job as recently explored in Fujita and Ramey (2007) as well as heterogeneity across firms, as suggested in Menzio and Shi (2009). We argue that all three ingredients are necessary to account for observed cross country differences. Our model uses a discrete choice mechanism as developed in Jung (2007) and delivers simple closed form approximation for all second moments. It also allows us to estimate the model and to compare not only second moments but the entire prediction path of all endogenous variables. Our data analysis suggests that endogenous separations are needed to account for the observed pattern, and search on the job as a result of pro-cyclical search activity, appears to be important as well. Quits are highly pro-cyclical in German data, co-move with vacancy posting very closely and show substantial average wage gains of around 5% compared to the pre-quit wage. The latter observation points towards an important role of heterogeneity across matches. We use a simple labor market search framework, focussing on two types of matches, that we label as good and bad. We argue that most jobs created are of a low productivity type, and will get endogenously destructed fairly quickly either due to firings or due to quits, in line with the empirical evidence. The endogenous decision of destructing the match or searching for a better job shapes the average quality of observed matches. This leads to the fact that most observed jobs in society will end up being of the good type. The surplus for workers being in good jobs will be substantial, for Germany amounting to roughly one year of pay. Yet, the expected surplus from hiring will be low, given that the likelihood of creating a bad match is high. The mechanism therefore allows a small surplus calibration as in Hagedorn and Manovskii (2008) while generating a high surplus for the average worker. We argue that the time-cost of searching embedded in high quality matches driven by differences in the separation rates might be important. To evaluate the fit we back out, given the structure of the model, the underlying exogenous driving process, in our case a simple TFP shock. Predicting the time-series of all endogenous variables for both Germany and the U.S. we show that the model does a good job in approximating the entire observed time-path for both countries. The good fit of the model allows us to trace the differences across countries back to some structural parameters. Our results suggest that the underlying structure of the U.S. and Germany cannot be too far apart and most differences in observed variables can be traced to differences in the surplus of the match, likely due to differences in the bargaining power across countries. To that extend unions might indeed matter.

We now proceed in 7 steps. Section 2 describes the data and documents aggregate facts, while section 3 focusses on disaggregate facts of tenure. Section 4 reports the wage behavior for Germany. Section 5 describes the model, section 6 provides a calibration and estimation exercise that documents the fit of our suggested model. Section 7 concludes. The technical appendix provides much more detailed information where we discuss differences that arise for different sex groups, education or other observable features of the data. Also a more detailed disentangling of flows across full-time and part-time measures is delegated to the appendix.

2 Data description and aggregate dynamics

Our dataset is the IAB employment panel that is a 2% representative subsample taken from the German social security and unemployment records. The sample contains employees that are covered by the compulsory German social security system, it excludes self-employed and civil servants ('Beamte'). Still, it covers about 80% of Germany's labor force. Once an individual has been put into the sample, we observe the full employment history of this individual during the sampling period. The sampling period covers January 1975 to December 2004. The employment history is given as a collection of employment spells on a daily basis. A new spell can either occur due to administrative reasons of the social security system or changes within a given firm, due to a quit to a new firm, the begin of an unemployment or a non-employment spell. Regularly, individuals have periods of parallel employment in the sample. This is reported as multiple spells. We use a hierarchical ordering to aggregate to a single spell.[5]

The income reported at one spell is the average daily income of an individual during the employment spell[6]. We do not observe hours worked but observe whether the person is full-time, part-time, or from 1999 on in marginal employment. Aggregate facts on total hours as well as GSOEP data suggest that the volatility in hours worked per person employed does not vary much with the cycle. Hence, in this paper all results referring to wages are interpreted as daily labor income which we think is the appropriate margin for any search model, given that profits are driven by wage times hours worked.

Since social security contributions have only to be paid up to a threshold level ('Beitragsbemessungsgrenze'), we do not observe income above this threshold. We impute data above the threshold using the approach proposed by Gartner (2005). However, for most of the analysis we focus on the median wage that is unaffected by censoring[7].

With every spell we observe some personal characteristics of the individual like year of birth, education, industry, and location of the employer. Fitzenberger et al. (2005) point out that the education variable may be subject to higher measurement error and provide imputation and correction rules for this variable. We adopt their imputation and correction procedure and determine the highest attained education level of an individual over the employment history to group persons into education classes. [8]

[5] The aggregation procedure can be found in the appendix.

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

[7] Further details can be found in the appendix.

[8] For all variables regarding the job status the income paid on the job, and the duration of the job the data contains virtually no measurement error because it is taken from the social security and unemployment records that are used to determine social security contributions and benefits. We consider this an additional virtue of the dataset compared to

The German reunification yields employment spells that are located in East Germany. Since the East German labor market was subject to additional regulations and restructuring after the reunification we exclude all persons with employment spells in the East from our sample[9].

Our basic time-period will be one month. Most other studies using the IAB-panel use a quarterly frequency, see Gartner, Merkl, and Rothe (2009) and Bachmann (2005). Using a monthly frequency allows us, among other things, to better disentangle quits, firings and other transitions. We adopt the ILO timing convention to measure the employment status of a person in a given month. For each month we determine the Monday of the second week in the month and take the week starting from this Monday as our reference week. We look at all spells that overlap with this week. If only one spell overlaps, then this spell determines the labor market status. If several spells overlap, we use a hierarchical ordering of spells where a full-time employment spell dominates part-time spells and any employment spell beats unemployment or non-employment spells. From this classification of monthly employment states, we construct time-series at monthly frequency[10]. By tracking the employment histories through time, we can generate additional labor market statistics like tenure on the current job, overall job experience or changes in income over time. Although, we follow the ILO in their timing convention to determine the labor market status of an individual, the definition of who is counted as unemployed follows from the content of the dataset. We define a person as unemployed who receives unemployment benefits or other benefits on the basis of the Social Security Code III ('Sozialgestzbuch III'). We can not follow the ILO definition that is based on interview questions on job search because this is unobservable in our sample. However, the two concepts should mostly cover the same individuals because they measure similar unemployment rates as can be seen from figure 1 where we plot unemployment rates based on our sample in comparison to the unemployment rate based on the ILO concept. The picture confirms that our unemployment measure although it differs temporarily from the aggregate unemployment rate in level it still captures the cyclical properties of the official measure with a correlation of .92 from 1979 onwards[11] [12]. The same approach has been taken by Petrongolo and Pissarides (2009) who study labor market dynamics in the UK, France, and Spain. They also use unemployment benefit data and find that this data is in levels but especially with respect to its cyclical behavior almost identical to the ILO dataseries. Before delving into a more detailed analysis, we now present basic properties with respect to business cycle characteristics on an aggregate level of the German labor market. These properties

dataset based on self-reporting like the GSOEP in Germany or the CPS in the U.S..

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

[10] For the U.S. some scholars even work with a two week period as a model period. However, given the small transition probabilities in Germany a monthly period appears to work fine.

[11] Note that the level shifts can either be due to a different measure of the numerator by different treatment of unemployment or due to a different treatment of the de-numerator by not accounting for self-employed and governmental workers. In any case the cyclical component correlates with .92, so the business cycle component might be captured well.

[12] There is an important problem in the definition of unemployment before the year 1979 leading to a strong deviation of the de-numerator, that is the state measure of unemployed workers. In most of our analysis on tenure we naturally have to start in 1980, so the problem does disappear.We discuss this problem in more detail below.

are aimed at capturing the same cyclical properties as their U.S. counterparts that can be found, among others, in Shimer (2005), Fujita and Ramey (2007) and Elsby, Michaels, and Solon (2009).

Aggregate data are taken from the statistic office. We use nominal GDP and convert it to real GDP by the CPI deflator from the Bundesbank. We deflate nominal wages in the IAB sample using again the same CPI deflator.[13] Productivity measures are obtained by dividing through total employment or total hours worked, as is done by the statistical office. This measure is rather noisy and does not correspond to the BLS productivity measure for the U.S. who use a more disaggregate procedure, but still suffers from aggregation problems highlighted when discussing wages below. After 1991, we only observe GDP for the unified Germany. At that point there is an obvious structural break in all variables leading to problems for any kind of filtering. We use the X-12 ARIMA method to align the series in the fourth quarter of the year 1991 to avoid jumping behavior of the series.

2.1 Basic Properties

The stylized labor market facts of the German data are highlighted in table 1 and refer to all workers. In the appendix we give the flows separated by sex and education.[14] For a better comparison we also present the corresponding U.S. statistics in table 2.[15]

Discussion: The main findings the tables offer can be summarized as follows. Comparing the means we confirm the well established fact that turnover in Germany is substantially smaller than in the U.S. Average job-finding rates are 1/5 of the U.S. and firing rates are 1/4 on average. Similar patterns hold for flows in and out of non-employment. Turning to cyclical feature we find that a.) while aggregate output is as cyclical in the two countries aggregate unemployment rates and vacancy rates[16] are even more volatility in Germany, a point discussed in detail in Gartner, Merkl, and Rothe (2009). b.) Firing Rates defined as flows from employment to unemployment expressed as percentage deviation from their respective mean rates [17] are highly counter-cyclical. The volatility in Germany is substantially higher than in the U.S., Job-finding rates are pro-cyclical in both countries, have the same relative volatility but are considerably more correlated with the cycle in the U.S. than in Germany. c.) Quit rates (E to E flows), defined as on the job transitions to a new establishment within a month, are highly pro-cyclical

[13] CPI deflator might be the right concept given that it determines the real value of a wage from the perspective of the union.

[14] Results for different cohorts are available upon request.

[15] US output data are taken from the NIPA and are deflated by the GDP deflator, productivity and unemployment rate data are taken from the BLS, vacancy postings are taken measured by the Help wanted index, and the labor market transition probabilities are taken from Shimer (2005). For Germany, we use aggregate data from the German Bundesbank, and our transition measures are calculated from the IAB data as outlined above.

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

[17] It is a priori not clear whether one should report business cycle fluctuations of "rates" on log-scale or not. We follow Shimer (2005) and report statistics in percentage deviation from steady state (log-scale). However, a country with the same fluctuations in the rate but with different means would induce a higher percentage deviation.

Table 1: Basic Properties Germany: Sample West A (1977 : 1 to 2004 : 4)

Name	Mean	Std	Rel Std - y	Corr - y	Corr - Y-P	Auto-Corr
Aggregate Data						
GDP	-	0.030	1.20	0.95	0.87	0.97
GDP per Capita	-	0.025	1.00	1.00	0.82	0.96
GDP per Employed	-	0.018	0.73	0.82	1.00	0.94
GDP per Hour	-	0.021	0.83	0.83	0.96	0.97
IAB-Data:						
Median Wage	-	0.016	0.63	0.95	0.77	0.98
U-Rate IlO	0.067	0.143	5.76	-0.82	-0.50	0.98
U-Rate West	0.079	0.178	7.19	-0.86	-0.56	0.98
Vacancies-West	-	0.338	13.63	0.86	0.64	0.98
IAB-Urate	0.071	0.213	8.59	-0.73	-0.49	0.94
IAB-Erate	0.929	0.012	0.49	0.69	0.28	0.97
IAB-Transition Rates:						
Firm Exit	0.024	0.054	2.16	0.51	0.29	0.74
Employment Exit	0.015	0.041	1.64	-0.50	-0.35	0.49
EU	0.005	0.207	8.33	-0.75	-0.61	0.90
EN	0.010	0.067	2.69	0.61	0.50	0.77
UE	0.067	0.117	4.70	0.36	0.11	0.59
UN	0.055	0.130	5.23	0.37	0.40	0.60
NE	0.072*	0.199	8.01	0.35	0.07	0.83
NU	0.024*	0.221	8.90	-0.26	-0.24	0.82
Quits	0.009	0.160	6.44	0.71	0.45	0.93

All data are in logs and are HP-filterer with λ=100000. GDP data is nominal GDP from the statistic office deflated by the CPS, taken from the Bundesbank. Employment and total hours worked are also taken from the statistics office. IAB data are quarterly averages of monthly data. Firm Exit is defined as the sum of EU+EN+Quits. Employment Exit is defined as EU+EN. Quits are defined as job-job transitions between two consecutive dates and a change in the firm counter as defined in the IAB-data. All IAB-rates are authors calculations. The star at the non-employment flows indicate that the denominator, that is the state of non-employed workers is measured with problems given that we do not have the corresponding universe of searching non-employed. We partially control for this by dropping (early)-retired and only look at workers that eventually will return to the labor market in our sample period. The (log)-volatility measures might be less affected by the problem.

in Germany. For the U.S., we do not have comparable available data, but the analysis in Nagypal (2005) suggests that this also holds in the U.S.. d.) Separation rates from the firms perspective, that is the sum of EE, EN and EU rates is pro-cyclical implying that the behavior of quits and non-employment flows dominates the behavior of firings. Given that both rates have counteracting correlation signs overall separation is rather a-cyclical.[18]. Employment exit rates, defined as the sum of transitions from

Table 2: Basic Properties US: Sample (1977:1 to 2004:4)

Name	Mean	Std	Rel Std - y	Corr - y	Corr - Y-P	Auto-Corr
Aggregate-Data:						
BLS GDP	-	0.03	1.00	1.00	0.54	0.93
BLS output per employed	-	0.02	0.59	0.54	1.00	0.88
BLS output per hour	-	0.02	0.54	0.29	0.91	0.89
BLS Wage	-	0.02	0.61	0.48	0.62	0.94
U-Rate	-	0.16	5.60	-0.91	-0.23	0.96
Employment	-	0.02	0.84	0.81	-0.06	0.97
Vacancies	-	0.21	7.34	0.86	0.20	0.96
Shimer-Data:						
Aggregate-Job-Finding-Prob	0.427	0.11	3.92	0.87	0.15	0.94
Aggregate-Emplyoment-Exit	0.036	0.05	1.81	-0.52	-0.61	0.65
EU	0.020	0.08	2.69	-0.76	-0.55	0.63
EN	0.028	0.04	1.59	0.46	0.26	0.44
UE	0.309	0.12	4.10	0.83	0.13	0.89
UN	0.267	0.09	3.32	0.77	0.15	0.89
NE	0.043	0.06	2.09	0.65	0.27	0.59
NU	0.036	0.07	2.46	-0.56	-0.20	0.69

All data are in logs and are HP-filter with λ=100000. Aggregate Data are taken from the BLS productivity database. Labor market transition Rates are taken from Shimer (2005) and are quarterly averages of monthly rates.

employment to unemployment or non-employment are counter-cyclical both in the U.S. and in Germany. e.) Employment to non-employment rates are pro-cyclical in both countries and are mirroring the behavior of quits on the job, suggesting that they reflect quitting behavior, not firing behavior. f.) Median earnings obtained from the IAB data are highly pro-cyclical in Germany when compared to GDP but less volatile. Finally, it is important to notice that the correlation structure in almost all labor market variables is considerably more pronounced when we look at a broad aggregate measure, GDP per capita, instead of a productivity measure like output per person or per hour. Productivity measured as output per employed or per hour will be a problematic concept in our framework when viewed, within the model, as an exogenous TFP shock. Productivity will suffer from the same composition effects Haefke, Sonntag, and vanRens (2007) highlight for wages which we will extensively discuss below. However, for Germany due to the re-unification the bias might be particularly severe.[19] We therefore rely on a broader measure of economic activity like GDP, which seems less affected.

[18] We lack a precise counterpart of this variable for the U.S, given that we do not observe quits on the job directly.

[19] To see this in our framework consider a world with two types of agents, low skilled and high skilled. Output (y) is

Our findings suggest that the broad picture is rather similar across the two countries which is remarkable given the differences in mean rates and institutions. Despite the differences in long run trends both countries aggregate unemployment rates react rather similar to aggregate shocks. However, as a disaggregate view makes clear, German unemployment volatility is mainly driven by variations in firings, while the U.S. unemployment volatility is dominated by the behavior of the job-finding probabilities, though firing rates are clearly non-negligible and account for a substantial part of the volatility. The next subsection will make these statements quantitatively precise.

2.2 The role of firings vs. job-finding for aggregate unemployment volatility

To address the importance of firings vs. job-finding in explaining unemployment volatility we use the methodology proposed in Fujita and Ramey (2007). Their estimates are based on a first order approximation around the steady state of the unemployment rate u_t given by:

$$\begin{aligned}
u_t^{ss} &\sim \frac{\pi_{eu,t}}{\pi_{eu,t}+\pi_{ue,t}} \\
\ln(\frac{u_t^{ss}}{\overline{u_t^{ss}}}) &= (1-\overline{u_t^{ss}})\log(\frac{\pi_{ue,t}}{\overline{\pi_{ue,t}}}) - (1-\overline{u_t^{ss}})\log(\frac{\pi_{eu,t}}{\overline{\pi_{eu,t}}}) + \epsilon rror_t \\
du_t^{ss} &= d\pi_{ue,t} + d\pi_{eu,t} + \epsilon rror_t
\end{aligned}$$

where a bar denotes deviation from trend, and $\pi_{eu,t}$ is the firing probability while $\pi_{ue,t}$ is the hiring probability. Fujita and Ramey (2007) show that the variance of $\ln(u_t^{ss}/\overline{u_t^{ss}})$ can then be decomposed such that $1 = \beta_{\pi_{ue}} + \beta_{\pi_{eu}} + \beta_{error}$ where $\beta_x = \frac{cov(du_t^{ss}, d_{\pi x})}{var(du_t^{ss})}$, allowing us to obtain three separate components, each of which expresses the importance of the respective series in explaining the cyclical variation of the unemployment rate. We find that the coefficient on job-finding is .23, the coefficient on firing is .82 and the residual is $-.05$ in the German data.

This suggests that firings rates are more important in Germany than in the U.S., explaining around 80% of the total variation. Firing rates are also important in the U.S. but to a significantly smaller extend.[20]

produced according to

$$\begin{aligned}
y_t &= e^{a_t}A_1 l_{1,t} + e^{a_t}A_2 l_{2,t} && (1)\\
l_t &= l_{1,t} + l_{2,t} && (2)
\end{aligned}$$

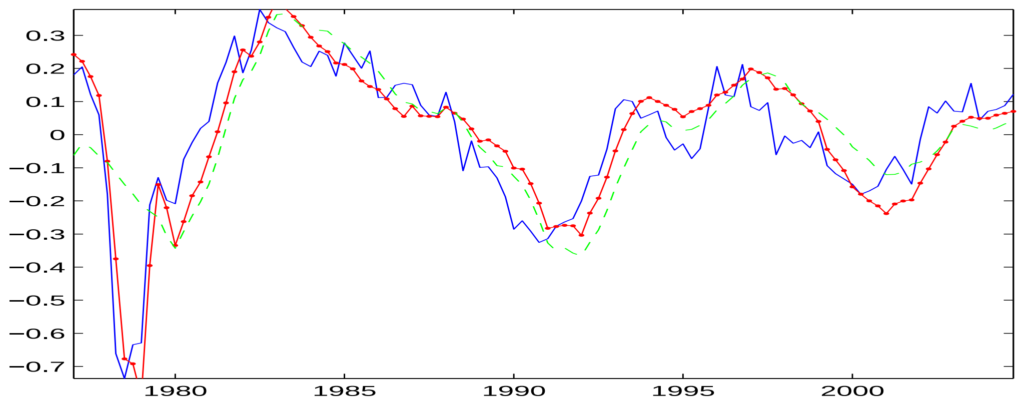
where output is normalized to one in steady state, w.l.g and $A_1 > 1, A_2 < 1$ $\frac{A_1+A_2}{2} = 1$. The TFP process a_t relative to measured productivity by the BLS or in Germany is given by

$$\begin{aligned}
\log(y_{t+1}) - \log(y_t) - \log(l_{t+1}) + \log(l_t) &\sim \Delta p_{t+1} \\
&\sim \Delta a_{t+1} + (A_1-1)\Delta\widehat{l_{1,t+1}} + (A_2-1)\Delta\widehat{l_{2,t+1}} && (3)
\end{aligned}$$

Obviously the measure does not correspond to TFP, as is well known. The bias in Germany, however, can be quite large. The raw productivity measure for Germany that simply divides aggregate output by aggregate employment, therefore not weighting by efficiency units, might induce a problematic correlation structure in particular after the reunification where a substantial fraction of workers entered the market that had rather distinct characteristics and different skill levels from the pre-reunification population.

[20] A similar conclusion would be drawn when using the metric proposed in Shimer (2005) who uses the predicted unemployment rate when fixing either firings or job-findings at their steady state levels to their actual counterparts. Again, firing rates explain almost everything.

Figure 1: Labor Market Flows - HP-Detrended - Germany



The blue solid line reports the HP-filtered firing rate from our IAB sample. The green dashed line reports the HP-filtered firing rate. The red pointed line reports the IAB unemployment rate. The green-dashed line reports the official unemployment rate. We use an HP-filter with weight $\lambda = 100,000$.

Figure 1 visualizes the fundamental fact of the German labor markets by plotting the HP-filtered firing rate against the cyclical component of the unemployment rate as measured in the data and to the official unemployment rate. It is evident that firings lead the unemployment rate by one quarter and are almost perfectly correlated with the unemployment rate. Our measured unemployment rate follows the official unemployment rate close. However, during the year 1978 there is an important deviation between the rates, essentially caused by an a-typical drop in unemployment rates and correspondingly in most other rates. For most of the analysis we therefore will start in 1980[21]. From that time on the series seems much more reliable.

The job-finding rate is pro-cyclical, but considerably less than in the U.S.. Clearly, in both countries both rates co-move with the business cycle and with each other in a systematic way. However, given that job-findings are much smaller in Germany on average, variability in firings, hitting all employed, are quantitatively much more important in Germany.

Petrongolo and Pissarides (2009) analyze the contribution of job in- and outflows to the fluctuations in unemployment for UK, France, and Spain. They find a decomposition for Spain that is qualitatively similar to our results for Germany suggesting a stronger contribution of job inflows. For the UK, they report a decomposition that is similar to the lower end of the U.S. estimates suggesting a 50/50 decomposition. Their results for France suggest that job outflows drive the fluctuations almost completely. They associate this result with the strong employment protection in France.

[21] Unemployment before 1980 might be affected by measurement problems as discussed in Bachmann (2005).

2.3 Total Separation, Employment Exit and Quits on the Job

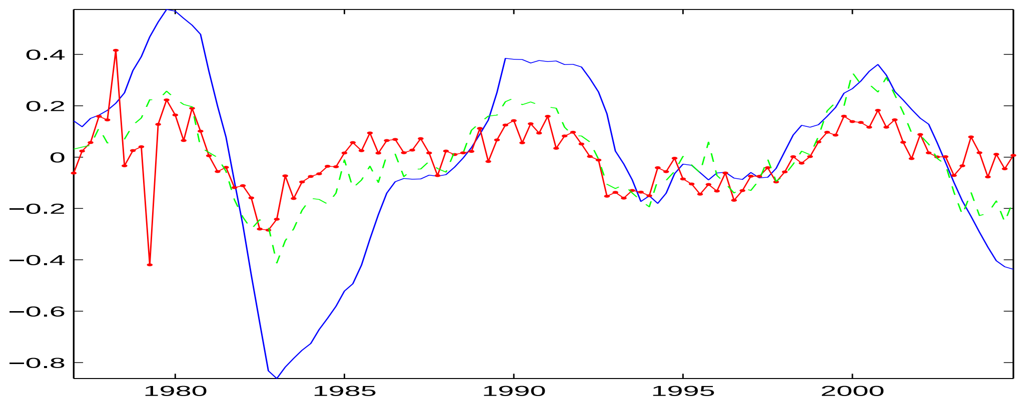
The above analysis has focussed on one particular separation margin that drives measured unemployment rates substantially. However, from a firms perspective, the duration of the match (and therefore expected profits) does not depend on the firing margin alone, but is driven by the firms exit rate, measured as the sum of employment flows to unemployment (Firings), transitions to different firms (Quits) and transitions to non-employment (Not classified). From the workers perspective quits and, potentially, non-employment transitions, might be economically very different from transitions into unemployment. As documented in table 1 both the employment exit rate (measured as the sum of transitions into unemployment and non-employment) as well as the firms exit rate does not vary much over the cycle when using the unconditional standard deviations as a metric. The former concept, though is pro-cyclical, the latter one is counter-cyclical. The opposing effects are driven by the fact that employment to non-employment transitions behave almost identical to quits on the job. In fact, as documented in Nagypal (2005) also for the U.S. most employment to non-employment transitions are followed by a transition to a new job within the next month, mimicking the behavior of quits with a lag of one month potentially due to moving time and similar motives. Given that both effects tend to cancel each other, total separations behave somewhat a-cyclical. However, it appears to be misleading to conclude that separation rates are constant, at least for the German labor market. While we cannot disentangle for sure whether the exit transition has been firm or worker initiated or was the outcome of an efficient joint separation decision it appears that, qualitatively, direct transitions on the job behave completely opposite to transitions into unemployment over the cycle. Pooling them into a joint exit decision will therefore lead to misleading results. Viewed through the lens of a matching model the data seem to suggest that there is a common matching market for unemployed as well as employed workers who search for a new job. To see this, note that the correlation between quits on the job and our (crude) measure of vacancy posting[22] is 0.85. Figure 2 confirms the intimate relation between both series on an HP-filtered ($\lambda = 100,000$) scale.[23]

Time aggregation issues highlighted in Shimer (2005) might cause a comparison problem across countries. In Germany, job-finding rates are rather low given that a worker remains unemployed, unconditionally, for more than a year. In contrast, the U.S. worker remains unemployed, unconditionally, around $2-3$ month, with a substantial fraction finding jobs very quickly. The concept of search used in CPS data opposed to our measure of receiving benefits might therefore lead to different classification of similar phenomena, that is our EE flow measure of quits might be related to the EN flow measure for U.S. data. The aggregate picture, discussed above, masks important differences in the behavior of firing and quits with respect to observable characteristics of the worker. We now turn to a discussion of these disaggre-

[22] The measure does not reflect all vacancies posted in the economy but only positions that are flagged to the employment agencies. Likely a selection process is taking place.

[23] Notice that both time series are obtained from completely independent sources, so there common movements seems at least suggestive for a common search pool.

Figure 2: Quits, Jobfindings, and Vacancies



The blue solid line reports the HP-filtered (log)-vacancy rate for West-Germany obtained from the bureau of labor. The red pointed dashed line reports the HP-filtered (log)-job-finding rate. The green dashed line reports our measure of (log)-quits. We use an HP-filter with weight $\lambda = 100000$.

gated facts.

3 Disaggregation of Firings, Quits and Job-finding by Tenure

German employment protection ranks high on many summary measures like the employment protection measure by Allard (2005) based on employment protection legislation. Many scholars believe them to be responsible for some of the problems of the German labor market. It therefore appears surprising that the German unemployment volatility is driven by firings, not by job-findings.

To document that tenure plays an important role on the behavior of aggregate firing rates, we construct cell classes of tenure with a particular firm. We calculate statistics from 1981 onwards to deal with the truncation problem. That is in 1975 we do not observe tenure of a particular worker. Given that our maximum tenure class is 5 years and above, we do know until 1981 the true tenure state. We focus on full-time employed males to discuss in a clean way the interaction of tenure and wages, though including females does not change any of the results qualitatively.

Table 3 reports the basic statistics for firings, quits and job-findings disaggregated by the particular tenure classes. We see that the average firing risk is dramatically different for workers having low tenure. The risk of being fired drops from 1.8% for low tenured workers to .15% of high tenured workers. The relative share measure reports the number of firings that are due to the particular tenure class. We see that 70% of all firings fall into the class of workers having tenure of less than 2 years. Correlation and standard deviation suggests that the high negative correlation declines over tenure classes, making the reaction of high tenured workers less pronounced. A similar pattern arises once we look at quits. Here, mean

Table 3: The Role of Tenure on the Job - 1981:1 to 2004:12

Quits	< 365 days	$365 - 730$ days	$730 - 1825$ days	> 1825 days	*overall* days
mean	0.0182	0.0110	0.0078	0.0037	0.0081
std	0.0028	0.0022	0.0017	0.0010	0.0016
rel. share	0.4148	0.1502	0.2177	0.2173	NaN
rel. wage	0.9005	0.9307	0.9259	0.9205	NaN
corr (per capita)	0.4513	0.4263	0.5002	0.3647	0.5148
corr (per empl.)	0.0818	0.1278	0.1370	0.1541	0.1331
Firings	< 365 days	$365 - 730$ days	$730 - 1825$ days	> 1825 days	*overall* days
mean	0.0178	0.0066	0.0036	0.0015	0.0055
std	0.0039	0.0013	0.0009	0.0004	0.0009
rel. share	0.5846	0.1349	0.1455	0.1349	NaN
rel. wage	0.8544	0.8205	0.8050	0.8127	NaN
corr (per capita)	-0.6649	-0.6318	-0.6354	-0.4861	-0.6719
corr (per empl.)	-0.2920	-0.2999	-0.2687	-0.1233	-0.3109
Jobfindings	< 180 days	$180 - 365$ days	$365 - 730$ days	> 730 days	*overall* days
mean	0.0920	0.0426	0.0295	0.0198	0.0596
std	0.0175	0.0086	0.0082	0.0051	0.0147
rel. share	0.7080	0.1500	0.0842	0.0579	NaN
corr (per capita)	0.2468	0.0261	0.3603	0.3781	0.2438
corr (per empl.)	-0.0932	-0.1782	0.0721	-0.0332	-0.1629

Tenure is calculated from 1975 onwards. The first five years generate sample selection given that the data are truncated from the left. Rel. share reports the percentage of all flows that fall within that tenure class. Rel. wage measures the median wage of all fired worker in that month relative to her the median wage of all workers not fired in that tenure group.

quit rates decline monotonically with tenure, while the correlation structure is again less pronounced for higher tenure groups than for lower tenure groups. Again, most quits (56%) occur for workers having tenure below 2 years. Finally, the job-finding probability is non-linear over tenure of being unemployed. In fact, the probability of finding a job conditional on not having found a job in the first 6 month of an unemployment spell drops by half and monotonically declines further for higher tenure classes.

To interact these observations with wages, we report the (time-averaged) median wage of a worker who was not fired *relative to the same tenure* cohort of workers. Our data suggest that the destructed jobs come from the lower end of the skill distribution. The discount is $15 - 20\%$ for destructed jobs, and $7 - 10\%$ for quitters. As we will point out below when discussing wages more carefully, quitters indeed make on average around 5% increase relative to their pre-quit wage.

Of course, the above measures might be affected by composition effects. Table 10 reports the same statistics for full-time employed males but controls for different education levels. Some results are worthwhile to mention. First, the broad picture remains the same for all education groups. Most firings, for all education levels, occur in the first 2 years and the probability of being fired drops dramatically over tenure. Second, job-finding is substantially lower for low skilled compared to medium and high skilled workers. Medium skilled workers even have a mildly higher job-finding probability compared to high-skilled workers, suggesting a selection effect in our measure. Third, the crucial difference across education classes is due to the fact that average firing of high-skilled is half of medium or low skilled. In particular, workers with tenure below a year have a 3 to 4 times higher chance of getting fired. In higher tenured classes chances are still roughly 2 times higher. The correlation with the business cycle is less pronounced for high skilled. The wage discount, now always expressed relative to the peer tenure-education group shows a similar pattern as the average, though the discount for firings gets higher for high skilled workers.

The results suggest that the basic numbers outlined above do capture the essence of the the dynamics across tenure classes and composition effects will likely play only a minor role. They also suggest that tenure on the job is important in understanding labor market dynamics. Though the employment protection legislation will likely influence the average firing rates across tenure cells, there still seems an important role for match heterogeneity. Workers who get fired had bad jobs before, facing an average discount relative to the median of 10%. Workers who quit also come, on average, from badly paid jobs. We now take a more detailed look at the role of wages for the different groups.

4 Wages

In a recent survey article Pissarides (2009) discusses the empirical evidence on wage rigidity for the U.S. and Europe. He concludes that the available evidence suggests a stronger co-movement of wages in Europe with the business cycle than in the U.S. We provide strong support for this claim.

The main problem in studying the wage reaction to the business cycle is due to composition bias, see Solon, Barsky, and Parker (1994), which leads to a downward bias in the cyclicality of wages and is extensively discussed in Haefke, Sonntag, and vanRens (2007).

To control for composition effects we offer three procedures. The long panel dimension and the high quality of the income data allows us to identify ongoing job relations not only on a year by year basis but also over longer horizons. This makes it possible to distinguish groups in the labor markets much more accurately than with labor market histories of only several month like in the CPS data for the U.S. used by Haefke, Sonntag, and vanRens (2007). Exploiting this clear identification scheme, we look at a particular sub-group of workers: workers who had a job in 1975 and were continuously full-time employed until 2004 *at the same firm*. That is, for this non-representative group, we ensure that no quit and no firing happened during their entire work experience nor, of course, any non-employment spell. The group still consists of approximately $12,000$ workers and is therefore large enough to provide reasonable estimates. Essentially this group also represents to core group of worker being of around 25 when entering and 55 when ending their life. For this group we only have spell information on a yearly base. In contrast to part of the business cycle literature we will therefore have to move to a yearly frequency. However, as it turns out, the yearly frequency might actually be the more natural frequency given that bonus payments and the like are typically not paid out on a regular quarterly basement. However, these wage payments are likely part of the bargaining set workers and firms build expectations about. Given that, at least in models with risk-neutral agents the precise timing of the wage payment is undetermined, we believe that a yearly frequency offers some advantages to a quarterly analysis.

Our findings suggest that wages for the continuously employed group move one to one with the cycle. This finding holds also for all percentiles of the wage distribution, with the exception of the 90% percentile which is truncated. We contrast our findings for this group with all workers in the sample who were continuously employed *at the same firm* on a year to year basis. We show that the elasticity is still substantial and the co-movement is around .8 but composition effects already seem to dampen wages.

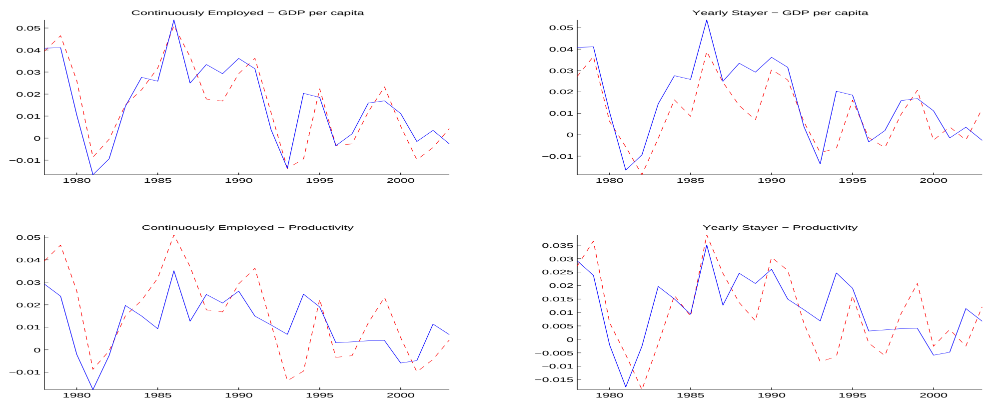
To show how wages of newly employed workers behave, we use in the second step of our analysis the wage index construction proposed in Haefke, Sonntag, and vanRens (2007). They suggest to regress out observable characteristics like age, sex, education and experience and to focus on the behavior of the residual. We construct monthly indices for job-finder and quitter and compare the averaged yearly index to the stayer index. Again, both co-move with the cycle. Stayer have an elasticity of around .7, while job-finder and quitter wages are less reactive to the cycle, still having an elasticity around .5.

Finally, we use an independent procedure by looking at growth rates of individual wages. This allows us to remove worker specific fixed effects. When looking at individual growth rates, we face the problem that unemployed worker do not have a growth rate for the period we look at. However, we can use the panel dimension of our data-set (which is not possible in the CPS data for example) and use the last employment wage to calculate the growth rate. Though a proxy the last wage should still be a good measure for individual potential earning ability given that the duration of unemployment as shown above is mostly short and jobfinder find a new job within one year. This implies that their last observed wage might still serve as a good proxy. For quitters, the problem does not exist, given that we observe daily income in both jobs. We show that job-finder and quitter behave rather similar. Again we find that growth rates of stayer react stronger to the cycle then wages for newly employed workers, still, the elasticity for all groups is similar to the ones we find using the index construction. We conclude that, according to our data, labor income in Germany is not rigid. We now present the results for the different subgroups.

4.1 Continuously Employed Worker

The left panel of Figure 3 plots the wage growth rate together with output per capita as a measure of the business cycle. We also report the results for output per person. However, we stress again that

Figure 3: Median Wage Growth of Continuously Employed Worker and Yearly Stayer



The blue solid line reports the wage growth rates for the Germany. The red dashed line in the upper panel reports output per capita growth as a measure of business cycle while the lower panel reports GDP per employed as a measure of productivity. The left panels are the group of continuously employed workers that are continuously observed and employed during the years 1975 − 2004 and who never quitted on the job or got fired. The right graphs shows the corresponding median wage behavior of workers who were continuously employed during any given year only.

aggregate productivity measures face the same composition bias that was discussed above. They can not be taken as a direct measure of the technology process because they are not adjusted for different skill levels, education and age. They are affected by in- and outflows in the same way as wages are. We therefore focus on a broad measure, that is GDP per capita. Note that output and unemployment have a strong negative correlation and move almost one to (minus) one. So regressing on output yields, with the obvious switch in sign and adjustment to the quantitative interpretation, will give similar results as regressing on unemployment, which would be the alternative approach.

The figure graphically documents that the movement is essentially one to one. The correlation between the two series is .86. The elasticity estimates are contained in table 4 and show numerically what is graphically clear. The elasticity across the two series is around .85. The same picture and correlation structure is obtained when focussing on any other percentile instead of the median.[24]

The right panel shows the median growth rate of all worker that have been, in a given year, continuously employed with the same employer.[25] The data have a similar correlation structure than the subgroup of continuously employed workers, but have a lower variance. We obtain the same pictures and correlations if we look at the median of the individual growth rates instead of the growth rate of the median.

Note that the group of stayers essentially drives the median wage and the cyclical correlation reported above, given that turn-over rates in Germany are low compared to the U.S. and the composition effect is not so strong. In contrast to findings for the U.S. labor income strongly co-move with the business cycle

[24] With the exception of the 90% percentile which is truncated.

[25] This group has, on average $267,459$ observations in a given year.

and we do not find many signs of wage rigidity in the data for any measure of continuously employed workers. The question remains whether newly bargained wages, either for job-finder or job-quitter, react similarly. We turn to this question next.

4.1.1 Wage Index Construction

The personal characteristics of workers who are employed, get hired or fired changes in the course of the business cycle. This point has been made by Solon, Barsky, and Parker (1994) who show that this change in the composition of workers can induce mismeasurement in the cyclicality of wages and induces a *composition bias* towards less cyclicality of wages. To deal with this problem, Haefke, Sonntag, and vanRens (2007) propose the construction of a wage index that corrects for composition effects over time. Other approaches like taking first differences for individual workers (see Bils (1985)) to control for heterogeneity can not be easily applied to study the wage cyclicality of newly hired workers because it requires two consecutive wage observations for all workers in this group. However, wages for unemployed workers are in general not observed and the approach is limited to workers that are employed and earn income in two consecutive periods. For comparison, we follow the approach and construct the wage index like in Haefke, Sonntag, and vanRens (2007).

The construction of the wage index follows a two step procedure. In the first step, we run separately for full-time and part-time employment spells a Mincerian wage regression (see equation 4) on the pooled sample of all employment spells[26]

$$\log w_{i,s} = x'_{i,s}\beta + \log \varepsilon_{i,s} \tag{4}$$

where $w_{i,s}$ is the observed income in spell s of person i, $x_{i,s}$ are the personal characteristics of individual i at spell s, and $\varepsilon_{i,s}$ is the resulting residual of this spell. This residual is orthogonal to the individual characteristics $x_{i,s}$ but might still depend on the aggregate state of the economy. The vector of personal characteristics $x_{i,s}$ contains a sex dummy, a foreigner dummy, dummies for education groups[27] and a fourth order polynomial in experience[28]. In the second step, we obtain the wage index for group j in period t as the mean residual of all spells of group j in period t[29]. The wage index constructed this way controls for composition effects of a group by removing shifts in the mean wage that can be associated with mean shifts in the regressors from the Mincerian wage regression. When we construct the wage index, this is done at monthly frequency using the monthly employment observations constructed above

[26] For this step, we use the sample with imputed wages to replace censored wage observations. We apply the method by Gartner (2005) that uses a censored regression approach together with a log normality assumption to impute the censored wages. We also correct for the structural break in the wage series 1984. The method we use and further discussion can be found in Fitzenberger (1999).

[27] To capture individual skills appropriately, we use the highest attained education level over the employment history to group agents into education classes.

[28] We follow Haefke, Sonntag, and vanRens (2007) and use potential experience as measure of experience.

[29] An equivalent alternative would be to introduce period fixed effects in the first step regression and use the coefficients on the dummies as wage index. However, this would inflate the number of regressors in the estimation dramatically.

to measure the labor market flows. This implies that for every individual there can be at most one spell per month, so no weightening is necessary.

4.2 Stayer, Quitter and Job-Finder

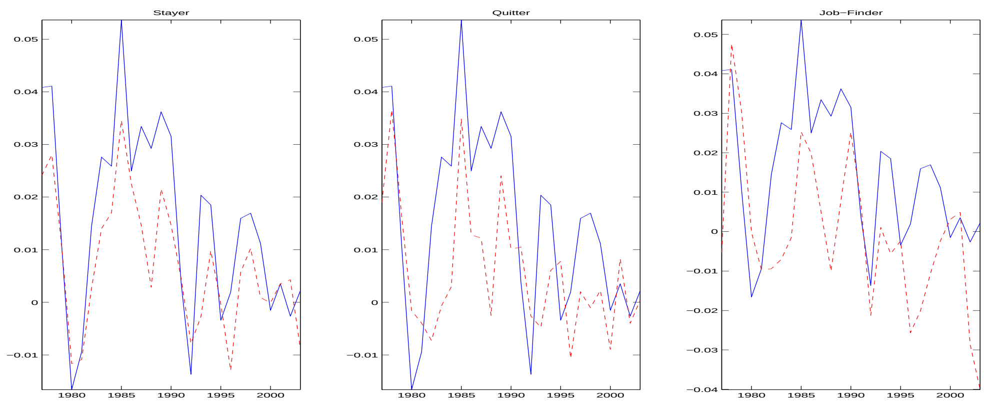
We now document that subgroups of the labor market react rather similarly to business cycle conditions than the stayer group. As shown above, quits on the job are highly pro-cyclical, so is job-finding. The group of quitters is larger than the group of job-finders. Figure 4 shows the plot of the wage-index and 5 shows how the median of the individual growth rates move over time. Both measures reveal that there is a strong decline in the gains from quitting. The wage change of a job-finder, coming out of unemployment, was positive in the eighties, but declined rather drastically afterwards. In both measures quitter do make on average more after a transition than the job-finder do, suggesting that there are some differences across these two transition states. However, for long term unemployed, this last employment wage might be older than 2 years, so we likely overstate the wage growth of job-finders. Individual growth rates as well as the wage index show a similar reaction to the cycle. Table 4 reports the regression of the different measures on GDP growth and a time trend. The elasticity estimates are between .4 and .6. They are higher for stayer and substantially smaller than the estimates for continuously employed, as reported above. Note that growth rates are a particular high-frequency filter that, to some extend, over-emphasize high frequency behavior of the data. The correlation coefficient also suggest a substantial co-movement. The overall picture appears to be that wages do react quite a bit to the cycle. Wages in ongoing jobs react strongest, wages for newly employed workers seem to react a bit less.

Table 4: Elasticities (Yearly) -Estimates:

Individual Wage-Growth-Regression:	Quitter	Jobfinder	Stayer	Cont.Employed
$dlog(\frac{w}{y})$	0.35	0.45	0.70	0.88
(Std error)	(0.09)	(0.13)	(0.10)	(0.11)
Wage-Index-Regression:				
$dlog(\frac{w}{y})$	0.41	0.45	0.59	-
(Std error)	(0.18)	(0.11)	(0.07)	-
Corr(w,y)	0.49	0.66	0.70	0.86

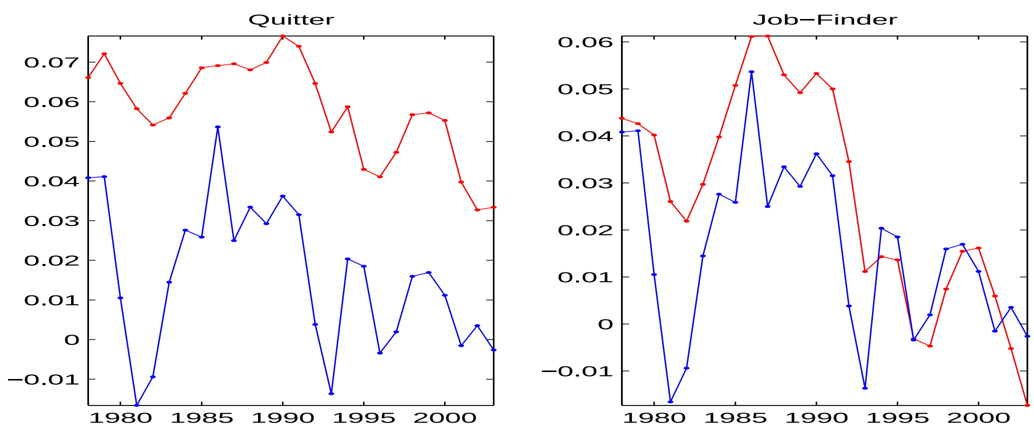
Results are for yearly averages of monthly index wage or individual growth data. The first line gives the coefficient of a regression of (log-first differences)-wages (w) on an aggregate business cycle measure (y), GDP per capita, and a time-trend. Standard errors are in parentheses. The second half reports the same regression for our wage-index regression, that is first difference-wage residual on output-growth.

Figure 4: Wage Index- Stayer, Quitter and Job-finder



The blue solid line reports the GDP per capita. The red dashed line reports the wage index for stayer, quitter and job-finder, constructed as described in the text. Results are for yearly averages of monthly data.

Figure 5: Median of Individual Wage Growth Rate of Quitter and Job-finder



The left panel reports the yearly average of the seasonally adjusted monthly median growth rate of quitters. The right panel reports the corresponding growth rate for job-finder. Results are for yearly averages of monthly data.

5 Model

In this section, we develop a simple labor market model that stays, essentially, within a representative agent framework, though we allow for some idiosyncratic risk. The model is designed to deliver aggregate dynamics that will not depend on the distribution of types to highlight crucial relations that govern business cycle dynamics. In an extension, we will then introduce heterogeneity across matches in a simple form that allows us to capture the important differences across groups of workers as documented in the empirical analysis. Based on this model, we trace out the structural parameters that can be associated to institutional differences across countries and are able to explain the empirical differences between the U.S. and Germany as a typical European labor market.

Timing: Time is discrete. Workers are risk-neutral and can be in two states $\widetilde{e} \in [e, u]$ where e denotes employment (being in a match) and u denotes unemployment. The total measure of workers is one. At the beginning of the period, workers who are currently in a match relation bargain about the wage and the separation decision for next period. If the bargaining is successful, they produce output with the aggregate technology A_t assumed to evolve exogenously and common to all matches. At the end of the period, after production has taken place, the worker might decide to search for a different job. He searches with exogenous probability s and receive an outside offer from a competing firm with probability π_{ee} which he accepts for sure.[30] The decision to search is taken as exogenously and random, reflecting idiosyncratic utility attached to the particular match. If the worker has decided not to search or has not received an offer the firm, at the end of the period, receives an idiosyncratic cost shock where ϵ_{it} is a random shock logistically distributed with mean zero and variance $\frac{\pi^2}{3}\psi^2$ the firm has to invest to continue the production process. We assume that these shocks are independent and identically distributed across firms and time. Though all firms are ex ante identical, they will differ ex-post. Yet, these cost are sunk after this period, so they will not be relevant for any future decision. Only firms that continue their match into the next period incur these costs. Firms that separate from workers instead incur re-organization payment τ reflecting re-organizational cost as well as firing protection laws.[31] We let ω_t be the threshold for these continuation costs. This threshold level will be part of the bargaining set and will be efficiently bargained about by worker and firm. All matches with realizations above that threshold will be dissolved. If the worker/firm is willing to pay the cost, the match continues. Otherwise the match is resolved and the worker becomes unemployed. An unemployed worker searches for a job and is matched in a matching market governed by a standard Cobb-Douglas matching function. They are matched with probability $\pi_{ue,t}$ and become employed, with probability $(1 - \pi_{ue,t})$ they remain unemployed and keep on searching. When unemployed they receive unemployment benefits $b < 1$.

Firm surplus:

Consider a worker/firm pair at the beginning of the period. The firm discounts the future, as does the agent, with a constant discount factor β. If the match decide to produce, the firm receive a price of A_t for its output, and pays the wage w_t to the worker. The firm then receives the idiosyncratic cost shock ϵ_{it}. If the firm decides to pay the cost, and the worker does not quit, the match continues.

[30] It is straightforward to make the search decision also a discrete choice and endogenous. Though it helps in making aggregate quits more volatile, we decided to keep it exogenous in this version for simplicity. Results for endogenous search are available upon request.

[31] We assume that these cost are not direct severance payments to the worker which, under efficient bargaining would simply be bargained away and would reduce the average wage-payment by the properly adjusted flows without having any bearing on the separation decision, as can be easily verified.

The firm's surplus follows a recursive formulation

$$
\begin{aligned}
J_t &= A_t - w_t + (1-\pi_{ee,t}s)\left[\int_{-\infty}^{\overline{\omega}_t}[\beta E_A J_{t+1}(A_{t+1}) - \epsilon_t]df(\epsilon_t) - \int_{\overline{\omega}_t}^{\infty}\tau df(\epsilon_t)\right] \\
&= A_t - w_t + (1-\pi_{ee,t}s)\left[(1-\pi_{eu,t})E\beta J_{t+1} - \pi_{eu,t}\tau + \Psi_t\right] \qquad (5) \\
\Psi_t &= -\psi\left[(1-\pi_{eu,t})\log(1-\pi_{eu,t}) + \pi_{eu,t}\log(\pi_{eu,t})\right] \qquad (6)
\end{aligned}
$$

where $(1-\pi_{ee}s)$ is the probability that the worker does not quit and the last step follows from standard properties of a logistic random variable, see Jung (2007) for the details. Here $\overline{\omega}$ denotes the (endogenous) cut-off value where the match is terminated and which is determined below. The term

$$-\psi\left[(1-\pi_{eu,t})\log(1-\pi_{eu,t}) + \pi_{eu,t}\log(\pi_{eu,t})\right] > 0$$

captures the option value of having the choice to continue the match. This value is always positive. The reason is that although the idiosyncratic shock has an unconditional mean of zero the manager only continues if the continuation value is positive, the payoff resembles the payoff profile of an option and is therefore also increasing in the variance ψ of the shock.

Worker Surplus:

$V_{e,t}, V_{u,t}$ denote the value of being employed or unemployed, respectively. The worker is risk neutral and faces the following stream of utility

$$
\begin{aligned}
V_{e,t} &= w_t + \beta(1-\pi_{ee,t}s)[(1-\pi_{eu,t})E_tV_{e,t+1} + \beta\pi_{eu,t}E_tV_{u,t+1}] \\
&\quad + \beta\pi_{ee}s[(1-\pi_{eu,t})E_tV_{e,t+1} + \beta\pi_{eu,t}E_tV_{u,t+1}] \\
&= w_t + \beta[(1-\pi_{eu,t})E_tV_{e,t+1} + \beta\pi_{eu,t}E_tV_{u,t+1}] \\
V_{u,t} &= b + \beta\pi_{ue,t}E_tV_{e,t+1} + \beta(1-\pi_{ue,t})E_tV_{u,t+1} \qquad (7)
\end{aligned}
$$

where w_t denotes the wage rate, $\pi_{eu,t}$ denotes the endogenous probability of being fired (or transited into unemployment) and $\pi_{ue,t}$ denotes the probability of finding a match.

The workers' surplus can be defined as

$$\Delta_t = w_t - b + (1-\pi_{eu,t} - \pi_{ue,t})E\beta\Delta_{t+1} \qquad (8)$$

We assume that the worker, upon quitting might be fired in the same period. This assumption assures a symmetry between staying and quitting and is done purely for convenience. In the current framework a quit is done purely for exogenous reasons given that all firms are the same, so there is no intrinsic motive for quitting. We give up this assumption in the extension below.

Matching:

New matches are formed by a standard Cobb-Douglas matching technology that links the measure of searching workers workers to the measure of vacancies. We denote vacancies posted by firms by v_t. The measure of searching workers is the sum of unemployed workers and the fraction of workers searching on the job. We denote the resulting matches by m_t.

$$m_t = \varkappa v_t^{\varrho}(u_t + se_t)^{1-\varrho} \tag{9}$$

Denoting the vacancy to search ratio as our measure of labor market tightness by $x_t := v_t/(u_t + se_t)$. The probability of a searching worker to find a new job is given by

$$\pi_{ee,t} = m_t/(u_t + se_t) = \varkappa x_t^{\varrho} \tag{10}$$

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

$$\pi_{ve,t} = m_t/v_t = \varkappa x_t^{-(1-\varrho)} \tag{11}$$

As highlighted in Fujita and Ramey (2007), it is important to have a measure of employed workers searching to ensure that the model delivers the right Beveridge curve. As our data described above make clear, the quitting behavior of workers is intimately related to the vacancy posting behavior of firms implying that a substantial fraction of workers are searching on the job. The results from the empirical section show also that job-finding and quitting are tightly related suggesting a common matching market for the two classes of worker.[32]

Free entry:

To determine the number of vacancies posted, we use a standard free entry condition. In equilibrium the cost to post a vacancy κ_v equals the expected profits of a match

$$\begin{aligned}\frac{\kappa_v}{\pi_{ve,t}} &= (1-\pi_{eu,t})E\beta J_{t+1} - \pi_{eu,t}\tau \\ &\quad -\psi\left[(1-\pi_{eu,t})\log(1-\pi_{eu,t}) + \pi_{eu,t}\log(\pi_{eu,t})\right] && (12)\\ &\equiv \Pi_t && (13)\end{aligned}$$

Remember that our timing of events is such that the worker might find a match but that the firm decides not to pay the continuation cost after the realization of the shock and immediately fires the worker. This assumption ensures a symmetry between employed and unemployed workers. With this timing it is also from a social planners perspective, ex-ante not beneficial to fire a worker to avoid to pay the fixed cost of the match. As a consequence, the probability of finding a job is given by

$$\pi_{ue,t} = \pi_{ee,t}(1-\pi_{eu,t})$$

We now turn to the key problem of determining wages and firings in this economy.

[32] We do not have a formal test for the assumption of a common matching market. Job-finders wages behave similar to quitters wages over the cycle, though they do show different trends. It is therefore not entirely clear whether the assumption of a common matching market is actually accurate. At a first pass, we think our findings are at least indicative to model them as common.

Bargaining:

We use standard Nash-bargaining jointly over wages and destruction decisions. We denote the bargaining power of the worker by μ. The outcome of the bargaining is then the solution to the following problem

$$(w_t, \pi_{eu,t}) \in \arg \max_{w_t, \pi_{eu,t}} (\Delta_t)^{\mu} J_t^{1-\mu}$$

We get after some easy steps

$$\begin{aligned} \pi_{eu,t} &= \frac{1}{1 + e^{\frac{\beta E \Delta_{t+1} + \beta E J_{t+1} + \tau}{\psi}}} \\ \frac{\mu}{\Delta_t} &= \frac{1-\mu}{J_t} \end{aligned}$$

Note that the probability of destructing the match is inversely related to the total surplus of the match $\beta E_t \Delta_{t+1} + \beta E_t J_{t+1}$ and the mean restructuring cost τ. Note that τ could have also been introduced as the average fixed cost of the match when continuing to produce; both formulations would have the same implications. Essentially, we need two parameters that pin down the mean and variance of the distribution.

This bargaining setup implies that worker and firm can condition upon the realization of the cost shock ϵ_{it} and will form a jointly efficient decision.

Total surplus S_t of the match is the sum of firm's surplus J_t and worker's surplus Δ_t.

$$\begin{aligned} S_t &= J_t + \Delta_t \\ &= w_t - b + \beta(1 - \pi_{eu,t} - \pi_{ue,t}) E \Delta_{t+1} \\ &\quad + A_t - w_t + (1 - \pi_{ee,t} s)[(1 - \pi_{eu,t}) E(\beta J_{t+1}) - \pi_{eu,t} \tau + \Psi_t] \\ &= A_t - b + \beta(1 - \pi_{eu,t} - \pi_{ue,t}) E S_{t+1} + x_t \kappa_v (1 - s) - \pi_{eu,t} \tau + \Psi_t \end{aligned}$$

Now observing that $J_t = (1-\mu) S_t$ and $\Delta_t = \mu S_t$ yields a description of the solution to the model characterized by the following equations

$$\begin{aligned} S_t &= A_t - b + \beta(1 - \pi_{eu,t} - \pi_{ue,t}) E S_{t+1} + \kappa_v x_t (1 - s) - \pi_{eu,t} \tau + \Psi_t \\ \pi_{eu,t} &= \frac{1}{1 + e^{\frac{\beta E S_{t+1} + \tau}{\psi}}} \\ \frac{\kappa_v}{\varkappa} x_t^{(1-\varrho)} &= \Pi_t \\ \Pi_t &= (1 - \pi_{eu,t}) E \beta (1-\mu) S_{t+1} - \pi_{eu,t} \tau + \Psi_t \\ \pi_{ee,t} &= \varkappa x_t^{\varrho} \\ \pi_{ue,t} &= \pi_{ee,t} (1 - \pi_{eu,t}) \end{aligned}$$

Law of motion of state variables:

Technology evolves according to the standard $AR(1)$ process

$$
\begin{aligned}
A_t &= e^{a_t} \\
a_{t+1} &= \rho a_t + \eta_{t+1}
\end{aligned} \tag{14}
$$

while unemployment evolves according to

$$u_{t+1} = u_t(1 - \pi_{ue,t} - \pi_{eu,t}) + \pi_{eu,t}$$

5.1 Results

We can now give the first order approximation in closed form noticing that the productivity shock is the minimal state variable for all endogenous (with the exception of vacancy posting and the law of motion for unemployment) to discuss the main dynamic effects of this model. We do this by guessing and matching coefficients f_i of the first order approximation for $S_t \sim f_1 a_t$, $\pi_{eu,t} \sim f_2 a_t$, $x_t \sim f_3 a_t$, $\pi_{ee,t} \sim f_4 a_t$, $\pi_{ue,t} \sim f_5 a_t$, and $w_t \sim f_6 a_t$

Proposition 1. *Up to a first order approximation the coefficients of the model are given by*

Surplus:

$$
\begin{aligned}
f_1 &= \frac{1 - \overline{S} f_5 + \kappa_v (1-s) f_3}{(1 - \beta(1 - \overline{\pi_{eu}} - \overline{\pi_{ue}})\rho - \beta\overline{S}(\overline{\pi_{eu}}(1 - \overline{\pi_{eu}})\rho - \tau^{\pi_{eu}}\overline{\pi_{eu}}(1 - \pi_{eu})\beta\rho - \beta\rho)} \\
&= \frac{1}{1 - \beta(1 - \overline{\pi_{eu}} - \overline{\pi_{ue}})\rho + \{\beta\overline{S}\overline{\pi_{ue}}\frac{\varrho}{(1-\varrho)} - \kappa_v \overline{x}(1-s)\}\frac{(1-\overline{\pi_{eu}})\beta\rho[(1-\mu)+\overline{\pi_{eu}}\frac{\beta\mu\overline{S}}{\psi}]}{\Pi} + \beta\overline{S}\overline{\pi_{ue}\pi_{eu}}\frac{\beta\rho}{\psi}}
\end{aligned}
$$

Firing:

$$f_2 = -\overline{\pi_{eu}}(1 - \overline{\pi_{eu}})\frac{\beta\rho}{\psi} f_1$$

Vacancy-Unemployment Ratio:

$$f_3 = \frac{\overline{x}(1 - \overline{\pi_{eu}})\beta\rho[(1-\mu) + \overline{\pi_{eu}}\frac{\beta\mu\overline{S}}{\psi}] f_1}{(1-\varrho)\Pi}$$

Match-finding:

$$f_4 = \varrho \frac{\overline{\pi_{ee}}}{\overline{x}} f_3$$

Job-finding:

$$f_5 = (1 - \overline{\pi_{eu}}) f_4 - \overline{\pi_{ee}} f_2$$

Wage-setting:

$$f_6 = \mu f_1(1-\beta(1-\overline{\pi_{eu}}-\overline{\pi_{ue}})\rho)+\mu\beta\overline{S}(f_4+f_2)$$

Productivity Variance:

$$var(a_t) = \frac{\sigma^2}{1-\rho^2}$$

Unemployment Rate Variance:

$$var(u_t) = var(a_t)\frac{(\overline{u}f_5-f_2(1-\overline{u}))^2(1+(1-\overline{\pi_{ue}}-\overline{\pi_{eu}})\rho)}{(1-(1-\overline{\pi_{ue}}-\overline{\pi_{eu}})^2)(1-(1-\overline{\pi_{ue}}+\overline{\pi_{eu}})\rho)}$$

Covariance between Productivity and Unemployment:

$$E(\widehat{u_t}a_t) = \frac{((1-\overline{u})f_2-\overline{u}f_5)\rho}{(1-(1-\overline{\pi_{ue}}+\overline{\pi_{eu}})\rho)}var(a_t)$$

Beveridge-Curve between (log)-Unemployment and (log) Vacancies:

$$\begin{aligned}
Cov(\widehat{v_t},\widehat{u_t}) &= E(\frac{x_t}{\overline{x}}+\frac{(1-s)u_t}{(\overline{u}(1-s)+s)},\frac{u_t}{u}) \\
&= \frac{f_3}{\overline{xu}}E(u_ta_t)+\frac{(1-s)var(u_t)}{u(\overline{u}(1-s)+s)}) \\
&= \frac{f_3}{\overline{xu}}\frac{((1-\overline{u})f_2-\overline{u}f_5)\rho}{(1-(1-\overline{\pi_{ue}}+\overline{\pi_{eu}})\rho)}var(a_t)+\frac{(1-s)var(u_t)}{\overline{u}(\overline{u}(1-s)+s)})
\end{aligned}$$

Proof. Straightforward but messy calculations. ∎

5.2 Discussion

Though the formulas are slightly more complicated relative to a model with exogenous firings the basic mechanisms and calibration problems can still be seen.

As can be easily seen from the formula for f_1, the surplus S_t is heavily influenced by the presence of endogenous destruction. The denominator is driven by the autoregressive component $(1-\beta(1-\pi_{eu}-\pi_{ue})\rho)$ and a term that comes from the endogeneity of the separation rate and would be absent in the basic model. If vacancy posting cost are small the last term is less important. The main driver in the numerator is given by the average surplus $\overline{S}$ interacting with the endogenous hiring decision. The smaller the surplus the bigger f_1 will be.

The volatility of all other variables is directly proportional to f_1. In particular, the volatility of firings (f_2) is increasing in the volatility of the surplus and decreasing in the idiosyncratic shock. Intuitively ψ is parameterizing the mass of workers living around the cut-off value that determines endogenous firings. The higher the variance the less likely it is that many matches stay around that point. Variations in the cut-off value will therefore hit only a few workers and firings will be roughly constant. To the contrary, if ψ is small the firm will act substantially to the aggregate shocks given that many firms will just live around the point. Firings will be counter-cyclical. Any increase in the reaction of the surplus making the job-finding rate more volatile will induce firings to become more volatile as well, ceteris paribus. The quantitative implications for policy over the cycle within an endogenous firing framework has been discussed in Jung (2007).

As is well known the vacancy to unemployment ratio f_3, assuming that average firing probability is small and the term in π_{eu} will drop, is directly increasing the smaller equilibrium profits become. This is the crucial channel highlighted among others by Hagedorn and Manovskii (2008) who choose a calibration essentially making the outside option close to productivity and making profits small. We also will need to follow their lead given that there exists no other calibration within the context of this model that can achieve the goal of generating enough volatility. Wages need to be close to productivity for newly hired workers, a time honored outcome of competitive market models. Job-finding and match finding probabilities are straightforward functions of the vacancy to unemployment ratio. Wages are only residually generated and essentially irrelevant. For our purpose it is important to notice that the bargaining power μ mainly drives f_6 and the average surplus.

Though the timing of actual wage payments is not specified, the cyclicality of the match surplus determines endogenous firings. As argued in Shimer (2005), fluctuating firing rates have the problem that they potentially destroy the beveridge curve, making vacancies more pro-cyclical. As the proposition makes clear this claim is true in our model if search on the job is ruled out, $s = 0$. While the covariance between unemployment and productivity is negative, such that $\frac{f_3}{xu} \frac{((1-\overline{u})f_2 - \overline{u} f_5)\rho}{(1-(1-\overline{\pi}_{ue}+\overline{\pi}_{eu})\rho)} var(a_t) < 0$ given that $f_2 < 0$, $f_3, f_5 > 0$ endogenous firings might destroy the Beveridge curve if the covariance is influenced by the positive term $\frac{var(u_t)}{\overline{u}^2}$. This effect gets weaker the more workers search on the job and the bigger s is. The intuition is quite simple. The denominator in the matching function increases with searching employed workers. This implies that a burst in destruction due to a negative technology shock will not too strongly influence the probability of finding a worker from a firms perspective when making the hiring decision. It will therefore not lead to a dramatic inflow of vacancies trying to hire these additional workers and inducing a positive co-movement between vacancies and unemployment. As we documented above, 50% or more of new matches behave like a quit, according to our definition, not like a job-finding out of unemployment. This implies that indeed the matching function should account for searching workers.

Though the model captures the essential features of the labor market it has the well known and discomforting side effect that the surplus of a match needs to be small to match aggregate volatilities. This manifests itself in a high choice of the outside option. The main reason for this potentially unrealistic feature of the model is the complete lack of heterogeneity. Staying within the representative firm framework, though convenient as a modeling choice, does not allow us to capture certain features highlighted above. In particular, in the benchmark model, quits on the job occur randomly and exogenous, given that the worker is indifferent between staying or quitting. However, as the data makes clear, the average gain from quitting expressed in percentage changes to former wages is on the median around 5% (though the variance is quite high). Also firings occur at least in Germany, mainly for workers having low tenure and, compared to their reference group, low wages. To capture these features, we extend the model to allow for heterogeneity in the simplest possible form.

5.3 Extension

Assume that there are two types of jobs, $z \in [g, b]$. Productivity is given by

$$y_{z,t} = A_t B_z \tag{15}$$

where $B_{good} > B_{bad.}$ When firms open a position they randomly draw a job type. With probability π_z the new job is good and with probability $1 - \pi_z$ it is bad. The value of a match then becomes

$$\begin{aligned} J_{b,t} &= A_t B_b - w_{t,b} + (1 - \pi_{ee,t} s)[(1 - \pi_{eu,b,t}) E\beta J_{b,t+1} - \pi_{eu,b,t}\tau + \Psi_{t,b}] \\ J_{g,t} &= A_t B_g - w_{t,g} + (1 - \pi_{eu,g,t}) E\beta J_{g,t+1} - \pi_{eu,g,t}\tau + \Psi_{t,g} \end{aligned}$$

where only the bad types face gains from searching while the good types do not search. Whenever a searching worker receives a job, she accepts. It then randomly realizes whether the job is good or bad. This captures the fact that many quits, roughly 35%, are not associated with a wage increase afterwards. The value flows of the different types are given by

$$\begin{aligned} V_{e,b,t} &= w_{t,b} + (1 - \pi_{ee} s)[(1 - \pi_{eu,b,t}) E\beta V_{e,b,t+1} + \pi_{eu,b,t} E\beta V_{u,t+1}] \\ &\quad + \pi_{ee} s[\sum_z \pi_z((1 - \pi_{eu,z,t}) E\beta V_{e,z,t+1} + \pi_{eu,z,t} E\beta V_{u,t+1})] \\ V_{e,g,t} &= w_{t,z} + \ [(1 - \pi_{eu,g,t}) E\beta V_{e,g,t+1} + \pi_{eu,g,t} E\beta V_{u,t+1}] \qquad (16) \\ V_{u,t} &= b + \pi_{ee,t}[\sum_z \pi_z (1 - \pi_{eu,z,t}) E\beta V_{e,z,t+1}] \\ &\quad + \pi_{ee,t}[\sum_z \pi_z \pi_{eu,z,t} E\beta V_{u,t+1}] \\ &\quad + (1 - \pi_{ee,t})[\sum_z \pi_z (1 - \pi_{eu,z,t}) E\beta V_{u,t+1}] \qquad (17) \end{aligned}$$

The free entry condition adjusts to account for the fact that stochastically two types of jobs are offered.

$$\frac{\kappa_v}{\pi_{ve,t}} = \sum_z \pi_z [(1 - \pi_{eu,z,t})(E\beta J_{t+1,z}) - \pi_{eu,z,t}\tau_z + \Psi_{z,t}] \tag{18}$$

The law of motion for the state variables is given by

$$
\begin{aligned}
l_{g,t+1} &= l_{g,t}(1-\pi_{eu,g,t}) + l_{b,t}s\pi_{ee}\pi_g(1-\pi_{eu,g,t}) + u_t\pi_{ee,t}\pi_g(1-\pi_{eu,g,t}) \\
u_{t+1} &= u_t(1-\pi_{ee,t}) + \sum_z u_t\pi_{ee,t}\pi_g\pi_{eu,g,t} + l_{g,t}\pi_{eu,g,t} \\
&\quad + l_{b,t}s\pi_{ee,t}\sum_z \pi_g\pi_{eu,g,t} + l_{b,t}(1-s\pi_{ee,t})\pi_{eu,b,t} \qquad (19) \\
1 &= l_{g,t} + l_{b,t} + u_t \qquad (20)
\end{aligned}
$$

where the number of good jobs has become an additional state variable.

The matching function becomes

$$m_t = \varkappa v_t^{\varrho}(u_t + sl_t^b)^{1-\varrho} \qquad (21)$$

because now only a fraction of workers in bad matches engage in on the job search. Solving the bargaining problem delivers

$$
\begin{aligned}
\pi_{eu,z,t} &= \frac{1}{1+e^{\frac{\beta E(\Delta_{z,t+1})+[E\{\beta J_{z,t+1}+\tau\}}{\psi_z}}} \qquad (22) \\
\frac{\mu}{\Delta_{z,t}} &= \frac{1-\mu}{J_{z,t}} \qquad (23)
\end{aligned}
$$

where the surplus $\Delta_{z,t}$ is defined as $\Delta_{z,t} \equiv V_{e,z,t} - V_{u,t}$.

Finally, total output is given by

$$y_t = \sum_z A_t B_z \qquad (24)$$

6 Calibration and Estimation

We first report results for the benchmark version of the model and then turn to a discussion how heterogeneity will change the results.

The model delivers closed form solutions for all second moments. A simple search through the parameter space as well as economic intuition reveal that there exists no solution that reproduces jointly enough volatility in job-finding and firing rates and does not rely on a version of a small surplus. Taking this as given, one could either evaluate the quality of the model in terms of matching a few restricted moments by simulating the model, as is practice in one strand of the literature, or alternatively, one could add 6 additional shocks to do a Bayesian estimation procedure to estimate all endogenous variables jointly. Both approaches have their merits and short-comings. In this paper, we propose instead to use the predictive power of the model to test whether the basic mechanisms can reproduce **jointly** important feature of the data along all endogenous dimensions. To this end, we use a Kalman filtering procedure on **one** variable to back out, given the model, the underlying technology shock. We then use this series as well as the laws of motions of the model to predict all endogenous variables and compare the predictions of the model to the data. Note that, having only one shock available, this implies that model and data will typically deviate. However, it also allows us to discuss were the model fits well or could be improved upon.

The model period is one month and we aggregate to quarterly frequency. Our calibration strategy works as follows: We use German data as the benchmark case. We estimate given the linearized model the productivity state using the Kalman filter on GDP growth rates[33]. We target the average firing, quit and job-finding probabilities as well as the three standard deviations of the job-finding rate, the firing rate and wage-income for Germany.

We proceed in a similar manner also for the U.S.. To obtain estimates for the U.S., we further impose cross country restrictions by assuming that the underlying technology constraints are identical for both countries. We set the shape and parameters of the matching function, the cost to post a vacancy, the discount rates as well as the volatility of the idiosyncratic shocks to be the same for both countries. We only allow the bargaining power, the search intensity, the outside option and the fixed cost of producing to vary. We use the differences across countries in the mean rates as well as the standard deviation of job-finding to pin down these four parameters. By imposing the joint restrictions on the primitives of the model, we are able to see how differences in the means and standard deviations across countries can inform us about the underlying institutional differences associated to certain model parameters. In particular, we allow the bargaining power to vary for the U.S. reflecting potential differences across countries in the power of unions. The second free labor market parameter, the exogenous search probability, pins down average quits across country. Note that due to data limitations for the U.S. we associate a quit with the non-employment to employment flows because as documented in Nagypal (2005) many of the E-N flows lead to hirings the month after and could possibly be viewed as quits on the job. The outside option as the third institutional parameter reflects differences in the unemployment benefit schemes as well as differences in home-production opportunities. The parameters governing endogenous firing are also allowed to differ given that they potentially reflect a condensed distribution for Germany or differences in the fixed cost of entertaining a match. Table 6 reports our strategy:

Given the estimated technology process as well as the parameters, we now predict all endogenous variables for both countries and apply an HP-filter ($\lambda = 100,000$) to the resulting timeseries. We also report the results for the Bandpass-filter. Figure 6 and 7 show the results.

[33] We consider GDP the cleanest measure of aggregate activity because in particular official productivity parameters are heavily affected by the German reunification and the trends in hours worked and employment.

Table 5 reports the standard deviations of the estimated series as well as the correlation between predicted and actual values.

Table 5: Summary Statistics - Germany

Name	Std (GER)	Std - Model	Corr(actual,predicted)	Std (US)	Std Model	Corr(actual,predicted)
U-Rate	0.181	0.204	0.93	0.159	0.18	0.92
Productivity	0.018	0.014	0.61	0.017	0.023	0.60
Wage Income	0.016	0.013	0.84	0.0173	0.021	0.39
Quits (NE)	0.199	0.101	0.72	0.059	0.11	0.54
Firings	0.164	0.165	0.82	0.076	0.08	0.77
Job-Finding	0.104	0.102	0.65	0.12	0.11	0.77
Vacancies	0.341	0.100	0.43	0.21	0.09	0.72

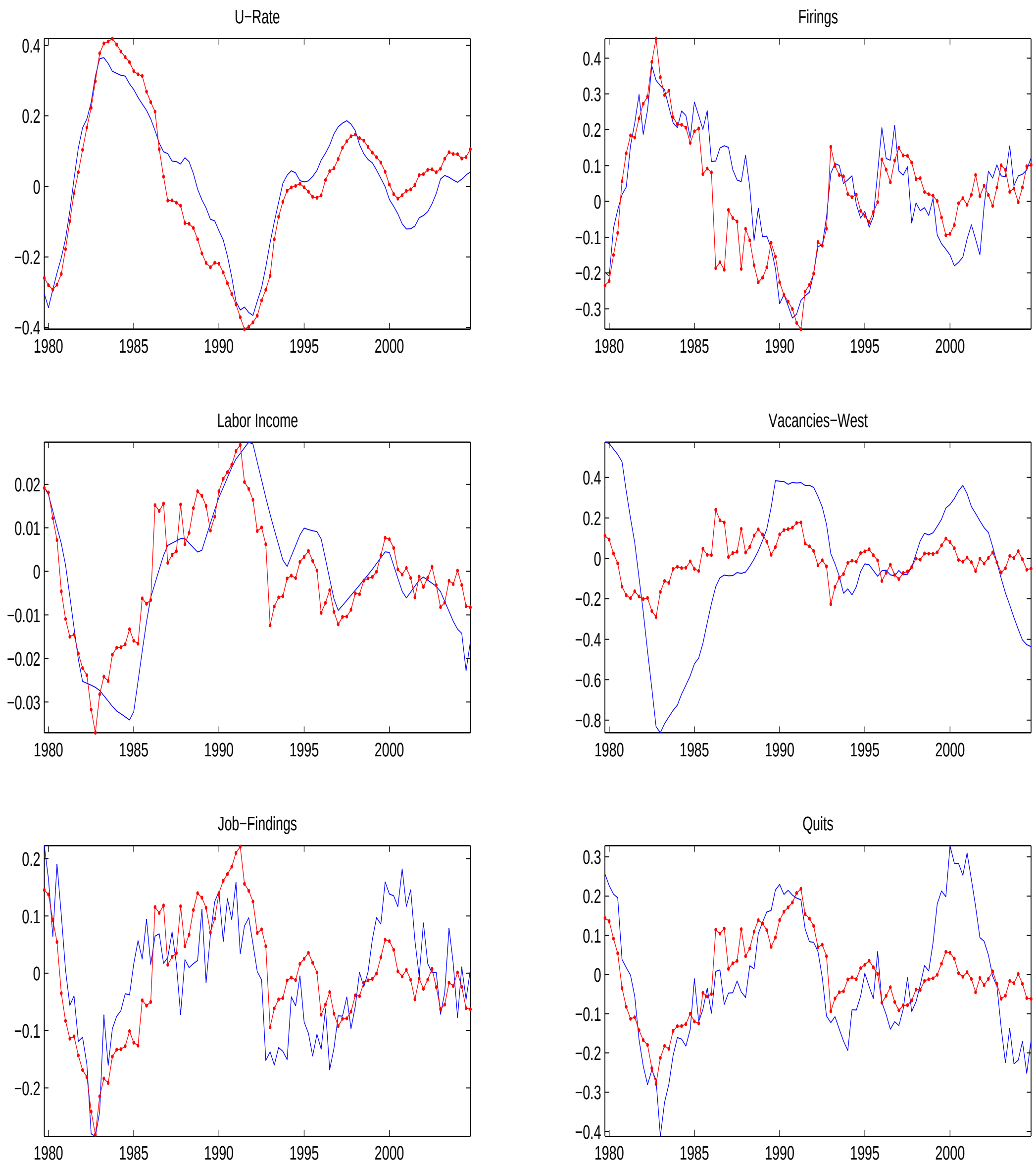
The table reports summary statistics for all endogenous variables predicted by the model and compares them to the data. Note that for quits in the U.S. we do not have corresponding data and proxy by the NE flows. However, the proxy might capture very distinct phenomena and should be interpreted with care.

6.1 Results for the homogeneous match case

The results are quite striking. The graphs document that the model is able to reproduce the time pattern of the endogenous variables to a reasonable extend, given the simplistic shock structure. In both countries the correlation between the predicted and the actual unemployment rate is very high, in fact around .93 for the unemployment rate. This implies that the second moments contain enough information that together with the endogenous working of the model, we can match the time pattern very well. For Germany, we match labor income, quits and firings also very well. Our measure of vacancies, that reflects only a fraction of job-openings registered at the unemployment agency and misses all privately posted jobs, is exceptionally volatile and the model is unable to reproduce such a high volatility. We do match the pro-cyclicality though. For the U.S. we also match firings, the job-finding probability as well as vacancies fairly well, all having a correlation above .74. Our measure of quits, using non-employed to employed as a proxy does correlate with the quits predicted by the model, though weaker. The model predicts for Germany almost perfectly the behavior of labor income obtained from the micro-data. German labor income is not sticky and the model, driven by a high bargaining power, provides a mechanisms for substantial wage flexibility. For the U.S., the model would predict a lower elasticity of wages with respect to the cycle. However, as the plots reveal, the model is incapable of reproducing observed aggregate labor income data for the U.S.. The model overshoots in the beginning of the sample and is unable to explain the puzzling downturn in the mid-nineties.[34] The failure is partly due to the filtering procedure, we do better when applying the BP filter. Still, the model has problems in reproducing the particular aggregate labor income series used for this study. Potentially better micro-data on wages could rectify the problem. We decided to fix all primitives of the model and view the bargaining power, the fixed cost associated with a match and the outside option as partly influenced by institutions, so we let them freely move to

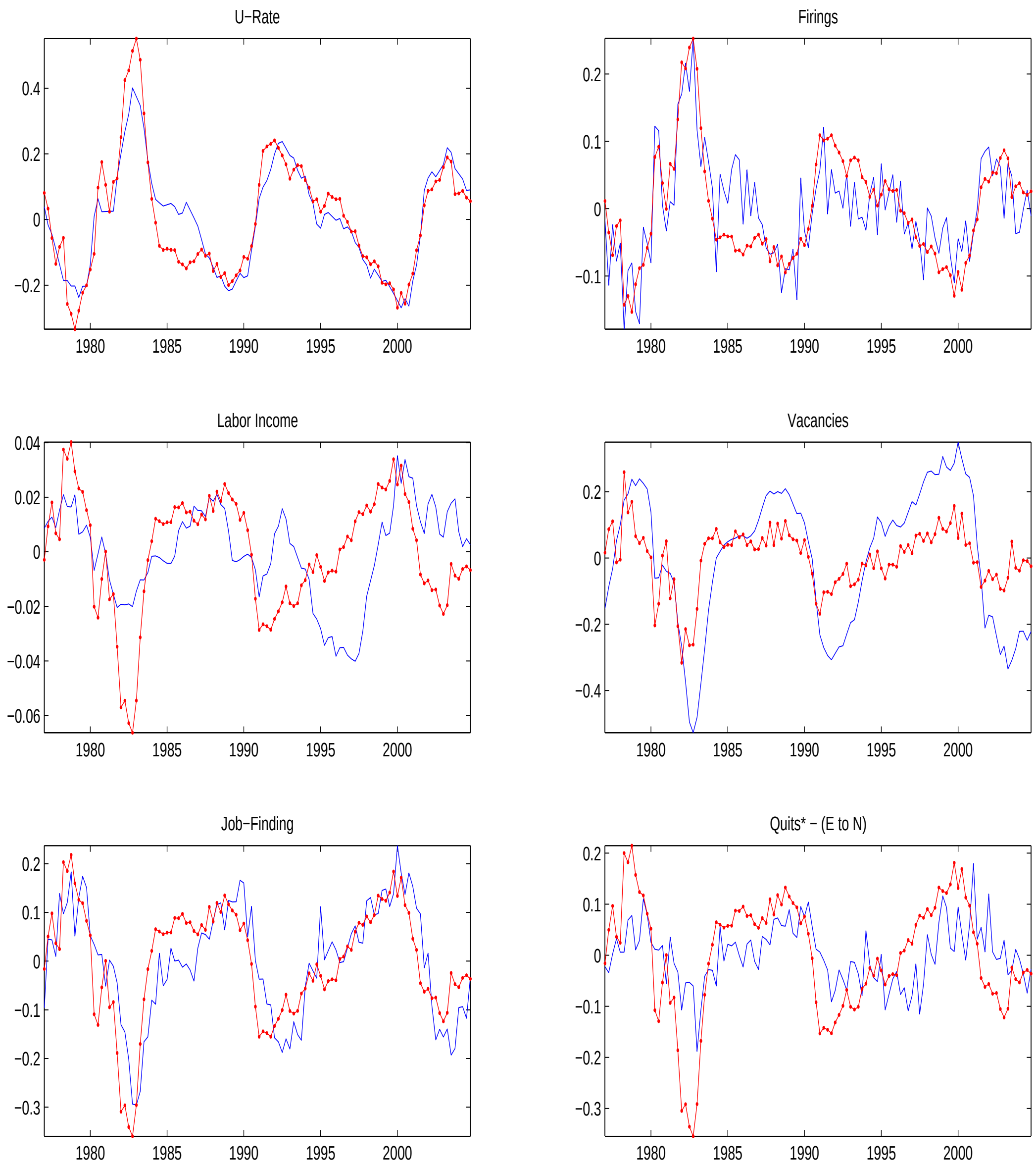
[34] Note that the misalignment to wages hold for all parameter values we have checked and is fairly independent of the bargaining power or other re-parameterizations.

Figure 6: Comparison Data vs Model - Germany



The red dotted line shows the prediction of the model estimated on one productivity shock using aggregate GDP growth. The blue solid shows the actual data. All data are logs. We report results on a HP-filtered (λ=100000)

Figure 7: Comparison Data vs Model - US



The red dotted line shows the prediction of the model estimated on one productivity shock using aggregate GDP growth. The blue solid shows the actual data. All data are logs. We report results on a HP-filtered (λ=100000) account for the mean rate differences observed in the data.[35]

The model demands, for both countries, a high outside option, though a weaker one for the U.S.. This does not imply that the surplus is higher in the U.S.. To the contrary, due to the mean differences, the surplus is lower. Note that the utility difference between working and being unemployed corresponds to 1.12 of a monthly wage in Germany, while for the U.S. this surplus is considerably smaller, only 1/3 of a monthly wage. This is due to the fact that the bargaining power for employed workers is higher and the job-finding probability is lower in Germany leading to higher average wage and longer unemployment duration in Germany. The resulting surplus difference ultimately drives the result. The crucial aspect lies in the fact that differences in mean rates, even with a largely identical structure on the technology part, lead to differences in the endogenous surplus. Firing and job-finding are, given the model, driven by identical counteracting forces. The underlying structure across country is fairly comparable, yet, firing contributes more to unemployment volatility in Germany while job-finding contributes more in the U.S..

6.2 Results for the heterogeneous match case

As we documented above, heterogeneity across matches seems to play an important role. Many low productivity matches appear to be destructed quickly after creation while the endogenous search process typically leads to a wage increase afterwards. To explore the quantitative impact of heterogeneity across types, we follow the same calibration procedure as outlined above. Table 7 shows our calibration targets. Again, we calibrate to Germany and impose cross country restrictions for the U.S.. We take German data as our benchmark and allow four parameters, reflecting possibly institutional differences, to change as we did in the homogenous case. We target a permanent wage increase of 5% across match types, which is a conservative estimate on the average quit gains documented above. To pin down the offer probability, we target a rate of 50% of good jobs in the economy, which roughly corresponds to the fraction of high tenured jobs in Germany. We again use cross country differences in means to pin down relative parameter changes as we did above. With respect to aggregate predictions the model delivers almost identical results. All plots and correlation statistic are similar as in the case of homogenous workers. However, the crucial differences lies in the average surplus from the workers perspective. For the U.S. it has increased to 3.5 times the monthly wage, while for Germany it has increased to 6.5 times the monthly wage. That is, high skilled worker would demand a years worth of pay to voluntarily give up their current match, while low productivity worker would give up their job for half a month worth of pay. Given that roughly 50% of all jobs are good in the steady state of the economy, the average surplus is also high. This implies that there are, in this simple structure, substantial gains from having a good job.[36] Still, the model reproduces

[35] Note that the results are not unique to the extend, that we can generate almost identical cyclical behavior if we were allowed to change say the cost of posting a vacancy across country or the measure of workers living around the cut-off value. Without independent evidence on any of these parameters we have to restrict them in a sensible way.

[36] The average surplus of a match is substantial and a direct function of the assumed wage differential across matches. It is a direct function of the assumed differences in productivity. For a 10% wage differential for example the average surplus of a match from the workers perspective is a years worth of pay.

the aggregate facts fairly well. The reason is due to the substantial heterogeneity across types that is reinforced by our assumption of on the job search. Expected firm profits from hiring are still very low, because with a high probability the match is only a bad one. However, workers can search on the job and will, eventually, receive job offers that are actually good. Once on a good job, the likelihood of being destructed falls substantially compared to bad jobs. Turn-over rates in good jobs are much lower than in bad jobs implying that, over time, a substantial fraction of workers in society will be in these jobs. This mechanism shapes the average quality of jobs in society. The good jobs are characterized by a high surplus.[37] Additionally, the surplus of a good job not only reflects the direct effect of delivering a higher wage but, additionally, reflects the time-cost spend searching for it. Once unemployed, the worker will spend some time in unemployment and will, likely, need time to find a good job again. This time cost can be substantial and suggest that the search process in itself generates a high surplus for these groups. For low productivity matches the surplus needs still to be low to generate the observed volatility. The basic mechanism outlined above remains unchanged. Yet, the average surplus is now substantial.

7 Conclusion

This paper documents substantial differences in labor market dynamics between Germany and the U.S.. This confirms the recent evidence surveyed in Pissarides (2009) that European labor markets behave differently to their U.S. counterparts. Firing rates are considerably more important in Germany, explaining 80% of all the unemployment volatility. This runs counter to the intuition that European labor markets face typically higher employment protection than their U.S. counterparts. To explore this puzzling result we point at the strong differences across tenure groups in the German labor market. We show that 75% of all firings happen to workers with tenure of 2 years or less. In this tenure classes employment protection might be less of a constraint for firms, given that the amount of obligatory severance payments and other components of employment protection are increasing in tenure.

An alternative interpretation of the data that does not rely on employment protection suggests itself when looking at who is quitting and who gets fired. We show that the destructed jobs were typically low productivity jobs living substantially below the median income of the same tenure class. This result holds true also when controlling for different education classes and across sex and age. Similarly, most quits on the job occur when job tenure is still low. Again, workers move from below the median to on average better jobs. Firing and quits showed strong correlations with the business cycle. The correlation pattern holds across all tenure groups though it is less pronounced for high-tenured workers who are less affected by changing aggregate conditions. This points towards heterogeneity across matches that induce differences in the search behavior of workers and the firing behavior of firms.

[37] Recall that we fixed the outside option as a parameter value, so the distance between productivity and unemployment increased.

We do find that quits and job-finding probabilities strongly co-move over the cycle, suggesting a common matching market. Jobfinders' labor income and quitters' labor income follow each other closely. However, quitters do receive a premium on average compared to job-finder.

Turning to the behavior of wages in more detail, we find that they are highly flexible over the cycle and follow aggregate productivity or output very closely. Their is no evidence of a strong form of wage rigidity in the data. In particular, we construct a sub-sample of workers that have never quitted or got fired over their entire working life which due to the large panel dimension is covered over 30 years. Fixing this group to rule out composition effects, we find that wages of this group moves practically one to one with aggregate measures. Controlling for composition effects, we find that wages for worker in ongoing jobs have an elasticity of around .7 with respect to aggregate measures while job-finder and quitter wages have an elasticity of around .5. Most of the decline is due to the fact that quitter and job-finder wages appear to lag the cycle by roughly half a year.

To explain part of the cross-country differences in observed labor market dynamics we provide a simple labor market search and matching model featuring quits via a common matching market for searching workers, endogenous firings decision and heterogeneity across types. We calibrate the model to German data and use differences in means across countries to pin down changes in institutional settings for Germany and the U.S.. We then ask the model whether it can predict, based on an estimated technology process, all of the German and the U.S. labor market variables jointly. We show that the model captures the important features of the data very well for both countries. Interestingly, differences in the bargaining power inducing differences in the average surplus across countries seem to be able to explain a large part of the differences. We show that heterogeneity across matches does not change the reaction of the model to aggregate shocks significantly, however, it provides a simple channel that produces a substantial average surplus, avoiding part of the criticisms that have been raised with respect to the small surplus calibration proposed in Hagedorn and Manovskii (2008). For Germany, a worker would pay on average half a year of labor income to keep his current job while in the U.S. he would still be willing to pay a quarter of yearly labor income. The difference is due to higher turnover rates, possibly reflecting higher competition among firms in the U.S., such that it is less costly for Americans to find a good match.

Overall our results suggest that based on the model, the underlying structure between Germany and the U.S. might well be similar. However, institutional differences particularly in the bargaining power of unions might likely lead to the observed cross-country differences found in the data.

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8 Appendix

The appendix provides additional information on the role of education.

8.1 Calibration

The tables report our calibration procedure both for the homogenous as well as the heterogenous case.

8.1.1 Homogenous Case

Table 6: Parameters - Benchmark

Parameter	*Value-GER*	*Value-US*	*Target (Germany)*	*Source*
Common:				
β	=.997	=.997	Annual real rate of 4 percent.	Cooley/Prescott
$\varkappa$	=.296	=.296	$\pi_v = .54$	Normalization
κ	=.07	=.07	Mean u=.07	Data
ϱ	=.7	=.7	Matching - Elasticity	Petronglo/Pissarides
ψ_{eu}	=.48	=.48	Std(π_{eu})	Kalman Estimate
ρ	=.975	=.975	Auto-correlation	Kalman Estimate
Estimated:			*Target (Germany),(US)*	
b	=.918	=.878	Std(π_{ue})	Kalman Estimate
μ	=.90	-	Std(w)	Kalman Estimate
Mean-Differences:				
s	=0.11	=.06	Mean quits=.0085 (GER), =.02 (US)	Data
t	=0.86	=0.99	Mean π_{eu} = .005 (GER), =.02 (US)	Data
μ	-	.6	U-Rate=.055 (US)	Data

Notes: This table documents our chosen parameters and outlines the Calibration procedure. The benchmark world is Germany given that we have more reliable data here. We then impose cross country restrictions on the parameters also for the U.S.. We allow for parameters to differ to capture the mean differences as well as potentially the differences in the surplus.

8.1.2 Heterogenous Case

Table 7: Parameters - Heterogeneity

Parameter	*Value-GER*	*Value-US*	*Target (Germany)*	*Source*
β	=.997	=.997	Annual real rate of 4 percent.	Cooley/Prescott
$\varkappa$	=0.28	=.28	$\pi_v = .54$	Normalization
κ	=0.08	=.08	Mean u=.06	Data
ϱ	=.7	=.7	Matching - Elasticity	Petronglo/Pissarides
ρ	=.975	=.975	Kalman filter estimates	Solow Residual
Additional	*Heterogeneity*			
t_1	=1.09	-	Mean π_{eu} = .0055 (GER)	Data
t_2	=1.09	-	Harmonization	Data
$\psi_{eu,1}$	=.36	=.36	Std(π_{eu})	Kalman Estimate
$\psi_{eu,2}$	=2.24	=2.24	Mean $\pi_{eu,2}$ = .015 (GER)	Kalman Estimate
B_1	=0.975	=.975	5%	Data
B_2	=1.025	=1.025	Normalization	Data
π_g	=.062	=.062	fraction of high tenured jobs (50%)	Data
Cross-Country Diff.:				
b	=.90	=.88	Std(π_{ue})	Kalman Filter Estimate
s	=.25	=.15	Mean quits=.008 (GER), =.02 (US)	Data
μ	=.9	=.63	Wage elasticity (GER), mean u (US)	Data
t_1	=-	1.27	Mean π_{eu} = .02 (US)	Data
t_2	=-	1.27	Harmonization	Data

Notes: This table documents our chosen parameters when looking at heterogeneity and outlines the calibration procedure. The benchmark world is Germany given that we have more reliable data here. We then impose cross country restrictions on the parameters also for the U.S.. We allow for parameters to differ to capture the mean differences as well as potentially the differences in the surplus.

8.2 Transitions by Education and Sex

Table 8: Transition Rates by Education and Sex (1977:1 to 2004:4)

Name	Mean	Std	Rel Std - y	Corr - y	Corr - Y-P	Auto-Corr
Females						
Firm Exit	0.024	0.057	2.30	0.62	0.34	0.82
Employment Exit	0.016	0.034	1.37	-0.14	-0.05	0.31
EU	0.005	0.178	7.18	-0.61	-0.51	0.85
EN	0.011	0.064	2.56	0.56	0.49	0.69
UE	0.057	0.126	5.09	0.43	0.17	0.61
UN	0.062	0.137	5.52	0.17	0.17	0.53
NE	0.061	0.198	7.98	0.32	0.02	0.84
NU	0.017	0.233	9.40	-0.08	-0.13	0.82
Quits	0.008	0.158	6.37	0.72	0.40	0.94
Males						
Firm Exit	0.0250	0.089	4.055	0.600	0.5129	0.710
Employment Exit	0.0192	0.088	3.981	0.303	0.4622	0.647
EU	0.0057	0.219	9.924	-0.441	-0.0135	0.829
EN	0.0136	0.116	5.290	0.641	0.4701	0.719
UE	0.0453	0.167	7.578	0.344	-0.0874	0.682
UN	0.0515	0.145	6.587	0.376	0.4085	0.515
NE	0.1138	0.237	10.732	0.420	-0.0607	0.837
NU	0.0497	0.257	11.630	-0.204	-0.1460	0.763
Quits	0.0058	0.228	10.331	0.622	0.2609	0.851
Males - Education (low skilled)						
Firm Exit	0.0250	0.0896	4.055	0.600	0.5129	0.710
Employment Exit	0.0192	0.0880	3.981	0.303	0.4622	0.647
EU	0.0057	0.2193	9.924	-0.447	-0.0135	0.829
EN	0.0136	0.1169	5.290	0.641	0.4701	0.719
UE	0.0453	0.1674	7.578	0.344	-0.0874	0.682
UN	0.0515	0.1455	6.587	0.376	0.4085	0.515
NE	0.1138	0.2371	10.732	0.420	-0.0607	0.837
NU	0.0497	0.2570	11.630	-0.204	-0.1460	0.763
Quits	0.0058	0.2283	10.331	0.622	0.2609	0.851
Males - Education (Medium skilled)						
Firm Exit	0.0236	0.0522	2.361	0.366	0.087	0.635
Employment Exit	0.0145	0.0573	2.591	-0.440	-0.041	0.636
EU	0.0056	0.2403	10.877	-0.671	-0.215	0.911
EN	0.0089	0.0756	3.419	0.690	0.267	0.801
UE	0.0801	0.1211	5.479	0.184	-0.183	0.584
UN	0.0483	0.1351	6.116	0.541	0.407	0.713
NE	0.0894	0.2035	9.210	0.248	-0.176	0.796
NU	0.0393	0.2298	10.401	-0.406	-0.207	0.826
Quits	0.0090	0.1610	7.285	0.565	0.101	0.903
Males - Education (High-skilled)						
Firm Exit	0.0235	0.0896	4.056	0.389	0.240	0.73
Employment Exit	0.0130	0.0883	3.998	0.142	0.2439	0.479
EU	0.0031	0.2100	9.504	-0.415	-0.1065	0.796
EN	0.0099	0.1298	5.876	0.317	0.2126	0.564
UE	0.0686	0.1538	6.959	0.161	-0.1945	0.629
UN	0.0568	0.1434	6.491	0.102	0.0495	0.312
NE	0.0639	0.2506	11.341	-0.023	-0.1879	0.742
NU	0.0126	0.3037	13.741	-0.299	-0.2299	0.694
Quits	0.0105	0.1391	6.296	0.450	0.1619	0.849

All data are in logs and are HP-filterer with $\lambda = 100,000$. GDP data is nominal GDP from the statistic office deflated by the CPS, taken from the Bundesbank. Employment and total hours worked are also taken from the statistics office. IAB data are quarterly averages of monthly data. Firm Exit is defined as the sum of EU+EN+Quits. Employment Exit is defined as EU+EN. Quits are defined as job-job transitions without an intervening non-employment spell (less than a week) and a change in the firm counter as defined in the IAB-data. All IAB-rates are authors calculations.

8.3 Tenure flows Non-employment

The table reports tenure transition rates for EN and NE flows.

Table 9: Tenure-Job Finding

$E \rightarrow N$	<365 days	$365-730$ days	$730-1825$ days	>1825 days	$overall$ days
mean	0.0191	0.0057	0.0041	0.0018	0.0059
std	0.0025	0.0010	0.0008	0.0005	0.0008
rel. share	0.5913	0.1065	0.1532	0.1489	NaN
rel. wage	0.7195	0.7704	0.7769	0.7843	NaN
corr (per capita)	0.1154	0.0971	0.2016	0.1950	0.3208
corr (per empl.)	0.0216	0.3294	0.4236	0.4586	0.2626
$N \rightarrow E$	<180 days	$180-365$ days	$365-730$ days	>730 days	$overall$ days
mean	0.0916	0.0429	0.0309	0.0284	0.0434
std	0.0198	0.0206	0.0172	0.0242	0.0217
rel. share	0.4646	0.1243	0.1090	0.3022	NaN
corr (per capita)	0.3229	0.0741	0.0345	0.0135	0.1037
corr (per empl.)	-0.2001	-0.2802	-0.2770	-0.3224	-0.3102

8.4 Tenure - By Education

Table 10: Tenure - Job Finding, firing, and quitting

Low skilled					
Quits	< 365 days	365 − 730 days	730 − 1825 days	> 1825 days	*overall* days
mean	0.0138	0.0074	0.0047	0.0026	0.0052
std	0.0038	0.0031	0.0020	0.0013	0.0020
rel. share	0.4316	0.1191	0.1556	0.2936	*NaN*
rel. wage	0.8607	0.8520	0.9031	0.9231	*NaN*
corr (per capita)	0.3144	0.0939	0.2663	0.0564	0.3257
corr (per empl.)	0.0097	0.0201	0.0234	0.0770	0.0808
Jobfindings	< 180 days	180 − 365 days	365 − 730 days	> 730 days	*overall* days
mean	0.0627	0.0289	0.0198	0.0090	0.0363
std	0.0183	0.0092	0.0077	0.0046	0.0120
rel. share	0.6754	0.1542	0.1030	0.0675	*NaN*
corr (per capita)	0.1480	0.2936	0.2543	0.1631	0.1806
corr (per empl.)	−0.1350	−0.0079	0.0337	−0.0746	−0.1408
Firings	< 365 days	365 − 730 days	730 − 1825 days	> 1825 days	*overall* days
mean	0.0234	0.0088	0.0036	0.0019	0.0061
std	0.0061	0.0041	0.0018	0.0008	0.0019
rel. share	0.5986	0.1174	0.0976	0.1864	*NaN*
rel. wage	0.8888	0.8203	0.8461	0.8918	*NaN*
corr (per capita)	−0.5770	−0.5149	−0.3568	−0.2863	−0.5535
corr (per empl.)	−0.2652	−0.2519	−0.1435	0.0291	−0.1912
Medium skilled					
Quits	< 365 days	365 − 730 days	730 − 1825 days	> 1825 days	*overall* days
mean	0.0205	0.0117	0.0079	0.0038	0.0084
std	0.0035	0.0023	0.0016	0.0010	0.0016
rel. share	0.4317	0.1416	0.1967	0.2300	*NaN*
rel. wage	0.8910	0.9170	0.9133	0.8981	*NaN*
corr (per capita)	0.4622	0.4121	0.4534	0.3162	0.4777
corr (per empl.)	0.0946	0.1530	0.1409	0.1590	0.1253
Jobfindings	< 180 days	180 − 365 days	365 − 730 days	> 730 days	*overall* days
mean	0.1087	0.0490	0.0315	0.0210	0.0694
std	0.0237	0.0126	0.0100	0.0071	0.0198
rel. share	0.7319	0.1376	0.0770	0.0535	*NaN*
corr (per capita)	0.2089	−0.0073	0.3417	0.3111	0.2021
corr (per empl.)	−0.0885	−0.1959	0.0307	−0.0854	−0.1702
Firings	< 365 days	365 − 730 days	730 − 1825 days	> 1825 days	*overall* days
mean	0.0215	0.0074	0.0039	0.0015	0.0060
std	0.0052	0.0018	0.0011	0.0005	0.0012
rel. share	0.6178	0.1242	0.1345	0.1236	*NaN*
rel. wage	0.8585	0.8430	0.8268	0.8444	*NaN*
corr (per capita)	−0.6891	−0.6348	−0.6368	−0.4674	−0.6942
corr (per empl.)	−0.3321	−0.3147	−0.2830	−0.1162	−0.3487
High skilled					
Quits	< 365 days	365 − 730 days	730 − 1825 days	> 1825 days	*overall* days
mean	0.0158	0.0128	0.0106	0.0053	0.0098
std	0.0026	0.0033	0.0025	0.0019	0.0020
rel. share	0.3316	0.1819	0.2755	0.2109	*NaN*
rel. wage	0.8505	0.9324	0.9448	0.9782	*NaN*
corr (per capita)	0.0894	0.1223	0.1945	0.2349	0.2552
corr (per empl.)	−0.0018	−0.0224	−0.0110	0.0564	0.0108
Jobfindings	< 180 days	180 − 365 days	365 − 730 days	> 730 days	*overall* days
mean	0.0870	0.0475	0.0381	0.0298	0.0611
std	0.0185	0.0160	0.0161	0.0218	0.0160
rel. share	0.6581	0.1626	0.1127	0.0666	*NaN*
corr (per capita)	0.2535	−0.0446	0.2092	0.1193	0.2416
corr (per empl.)	−0.1213	−0.1395	0.0223	0.0322	−0.1521
Firings	< 365 days	365 − 730 days	730 − 1825 days	> 1825 days	*overall* days
mean	0.0076	0.0039	0.0024	0.0009	0.0030
std	0.0020	0.0012	0.0008	0.0005	0.0006
rel. share	0.5098	0.1794	0.1962	0.1146	*NaN*
rel. wage	0.7094	0.7179	0.7036	0.8083	*NaN*
corr (per capita)	−0.3940	−0.2682	−0.3126	−0.2507	−0.3544
corr (per empl.)	−0.0430	−0.0443	0.0185	0.0680	−0.0017

Job finding, firing, and quitting rates across tenure classes for males in West Germany starting from 1981. The tenure refers to the duration of the current job spell respectively the duration of the current unemployment spell. The column *overall* refers to the unconditional average.

A Data

A.1 Sample selection

In a first step sample selection, we drop all individuals where the East-West information is missing (2,787 individuals dropped) or information regarding the current job[38] (14,490 individuals dropped).

[38] stib information missing.

Furthermore, we drop homeworkers ('Heimarbeiter') from the sample ($7,315$ individuals dropped). This results in a dropping rate of 1.81% for the whole sample, and leaves us with a sample of employment histories for $1,336,357$ individuals.

A.2 Construction of monthly spells

For every spell, we observe whether it is a full-time, part-time, or marginal employment. To avoid mismeasurement, we drop all marginal employment spells in the beginning because they are only observed for the last five years of the sample period. For the analysis we then only consider what we call *primary spells*. The idea is to consider the employment spell that generates the most income and occupies the most working time of an individual. To identify the primary spell, we apply some hierarchical selection procedure. If a person is at the same time full-time and part-time employed, we label him or her as full-time employed and drop the part-time spells, if a person has two part-time employments, we follow the ordering in the dataset that follows the same hierarchical ordering over parallel spells, finally, if a person has employment and unemployment spells, we label the employment spells as primary to be consistent with the further procedure of determining the employment status below. We label inactive employment that is reported in the dataset as non-employment and construct additional non-employment spells as residual spells in the dataset. The additional spells are included if a person is not observed in the sample for some time period between two spells. To deal with persons entering the sample or dropping out of the sample, we introduce additional labor market states that we label *labor market entry* and *retirement*. The labor market entry state is an artificial state that we add before the first employment state. The retirement state is an artificial state at the end of the labor market history. We assign it to persons that are of age 55 or older when they have their last observed spell. The retirement state is by construction an absorbing state.Persons that are below 55 and disappear from the sample are labeled as *other employment* and are no longer considered after the transition into this non-employment state.

For the wage analysis, we also used wages that have been aggregated across parallel spells before aggregating parallel spells and it turned out that the cyclical properties of the wages did not change much. We keep therefore only the wage of the primary spell for the analysis in this paper.

A.3 Imputation of wages and correcting for structural breaks

Wages in the sample are top-censored at the upper contribution limit ('Beitragsbemessungsgrenze') of the German social security system, and bottom censored at the marginal employment contribution level ('Geringfuegigkeitsgrenze'). For some of steps of the analysis we need an uncensored income distribution. For these steps we impute wages above and below the two censoring points using the method proposed in Gartner (2005). The imputation uses a censored regression together with the log-normality assumption for income to impute the censored observations. For details see Gartner (2005).

Starting 1984 the income data also includes overtime and bonus payments. We correct for this structural break using the method proposed in Fitzenberger (1999). His procedure leaves the median and all observations below the median unchanged and corrects income observations only above the median. The approach is based on measuring the excess growth of the upper wage quantiles between 1983 and 1984. For details see Fitzenberger (1999).