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Ex-Ante Heterogeneity, Separations, and Labor Market Dynamics*

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Abstract

Our paper documents the importance of workers' ex-ante heterogeneity for labor market dynamics and for the composition of the unemployment pool. We show that workers with high wages have both lower separation rates and larger log-deviations of these separations over the business cycle than those with low wages. Thereby, more high-wage workers enter the unemployment pool in recessions, leading to a positive correlation between unemployment and the prior wage of those losing their job. Based on administrative data for Germany and two-way fixed effects, we show that worker fixed effects are key for the documented facts. We contrast our empirical results with a search and matching model with worker ex-ante productivity heterogeneity. The simulated model can replicate the empirical facts when calibrated to the measured flow rates and to the relative residual wage dispersion from the administrative data for different wage groups. It is the combination of low steady state separation rates and low residual wage dispersion for high-wage workers that generates the patterns documented in the data.

Keywords: Labor Market Flows, Separations, Fixed Effects, Labor Market Dynamics
JEL Classifications: E24, E32, J31, J60, J64

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1 Introduction

In the United States, the pool of unemployment consists of a larger share of (former) high-wage workers during recessions than during booms (Mueller, 2017). This pattern is connected to the stronger co-movement of the separation rate with aggregate unemployment for high-wage workers than for low-wage workers. Mueller (2017) shows that these facts are difficult to reconcile with standard labor market flow theories. Relatedly, Cairó and Cajner (2018) find that workers with a university degree in the United States have less volatile separation rates than those without a university degree. As university graduates earn on average higher wages than those with lower formal education, these findings seem to contradict each other.[1]

Based on German administrative data, we document that the cyclical patterns across wage and education groups for the United States are very similar in Germany despite of very different labor market institutions. Grouping workers by their daily wage, those above the median wage have more cyclical unemployment fluctuations in relative terms, which are driven by the higher cyclicality of the separation rate for high-wage workers. However, once we control for worker fixed effects, the co-movement of the separation rate with aggregate unemployment above and below the median residual wage is basically the same. In addition, controlling for worker fixed effects, the positive co-movement of unemployment and prior wages of those who lose their job disappears. These empirical results point to an important role of worker ex-ante heterogeneities for labor market dynamics. The importance of ex-ante heterogeneities is confirmed by our search and matching model with different ex-ante productivities at the worker level. As in the data, the quantitative model generates larger log-deviations and smaller absolute deviations of the separation rate for high-wage workers than for low-wage workers in response to aggregate shocks. It is the combination of ex-ante worker heterogeneity, targeted separation rates and the targeted relative residual wage dispersion that allows us to reconcile the aggregate patterns in the model with those in the data.

For the empirical analysis, we use the Sample of Integrated Employment Biographies (SIAB), which contains employment biographies of a random 2 percent of the German workforce. Thereby, we can construct transitions rates for workers with (residual) wages above/below the median and examine their co-movement with the unemployment rate. This exercise shows that high-wage workers have considerably more cyclical separations relative to low-wage workers, both in terms of the raw wage and in terms of the residual wage (controlling for standard observables). We show that this pattern holds in relative terms and it is consequently not in contradiction with the vastly documented cleansing effect of recessions and the observation that lower educated workers face larger unem-

[1] In this paper, we show that an understanding of the role of ex-ante worker heterogeneity and relative versus absolute deviations over the business cycle can reconcile these two empirical findings.

ployment and separation rate fluctuations (e.g., Cairó and Cajner (2018) and Mukoyama and Şahin (2006)). Table 1 illustrates this point based on unconditional moments of the separation rate for different worker fixed effect quartiles and for different education groups. The divergence of the absolute and relative deviations is due to very different separation rate levels across education groups and across worker fixed effects groups (see Appendices B and C for details).

Table 1: Volatilities of Separation Rates for Different Groups: Unconditional Moments

Worker Fixed Effect Quartiles	1	2	3	4
Separation Rate (Logs)	1.00	1.35	1.26	1.23
Separation Rate (Levels)	1.00	0.75	0.37	0.24
Education	No vocational training	Vocational training	University degree	
Separation Rate (Logs)	1.00	0.99	1.03	
Separation Rate (Levels)	1.00	0.62	0.59	

Note: the table shows unconditional standard deviations of the separation rate (first group normalized to 1). The upper part shows quartiles of the worker fixed effects distribution. The lower part shows different education groups. The sample consists of West-German full-time workers aged 20-60 and in employment subject to social security contributions. SIAB, 1986-2017, 128 quarterly observations, seasonally adjusted and de-trended using a HP-filter with $\lambda = 1600$.

We analyze whether the more cyclical separations for high-residual wage workers reflects permanent differences at the worker or the firm level. For this, we include AKM two-way fixed effects (Abowd et al., 1999; Card et al., 2013; Bellmann et al., 2020) in the wage equation and re-evaluate the cyclical behavior of the transition rates. From this exercise, we show that the worker fixed effects are the key driver for the observed patterns. Once we control for them (independently whether we do so based on a one-sided fixed effect or based on two-way fixed effects), the separation rate in the upper part of the residual wage distribution is no longer more volatile than in the lower part. We show that recessions are periods when more workers with high fixed effects lose their jobs. Thus, the empirical results point to the importance of ex-ante differences between workers.

We contrast these empirical results with a search and matching model with separate labor market segments representing different permanent worker ex-ante productivity levels. When calibrating the labor market flow model to the empirical flow rates and the relative residual wage dispersion, the ordering of the volatility of the log-separation rates in model simulation and in the data are the same. Workers with the largest ex-ante productivity show the largest log-deviations of their separation rate in response to aggregate productivity shocks. This pattern is closely connected to smaller steady state separation rates for these groups. The positive correlation between aggregate unemployment and prior wages of those who were separated is also matched in the quantitative model.

Data and model combined allow us to tell a coherent structural story about the underlying mechanics. Recessions are periods when relatively more workers with (persistently) higher wages are separated. They crowd the pool of unemployed and thereby push up the average prior wage of unemployed, while aggregate unemployment goes up at the same time. Interestingly, although the German labor market has very different labor market institutions and different labor market flows levels as the United States, the key facts documented by Cairó and Cajner (2018) and Mueller (2017) are very similar. However, in contrast to Mueller (2017), we can use administrative data for Germany. Thereby, we can disentangle the role of firm and worker ex-ante heterogeneity, showing that worker heterogeneity is the key driver for the patterns in the data. Furthermore, based on our administrative panel data, we have detailed labor market flow and wage information. Thereby, we can establish a connection between the low separation rates for high-wage workers and their small residual wage dispersion to the documented facts. While Mueller (2017) shows that both a model with financially constrained firms and a model where high-ability workers have a lower variance of match-specific productivity can replicate important patterns in the data, we show that the latter mechanism is a key driver in Germany.

Our empirical results highlight the importance of the separation rate margin for understanding labor market phenomena. While the relative comovement of the separation rate with unemployment increases with the worker fixed-effect level, we do not find similarly distinct patterns for the job-finding rate. Thus, our paper contributes to a recent macroeconomic literature that emphasizes the importance of the separation rate. Cairó and Cajner (2018) document that differences in employment stability across education groups in the United States are driven by differences in separation rates. For Germany, Jung and Kuhn (2014) document that separation rate fluctuations are an important source for unemployment fluctuations; even more so than in the United States. Hartung et al. (2024) show the importance of the separation rate margin in the context of unemployment insurance reforms.

Furthermore, our paper contributes to a recent and emerging literature on the role of heterogeneities at the worker level for aggregate labor market dynamics. Hall and Schulhofer-Wohl (2018) show the importance of the heterogeneity of matching efficiency across workers for aggregate matching efficiency. Hall and Kudlyak (2019) document different types in the labor market, where some have a much larger likelihood to remain in unemployment. Ahn et al. (2023) use machine learning methods to classify the labor market into three different labor market segments. They point out a strong labor market dualism in the United States, where observable labor market characteristics only explain a small part. While most of the papers are focused on the US labor market, we analyze the German labor market due to the availability of high-quality administrative data. This allows us to document the importance of different worker fixed effects for labor market dynamics. These worker fixed effects measure time-invariant unobserved heterogeneity. We show that they are very important beyond typical observables (such as education or experience).

The rest of the paper proceeds as follows. Section 2 provides a data description. Section 3 documents various empirical facts for Germany based on the SIAB. Section 4 derives a search and matching model with different labor market segments. The simulation results are compared to the data. Furthermore, the quantitative model is used for counterfactual exercises. Section 5 briefly concludes.

2 Data

2.1 Data Sources

The main data source for this study is the weakly anonymized Sample of Integrated Labor Market Biographies (SIAB). The SIAB is a representative 2 percent random sample of the universe of workers subject to German social security contributions. It includes both employment and unemployment spells exact to the day. In addition, the data contains demographic characteristics such as age, gender, nationality, and education, as well job information such as tenure, occupation, and the daily wage, calculated as annual earnings divided by annual days worked at the employer. Using the establishment identifiers, we link the SIAB to the Establishment History Panel (BHP), which provides information on industry, size, workforce composition, federal state, and the median wage of the establishment recorded as of June 30th each year. Finally, using unique worker and firm identifiers, we link the SIAB with AKM worker and firm effects for the period 1985-2017, estimated by Bellmann et al. (2020) on the universe of employment biographies.[2]

2.2 Sample Construction and Variable Definitions

We restrict our observation period to 1985-2017 due to the availability of AKM effects for this period. In addition, we restrict the sample to employment and unemployment spells (benefit recipiency) of West-German full-time workers in working age (20-60) and in employment subject to social security contributions. These restrictions ensure that our sample restrictions are in line with those from the AKM estimation in Bellmann et al. (2020), which in particular focuses on full-time employees as the German administrative

[2]The AKM effects from Bellmann et al. (2020) are estimated on the universe of employment biographies, such that concerns over limited mobility bias in our analysis are minimized. For computational reasons, the AKM effects are provided in five sub-intervals covering the period 1985-2017. We normalize the effects to be comparable across the estimation sub-intervals (see Appendix A).

Table 2: Summary statistics

Variable	AKM worker FE quartile				All
	Q1	Q2	Q3	Q4	
	A. Worker				
Real daily wage (2015 Euros)	65.53 (22.89)	88.95 (20.54)	102.84 (22.23)	118.87 (26.41)	94.05 (30.29)
AKM worker FE (z-score)	-0.84 (0.59)	-0.09 (0.11)	0.26 (0.1)	0.78 (0.32)	0.03 (0.68)
Age	38.60 (11)	37.89 (10.96)	38.85 (10.99)	40.64 (11.14)	38.99 (11.07)
Women (%)	0.64 (0.48)	0.33 (0.47)	0.28 (0.45)	0.29 (0.45)	0.38 (0.49)
Tenure (years)	5.88 (6.05)	7.55 (6.93)	9.21 (7.68)	9.94 (7.99)	8.14 (7.37)
no vocational training (%)	0.26 (0.44)	0.15 (0.36)	0.08 (0.27)	0.05 (0.21)	0.13 (0.34)
vocational training (%)	0.69 (0.46)	0.81 (0.39)	0.87 (0.34)	0.79 (0.41)	0.79 (0.41)
university degree (%)	0.03 (0.16)	0.03 (0.16)	0.04 (0.2)	0.15 (0.36)	0.06 (0.24)
missing education (%)	0.03 (0.17)	0.01 (0.11)	0.01 (0.09)	0.01 (0.09)	0.01 (0.12)
	B. Firm				
Log firm size	1.41 (0.61)	1.56 (0.55)	1.61 (0.53)	1.59 (0.54)	1.54 (0.56)
Log median wage in firm	4.34 (0.37)	4.54 (0.28)	4.63 (0.26)	4.66 (0.28)	4.54 (0.33)
AKM firm FE (z-score)	0.44 (0.68)	0.71 (0.56)	0.79 (0.51)	0.70 (0.57)	0.66 (0.6)
Number of observations (worker x quarter)	6005725	6031619	6018562	5975433	24031339

Note: SIAB 1985-2017. Standard errors in parentheses.

data does not record exact working hours.[3] Concerns over breaks and heterogeneity in the transition rates following reunification are minimized, as we exclude workers with any recorded employment spell in East Germany. Following the focus on West Germany, we use the official unemployment rate for West Germany from the Federal Employment Agency as our business cycle indicator.

In the SIAB, wages are right-censored at the social security contribution ceiling. We base our analysis on uncensored wage observations following Stüber (2017) and Bauer and Lochner (2020). To preserve the completeness of the employment biographies, we exclude all spells from workers who cross the maximum contribution ceiling at least once. Otherwise, there may be the danger that the imputation procedure artificially affects the comovement of unemployment with prior wages, as it is unclear how well imputation methods work in the cyclical dimension.

Based on the spell information, we construct a quarterly panel dataset and compute separation and job-finding rates based on the observed transitions from employment to unemployment (and vice versa), as well as job-to-job transitions based on the observed transitions between employers without intermediate unemployment periods. As we require to observe the wage (or fixed-effect) of the prior period in order to group transitions into high- and low-wage (fixed-effect) transitions, we consider transition rates from 1986 onward in the analysis. More details on the sample definition and on the definition of transition rates can be found in Appendix A.

Table 2 gives an overview of our final estimation sample, which consists of about 24 million worker-quarter observations from around 670 thousand workers. Grouping workers by their quartile in the AKM worker fixed-effect distribution, a number of patterns are visible. Average log daily wages increase with AKM worker FE, as well as age, tenure, and the incidence of German nationality, while the share of women is considerably lower above the median worker fixed-effect. Education increases with worker fixed-effects, as measured by an increasing share of workers with an university degree and a lower share of workers without vocational training. The distribution of firm characteristics also changes with worker fixed-effects. Workers with higher fixed effects tend to work in larger firms with higher wages, as measured by the median wage in the firm and the AKM firm fixed-effect.

[3] We obtain similar results when including part-time employment spells and estimating wage equations with a one-way worker fixed-effect (available on request).

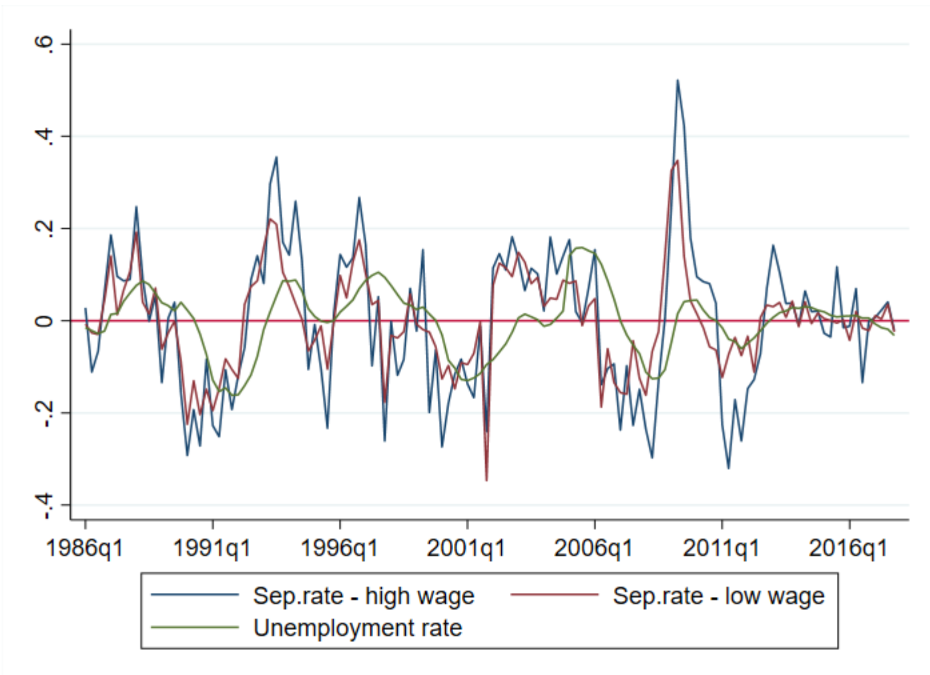
3 Empirical Facts

3.1 The Cyclicality of Transitions by Worker Groups

To understand the cyclical properties of unemployment and transition rates across worker groups and to be comparable to Mueller (2017), we start by grouping workers below and above the median wage in each year and by computing group-specific transition rates into and out of unemployment (separation rates and job-finding rates) as well as their respective co-movement with the aggregate unemployment rate.

Table 3 reports the co-movement of the cyclical component of each transition rate with the aggregate unemployment rate (i.e., a measure of cyclicality or conditional moment). The cyclicality of the separation rate for high-wage workers is about twice as large as for low-wage workers (see columns headed by "Raw median wage"). Figure 1 illustrates this, by showing the log-deviations of the separation rate for workers above and below the median wage. The log-deviations of the separation rate have considerably more amplitude for high-wage workers than for low-wage workers. By contrast, job-finding rates above and below the median wage show similar conditional moments (see Table 3). These findings are in line with Mueller (2017) for the United States, in spite of the quite different labor market institutions prevalent in Germany.

Figure 1: Cyclical Component of Separation Rate by Wage Group, 1986-2017



Note: SIAB, 1986-2017. Series are quarterly observations, seasonally adjusted using X-13ARIMA-SEATS and HP-filtered using a smoothing parameter of 1600 to obtain the cyclical component. Workers are grouped based on the median daily wage for full-time workers in each year.

More cyclical separations for high-wage workers could potentially reflect worker heterogeneity (e.g., workers with higher productivity may have more cyclical separation

Table 3: Cyclicality and Level of Transition Rates by Worker Groups

		Raw median wage		Residual median wage		Residual median wage additionally controlling for firm covariates		Residual median wage additionally controlling for AKM worker FE		Residual median wage additionally controlling for one-way worker FE	
		Below	Above	Below	Above	Below	Above	Below	Above	Below	Above
SR	Cyclicality	0.46***	0.90***	0.46***	0.73***	0.47***	0.64***	0.57***	0.52***	0.52***	0.55***
	Mean	2.14	0.57	1.86	0.84	1.62	1.06	1.40	1.27	1.47	1.21
JFR	Cyclicality	-0.24***	-0.22**	-0.25***	-0.24***	-0.26**	-0.23***	-0.20***	-0.29***	-0.16	0.34***
	Mean	13.6	15.5	13.1	16.1	12.4	16.8	13.2	14.9	12.3	15.9
J2J	Cyclicality	-0.96***	-0.66***	-1.00***	-0.67***	-0.90***	-0.82***	-0.86***	-0.88***	-0.91***	-0.91***
	Mean	3.07	1.36	2.65	1.80	2.33	2.12	2.38	2.07	2.51	1.93

Note: JFR stands for job-finding rate, SR for separation rate, U for unemployment rate, J2J for job-to-job transition rate. Following Mueller (2017), the cyclicality of the series measured as the coefficient β in the regression $ln(x_{i,t}) = \alpha + \beta \times ln(U_t) + \epsilon_{i,t}$, where $x_{i,t}$ is the separation, job finding, or job-to-job of group i at time t and U_t is the West-German unemployment rate. All series are seasonally-adjusted using X-13ARIMA-SEATS, detrended using an HP filter with smoothing parameter of 1600. Newey-West standard errors with lag order of 4 and 128 quarterly observations are used in the regressions. Residual wages are obtained from regression controlling first for observable worker covariates: third-order polynomial in age and tenure, gender, German nationality, education (3 categories), occupation (2-digit) and year dummies. In a second step, we add firm covariates: log establishment size, log median wage in the establishment, AKM firm fixed-effects. In a third step, we add AKM worker fixed effects. SIAB 1986-2017. ***p<0.01, **p<0.05, *p<0.10

rates) or firm heterogeneity (e.g., high-wage workers may work at better paying and more cyclical firms). To understand the relative importance of worker and firm heterogeneity for the cyclicality of separation rates across worker groups, we estimate the cyclicality of transition rates based on residual wages (see Table 3). Importantly, the administrative data allows us to account for a rich set of worker and firm characteristics, which we control for sequentially in order to understand the relative importance of the two margins.

In Table 3, we start by controlling for a rich set of observable worker characteristics, such as a polynomial in age and tenure, as well as dummies for gender, nationality, education, and two-digit occupation (see columns headed by "Residual median wage"). After accounting for observable worker characteristics, separations are still more cyclical for high-wage workers by a factor of 1.6. In accordance with Mueller (2017), this exercise also shows that observable worker characteristics are important for explaining differences in wage dynamics above and below median. Including them reduces the gap between the two groups considerably, but not fully.

We sequentially account for firm heterogeneity, adding variables such as size, median wage in the firm and the AKM firm fixed-effect (see columns headed by "(...) additionally controlling for firm covariates"). Interestingly, we still observe more cyclical separation rates for workers with high residual wages (factor: 1.4), indicating that even after netting out the impact of firm characteristics and comparing observationally similar workers in identical firms, separations remain more cyclical for those workers with high (residual) wages. More generally speaking, although firm characteristics reduce the gap above and below median a bit, they seem to be much less important than worker characteristics (despite including a firm fixed effect).

Finally, we show the importance of unobserved time-invariant worker heterogeneity by additionally controlling for AKM worker fixed-effects (see columns headed by "(...) additionally controlling for AKM worker FE"). Once we control for worker fixed effects on top of other observables, the differences in terms of the comovement of the separation rate with aggregate unemployment (below and above median) basically disappear. A similar result holds when we use one-way worker fixed effects instead of two-way AKM fixed effects (see columns headed by "(...) additionally controlling one-way worker FE").[4] In both cases, controlling for unobserved time-invariant worker heterogeneity removes all remaining differences between groups in terms of their separation rate cyclicality. This points toward the importance of time-invariant worker heterogeneity for the dynamics of the separation rate.

[4]When controlling for a one-way worker fixed-effect, we keep the size and median firm wage controls but remove the AKM firm fixed-effect and include dummies for 2-digit industry and federal state instead. Controlling for a worker fixed-effect does not restrict the sample to workers in the largest connected set as is the case with the AKM worker fixed-effect. However, it may be contaminated by firm-specific unobserved heterogeneity.

Table 4: Cyclicality of Transition Rates by AKM Worker FE Groups

		AKM Worker FE Quartile			
		1	2	3	4
SR	Cyclicality	0.40***	0.73***	0.85***	0.87***
	Mean	2.6	1.5	0.8	0.5
JFR	Cyclicality	-0.60***	-0.14	-0.06	-0.21**
	Mean	10.7	17.9	19.9	15.6
J2J	Cyclicality	-1.04***	-0.78***	-0.80***	-0.70***
	Mean	2.7	2.5	2.0	1.7

Note: The cyclicality of the series measured as the coefficient β in the regression $ln(x_{i,t}) = \alpha + \beta \times ln(U_t) + \epsilon_{i,t}$. All series are seasonally-adjusted using X-13ARIMA-SEATS, detrended using an HP filter with smoothing parameter of 1600. Newey-West standard errors with lag order of 4 and 128 quarterly observations are used in the regressions. SIAB 1986-2017. ***p<0.01, **p<0.05, *p<0.10

To gain further insights about the underlying dynamics, we group workers in terms of their AKM worker fixed effects into four quartiles (see Table 4). This exercise confirms the importance of worker fixed effects for the dynamics of the separation rate. The cyclicality of the separation rate is upward sloping over the worker fixed effects quartiles. Very importantly, this exercise illustrates the importance of different separation rate levels across different quartiles[5]. The separation rates are about five times larger in first quartile than in the fourth quartile. Workers with low wages have higher separation rates and lower log-deviations than those with high wages, but obviously larger absolute deviations. In terms of absolute deviations, the estimated coefficient is more than twice larger for the lowest quartile than for the highest quartiles[6]

Note that the more volatile separations in relative terms for high-wage workers are not in contradiction to the documented cleansing effect of recessions (Mortensen and Pissarides (1994); Caballero and Hammour (1994)), which is based on absolute rather than relative deviations. High-wage workers have a much lower separation rate level than low-wage workers . The separation rate for workers above the median wage is only about a quarter of that for workers below the median wage (see Table 3). These level differences affect the relative volatility, an issue already pointed out by Cairó and Cajner (2018) in the context of separation rates across educational groups (see Appendix B for unconditional moments of different educational groups). Thus, our findings show that,

[5]The pattern for the job-finding rate is a bit messier. This is due to the fact that different groups have a different lead-lag pattern of their job-finding rate with aggregate unemployment. If we look at unconditional moments for log-deviations instead, they are broadly similar across groups. See Appendix C for details.

[6]We estimated the cyclicality in terms of absolute deviations, i.e., $x_{it} = \alpha + \beta * U_t + \epsilon_{i,t}$, where x_{it} are the separation rates in levels instead of logs. Results are available on request.

in relative terms, high-wage workers enter the pool of the unemployed at a higher rate during recessions, while in absolute terms low-wage workers do so (i.e., the cleansing effect of recessions). See also Appendix C for unconditional moments of different worker fixed effects groups.

3.2 The Composition of the Unemployment Pool

More cyclical separations for high-wage workers have a direct implication on the quality of the pool of the unemployed, as it implies that recessions are times when more high-wage workers enter unemployment, thus increasing the average quality of the pool of unemployed. To examine the cyclicality of the composition of the pool of unemployed, we follow Mueller (2017) and calculate the average wage of the previous year for those keeping their jobs ("employed") and those losing their jobs ("unemployed"). For the employed and unemployed in year t, we use the daily wage reported in year $t-1$.[7]

Figure 2 (panel a) shows a strong positive comovement of the wage of those losing their job with unemployment (less so for employed). To rule out that our result on the raw daily wage is driven by differences in wage dispersion over the business cycle, following Mueller (2017), we provide results in terms of the wage rank. For this, we attribute each worker in each year a rank within the unit interval by lining workers from low to high daily wages. Figure 2 (panel b) shows that recessions are periods when workers with higher wage ranks lose their jobs.

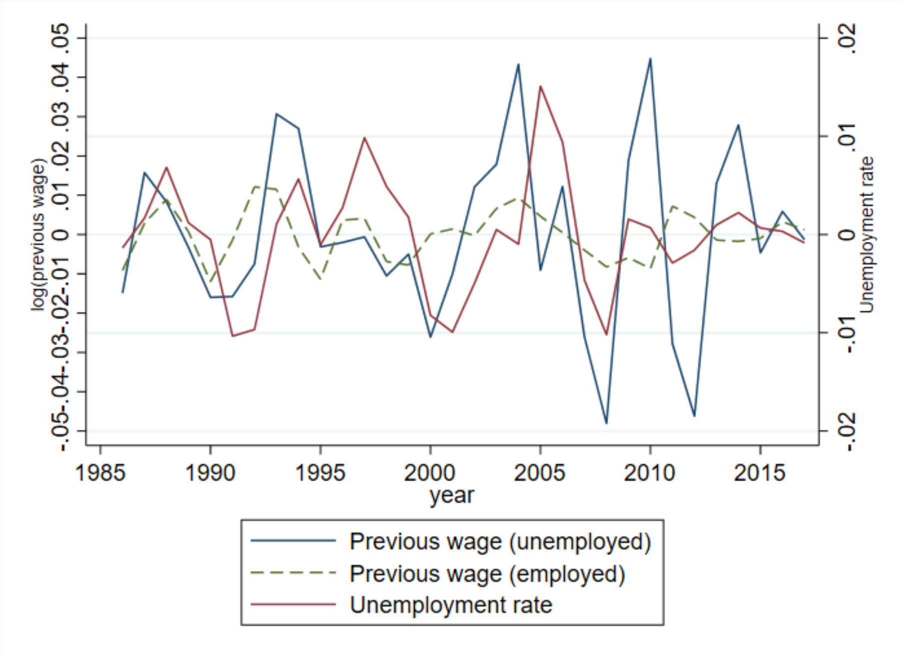
As we have the (prior) estimated worker fixed effects for separated workers, we can compare the comovement of those with aggregate unemployment. Figure 3 shows a strong positive comovement of the fixed effects of those losing their job with unemployment (again, less so for employed). This picture illustrates that recessions are periods when more workers with a large worker fixed effect crowd the pool of unemployment. Actually, when comparing Figure 2 (panel a) and Figure 3, the comovements with unemployment look similarly strong. This illustrates that worker fixed effects are an important driver for the raw wage dynamics.

To illustrate this point further, we estimate the comovement of wages and fixed effects of unemployed workers with aggregate unemployment. Table 5 shows the results. The estimated coefficient shows pronounced comovements between aggregate unemployment and both the raw wage and the fixed effects. In addition, we estimate the co-movement of the previous residual wage (without worker fixed effects) of those losing their job (see Appendix D). Additionally controlling for worker fixed effects yields the co-movement

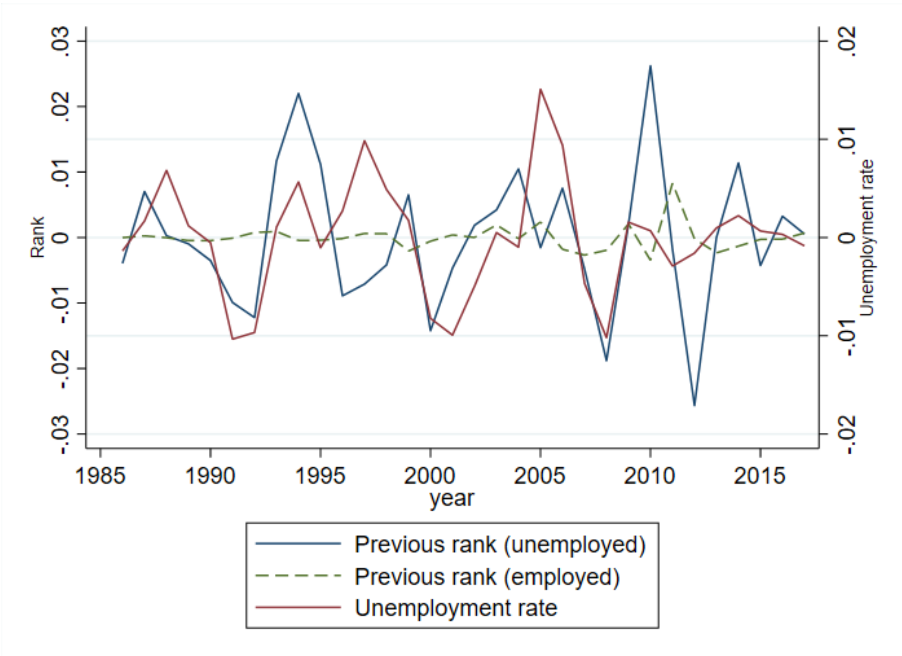
[7] We take the worker observation each June 30th (either in employment or in unemployment), impute the observed workers' daily wages or rank from June 30th of the previous year, and average separately across employed and unemployed workers in each year. We use the corresponding unemployment rate as of June each year to evaluate the cyclicality. For the unemployed, we only use the daily wage from the last observed job in the first year of unemployment, such that we focus on the flow of unemployed, consistent with our model-based calculations.

Figure 2: Previous wage of the (un-)employed over the business cycle, 1986-2017

(a) Raw daily wage

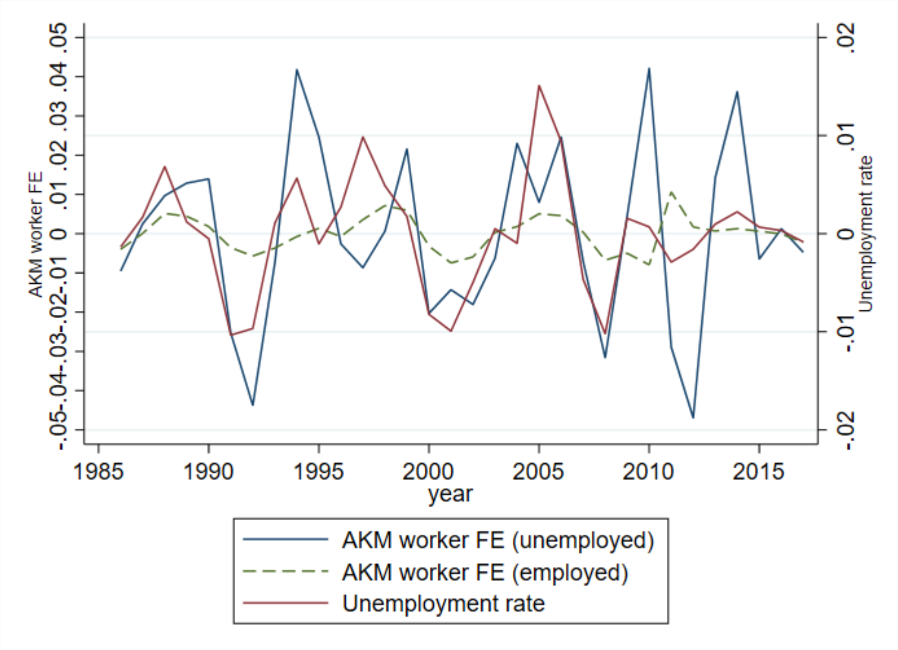


(b) Wage rank



Note: SIAB, 1986-2017. Each series is generated by keeping the worker observation each June 30th (either in employment or in unemployment), imputing the observed workers' daily wages or rank from the previous year, and calculating the average yearly series for the employed and unemployed separately. The unemployment rate is not logged. All series are HP-filtered using a smoothing parameter of 6.25.

Figure 3: Previous worker fixed effects of the (un-)employed over the business cycle, 1986-2017



Note: SIAB, 1986-2017. Each series is generated by keeping the worker observation each June 30th, using the observed AKM worker fixed-effect (z-score) from the previous year, and calculating the average yearly series for the employed and unemployed separately.The unemployment rate is not logged. All series are HP filtered with $\lambda = 6.25$.

Table 5: Cyclicality of previous Wage among the Unemployed

Co-movement with	Unemployed, measure from previous year	
	Raw wage	Wage Rank
Unemployment rate	1.45**	0.71**
Observations	32	32
	AKM worker fixed effect	Residual wage (additionally controlling for AKM worker FE)
Unemployment rate	2.14***	0.26
Observations	32	32

Note: the table shows the coefficient from the regression $y_t = \alpha + \beta u_t + \epsilon_t$, where y_t refers to the average previous log (residual) wage, worker fixed-effect, and rank of the unemployed and u_t to the unemployment rate (not in logs). Newey-West standard errors with lag order of 2 and 32 yearly observations based on June 30th. All series are HP filtered with $\lambda = 6.25$. SIAB 1986-2017. ***p<0.01, **p<0.05, *p<0.10

of the residual wage with unemployment statistically insignificant at conventional levels. The same result holds when accounting for a one-way worker fixed effect (see Appendix D). This exercise shows the importance of worker heterogeneity for the comovement of unemployment with the prior wage of those losing their jobs.

Motivated by our empirical findings, we derive a search and matching model with ex-ante heterogeneity in which workers have permanently different productivity levels and we calibrate it to important targets from the data. Such a framework allows us to better understand the driving forces and to perform counterfactual exercises.

4 Theory

4.1 Model Environment

To analyze the role of ex-ante heterogeneities, we assume that there is a finite number of separate labor market segments denoted with index j. We assume that workers in each of these separate segments have different productivities and they are permanently attached to one of those segments. We assume that matches in each of those segments are driven by separate contact functions and vacancy free entry conditions. In addition, existing worker-firm pairs draw a shock realization from idiosyncratic match-specific cost distributions and may thereby be separated endogenously. When we assume only one labor market segment, our model nests the standard framework by Mortensen and Pissarides (1994).

4.1.1 Matching and Separations

Matches, $m_{t,j}$, in each of the labor market segments j are generated by a Cobb-Douglas constant returns contact function:

$$m_{t,j} = \chi_{t,j} u_{t-1,j}^{\alpha} v_{t,j}^{1-\alpha}, \tag{1}$$

where $\chi_{t,j}$ is the matching efficiency, $u_{t-1,j}$ are unemployed workers and $v_{t,j}$ are vacancies, and α is the elasticity of the matching function with respect to unemployment.

The job-finding rate, $p_{t,j}$, and the worker-finding rate, $q_{t,j}$, are functions of market tightnesses in the respective segments ($\theta_{t,j} = v_{t,j}/u_{t-1,j}$):

$$p_{t,j} = \frac{m_{t,j}}{u_{t-1,j}} = \chi_{t,j} \theta_{t,j}^{1-\alpha}, \tag{2}$$

$$q_{t,j} = \frac{m_{t,j}}{v_{t,j}} = \chi_t \theta_{t,j}^{-\alpha}. \tag{3}$$

The value of a vacancy, $V_{t,j}$, is equal to linear vacancy posting costs, $-\kappa_j$, plus the expected return from posting a vacancy:

$$
\begin{aligned}
V_{t,j} = & -\kappa_j + q_{t,j} E_t \delta \left[(1-\sigma_j)(1-\phi_{t,j}) J^I_{t,j} \right. \\
& \left. + (1-(1-\sigma_j)(1-\phi_{t,j})) V_{t+1,j} \right] + (1-q_{t,j}) E_t V_{t+1,j},
\end{aligned} \tag{4}
$$

where σ_j is the exogenous separation rate (which we define as an exogenous transition to a different firm) and $\phi_{j,t}$ is the endogenous separation rate to be defined below. J^I is the expected present value of an incumbent worker conditional on not being separated (which will be defined below).

In equilibrium, due to the free entry of vacancies, the value of vacancies is driven to zero. Thus, vacancies are posted up to the point where hiring costs (κ/q_t) are equal to the expected discounted profits from hiring:

$$
\frac{\kappa_j}{q_{t,j}} = \delta E_t \left[(1-\sigma_j)(1-\phi_{t,j}) J^I_{t,j} \right]. \tag{5}
$$

Existing worker-firm pairs i draw a realization each period, ε_{ijt}, from an idiosyncratic match-specific shock distribution. The shock is drawn from a stable density function $g(\varepsilon_{ijt})$. The shock is iid across workers and time. The value of an existing match with shock realization ε_{ijt} is

$$
J^I(\varepsilon_{ijt}) = a_{t,j} - w(\varepsilon_{ijt}) - \varepsilon_{ijt} + E_t (1-\sigma_j)(1-\phi_{t+1,j}) \delta J^I_{t+1,j}, \tag{6}
$$

where $a_{j,t}$ is the productivity in the respective labor market segment (subject to aggregate shocks), w is the wage. New and existing matches are hit by idiosyncratic cost-shocks and may therefore split up.

Based on this shock realization, firms decide which workers they want to keep and which workers they want to fire. Firms are indifferent between separating and not separating at the cutoff point $\tilde{\varepsilon}_{ijt}$, where $J^I(\tilde{\varepsilon}_{ijt}) = 0$:

$$
\tilde{\varepsilon}_{ijt} = a_{t,j} - w(\tilde{\varepsilon}_{ijt}) + E_t (1-\sigma_{j,t})(1-\phi_{t+1}) \delta J^I_{t+1,j}. \tag{7}
$$

This allows us to define the endogenous separation rate ϕ_t, which is defined as:

$$
\phi_{t,j} = 1 - \int_{-\infty}^{\tilde{\varepsilon}_{ijt}} g(\varepsilon_{ijt}) \, d\varepsilon_{ijt}. \tag{8}
$$

Finally, firms calculate the expected ex-ante present value for a match (relying on the expected realization of the match-specific shock):

$$
J^I_{t,j} = a_t - \bar{w}_{t,j} - H(\tilde{\varepsilon}_{ijt}) + E_t (1-\sigma_j)(1-\phi_{t+1,j}) \delta J^I_{t+1,j}, \tag{9}
$$

where we define the average expected realization of the idiosyncratic shock and the expected wage as:

$$H\left(\tilde{\varepsilon}_{ijt}\right) = \frac{\int_{-\infty}^{\tilde{\varepsilon}_{ijt}} \varepsilon_{ijt} g\left(\varepsilon_{ijt}\right) d\varepsilon_{ijt}}{1-\phi_{t,j}}, \tag{10}$$

$$\bar{w}_{t,j} = \frac{\int_{-\infty}^{\tilde{\varepsilon}_{ijt}} w\left(\varepsilon_{it}\right) g\left(\varepsilon_{it}\right) d\varepsilon_{ijt}}{1-\phi_{t,j}}. \tag{11}$$

Workers who are not separated endogenously in the current period and those who are newly matched (and not immediately separated) are employed. Thus, the employment rate, n, is defined as:

$$n_{t,j} = \left(1-\phi_{t,j}\right)\left(n_{t-1,j} + p_{t,j} u_{t-1,j}\right), \tag{12}$$

with unemployment rate, u:

$$u_{t,j} = 1 - n_{t,j}. \tag{13}$$

We assume that workers who leave the firms exogenously transition to another firm in the same labor market segment. Therefore, exogenous separations do not show up in the aggregate employment dynamics equation.

4.1.2 Wage Formation

Under standard Nash bargaining, workers and firms split the joint surplus. The match is separated whenever there is no surplus or they do no not agree. Thus, a firm's value of production with idiosyncratic shocks realization ε_{ijt} is

$$J^I\left(\varepsilon_{ijt}\right) = a_{t,j} - w\left(\varepsilon_{ijt}\right) - \varepsilon_{ijt} + E_t\left(1-\sigma_j\right)\left(1-\phi_{t+1,j}\right)\delta J^I_{t+1,j}, \tag{14}$$

and the fallback-option is that the match is destroyed:

$$\bar{J}^I\left(\varepsilon_{ijt}\right) = 0. \tag{15}$$

The worker's value is

$$\begin{aligned} W\left(\varepsilon_{ijt}\right) =& w\left(\varepsilon_{ijt}\right) + \delta E_t\left(1-\sigma_j\right)\left(1-\phi_{t+1,j}\right) W_{t+1,j} \\ &+ \delta E_t\left(1-\left(1-\sigma_j\right)\left(1-\phi_{t+1,j}\right)\right) U_{t+1,j} \end{aligned} \tag{16}$$

The fallback option is unemployment:

$$\begin{aligned} U_{t,j} =& b + \delta E_t p_{t+1,j}\left(1-\sigma_j\right)\left(1-\phi_{t+1,j}\right) W_{t+1,j} \\ &+ \delta E_t\left(1-p_{t+1,j}\left(1-\sigma_j\right)\left(1-\phi_{t+1,j}\right)\right) U_{t+1,j}. \end{aligned} \tag{17}$$

Thus, the Nash product is:

$$\Lambda\left(\varepsilon_{ijt}\right)=\left[J\left(\varepsilon_{ijt}\right)\right]^{1-\gamma}\left[W\left(\varepsilon_{ijt}\right)-U_{t,j}\right]^{\gamma}, \tag{18}$$

where γ is a worker's bargaining power.

Maximizing the Nash product with respect to wages yields (see Appendix G for details):

$$w\left(\varepsilon_{ijt}\right)=\gamma\left(a_{t,j}-\varepsilon_{ijt}+\kappa E_t\theta_{t+1,j}\right)+\left(1-\gamma\right)b, \tag{19}$$

where γ is the bargaining power of workers.

4.1.3 Equilibrium

The labor market equilibrium can be described by the job-creation condition (in conjunction with the matching function), the endogenous cutoff point for separations, which is a function of the future value of incumbent workers, the separation rate, wage dynamics, employment dynamics and unemployment definition in the respective sectors. Finally, we have to aggregate the unemployment rates in the respective subsectors to obtain the economy-wide unemployment rate.

$$\frac{\kappa}{q_{t,j}}=\delta E_t\left[\left(1-\sigma_j\right)\left(1-\phi_{t,j}\right)J^I_{t,j}\right], \tag{20}$$

$$p_{t,j}=\chi_{t,j}\theta_{t,j}^{1-\alpha}, \tag{21}$$

$$q_{t,j}=\chi_t\theta_{t,j}^{-\alpha}, \tag{22}$$

$$\tilde{\varepsilon}_{ijt}=a_{t,j}-w\left(\tilde{\varepsilon}_{ijt}\right)+E_t\left(1-\sigma_j\right)\left(1-\phi_{t+1,j}\right)\delta J^I_{t+1,j}, \tag{23}$$

$$J^I_{t,j}=a_t-\bar{w}_{t,j}-H\left(\tilde{\varepsilon}_{ijt}\right)+E_t\left(1-\sigma_j\right)\left(1-\phi_{t+1,j}\right)\delta J^I_{t+1,j}, \tag{24}$$

with $H\left(\tilde{\varepsilon}_{ijt}\right)=\frac{\int_{-\infty}^{\tilde{\varepsilon}_{ijt}}\varepsilon_{ijt}g(\varepsilon_{ijt})d\varepsilon_{ijt}}{1-\phi_{t,j}}$, and $\bar{w}_{t,j}=\frac{\int_{-\infty}^{\tilde{\varepsilon}_{ijt}}w(\varepsilon_{it})g(\varepsilon_{it})d\varepsilon_{ijt}}{1-\phi_{t,j}}$.

$$\phi_{t,j}=1-\int_{-\infty}^{\tilde{\varepsilon}_{ijt}}g\left(\varepsilon_{ijt}\right)d\varepsilon_{ijt}, \tag{25}$$

$$w\left(\varepsilon_{ijt}\right)=\gamma\left(a_{t,j}-\varepsilon_{ijt}+\kappa\theta_{t+1,j}\right)+\left(1-\gamma\right)b, \tag{26}$$

$$n_{t,j}=\left(1-\phi_{t,j}\right)\left(n_{t-1,j}+p_{t,j}u_{t-1,j}\right), \tag{27}$$

$$u_{t,j} = 1 - n_{t,j}. \tag{28}$$

As we assume equally sized sectors j (in terms of the labor force size), the aggregate unemployment rate is the sum of the sector-specific unemployment rates divided by the number of sectors (denoted by S in the sum operator below):

$$u_t = \sum_{j=1}^{S} u_{t,j}/S. \tag{29}$$

4.2 Calibration Strategy

In our parametrization, we start by setting several standard parameter values. The discount factor is set to 0.99, the matching elasticity, α, and the bargaining power, γ, are both set to 0.5 (for all segments). Vacancy posting costs, κ, are normalized to 10 percent of productivity in the respective labor market segment.

We calibrate our model economy to four different segments ($S = 4$) with different ex-ante productivities. These segments correspond to the four different quartiles of worker fixed effects. The exogenous separation rates, σ_j, are set to the value of the job-to-job transitions in Table 4, namely: 2.72, 2.46, 1.98, and 1.73 percent.

We set the remaining parameters to hit certain calibration targets (see Table 6): First, we set the productivity, a_j, in each labor market segment to match the average empirical wage differences (relative to the lowest group). The productivity of the least productive labor market segment is normalized to 1 (see Table 7 for the parameter values). This results in a 87 percent higher productivity in the upper group relative to the lower group. Second, we target the average job-finding rates (proxied as unemployment-to-employment transition rate in the data). We use the matching efficiency in the respective sector to hit these targets.

Table 6: Calibration Targets

Quartile	1	2	3	4
Average wage (rel.)	1.00	1.36	1.57	1.82
Job-Finding Rate	0.107	0.179	0.199	0.156
Separation Rate	0.026	0.015	0.008	0.005
Wage dispersion (rel.)	1.00	0.61	0.55	0.62

Finally, we target the residual wage dispersion conditional on not being separated relative to the baseline group (see Appendix E for empirical details). To target both the separation rates and the dispersion, we set the benefits relative to productivity (i.e., replacement rates) and the dispersion of the idiosyncratic shocks jointly in the respective

Table 7: Parameter Values

Quartile	1	2	3	4
Productivity	1.00	1.39	1.61	1.87
Matching efficiency	0.07	0.15	0.15	0.13
Replacement rate	0.65	0.75	0.77	0.80
Dispersion parameter	1.16	0.70	0.61	0.68

segments.[8] For the idiosyncratic shocks, we assume a logistic distribution with scaling parameter s_j.[9] The dispersion of the idiosyncratic match-specific shock is a key determinant for the volatility of separations. Less dispersed idiosyncratic shocks increase the amplification of the separation rate with respect to aggregate shocks, as there is more mass around the cutoff point. Therefore, the rich German administrative data allows us to discipline this margin.[10]

We assume that the model economy is hit by symmetric aggregate productivity shock, i.e., these shocks trigger the same relative productivity fluctuations in each sector. Further, we assume that the autocorrelation of the aggregate productivity shock is 0.95. In analogy with the empirical data, we simulate the model for 136 quarters. We use a first-order Taylor approximation for all our simulations. We start by showing quarterly statistics. In addition, we aggregate the data to the annual level to be comparable with the empirical exercise. See Appendix H for details on the aggregation.

4.3 Quantitative Results

4.3.1 Underlying Mechanism

Figure 4 shows the reaction of our baseline calibration in response to a one percent aggregate productivity shock, which corresponds to a one percent productivity shock in each of the labor market segments. The log-deviations for the separation rate are very different across groups. The relative increase for the separation rate is roughly three times as large in the labor market segment with the largest ex-ante productivity as in the segment with the lowest ex-ante productivity (see lower left panel).

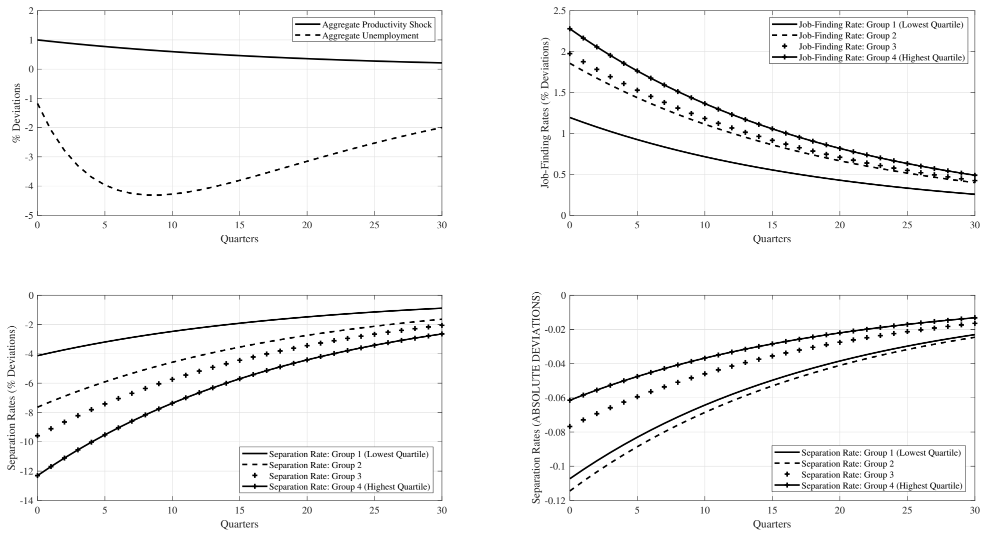
However, the lower right panel of Figure 4 shows a very different picture for the

[8] We normalize the replacement rate for the lowest group to 0.65 of productivity. Larger replacement rates for higher productivity groups in Table 7 may seem unrealistic. We show in Appendix J that our results do not hinge on this assumption.

[9] We normalize the mean of this idiosyncratic distribution to zero. The logistic distribution is close to the normal distribution, but allows for explicit analytical expressions. An observationally equivalent strategy would be to set the same replacement rate for all four groups and to choose different means of the idiosyncratic distribution.

[10] The strategy to target the residual wage dispersion conditional on not being separated is inspired by Chugh and Merkl (2016) who target the conditional training cost dispersion based on microeconomic evidence.

Figure 4: Impulse Response Functions to a One Percent Positive Productivity Shock.



absolute deviations of the separation rates. The absolute deviations for group 1 (with the lowest ex-ante productivity) are roughly twice as large as for group 4 (i.e., exactly the opposite pattern as for the log-deviations). As we calibrated the steady state separation rates to the counterpart from the data (see Table 6: 2.6 percent for the lowest quartile and 0.5 percent for the highest quartile), the separation rate in group 1 is roughly five times larger than in group 4. In line with the patterns in the data, the level differences in the separations rates explain the large gap between absolute and relative deviations.

Technically, two things affect the log-deviations of the separation rate. First, the dispersion of idiosyncratic shocks is an important determinant for the amplification of the separation rate in the respective sector. A less dispersed distribution leads to more volatility, as this creates more mass around a given point of the distribution (ceteris paribus). Thus, it is key that our microeconometric estimations provide a lot lower dispersion for the groups with larger ex-ante productivity. Second, groups with larger ex-ante productivity have a lower separation rate. Thus, for a distribution with curvature (unlike the uniform distribution), the cutoff point shifts into a thinner part of the distribution (ceteris paribus). Thus, it is a numerical question which of the two effects dominates. In our calibration, which is disciplined by the residual wage dispersion, the first effect dominates.

Figure 4 also shows that the log-deviations of the job-finding rate are most volatile for the high-productivity groups. This pattern will be discussed relative to the patterns in the data in the next section.

4.3.2 Labor Market Dynamics

In analogy with the empirical exercises, we compare the comovement of cyclical aggregate unemployment with segment-specific separation rates and job-finding rates. Table 8 shows the results (all Hodrick-Prescott filtered with a smoothing parameter of 1600). We obtain the same upward-sloping pattern for the comovement between the segment-specific separation rate and unemployment as in the data, i.e., groups with larger ex-ante productivity show larger fluctuations.[11]

It is important to emphasize that we did not target the more volatile relative separation rates for high-wage groups relative to low-wage groups. This is an outcome of our calibration strategy where we target the group-specific separation rates and the relative residual wage dispersion. Therefore, we consider the upward-sloping nature of the estimated comovement of group-specific separation rates with aggregate unemployment as a confirmation for the validity of our calibration strategy.

Table 8: Cyclicality of Separations and Job-Finding Rate in Data and Calibration

Wage Quartiles	1	2	3	4
Baseline: Cyclicality of Separations (Simulation)	0.75	1.42	1.84	2.32
Baseline: Cyclicality of Job-Finding Rate (Simulation)	-0.21	-0.33	-0.36	-0.41
Cyclicality of Separations (Data)	0.40	0.73	0.85	0.87
Cyclicality of Job-Finding Rate (Data)	-0.47	-0.14	-0.06	-0.21

Note: The table shows the estimated comovement of the group-specific separation and job-finding rate with aggregate unemployment. In analogy with the empirical data, simulated data is HP-filtered with smoothing parameter 1600.

The job-finding rate shows an upward-sloping pattern in terms of its comovement with aggregate unemployment, which is due to the higher replacement rates (and thereby smaller surpluses) for the groups with larger ex-ante productivity. This seems to stand in contraction to the results from the data. However, the unconditional moments of the job-finding rate show a different pattern as the conditional comovement with unemployment (see Appendix C). This is due to different lead-lad patterns of the job-finding rate in different worker fixed effect groups. In Appendix J, we show that our quantitative results are very similar in an extension with different ex-ante hiring costs across groups that generate almost the same volatilities of the job-finding rate across ex-ante productivity groups.

[11] The average comovement between separation rate and unemployment is somewhat larger in our baseline calibration than in the data. This can be partly remedied by reducing the surplus of a match (e.g., by ex-ante hiring costs). However, we leave this moment untargeted.

4.3.3 Wage Dynamics with Heterogeneity

Finally, we analyze the comovement of unemployment with the prior wage and with the fixed effects (approximated as the steady state wage within each productivity group) of those workers who lost their job. We aggregate our simulated data to the annual level in order to make it comparable with the IAB administrative data that is available at this frequency (see Appendix H for details). We do so in the same way as in the data: Wages are defined as average over the year and (un)employment is defined as the value at the end of the year. The model with ex-ante heterogeneity generates a positive comovement between unemployment and the prior wage of those who lost their job (see Table 9).

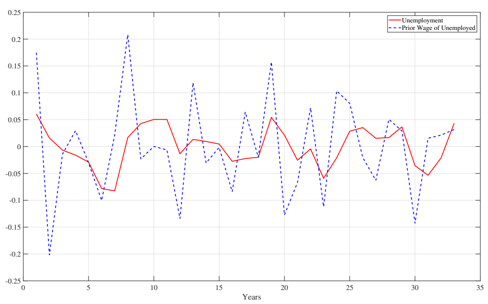
Table 9: Comovement of Prior Wages with Unemployment

	Estimated coefficient
Empirical Comovement (Data: Raw Wage)	1.45
Heterogeneous Model	0.87

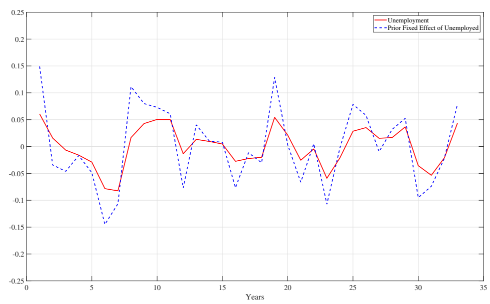
Note: The table shows the estimated comovement of prior wage of those who lost their job with aggregate unemployment (not in logs). In analogy with the empirical data, aggregated annual simulated data is HP-filtered with smoothing parameters 6.25.

The intuition is straightforward: The targeted empirical cross-sectional wage dispersion makes the idiosyncratic shock dispersion smaller for groups with the largest ex-ante productivity. This increases the response of their separation rate to aggregate shocks. Therefore, in case of a negative aggregate productivity shock, the group with the highest ex-ante productivity gets a larger weight in the unemployment pool due to larger log-deviations of the separation rate. As these workers earn (on average) substantially more than those in the lowest group, this composition effect pushes up the average prior wage of those workers who are separated in times of high unemployment.

Figure 5: Comovement of Unemployment and Prior Wage/Fixed Effects of Unemployed



5.1: Prior Wage of Unemployed



5.2: Prior Fixed Effects of Unemployed

Note: All time series are aggregated to the annual level and HP-filtered with smoothing parameter 6.25. The pictures show deviations from the HP-trend. Fixed effects are defined as the steady state wage within each group.

This point is further illustrated by Figure 5, which shows the simulated data that was aggregated to the annual level. As in the data, the left panel shows a positive comovement between the prior wage of those who lose their job and unemployment. The right panel shows the average prior fixed effects of those who lose their jobs[12] and unemployment. As in the data (see Figure 2 and Figure 3), the comovement between the average fixed effect and unemployment is more aligned (estimated coefficient in the simulated data: 1.76) than the comovement between prior wages and unemployment. Thus, in the model, recessions are periods when more workers with larger ex-ante productivity and thereby higher average wages and higher worker fixed effects enter the pool of unemployment.

In addition to having a larger comovement with unemployment, high-wage workers also have less cyclical wages (see Appendix F for details). In a prior version of this paper, we imposed wage rigidity for incumbent workers in an allocationally irrelevant manner in our model. This increases the comovement of unemployment with the prior wage from 0.87 to 1.23 and thereby reduces the quantitative gap to the data. However, as our model can replicate the positive comovement between unemployment and the prior wage of those losing their job without wage rigidity, we do not present these results. They are available on request.

4.3.4 Counterfactual Exercises

In order to understand the drivers for the positive comovement between the prior wage of workers who are separated and unemployment, we change two of the calibration targets. First, instead of targeting the residual wage dispersion from the data, we set the same replacement rate for all four groups. In this case, the dispersion parameters of the idiosyncratic shock are used to target the separation rates. Second, instead of targeting the actual group-specific flow rates from the data (with much larger separation rates in group 1 than in the the rest), we impose the flow rates of group 1 to all other groups (including the same exogenous separation rates). Finally, we give up both targets at the same time. See Appendix I for the parameters values in all three exercises.

Table 10 shows that when giving up both targets (lower right panel), the estimated comovement between unemployment and the prior wage of those who lose their job is negative (-0.64). This exercise basically removes heterogeneity. Although ex-ante productivities (and thereby wages) in all four groups are different, the flow rates are the same in all groups, and firms' surpluses relative to productivity are the same in all groups. In this case, the elasticities of the separation and job-finding rates with respect to unemployment are the same in all four groups due the same relative surplus. As pointed out by Mueller (2017), in models with homogeneous labor markets, recessions are periods when unemployment goes up and when the wage falls due to the negative aggregate shock.

[12] We define the fixed effect as the steady state level of the average prior wage within each heterogeneity group.

Thereby, in contrast to the data, these models generate a negative correlation between (prior) wages and unemployment.

Table 10: Estimated Comovement of Prior Wages with Unemployment: Four Scenarios

Combination of ...	Targ. Wage Dispers.	Untargeted Wage Dispers.
Targeted Flow Rates	0.87	-0.32
Untargeted Actual Flow Rates	0.31	-0.64

Note: The table shows the estimated comovement of prior wage of those who lost their job with aggregate unemployment. In analogy with the empirical data, aggregated annual simulated data is HP-filtered with smoothing parameter 6.25.

It is also visible in Table 10 that the combination of group-specific separation rates and the idiosyncratic wage dispersion is important for replicating the strong positive comovement from the data (see upper left panel). First, a low dispersion of idiosyncratic shocks generates a lass density mass around the separation cutoff point. Second, in combination with lower separation rates for workers with larger ex-ante productivity, this leads to large log-deviations from small levels of the separation rate.

5 Conclusion

Our paper shows that ex-ante worker heterogeneities are key for understanding the dynamics of the separation rate and the shift of the unemployment pool toward workers with prior higher wages in recessions. From an empirical perspective, the more volatile separation rate above the median residual wage disappears once we control for worker fixed effects. The same is true for the positive comovement of aggregate unemployment and the prior wage of unemployed. We show that recessions are periods when relatively more workers with larger worker fixed effects enter the pool of unemployment.

Due to the importance of worker fixed effects in our empirical analysis, we use a search and matching model with permanent worker ex-ante heterogeneity in productivity. In order to match model and data, we require two ingredients: lower separation rates and lower residual wage dispersion for high-wage workers than for low-wage workers. These two ingredients are supported by administrative data for Germany.

Finally, we also show that large relative fluctuations of the separation rate for high-wage workers do not stand in contraction to conventional wisdom that low-educated workers are hit harder by recessions. The separation rate and the unemployment rate for workers without vocational degrees in Germany fluctuate substantially more than for other educational groups in the economy (in terms of absolute deviations). However, this changes when looking at relative deviations. And the latter matters for the composition of the unemployment pool.

Overall, our paper provides a better understanding on the role of labor market heterogeneity for labor market flow and wage dynamics. While we did not analyze any economic policy measures, we believe that our results are relevant for a variety of labor market applications. Many labor market reforms are explicitly or implicitly targeted at special groups, such as hiring support for disadvantaged groups or unemployment benefit reforms that particularly affect certain groups. In addition, certain policy measures such as short-time work are typically used more by large firms with high pay. We showed in our paper that high-wage workers show the largest relative increase of their separation rate in recessions. We expect that such policy measures have different quantitative results when looking at them through the lens of a model with ex-ante heterogeneity. Thereby, cost-benefit analyses can be expected to show different results than under homogeneity. We leave these interesting questions for future research.

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A Data Details

A.1 Sample Selection

We restrict our observation period to 1985-2017 as the AKM effects are only estimated for this period.[13] In addition, we restrict the sample to employment and unemployment spells of West-German full-time workers in working age (20-60) and in employment subject to social security contributions. These restrictions ensure that daily wage rates are comparable and do not capture variation in hours worked (which are not well-measured in the data), that our sample restrictions are in line with those from the AKM estimation in Bellmann et al. (2020) and that concerns over breaks and heterogeneity in the transition rates following reunification are minimized, as we exclude workers with any recorded employment spell in East Germany. Unemployment periods are defined as episodes on benefit recipience or assistance payments as recorded in the Benefit Recipient History (LeH) and the Unemployment Benefit II Recipient History (LHG).[14]

Daily wages are deflated using the yearly CPI from the Federal Statistical Office with base year 2015. In the SIAB, wages are right-censored at the social security contribution ceiling and typically imputed following Dustmann et al. (2009) and Gartner et al. (2005). As we are also interested in within-individual wage variation, we base our analysis on uncensored wage observations following Stüber (2017) and Bauer and Lochner (2020).[15] Otherwise, there may be the danger that the imputation procedure artificially affects the residual wage dispersion among high-wage groups.

We follow Jung and Kuhn (2014) and based on the spell information construct a quarterly panel dataset by keeping the main spell at each of the end-of-quarter cutoff dates (March 31, June 30, September 30 and December 31). If several spells overlap, then a hierarchical ordering of spells is used, in which employment trumps unemployment and, for overlapping employment spells, the employment spell that yields the highest earnings is labeled as primary.

Bellmann et al. (2020) estimate AKM worker and firm fixed-effects for full-time workers aged 20-60 in five sub-intervals covering the period 1985-2017 following Card et al. (2013). Since the AKM models are estimated separately for each of the different sub-intervals and are identified up to a linear constant, the person and firm effects have different reference categories and are thus not directly comparable across the estimation sub-intervals. For this reason, we standardize (z-score) the AKM worker/firm FE to have mean 0 and standard deviation 1 in each of the different sub-periods, then calculate the

[13] In addition, bonus payments are included in the data from 1985 onward, such that wage series would suffer from a structural break in the 1984-1985 period otherwise.

[14] As information on registered unemployment is available from 2000 onward only, the benefit-based approach is chosen to obtain a long and consistent definition of unemployment.

[15] To preserve the completeness of the employment biographies, we exclude all spells from workers who cross the maximum contribution ceiling at least once.

average z-score for each person and firm across the time intervals and re-standardize the resulting average z-scores. This allows us to obtain a consistent ranking of worker and firm unobserved heterogeneity, similar to Bender et al. (2018). Finally, we group workers based into quartiles of AKM worker fixed-effects based on the obtained worker distribution. Alternatively, one-way worker fixed effects from a Mincer-regression deliver similar findings (see Table 3). For one-way worker fixed effects, no standardization is necessary. However, there is the caveat that the worker fixed-effect may be contaminated by firm heterogeneity in particular for those workers that do not change jobs.

A.2 Definition of Labor Market States and Transitions

A transition from one state to another at quarter t is recorded whenever an individual appears in one state in quarter t and was in a different state in quarter t-1, where the state space is given by full-time employment and benefit-based unemployment {E,U}[16]. In the baseline, we consider separations/job-findings from/into full-time employment spells as we require wage information to abstract from variation in working time for grouping transitions from/into high- and low-wage jobs and to be consistent with the AKM sample restriction [17].

Separation (job-finding) rates are defined as the number of EU (UE) transitions at quarter t divided by the stock of employed (unemployed) at quarter t-1. Similarly, job-to-job transitions are defined by the number of establishment switchers between quarter t-1 and t, divided by the employment stock in quarter t-1. As we require to observe the wage (or fixed-effect) of the prior period in order to group transitions into high- and low-wage (fixed-effect) transitions, we consider transition rates from 1986 onward.

[16]In principle, it is possible to define a third-state approximating out-of-labor force whenever an individual exits the data. We refrain from this as workers may leave the data if they temporarily drop out of the labor force, move abroad, become self-employed or employed in the public sector. Thus, this third state is highly ambiguous.

[17]As a robustness check, we replicate the main analysis based on daily earnings for full- and part-time workers with very similar results and available upon request.

B Unconditional Moments across Educational Groups

Table 11 shows the levels, absolute and relative deviations from the HP-filter of transitions rates for different education groups. As in the United States (see Cairó and Cajner (2018)), the absolute deviations of the separation rate and unemployment are much larger for low-skilled workers (no vocational training) than for higher-skilled workers (vocational training and university degree). By contrast, due to larger unemployment rates and separation rates, the log-deviations for low-skilled and higher-skilled workers are very similar.

Table 11: Relative, Absolute Deviations, and Means by Education

Log deviations	No voc. training	Vocational training	University degree
Separation rate	0.116	0.115	0.120
Job-finding rate	0.095	0.064	0.157
Unemployment rate	0.092	0.101	0.103
Absolute deviations	**No voc. training**	**Vocational training**	**University degree**
Separation rate	0.211	0.130	0.125
Job-finding rate	0.956	0.943	1.844
Unemployment rate	0.726	0.428	0.402
Levels (means)	**No voc. training**	**Vocational training**	**University degree**
Separation rate	1.75	1.08	0.97
Job-finding rate	9.92	15.1	13.6
Unemployment rate	8.63	4.12	3.64

Note: Sample refers to West-German full-time workers aged 20-60 and in employment subject to social security contributions. SIAB, 1986-2017, 128 quarterly observations, seasonally adjusted and de-trended using an HP-filter with $\lambda = 1600$.

C Unconditional Moments across Worker Fixed Effect Quartiles

Table 12 shows the levels, absolute and relative deviations from the HP-filter of transitions rates for different worker fixed effect groups. While the log-deviations are larger for higher worker fixed effects than for the lowest group, the opposite is the case in terms of absolute deviations.

Table 12: Relative, Absolute Deviations, and Means by AKM Worker FE

	AKM Worker FE Quartile			
Log deviations	1	2	3	4
Separation rate	0.101	0.136	0.127	0.124
Job-finding rate	0.082	0.083	0.079	0.082
Unemployment rate	0.094	0.113	0.111	0.102
Absolute deviations	1	2	3	4
Separation rate	0.278	0.209	0.104	0.067
Job-finding rate	0.857	1.477	1.602	1.256
Unemployment rate	1.023	0.596	0.301	0.204
Means	1	2	3	4
Separation rate	2.6	1.5	0.8	0.5
Job-finding rate	10.7	17.9	19.9	15.6
Unemployment rate	11.5	5.09	2.58	1.94

Note: Sample refers to West-German full-time workers aged 20-60 and in employment subject to social security contributions. SIAB, 1986-2017, 128 quarterly observations, seasonally adjusted and de-trended using an HP-filter with $\lambda = 1600$.

D Co-movement of Previous Residual Wage with Unemployment Rate

As in Table 3, we calculate the co-movement of the previous residual wage among those losing their job and the contemporaneous unemployment rate each year progressively adding firm covariates and fixed-effects. Consistent with Table 3, controlling for worker observables and adding firm covariates does not eliminate the comovement between the previous residual wage of the unemployed and aggregate unemployment. However, additionally controlling for one- or two-way (AKM) worker fixed-effects yields a statistically non-significant co-movement between the previous residual wage of those losing their job and aggregate unemployment.

Table 13: Cyclicality of previous residual wage among the Unemployed

Co-movement with	Unemployed, measure from previous year	
	Residual wage (worker observables)	Residual wage (additionally controlling for firm covariates)
Unemployment rate	0.98**	0.52**
Observations	32	32
	Residual wage (additionally controlling for AKM worker FE)	Residual wage (additionally controlling for one-way worker FE)
Unemployment rate	0.26	0.25
Observations	32	32

Note: SIAB, 1986-2017. Each series is generated by keeping the worker observation each June 30th (either in employment or in unemployment), imputing the observed workers' daily log wages or rank from the previous year, and calculating the average yearly series for the employed and unemployed separately. All series are HP-filtered using a smoothing parameter of 6.25.***p<0.01, **p<0.05, *p<0.10

E Residual Wage Dispersion across Worker Fixed Effect Quartiles

To obtain the residual wage dispersion for the AKM worker FE quartiles, we estimate the following wage equation on the sample of full-time West-German workers aged 20-60 from 1985-2017:

$$ln(w_{i,t}) = \alpha + \beta X_{i,t} + \gamma_i + \delta_j + \epsilon_{i,t} \tag{30}$$

where $X_{i,t}$ is a set of observable worker and firm characteristics. It consists of a third-order polynomial in age and tenure, log firm size, log median wage in the firm and dummies for occupations (2-digit), education (3 categories), German nationality and calendar year. γ_i and δ_j are AKM worker and firm fixed-effects respectively, which we do not estimate directly due to the small sample size of the SIAB but retrieve from Bellmann et al. (2020), who estimated them based on the universe of employment biographies. From this estimation equation, we obtain the residual term $\epsilon_{i,t}$, which captures idiosyncratic variation in wages after controlling for worker fixed-effects, firm fixed-effects and observable characteristics. We take the exponent of the estimate residual wages to get to the level of the residual wage, and then for each quartile of AKM worker fixed-effects compute the standard deviation. We take the standard deviations of residual wages in each group as our measure of residual wage dispersion (Table 14).

Table 14: Residual Wage Dispersion by AKM Worker FE Groups

	AKM worker FE quartile			
	1	2	3	4
Std. deviation of residual wage (level)	0.235	0.143	0.130	0.146
Normalized (quartile 1)	1.00	0.61	0.55	0.62

F Incumbent Workers' Wage Cyclicality across Worker Fixed Effect Quartiles

To quantify wage cyclicalities, we estimate the typical empirical model introduced by Bils (1985) separately in each quartile of the AKM worker FE distribution:

$$ln(w_{i,t}) = \beta_0 + \beta_1 u_t + \beta_2 NH_{i,t} + \beta_3(NH_{i,t} \times u_t) + \gamma X_{i,t} + \delta_i + \epsilon_{i,t} \tag{31}$$

where $ln(w_{i,t})$ is the real log daily wage, u_t the aggregate unemployment rate, and $NH_{i,t}$ and indicator for new hires, which we define based on the first employment spell in a firm. Consequently, β_1 gives the estimated wage cyclicality among incumbent workers and β_2 the incremental effect for new hires. To clean the reference group of stayers from cyclical changes in match quality over the business cycle, we classify a new hire to be a worker that changes firms between quarter or change occupations (2-digit) within firms (Gertler et al., 2020; Stüber, 2017; Bauer and Lochner, 2020).

Table 15 shows the estimated comovement of incumbent workers' wages with aggregate unemployment. The comovement of aggregate wages with unemployment is much stronger for the groups with lower worker fixed effects. These patterns are consistent with Figueiredo (2022) for the United States, who estimates lower wage cyclicalities for well-matched incumbent workers.

Although we do not model wage rigidities in the main part, the documented patterns would help us to increase the estimated comovement between unemployment and prior wages of those who lose their job. In this case, recessions are periods when more high-wage workers lose their jobs (in relative terms). In addition, these high-wage have more stable wages over the business cycle. Thus, a double composition effect (in terms of levels and in terms of the cyclicality) is at work and makes the comovement between unemployment and prior wages even more positive.

Table 15: Wage Cyclicality by AKM Worker FE Groups

	AKM Worker FE Quartile			
	1	2	3	4
Wage Cyclicality of Incumbent Workers	-1.25***	-0.66***	-0.63***	-0.31***
Incremental Effect for New Hires	-0.45***	-0.05*	-0.03	-0.07*
Observations	5805443	5949552	5966721	5918339
Adjusted R-Squared	0.67	0.60	0.63	0.68

Note: The dependent variable is the log real daily wage of full-time workers. The regression controls for a third-order polynomial in age and tenure, education (3 categories), occupation (2-digit), firm size, AKM firm fixed-effects, worker fixed-effects, a linear time trend and quarterly dummies. Standard errors are clustered at the worker level. SIAB 1986-2017. ***p<0.01, **p<0.05, *p<0.10

G Derivation of Nash Bargaining

The Nash product is:

$$\Lambda\left(\varepsilon_{ijt}\right) = \left[J\left(\varepsilon_{ijt}\right)\right]^{1-\gamma}\left[W\left(\varepsilon_{ijt}\right) - U_{t,j}\right]^{\gamma}. \tag{32}$$

Maximizing the Nash product with respect to wages yields:

$$
\begin{aligned}
\frac{\partial \Lambda_t}{\partial w(\varepsilon_{ijt})} &= \gamma \left(W(\varepsilon_{ijt}) - U_{t,j}\right)^{\gamma-1} \frac{\partial W(\varepsilon_{ijt})}{\partial w(\varepsilon_{ijt})} \left(J(\varepsilon_{ijt})\right)^{1-\gamma} \\
&+ (1-\gamma)\left(W(\varepsilon_{ijt}) - U_{t,j}\right)^{\gamma} \left(J(\varepsilon_{ijt})\right)^{-\gamma} \frac{\partial J(\varepsilon_{ijt})}{\partial w(\varepsilon_{ijt})} = 0.
\end{aligned}
\tag{33}
$$

Therefore:

$$
\gamma J(\varepsilon_{ijt}) = (1-\gamma)\left(W(\varepsilon_{ijt}) - U_{t,j}\right). \tag{34}
$$

When we substitute the present values from equations (14), (16), and (17) and use the one-period-forward iterated version of equation (34), we obtain:

$$
w(\varepsilon_{ijt}) = \gamma \left(a_{t,j} - \varepsilon_{ijt} + E_t p_{t+1,j}(1-\sigma_j)(1-\phi_{t+1})\,\delta J^I_{t+1,j}\right) + (1-\gamma)\,b. \tag{35}
$$

Using the job-creation condition from equation 5, we obtain:

$$
w(\varepsilon_{ijt}) = \gamma \left(a_{t,j} - \varepsilon_{ijt} + \kappa E_t \frac{p_{t+1,j}}{q_{t+1,j}}\right) + (1-\gamma)\,b. \tag{36}
$$

This corresponds to the wage that we show in the main part:

$$
w(\varepsilon_{ijt}) = \gamma \left(a_{t,j} - \varepsilon_{ijt} + \kappa E_t \theta_{t+1,j}\right) + (1-\gamma)\,b. \tag{37}
$$

H Annual Aggregation of Simulated Data

Wages in the data are available based on employment spells. This means that wage information is only available for the entire year if the employment spell lasts the entire year. For comparability reasons, we aggregate our simulated quarterly data to the annual level (for Figure 5 and Table 9).

Wages in the data are defined as the average daily wage over four quarters (if the employment spell lasts for four quarters). Therefore, in our simulation, we also define the wage based on four quarters.

Establishment-level employment in the data is defined as employment at the end of the respective year. Therefore, we also use the last of four quarters in the simulation when aggregating this information to the annual level.

In order to approximate the annual flow of workers that move into unemployment in a given year, we take the employment stock in the previous period and calculate the annual share of workers that gets separated during four quarters. This share is multiplied by the previous period's employment rate.

I Parameter Values in Robustness Checks

In Table 10, we show the simulation results for three alternative scenarios. The tables below show the full set of changed parameter values for these three scenarios.

Table 16 shows the scenario where we do not target the actual residual wage dispersion from the data. Instead, we impose the same replacement rate for all four groups and use the dispersion of the idiosyncratic shock to target the actual flow rates. The simulation results can be found in the upper right panel in Figure 10.

Table 16: Alternative Parameter Values: Untargeted Wage Dispersion; Same Replacement Rate

	1	2	3	4
Matching efficiency	0.07	0.11	0.12	0.10
Replacement rate	0.65	0.65	0.65	0.65
Dispersion parameter	1.16	0.98	0.93	1.21

Table 17 shows the scenario where we do not target the actual flow rates from the data. However, we target the residual wage dispersion from the data. Instead, we impose the flow rates of group 1 to all other three groups. The simulation results can be found in the lower left panel in Figure 10.

Table 17: Alternative Parameter Values: Untargeted Flows

	1	2	3	4
Matching efficiency	0.07	0.11	0.12	0.13
Replacement rate	0.65	0.85	0.88	0.88
Dispersion parameter	1.16	0.71	0.64	0.72

Table 18: Alternative Parameter Values: Untargeted Wage Dispersion and Untargeted Flows

	1	2	3	4
Matching efficiency	0.07	0.07	0.07	0.07
Replacement rate	0.65	0.65	0.65	0.65
Dispersion parameter	1.16	1.61	1.87	2.17

Table 18 shows the scenario where we do not target the actual wage dispersion from the data and we do not target the actual flow rates. Instead, we set the same replacement rates and the same matching efficiency. The surplus relative to aggregate productivity is the same in all four groups. Thus, we impose homogeneity. The simulation results can be found in the lower right panel in Figure 10.

J Model Simulation with Ex-Ante Hiring Costs

In our baseline calibration, we require different replacement rates to hit all our targets. The replacement rate for high-wage groups is larger than for low-wage groups. First, this may seem unrealistic. Second, other than in the data, this has the side-effect that the job-finding rate volatility for high-wage groups is larger than for low-wage groups.

To circumvent this issue, we set the same replacement rate (0.65) for all groups. We keep the same parametrization for the lowest quartile. However, in order to hit all calibration targets, we introduce ex-ante hiring costs in the spirit of Pissarides (2009) and Silva and Toledo (2009). These ex-ante hiring costs have to be paid whenever a match is created (e.g., training costs). They are sunk at the time of hiring and are thus have no direct effect on the wage.

Table 19: Parameter Values

Quartile	1	2	3	4
Productivity	1.00	1.39	1.61	1.87
Matching efficiency	0.07	0.11	0.12	0.09
Hiring costs	0.00	-0.55	-0.60	-0.95
Dispersion parameter	1.16	0.70	0.61	0.68

Table 19 shows the parameter values in these robustness checks. Note that the dispersion parameters of the idiosyncratic shock that drive the dynamics of the separation rate are basically the same as in the baseline version.

Technically, the ex-ante hiring costs change the steady state market tightness in our calibration. As negative ex-ante hiring costs increase the market tightness,[18] they lead to a larger steady state wage for groups with larger productivity. This allows us to reduce their replacement rates.

Table 20 shows the comovement of the separation rate and the job-finding rate change in this robustness check. The cyclicality of the separation rate is very similar the same as in the baseline version (compare to Table 8). However, due to our new parametrization, the cyclicality of the job-finding rate is now the same across groups. This is more in line with the unconditional moments in Appendix C.

[18]Negative hiring costs for some groups may seem. However, what matters is the relation relative to other groups. Alternatively, we could assign a positive hiring cost value for group 1 and negative deviations for all other groups.

Table 20: Cyclicality of Separations and Job-Finding Rate in Data and Calibration

Wage Quartiles	1	2	3	4
Baseline: Cyclicality of Separations (Simulation)	0.79	1.48	1.93	2.39
Baseline: Cyclicality of Job-Finding Rate (Simulation)	-0.23	-0.24	-0.24	-0.22

Note: The table shows the estimated comovement of the group-specific separation and job-finding rate with aggregate unemployment. In analogy with the empirical data, simulated data is HP-filtered with smoothing parameter 1600.

Table 21: Comovement of Prior Wages and Fixed Effects with Unemployment

	Estimated coefficient
Prior Wages	0.82
Fixed Effects	1.76

Note: The table shows the estimated comovement of prior wage of those who lost their job with aggregate unemployment. In analogy with the empirical data, aggregated annual simulated data is HP-filtered with smoothing parameters 6.25.

The comovements of unemployment with the prior wages and the fixed effects (Table 21) change very little relative to the baseline in this exercise (compare to Table 9 and the main text). This shows that our key results neither depend on the different replacement rate parameters nor do they depend on the different group-specific volatilities of job-finding rate across quartiles.