Discussion Papers
in Economics

No. 04/2024

Ex-Ante Heterogeneity, Separations, and Labor Market Dynamics

César Barreto
FAU Erlangen-Nürnberg

Christian Merkl
FAU Erlangen-Nürnberg

ISSN 1867-6707

Friedrich-Alexander-Universität Erlangen-Nürnberg
Institute for Economics
https://www.iwf.rw.fau.de/discussion-papers/

Ex Ante Heterogeneity, Separations, and Labor Market Dynamics*

César Barreto†[1,2] and Christian Merkl‡[2]

[1] *Organisation for Economic Co-operation and Development (OECD)*
[2] *Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU)*

September 2025

Abstract

Our paper documents the importance of ex ante worker heterogeneity for labor market dynamics and for the composition of the unemployment pool over the business cycle. In recessions, the unemployment pool shifts toward workers with higher wages in their previous jobs. Based on administrative data for Germany and two-way worker and firm wage fixed effects, we show that this shift is mainly connected to worker heterogeneity, not to firm heterogeneity. We calibrate a search and matching model with ex ante worker heterogeneity to the estimated relative residual wage dispersion across worker fixed-effect groups. We show that a lower idiosyncratic match-specific shock dispersion for high-wage workers is key for the larger relative fluctuations of their separation rate as well as for the positive comovement between prior wages and fixed effects of unemployed workers with aggregate unemployment. We argue that firm-based explanations, such as cyclical financial frictions, are unlikely to be key drivers for the documented empirical patterns.

Keywords: Labor Market Flows, Separations, Fixed Effects, Labor Market Dynamics
JEL Classifications: E24, J16, J31

*We thank Matteo Cacciatore, Isabel Cairó, Cynthia Doniger, Hermann Gartner, Jonas Hupp, Marianna Kudlyak, Ben Lochner, Andreas Mueller, Timo Sauerbier, and conference and seminar participants at the EALE, Verein für Socialpolitik, the ICMAIF conference, ifo Conference on Macroeconomics and Survey Data, the Chair of Macroeconomics at FAU, and the University of Texas at Austin for helpful comments and discussions. We thank Matija Lozej for discussing our paper. Data access was provided via on-site and remote use at the Research Data Center (FDZ) of the Institute for Employment Research (IAB). The views expressed in the paper are those of the authors and should not be attributed to the OECD or their member states. All errors are our own.

†OECD, 2, rue André Pascal, 75016 Paris, France. Email: cesar.barreto@oecd.org.
‡Corresponding author. FAU, Lange Gasse 20, 90403 Nürnberg. Email: christian.merkl@fau.de.

1 Introduction

Mueller (2017) documents for the United States that a larger share of high-wage workers enters the pool of unemployed in recessions than in booms. This increases the average prior wage of unemployed in recessions. Mueller (2017) shows in a search and matching model that the combination of ex ante worker heterogeneity with different match-specific idiosyncratic shock properties or with financial constraints can match the empirical patterns. However, testing these theoretical mechanisms with US survey data is difficult, given the inability to fully control for time-invariant unobserved worker and firm heterogeneity and limited firm-side information.

To address this, we use rich German administrative data to study labor market dynamics and the role of ex ante heterogeneity on both the worker and firm side. Administrative data does not suffer from major measurement error and it allows us to use two-way fixed effects. Despite institutional differences between the United States and Germany, we document similar cyclical patterns: high-wage workers' separation rates comove more strongly with aggregate unemployment than those of low-wage workers. In addition, average prior wages of workers who lose their jobs comove positively with aggregate unemployment. Yet, once we control for worker fixed effects, these facts vanish, highlighting the importance of ex ante worker heterogeneity. We further show that the residual wage dispersion is smaller among high-wage workers, consistent with differences in match-specific shocks, while financial frictions play little role. Based on these results, we calibrate a search and matching model with ex ante worker heterogeneity and endogenous separations to the relative residual wage dispersion from the data. As the quantitative results of the simulated model are consistent with the data, the model provides insights into the underlying driving forces of the empirical facts.

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. We show that high-wage workers experience more cyclical separations even after controlling for worker and firm observable characteristics. We analyze whether more cyclical separations for high-residual wage workers are related to time-invariant unobserved heterogeneity 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 by grouping workers based on their residual wages. We show that worker fixed effects are the key driver for the observed patterns, while firm fixed effects matter less. Once we control for worker fixed effects (independently whether we do so based on a one-way fixed effect or based on AKM 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 of the residual wage distribution. Furthermore, when controlling for worker fixed effects, the positive comovement between unemployment and prior residual wages is no longer statistically significant.

Given the documented importance of ex ante worker heterogeneity, we analyze whether interactions with match-specific shocks or financial frictions matter. Both channels have been identified as promising candidates by Mueller (2017). We show that the residual wage dispersion is systematically different across different worker fixed effect quartiles. In the upper part of the worker fixed effect distribution, the residual wage distribution is substantially less dispersed than in the lower part. In contrast, we find no evidence that financial frictions are a key driver for the compositional effects based on worker fixed effects. We approximate financial frictions with firm closures based on Hethey-Maier and Schmieder (2013). We find that, while separations among financially constrained firms are more cyclical than for all firms, they are too small in magnitude to be driving the aggregate patterns.

As our empirical results point to the importance of ex ante worker heterogeneity with different residual wage dispersion, we propose a parsimonious search and matching model with separate labor market segments in the spirit of Bils et al. (2012).[1] When calibrating the macroeconomic labor market model to the empirically observed ex ante worker heterogeneity, the 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. The positive comovement between aggregate unemployment and prior wages of those who were separated is closely in line with the data. In counterfactual exercises, we show that the different match-specific shock dispersions across heterogeneity groups are decisive for this pattern. A less dispersed distribution for high-wage workers generates more volatile separation rates.

Data and model together allow us to tell a coherent story about the underlying mechanism for the documented empirical facts. Recessions are periods when relatively more workers with (permanently) higher wages are separated. This compositional effect increases average prior wages and fixed effects of unemployed workers in recessions.

Our paper complements the existing evidence on the cleansing effect of recessions. While we find that a greater share of high-wage workers enters unemployment during downturns, this does not contradict the documented fact that low-educated workers experience larger increases in separation rates in absolute terms during recessions (see Cairó and Cajner (2018) and Mukoyama and Şahin (2006)). Indeed, our data confirms that separation rates for low fixed-effect or low-educated workers show the largest absolute deviations. However, because low-wage workers have higher average separation rates than

[1]Bils et al. (2012) focus on the interaction between wages and hours. Our administrative data is largely silent on hours and we focus on full-time workers. However, we can pin down the residual wage dispersion with administrative data and distinguish between different drivers at the firm and worker side.

high-wage workers, their relative deviations are smaller (see Appendix B and Appendix C for details). As a result, the share of low-wage workers among the unemployed actually falls in recessions. This finding contrasts with the assumption in Pries (2008), where recessions are modeled as shifting the unemployed pool toward lower-ability workers.

Our paper contributes to a recent macroeconomic literature that emphasizes the importance of the separation rate. Cairó and Cajner (2018) document the important role of the separation rate for different unemployment rates and employment volatility across education groups in the United States. 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. (2025) 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.

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 and simulates a search and matching model with ex ante worker heterogeneity. 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 (Berge et al., 2019). 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 and federal state of the establishment recorded as of June 30th each year (Ganzer et al., 2021). 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 to approximate the sample restrictions from Bellmann et al. (2020), which in particular focuses on full-time employees as the German administrative data does not record exact working hours. 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. For computational reasons, the AKM effects are provided in five sub-intervals covering the period 1985-2017. We normalize (z-score) and take the average z-score of worker and firm fixed effects for the effects to be comparable across the estimation sub-intervals.

In the SIAB, wages are right-censored at the social security contribution ceiling. We base our analysis on uncensored wage observations following Stüber (2017), Bauer and Lochner (2020) and Gartner et al. (2013). We focus on uncensored wages because the imputation procedure, while doing a fairly good job in predicting the upper tail levels of the distribution, is less suited for the analysis of idiosyncratic match-specific shock component of wages (see Appendix F.3 for a discussion). Nonetheless, we show results based on imputed wages in Appendix F.3, with similar findings. To preserve the completeness of the employment biographies, we exclude all spells from workers who cross the maximum contribution ceiling at least once.[3]

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

[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.

[3]For the sample of West-German full-time workers aged 20 to 60, about 11% of worker-quarter observations are right-censored. Excluding all spells from full-time workers that cross the maximum contribution ceiling at least once drops 14.3% of workers in our sample.

onward in the analysis. Table 9 in the Appendix gives summary statistics of our final estimation sample. More details on the data, sample definition and on the definition of transition rates can be found in Appendix A.

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 raw 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 comovement with the aggregate unemployment rate. To understand the role of worker and firm heterogeneity, we then estimate Mincer-type equations on the same sample of workers, in which we subsequently control for worker and firm variables. Based on the resulting residual wages of the Mincer-type regression, we re-group workers based on above or below the residual wage distribution and re-compute group-specific transition rates and their comovement with aggregate unemployment.

Table 1 reports the comovement of the cyclical component of each transition rate with the aggregate unemployment rate (i.e., a measure of cyclicality). The cyclicality of the separation rate for high-wage workers is about twice as large (factor 1.90) as for low-wage workers (see column I). Figure 3 in Appendix E 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 1). These findings are in line with Mueller (2017) for the United States, in spite of the quite different labor market institutions prevalent in Germany.

More cyclical separations for high-wage workers could potentially reflect worker heterogeneity (e.g., workers with higher productivity may have more cyclical separation 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 1). 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 1, we start by controlling for a rich set of observable worker characteristics, such as a polynomial in age, firm and occupational tenure, as well as dummies for gender,

Table 1: Cyclicality and Level of Transition Rates by Worker Groups

		(I) Raw wage		(II) + Baseline controls		(III) + Firm-level controls		(IV) + AKM worker FE		(V) + One-way worker FE	
		Below	Above	Below	Above	Below	Above	Below	Above	Below	Above
Separation Rate	Cyclicality	0.48***	0.91***	0.49***	0.71***	0.49***	0.67***	0.60***	0.50**	0.53***	0.58***
	Mean	2.1	0.6	1.8	0.9	1.7	1.0	1.4	1.3	1.5	1.2
Job-Finding Rate	Cyclicality	-0.23***	-0.21**	-0.23***	-0.24***	-0.24**	-0.23***	-0.20*	-0.25***	-0.18	-0.28***
	Mean	13.8	15.5	13.2	15.8	12.4	16.7	13.3	14.7	12.3	16.0
Job-to-Job Rate	Cyclicality	-0.93***	-0.66***	-0.95***	-0.69***	-0.95***	-0.79***	-0.91***	-0.84***	-0.92***	-0.82***
	Mean	2.8	1.3	2.4	1.7	2.2	1.9	2.2	1.9	2.4	1.8

Note: Following Mueller (2017), the cyclicality of the series is measured as the coefficient β in the regression $ln(x_{j,t}) = \alpha + \beta \times ln(U_t) + \epsilon_{j,t}$, where $x_{j,t}$ is the separation, job finding, or job-to-job rate of group j 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 3 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, occupation and firm tenure, gender, German nationality, education (3 categories), occupation (2-digit) and year dummies. In a second step, we add firm covariates: log establishment size, AKM firm fixed effects and dummies for labor market regions. In a third step, we add AKM worker fixed effects. In a fourth step, for the estimation with one-way worker fixed effects, we remove the AKM firm fixed effects and control for log establishment size, 3-digit industries and labor market regions instead. SIAB 1986-2017. ***p<0.01, **p<0.05, *p<0.10

nationality, education, and two-digit occupations (see column II). After accounting for observable worker characteristics, separations are still more cyclical for high-wage workers by a factor of 1.45. 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, workplace labor market region and the AKM firm fixed effect (see column III). Interestingly, we still observe more cyclical separation rates for workers with high residual wages (factor: 1.37), 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 column IV). Once we control for AKM worker fixed effects on top of other observables, the estimated comovement of the separation rate with unemployment is no longer more volatile for high-wage workers than for low-wage workers. This points toward the importance of time-invariant unobserved worker heterogeneity for the dynamics of the separation rate.

Based on one-way worker fixed effects[4] instead of two-way AKM fixed effects (see column V), the differences in the separation rate cyclicality between the groups are similar in economic terms, although not fully absorbed. This may reflect that one-way worker fixed effects capture in part firm-specific unobserved heterogeneity, particularly among workers that do not change firms (on average, full-time workers in our sample change firms about 1.45 times (see Table 9 in the Appendix). To rule out that low worker turnover is biasing the results, in Appendix F.4 we restrict the sample to a set of workers that change firms at least two times in the observation period. This leaves all of our main results unaffected, while improving the ability of the one-way worker fixed effect to absorb differences in the separation rate cyclicality.

To gain further insights about the underlying dynamics, we group workers in terms of their AKM worker fixed effects into four quartiles (see Table 2). 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. Table 2 also shows that different separation rates are remarkably different across different quartiles.[5] The separation rates are about five times larger in the first quartile than in

[4]When controlling for a one-way worker fixed effect, we keep the size and labor market region controls but remove the AKM firm fixed effect and include dummies for 3-digit industry instead.

[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

Table 2: Cyclicality of Transition Rates by AKM Worker FE Groups

		AKM Worker FE Quartile			
		1	2	3	4
Separation Rate	Cyclicality	0.42**	0.76***	0.86***	0.89***
	Mean	2.6	1.5	0.8	0.5
Job-Finding Rate	Cyclicality	-0.45***	-0.13	-0.06	-0.21**
	Mean	10.8	18.1	20.1	15.7
Job-to-Job Rate	Cyclicality	-1.01***	-0.76***	-0.81***	-0.70***
	Mean	2.4	2.3	1.9	1.7

Note: The cyclicality of the series is measured as the coefficient β in the regression $ln(x_{j,t}) = \alpha + \beta \times ln(U_t) + \epsilon_{j,t}$. 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 3 and 128 quarterly observations are used in the regressions. SIAB 1986-2017. ***p<0.01, **p<0.05, *p<0.10

the fourth quartile. Workers with low wages have higher separation rates and lower comovement with unemployment than those with high wages. However, the picture is different when looking at 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 1). 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, 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-

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., $x_{jt} = \alpha + \beta * U_t + \epsilon_{j,t}$, where x_{jt} are the separation rates in levels instead of logs. Results are available on request.

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 log wage reported in year $t-1$.[7]

Figure 1 (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 1 (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 1 (panel c) 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 panel a and panel c in Figure 1, the comovements with unemployment look similarly strong. The worker fixed effects is somewhat more synchronized with unemployment than the actual wage. This illustrates that worker fixed effects are an important driver for the raw wage dynamics.

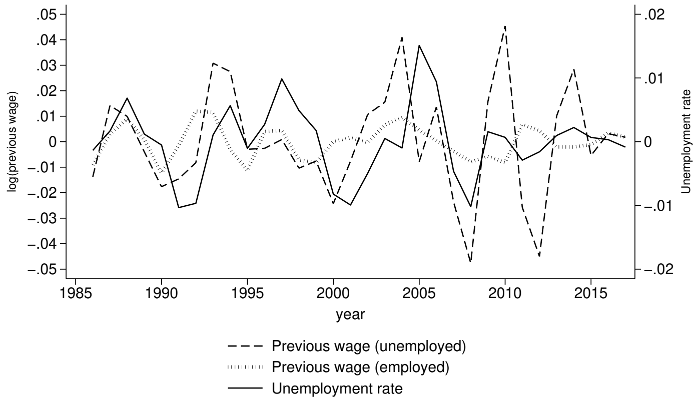
Table 3: Cyclicality of Previous Wage among the Unemployed

	Raw wage	Wage Rank	AKM worker fixed effect	Residual wage (+ AKM worker FE)
Unemployment rate	1.43**	0.70**	2.09***	0.24
Observations	32	32	32	32

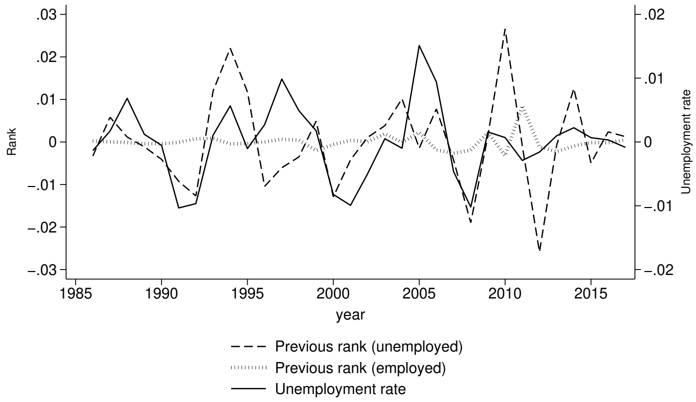
Note: the table shows the coefficient from the regression $y_t = \alpha + \beta u_t + \epsilon_t$, where y_t refers to the average previous residual wage, worker fixed effect, and rank of the unemployed and u_t to the unemployment rate (not in logs). Newey-West standard errors with lag order of 2 and 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

To illustrate this point further, we estimate the comovement of wages and fixed effects of unemployed workers with aggregate unemployment. Table 3 shows the results. The estimated coefficient shows pronounced comovements between aggregate unemployment

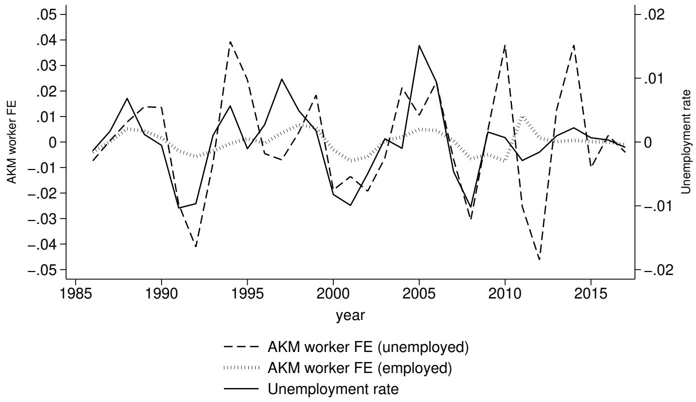
[7] We take the worker observation each June 30th (either in employment or in unemployment), impute the observed workers' log daily wages or rank from June 30th of the previous year, and average separately across employed and unemployed workers in each year. We use the corresponding unemployment rate 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.



(a) Raw daily wage



(b) Wage rank



(c) Worker Fixed Effects

Figure 1: Previous wage 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 30$^{\text{th}}$ (either in employment or unemployment), using the observed workers' daily wages, rank, or worker fixed effect 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 ($\lambda = 6.25$).

and both the raw wage and the fixed effects. In terms of the residual wage, additionally controlling for worker fixed effects (after including firm and worker covariates) makes the comovement of the residual wage with unemployment statistically insignificant at conventional levels.[8] This exercise shows the importance of ex ante worker heterogeneity for the comovement of unemployment with the prior wage of those losing their jobs.

3.3 Evidence for Competing Theoretical Mechanisms

Mueller (2017) shows that ex ante heterogeneity is required in order to match the quantitative patterns in the data and in a model simulation. Ex ante worker heterogeneity combined with either different match-specific idiosyncratic shock properties or financial frictions can reconcile data and model. As we use rich administrative data, we can test which of these channels is prevalent in the data. The administrative data does not suffer from major measurement error and allows controlling for a wide variety of potential confounders. In addition, it allows us to use firm closures or mass layoffs as proxies for financial frictions.

3.3.1 Match-Specific Idiosyncratic Shocks

If high-wage workers are subject to idiosyncratic shocks with less dispersion than low-wage workers, an aggregate shock leads to a larger relative movement of the separation rate for high-wage workers.[9] In addition to being of high-quality, a distinct advantage of our administrative data is that we can estimate the dispersion of match-specific idiosyncratic shocks while accounting for observed characteristics as well as unobserved, time-invariant heterogeneity at the worker and firm level. For this, we estimate residual wages on the sample of full-time West-German workers aged 20-60 from 1985-2017 using the following wage equation:

$$ln(w_{i,t}) = \alpha + \beta X_{i,t} + \gamma_i + \delta_j + \epsilon_{i,t} \quad (1)$$

where $X_{i,t}$ is a set of observable worker and firm characteristics. It consists of a third-order polynomial in age, firm and occupational tenure, log firm size and dummies for occupations (2-digit), education (3 categories), labor market regions, 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

[8] In Appendix D, we replicate the exercise from Table 1 by sequentially adding covariates, showing that the significant comovement between the unemployment rate and the residual wage only disappears once we control for worker fixed effects.

[9] Technically, a given movement of the cutoff point triggers larger separation rate movements due to more density around the cutoff point. See Section 4 for further details.

idiosyncratic variation in wages after controlling for observed and unobserved worker and firm heterogeneity. In order to obtain a measure for the absolute dispersion in line with our theoretical model, we take the exponent of the estimated residual wages and calculate the standard deviations of residual wages in each quartile of AKM worker fixed effects (Table 4).

Table 4: Residual Wage Dispersion by AKM Worker FE Groups

	AKM worker FE quartile			
	1	2	3	4
Std. deviation of residual wage (level)	0.252	0.153	0.138	0.150
Normalized (relative to quartile 1)	1.00	0.61	0.55	0.59

Note: The table shows the standard deviation of the level of residual wages from a Mincer-type regression controlling for a third-order polynomial in age, firm and occupational tenure, dummies for education, occupation, labor market regions, German nationality, calendar year and including AKM worker and firm fixed effects. Note: SIAB 1985-2017.

Table 4 shows that high fixed-effect workers show less dispersion of residual wages relative to low fixed-effect workers.[10] This is consistent with evidence from Card et al. (2013). Using these refined measures of residual wage dispersion, in Section 4 we calibrate a parsimonious search and matching model with ex ante worker heterogeneity to the flow rates and the relative residual wage dispersion from the data. In counterfactual analysis, we can analyze the effects of different residual wage dispersions.

3.3.2 Financial Frictions and Firm Closures

A competing explanation for the shift of the unemployment pool toward high-wage workers in recessions relates to the fact that recessions are periods in which firms face restricted access to credit (Mueller, 2017). When facing a cyclical productivity shock, financial constraints may induce separations among workers that the firm would otherwise retain (specifically, high-wage workers), but where the financial friction is prevalent. This in turn would produce a positive correlation between the previous wage of those unemployed and the aggregate unemployment rate.

In order for financial frictions to be meaningful in our context, two conditions are necessary. First, separations from financially-constrained firms need to be large enough in magnitude to be relevant for aggregate dynamics. Second, separations from financially constrained firms need to disproportionately shift toward high-wage workers in recessions.

The SIAB dataset does not provide balance-sheet information for firms to evaluate the role of cyclical cash-flow constraints directly. However, we can proxy for the existence of financial frictions based on firm closures. Firm closures are cases in which a firm shuts

[10]Interestingly, Mueller (2017) does not find any meaningful differences for the variance of the match-specific shock for workers above and below the mean wage based on the CPS and the NLSY79.

down, all workers in the firm separate and less than 30% of the workforce is re-employed together following the closure. Due to the restriction on clustered outflows, these type of events can be disentangled from restructuring and relabeling of firms that would otherwise introduce large biases in the analysis (Hethey-Maier and Schmieder, 2013).[11]

We can qualify the importance of plant closures to the separation rate by decomposing the separation rate as the sum of separations due to firm closures and all other separations and evaluating the cyclicality of each component:

$$SR_t = \frac{EU_t}{E_{t-1}} = \frac{EU_t^{closures}}{E_{t-1}} + \frac{EU_t^{other}}{E_{t-1}}. \tag{2}$$

Table 5 shows the cyclicality and the levels of the separation rate for workers above and below the median wage, based on including all separations, separations due to firm closures and other separations. In terms of cyclicalities, the difference in the separation rate cyclicality between high- and low-wage workers is larger for firm closures than for all separations. However, in terms of levels, firm closures only account for a small share of overall separations for both high and low-wage workers. Only about 3 to 4 percent of the overall average separation rate for high-wage (low-wage) workers can be attributed to firm closure events. Focusing on separations that exclude firm closure events yields a separation rate cyclicality that is almost identical to the baseline. The low weight of firm closures on overall separations implies that financial frictions are not driving the aggregate shift of the unemployed toward high-wage workers that we observe in the data. Excluding workers that ever experience a firm closure event or using more broadly defined mass-layoff events also leaves all of our main results unaffected (Appendix F.1 and Appendix F.2).

Table 5: Separation rate cyclicality and firm closures

	Separation rate concept					
	All separations (EU)		Firm closures only ($EU^{closures}$)		Excl. firm closures (EU^{other})	
	Below	Above	Below	Above	Below	Above
Cyclicality	0.49***	0.91***	0.33	1.40***	0.47***	0.90***
Mean	2.12	0.56	0.06	0.02	2.06	0.54
Observations	128	128	128	128	128	128

Note: The cyclicality of the series is measured as the coefficient β in the regression $ln(x_{j,t}) = \alpha + \beta \times ln(U_t) + \epsilon_{j,t}$. 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 3 and 128 quarterly observations are used in the regressions. SIAB 1986-2017. ***p<0.01, **p<0.05, *p<0.10

[11] While we do not observe all separations from plant closures, the SIAB data is a representative worker sample, which has been used to study the consequences of job loss following plant closures and mass-layoff events (Jarosch, 2023; Burdett et al., 2020).

Plant closures (or perhaps even mass layoffs) may be a too narrow definition of financial frictions. However, for Germany, Moser et al. (2021) find that, within firms, credit-supply shocks are associated with more separations among lower-wage workers, i.e., exactly the opposite direction compared to what would be required to match the patterns in the data.

Based on our own empirical results and results from the existing empirical literature, it is unlikely that the interaction of financial frictions and ex ante worker heterogeneity is a key driver for the documented facts. Therefore, we do not pursue this avenue in our theoretical modeling and simulation.

3.4 Empirical Robustness Checks

The empirical importance of ex ante worker heterogeneity is confirmed in a battery of robustness checks in the Appendix. Appendix F.1 shows that excluding workers that ever experience a plant closure leaves all of our main results unaffected. Appendix F.2 shows that an alternative definition for firms' financial frictions based on mass-layoff events (Schmieder et al., 2023; Davis and Von Wachter, 2011) yields similar findings as for plant closures. Appendix F.3 shows that including imputed wage observations does not change our main conclusions. Appendix F.4 shows that excluding workers with low turnover leaves all of our main results unaffected, in line with limited job mobility not biasing our interpretation on the role of worker fixed effects. Appendix F.5 shows that increasing the smoothing parameter for the Hodrick-Prescott filter to $\lambda = 100,000$ for quarterly data and to $\lambda = 100$ for annual data as in Mueller (2017) yields similar results. However, results are somewhat less pronounced due to different lead-lag patterns with the larger smoothing parameter. Appendix F.6 shows that attrition out of the pool of unemployed is not selected toward low fixed effect workers. Thus, the documented shifts in the pool of the unemployed are not driven by nonrandom attrition. Based on registered unemployed workers, Appendix F.7 shows that differential take-up rates of unemployment benefits across worker groups as in Trenkle (2023) do not impact our main findings.

Overall, our empirical analysis provides strong evidence for the importance of ex ante worker heterogeneity. Therefore, we derive a search and matching model with ex ante worker heterogeneity and calibrate it to the observed calibrate it to the relative residual wage dispersion from the data.

4 Theory

4.1 Model Environment

To analyze the role of ex ante worker heterogeneity in a theoretical model, 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 (similar to Bils et al. (2012)). Vacancy dynamics in each segment are determined according to the usual free-entry condition. 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 j, our model nests the standard framework in the spirit of 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:

$$m_{t,j} = \chi_{t,j} u_{t-1,j}^{\alpha} v_{t,j}^{1-\alpha}, \tag{3}$$

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.

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

$$p_{t,j} = \frac{m_{t,j}}{u_{t-1,j}} = \chi_{t,j} \theta_{t,j}^{1-\alpha}, \tag{4}$$

$$q_{t,j} = \frac{m_{t,j}}{v_{t,j}} = \chi_t \theta_{t,j}^{-\alpha}. \tag{5}$$

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:

$$\begin{aligned} V_{t,j} = & -\kappa_j + q_{t,j} E_t \Big[(1-\phi_{t,j}) J_{t,j}^I - h_j \\ & + (1-(1-\phi_{t,j})) \delta V_{t+1,j} \Big] + (1-q_{t,j}) E_t \delta V_{t+1,j}, \end{aligned} \tag{6}$$

where δ is the discount factor, 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). h are ex post hiring costs that have to be paid once at the beginning of the employment spell.[12]

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, $\kappa_j/q_{t,j}+h_j$, are equal to the expected discounted profits from hiring:

$$\frac{\kappa_j}{q_{t,j}} + h_j = E_t\left[\left(1-\phi_{t,j}\right) J^I_{t,j}\right]. \tag{7}$$

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 $g\left(\varepsilon_{ijt}\right)$. The shock is iid across workers and time. The value of an existing match with shock realization ε_{ijt} is

$$J^I\left(\varepsilon_{ijt}\right) = a_{t,j} - w\left(\varepsilon_{ijt}\right) - \varepsilon_{ijt} + E_t\left(1-\phi_{t+1,j}\right)\delta J^I_{t+1,j}, \tag{8}$$

where $a_{j,t}$ is the productivity in the respective labor market segment (subject to aggregate shocks, which will be defined in Section 4.1.3), $w\left(\varepsilon_{ijt}\right)$ is the wage for a specific idiosyncratic shock realization. New and existing matches are hit by idiosyncratic cost-shocks and may therefore split up endogenously.

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 $J^I\left(\tilde{\varepsilon}_{ijt}\right) = 0$:

$$\tilde{\varepsilon}_{ijt} = a_{t,j} - w\left(\tilde{\varepsilon}_{ijt}\right) + E_t\left(1-\phi_{t+1}\right)\delta J^I_{t+1,j}. \tag{9}$$

This allows us to define the endogenous separation rate $\phi_{t,j}$, which is defined as:

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

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

$$J^I_{t,j} = a_t - \bar{w}_{t,j} - H\left(\tilde{\varepsilon}_{ijt}\right) + E_t\left(1-\phi_{t+1,j}\right)\delta J^I_{t+1,j}, \tag{11}$$

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

$$H\left(\tilde{\varepsilon}_{ijt}\right) = \frac{\int_{-\infty}^{\tilde{\varepsilon}_{ijt}} \varepsilon_{ijt} g\left(\varepsilon_{ijt}\right) d\varepsilon_{ijt}}{1-\phi_{t,j}}, \tag{12}$$

[12] See Silva and Toledo (2009) and Pissarides (2009) for models with ex post hiring costs and Muehlemann and Pfeifer (2016) for empirical evidence.

$$\bar{w}_{t,j} = \frac{\int_{-\infty}^{\tilde{\varepsilon}_{ijt}} w\left(\varepsilon_{ijt}\right) g\left(\varepsilon_{ijt}\right) d\varepsilon_{ijt}}{1-\phi_{t,j}}. \tag{13}$$

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:

$$n_{t,j} = \left(1-\phi_{t,j}\right)\left(n_{t-1,j} + p_{t,j}u_{t-1,j}\right), \tag{14}$$

with unemployment rate, $u_{t,j}$:

$$u_{t,j} = 1 - n_{t,j}. \tag{15}$$

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.Thus, a firm's value of production[13] with idiosyncratic shocks realization ε_{ijt} is

$$J^I\left(\varepsilon_{ijt}\right) = a_{t,j} - w\left(\varepsilon_{ijt}\right) - \varepsilon_{ijt} + E_t\left(1-\phi_{t+1,j}\right)\delta J^I_{t+1,j}, \tag{16}$$

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

$$\bar{J}^I\left(\varepsilon_{ijt}\right) = 0. \tag{17}$$

The worker's value is

$$\begin{aligned} W\left(\varepsilon_{ijt}\right) = & \, w\left(\varepsilon_{ijt}\right) + \delta E_t\left(1-\phi_{t+1,j}\right) W_{t+1,j} \\ & + \delta E_t\left(\phi_{t+1,j}\right)\right) U_{t+1,j} \end{aligned} \tag{18}$$

The fallback option is unemployment:

$$\begin{aligned} U_{t,j} = & \, b_j + \delta E_t p_{t+1,j}\left(1-\phi_{t+1,j}\right) W_{t+1,j} \\ & + \delta E_t\left(1 - p_{t+1,j}\left(1-\phi_{t+1,j}\right)\right) U_{t+1,j}. \end{aligned} \tag{19}$$

where b_j is the fall-back option under unemployment, which consists of unemployment benefits and home production.

[13] As in Pissarides (2009), we assume that ex post hiring costs are sunk at the time of hiring and thereby not included in the bargaining for new matches. This gives us the same wage for entrants and existing matches.

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

$$w\left(\varepsilon_{ijt}\right)=\gamma\left(a_{t,j}-\varepsilon_{ijt}+E_t p_{t+1,j}\left(1-\phi_{t+1,j}\right)\delta J^I_{t+1,j}\right)+\left(1-\gamma\right)b_j, \tag{20}$$

where γ is the bargaining power of workers.

4.1.3 Aggregate Shocks

Productivity in each of the segments is subject to persistent shocks.

$$a_{t,j}=a^{\rho}_{t-1,j}a_j^{1-\rho}e^{\epsilon^a_t}, \tag{21}$$

where a_j is the average productivity in each segment. ρ is the persistence parameter, which we assume to be the same in all labor market segments. ϵ^a_t is the aggregate shock term. We assume that all segments are hit by the same aggregate productivity shock.

4.1.4 Equilibrium

The labor market equilibrium can be described by the job-creation condition in equation 7 (in conjunction with the job-finding and worker-finding rates in equations 4 and 5, derived from the matching function), the endogenous cutoff point for separations in equation 9, which is a function of the future value of incumbent workers in equation 11, the separation rate in equation 10, employment dynamics in equation 14 and unemployment definition described by equation 15 in the respective sectors, the wage in equation 20, and productivity shock in equation 21.

Finally, we have to aggregate the unemployment rates in the respective sectors to obtain the economy-wide unemployment rate. 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):

$$u_t=\sum_{j=1}^{S}u_{t,j}/S. \tag{22}$$

4.2 Calibration Strategy

In our parametrization, we start by setting several parameter values according to external sources (see upper part in Table 6 for a summary). The discount factor, δ, is set to the standard value of 0.99. In line with the surveyed range by Petrongolo and Pissarides (2001), the matching elasticity, α, is set to 0.5. In line with Hosios (1990) rule, the bargaining power, γ, is set to the same value as the matching elasticity (for all segments).

Vacancy posting costs, κ, are normalized to 10 percent of productivity in the respective labor market segment.

We target an average value of non-work, b, to 80 percent of productivity (replacement rate) across all four labor market segment. This value is taken from Kohlbrecher et al. (2016).[14] It is in spirit of Hall and Milgrom (2008)'s value of leisure of 0.71, which is also used by Mueller (2017), taking into account that the unemployment benefit system in Germany is more generous than in the United States.

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.[15]

Table 6: Model Parameters and Calibration Targets

Parameter	Letter	Value	Source
Discount factor	δ	0.99	Common Value
Matching elasticity	α	0.5	Petrongolo and Pissarides (2001)
Bargaining power	γ	0.5	Hosios (1990)
Vacancy posting costs	κ	$0.1a_j$	Normalization
Persistence of agg. productivity	ρ	0.91	Gehrke et al. (2019)
Std. dev. of agg. shock	ϵ_t^a	0.005	Normalization

Quartile	1	2	3	4
Average wage (rel.)	1.00	1.32	1.52	1.93
Job-Finding Rate	0.108	0.181	0.201	0.157
Separation Rate	0.026	0.015	0.008	0.005
Wage dispersion (rel.)	1.00	0.61	0.55	0.59
Market Tightness	1.00	1.00	1.00	1.00
Productivity	1.000	1.390	1.620	2.065
Matching efficiency	0.111	0.184	0.203	0.158
Replacement rate	$0.752a_1$	$0.794a_2$	$0.800a_3$	$0.853a_4$
Dispersion parameter	1.178	0.701	0.618	0.656
Hiring costs	$1.248a_1$	$0.514a_2$	$0.428a_3$	$0.208a_4$

Note: the upper part shows common model parameters, the lower part shows targeted variables and the parameters to match these targets.

We set the remaining parameters to hit certain calibration targets (see lower part of Table 6 for a summary): First, we set the productivity, a_j, in each labor market segment to match the ratio of worker fixed effects of each group relative to the first group. See

[14]Unemployment benefits in Germany are 60 or 67 percent of the prior earnings (depending on family status). Thus, our value takes into account a moderate value of leisure.

[15]In Appendix L, we show a robustness check where we also have exogenous separations. The key results are very similar.

Appendix G for empirical details. The productivity of the least productive labor market segment is normalized to 1.

Second, we target the job-finding rates in each segment. To hit these targets, we set the respective matching efficiencies.

Third, we jointly target the separation rates and the residual wage dispersions conditional on not being separated relative to the baseline group, by jointly setting the replacement rates (b_j as percent of the steady-state productivity, a_j, in the respective segment, with an average value of 80 percent as target, see above) and the dispersion of the idiosyncratic shock distribution. For the idiosyncratic shocks, we assume a logistic distribution with scaling parameter s_j that is used for targeting the dispersion of the idiosyncratic shock.[16] 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 estimations in Section 3.3.1 with rich German administrative data allow us to discipline this margin.[17] As the residual wage distribution is much less dispersed for the groups with higher fixed effects, we require less dispersed idiosyncratic shocks. Given this small dispersion, we require larger replacement rates for workers with higher productivity than for those with lower productivity.[18]

Fourth, we set hiring cost to normalize market tightness to 1 in each market segment. It is well known that the ability of the search and matching model to generate amplification of the job-finding rate depends on the surplus. As our calibration strategy required higher replacement rates for groups with higher productivity, this normalization imposes larger hiring costs on groups with lower productivity and thereby depresses their surplus. Larger hiring costs increase the ability of the search and matching model to generate amplification of the job-finding rate (Silva and Toledo (2009) and Pissarides (2009)). We compare the average hiring cost number in our calibration to empirical evidence. Muehlemann and Pfeifer (2016) show that the average hiring costs are roughly two thirds of the average quarterly wage. Although we did not target this dimension, the average hiring costs in the model (almost 60 percent) are relatively close to the reference point from the data.

Finally, 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.

[16] We normalize the mean of this distribution to zero. The logistic distribution is close to the normal distribution, but allows for explicit analytical expressions.

[17] 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.

[18] In our model, higher replacement rates for high-wage groups reduce the surplus and prevent zero endogenous separations in steady state. Larger replacement rates for high-wage workers may seem counterintuitive. In reality, a lower surplus for high-wage workers may, for example, be due to different production functions for high-wage and low-wage workers.

As estimated for Germany based on a search and matching model by Gehrke et al. (2019), we assume that the autocorrelation of the aggregate productivity shock is 0.91. We normalize the standard deviation of the shock to 0.5 percent. In analogy with the empirical data, we simulate the model for 132 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 I for details on the aggregation.

4.3 Quantitative Results

4.3.1 Underlying Mechanism

Figure 2 shows the reaction of our baseline calibration in response to a one percent aggregate productivity shock. The log-deviations for the separation rate are very different across groups. The relative increase for the separation rate is several times larger in the labor market segment with the largest ex ante worker productivity as in the segment with the lowest ex ante worker productivity (see lower left panel).

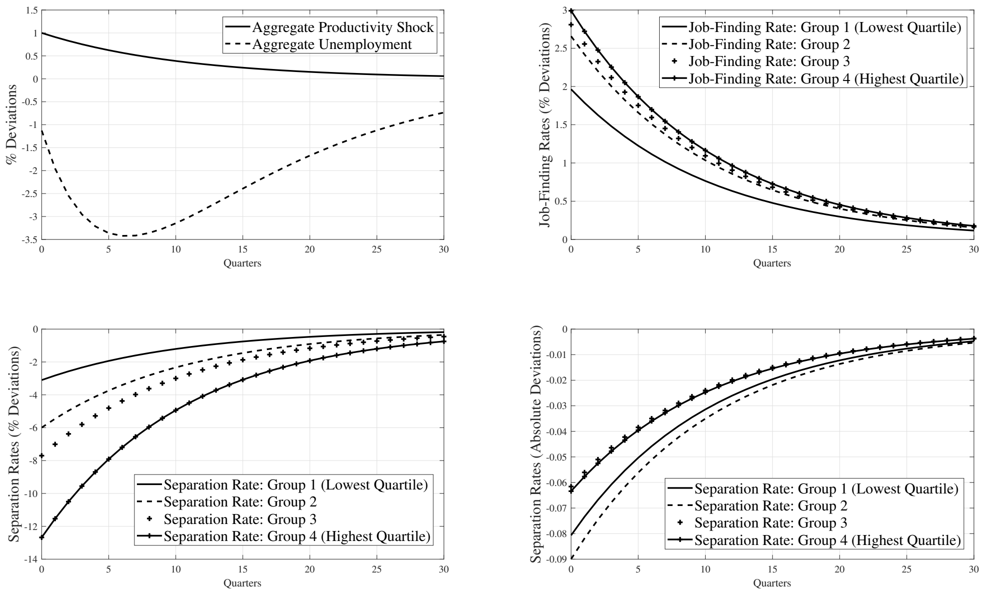


Figure 2: The figure shows impulse response functions for aggregate productivity, the aggregate unemployment rate as well as the job-finding and separation rates for different worker groups to a one percent positive productivity shock. For the separation rate, the figure shows the percentage and absolute deviation from the steady-state value. Group 1 is the lowest-productivity group, group 4 is the highest-productivity group.

However, the lower right panel of Figure 2 shows a very different picture for the absolute deviations of the separation rates. The absolute deviations for group 1 (with the lowest ex ante worker productivity) are larger than for group 4 (i.e., exactly the opposite pattern as for the log-deviations). Keep in mind that we calibrated the 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). In line with the patterns in the data, the level differences in the separation rates explain the large gap between absolute and relative deviations.

Technically, 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.

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 7 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.[19]

Table 7: Cyclicality of Separation Rate and Job-Finding Rate in Data and Calibration

Wage Quartiles	1	2	3	4
Separation Rate (Simulation)	0.59	1.18	1.55	2.71
Separation Rate (Data)	0.42	0.76	0.86	0.89
Job-Finding Rate (Simulation)	-0.36	-0.49	-0.51	-0.55
Job-Finding Rate (Data)	-0.45	-0.13	-0.06	-0.21

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

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

[19]It may seem surprising that the separation rate volatility is larger for group 4 than for group 3, despite a different ordering in the residual wage dispersion. However, the residual wage dispersion is measured as absolute number. The ordering of the residual wage dispersion and the volatility correspond to one another when normalizing by the wage level. In addition, smaller separation rates in group 4 than group 3 generate larger log-deviations.

as a confirmation for the validity of our calibration strategy.[20] Our calibration strategy leads to a comovement of the separation rate with unemployment that is too large in all groups. In Appendix K.1, we provide and discuss an exercise where we choose parameters to target the comovement of the separation rate for group 1 with aggregate unemployment.

Finally, while the cyclicality of the job-finding rate is smaller for high-productivity groups, the opposite is the case in our calibration. Two comments are in order: First, we set higher replacement rate for high-productivity groups in order to match the dispersion of the idiosyncratic shock. This depresses their surplus and increases the volatility. By targeting the same market tightness in each group, we reduce the surplus for low-productivity groups. The volatility of the job-finding rate for high-productivity groups is a bit higher than for low-productivity groups. Second, the standard deviations of the job-finding rate in the data (see Appendix C) speak a very different language as the comovements of job-finding rates with unemployment. They are very similar across groups. The job-finding rate in the data seems to be less synchronized with unemployment than the separation rate (i.e., it shows different lead-lag patterns).

4.3.3 Wage Dynamics with Heterogeneity and Counterfactual Exercises

Finally, we analyze the comovement of unemployment with the prior wage and with the fixed effects (defined as the deviation of the mean log average wage within each labor market segment from the overall mean) 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 I for details). We do so in the same way as in the data: Wages are defined as average over the year and unemployment is defined as the value at the end of the year. The model with our baseline calibration generates a positive comovement between unemployment and the prior wage of those who lost their job as well as their fixed effect (see Table 8). The estimated coefficients in model and data for the comovement with the prior wage are remarkably close (1.21 vs. 1.43). As in the data, the comovement of the fixed effects is more synchronized with unemployment than the comovement of the prior wage with unemployment. As the fixed effects represent the average wages, their dynamics is smoother than the one for the actual wage.

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.

[20] The comovement of the separation rate in the highest quartile is more volatile in the simulation than in the data. Keep in mind that these are log-deviations from a very low level (steady state separation rate is 0.005). Small absolute changes lead to large relative deviations. In Appendix K.2, we show that the wage dispersion in group 4 would have to be around 60 percent larger relative to group 1 to match the gradient of the separation rate from the data. Differences are smaller for groups 2 and 3.

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.

In order to understand the drivers for the positive comovement between the prior wage of workers who are separated and unemployment, we run two counterfactual exercises. First, we impose the much smaller flow rates (job-finding rate and separation rate) of group 1 to all other groups. We do so by adjusting the matching efficiencies and the replacement rate in the respective groups, while keeping all other parameters the same. Second, in addition, we impose the same surplus relative to productivity for all groups. We do by assuming the same replacement rate, the same hiring costs (relative to aggregate productivity) and the same matching efficiency. When imposing the same surplus relative to productivity, the standard deviation of the idiosyncratic match-specific shock changes. See Appendix J for parameter values.

Table 8: Estimated Comovement of Prior Wages and Fixed Effects with Unemployment

Comovem. with U	Data	Baseline	Same Flows	Same Surplus
Prior Wage of Unemployed	1.43	1.21	0.59	-0.71
Fixed Effect of Unemployed	2.09	2.06	0.88	0.00

Note: The table shows the estimated comovement of the prior wage and fixed effects of those who lost their job ("Unemployed") with aggregate unemployment in data and simulation. The scenario "Same Flows" imposes the same job-finding and separation rates on all labor market segments. In addition to this, the scenario "Same Surplus" imposes the same surplus relative to productivity in all segments. In analogy with the empirical data, aggregated annual simulated data is HP-filtered with smoothing parameter 6.25.

It is visible in Table 8 that the combination of group-specific separation rates and the idiosyncratic wage dispersion is important for replicating the strong positive comovement from the data. When we impose the same flow rates on all groups (scenario "Same Flows" in Table 8), the comovement between unemployment and the prior wage drops by roughly one half. Intuitively, the separation rate for workers with larger ex ante productivity increases and thereby log-deviations in response to a given aggregate shock fall (for a given idiosyncratic match-specific shock dispersion). Thus, composition effects over the business cycle become weaker. More importantly, when we impose the same relative surplus (scenario "Same Surplus" in Table 8), the comovement between prior wages and unemployment becomes negative. This shows that ex ante worker heterogeneity alone is not sufficient to generate the positive comovement between the prior wage and unemployment. It is the interaction with a different residual idiosyncratic match-specific shock across groups that matters, namely less dispersed shocks for high-wage workers. This confirms results by Mueller (2017) who proposed a similar mechanism in his quantitative model.

Unlike Mueller (2017), due to use of administrative panel data, we are able to compare the dynamics of fixed effects in data and model. In the scenario with the same flow rates and the same surplus, the comovement between the fixed effect and unemployment turns out to be zero. Intuitively, if all groups have the same flow rates and the same log-deviations of the separation rate, the composition of the pool of unemployment does not change over time.

In short, targeting the relative residual wage dispersion is crucial for obtaining simulation results that are in line with the patterns in the data. This exercise provides further support for the importance of the interaction of ex ante worker heterogeneity with less dispersed idiosyncratic match-specific shock for high-productivity workers.

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 substantially 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 ex ante worker heterogeneity in productivity. In order to match model and data, the lower idiosyncratic match-specific shock dispersion for high-wage workers is crucial, which we find in estimations based on administrative data. In short, our paper shows that the combination of ex ante heterogeneity with less dispersed idiosyncratic shocks for high-wage workers is key for many patterns in the data.

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.

References

Abowd, John M., Francis Kramarz, and David N. Margolis (1999) "High Wage Workers and High Wage Firms," *Econometrica*, Vol. 67, pp. 251–333.

Ahn, Hie Joo, Bart Hobijn, and Ayşegül Şahin (2023) "The Dual U.S. Labor Market Uncovered," NBER Working Paper 31241.

Bauer, Anja and Benjamin Lochner (2020) "History Dependence in Wages and Cyclical Selection: Evidence from Germany," *Labour Economics*, Vol. 67, p. 101932.

Bellmann, Lisa, Benjamin Lochner, Stefan Seth, and Stefanie Wolter (2020) "AKM Effects for German Labour Market Data," FDZ Methodenreport 01/2020, IAB Nuremberg.

Berge, Philipp Vom, Corinna Frodermann, Alexandra Schmucker, Stefan Seth, Tobias Graf, Stephan Grießemer, Steffen Kaimer, Markus Köhler, Claudia Lehnert, Martina Oertel, and Andreas Schneider (2019) "Schwach anonymisierte Version der Stichprobe der Integrierten Arbeitsmarktbiografien (SIAB) – Version 7519 v1."

Bils, Mark, Yongsung Chang, and Sun-Bin Kim (2012) "Comparative Advantage and Unemployment," *Journal of Monetary Economics*, Vol. 59, pp. 150–165.

Bils, M. J. (1985). Real Wages over the Business Cycle: Evidence from Panel Data. *Journal of Political Economy*, Vol. 93(4), 666–689. The University of Chicago Press.

Burdett, Kenneth, Carlos Carrillo-Tudela, and Melvyn Coles (2020) "The Cost of Job Loss," *The Review of Economic Studies*, Vol. 87, pp. 1757–1798.

Caballero, Ricardo and Mohamad L. Hammour (1994) "The Cleansing Effect of Recessions," *American Economic Review*, Vol. 84, pp. 1350–1368.

Cairó, Isabel and Tomaz Cajner (2018) "Human Capital and Unemployment Dynamics: Why more Educated Workers Enjoy Greater Employment Stability," *The Economic Journal*, Vol. 128, pp. 652–682.

Card, David, Jörg Heining, and Patrick Kline (2013) "Workplace Heterogeneity and the Rise of West German Wage Inequality," *The Quarterly Journal of Economics*, Vol. 128, pp. 967–1015.

Carrillo-Tudela, Carlos, Leo Kaas, and Benjamin Lochner (2023) "Matching Through Search Channels," IZA Discussion Papers 16583.

Chugh, Sanjay K. and Christian Merkl (2016) "Efficiency and Labor Market Dynamics in a Model of Labor Selection," *International Economic Review*, Vol. 57, pp. 1371–1404.

Dauth, Wolfgang and Johann Eppelsheimer (2020) "Preparing the Sample of Integrated Labour Market Biographies (SIAB) for Scientific Analysis: A Guide," *Journal for Labour Market Research*, Vol. 54, p. 10.

Davis, Steven J and Till M Von Wachter (2011) "Recessions and the Cost of Job Loss,"*Brookings Papers on Economic Activity*, Vol. 42, pp. 1–72.

Drechsel-Grau, Moritz, Andreas Peichl, Kai D Schmid, Johannes F Schmieder, Hannes Walz, and Stefanie Wolter (2022) "Inequality and Income Dynamics in Germany," *Quantitative Economics*, Vol. 13, pp. 1593–1635.

Dustmann, Christian, Johannes Ludsteck, and Uta Schönberg (2009) "Revisiting the German Wage Structure," *The Quarterly Journal of Economics*, Vol. 124, pp. 843–881.

Fitzenberger, Bernd and Ralf A Wilke (2010) "Unemployment Durations in West Germany before and after the Reform of the Unemployment Compensation System during the 1980s," *German Economic Review*, Vol. 11, pp. 336–366.

Figueiredo, A. (2022). Wage Cyclicality and Labor Market Sorting. *American Economic Review: Insights*, Vol. 4 (4), 425–442.

Ganzer, Andreas, Lisa Schmidtlein, Jens Stegmaier, and Stefanie Wolter (2021) "Establishment History Panel 1975-2019, Revised Version (v2) fromApril 2021."

Gartner, Hermann (2005) "The Imputation of Wages Above the Contribution Limit with the German IAB Employment Sample,"Technical report, Institut für Arbeitsmarkt-und Berufsforschung (IAB), Nürnberg [Institute for Employment Research].

Gartner, Hermann, Thorsten Schank, and Claus Schnabel (2013) "Wage Cyclicality under different Regimes of Industrial Relations," *Industrial Relations: A Journal of Economy and Society*, Vol. 52, pp. 516–540.

Gehrke, Britta, Wolfgang Lechthaler, and Christian Merkl (2019) "The German labor market during the Great Recession: Shocks and Institutions," *Economic Modelling*, Vol. 78, pp. 192–208.

Hall, Robert E. and Paul R. Milgrom (2008) "The Limited Influence of Unemployment on the Wage Bargain," *American Economic Review*, Vol. 98, p. 1653–74.

Hall, Robert E. and Sam Schulhofer-Wohl (2018) "Measuring Job-Finding Rates and Matching Efficiency with Heterogeneous Job-Seekers," *American Economic Journal: Macroeconomics*, Vol. 10, p. 1–32.

Hall, Robert and Marianna Kudlyak (2019) "Job-Finding and Job-Losing: A Comprehensive Model of Heterogeneous Individual Labor-Market Dynamics," NBER Working Paper 25625.

Hansch, Michelle (2025) "Smoothing the Turmoil: Harmonization of the 1988 Occupation Codes over Time,"Technical report, Institut für Arbeitsmarkt-und Berufsforschung (IAB), Nürnberg [Institute for Employment Research].

Hartung, Benjamin, Philip Jung, and Moritz Kuhn (2025) "Unemployment Insurance Reforms and Labour Market Dynamics," *The Review of Economic Studies*, p. forthcoming.

Hethey-Maier, Tanja and Johannes F Schmieder (2013) "Does the Use of Worker Flows Improve the Analysis of Establishment Turnover? Evidence from German Administrative Data," *Journal of Contextual Economics–Schmollers Jahrbuch*, pp. 477–510.

Hosios, Arthur J. (1990) "On The Efficiency of Matching and Related Models of Search and Unemployment," *The Review of Economic Studies*, Vol. 57, pp. 279–298.

Illing, Hannah, Johannes Schmieder, and Simon Trenkle (2024) "The Gender Gap in Earnings Losses after Job Displacement," *Journal of the European Economic Association*, Vol. 22, pp. 2108–2147.

Jarosch, Gregor (2023) "Searching for Job Security and the Consequences of Job Loss," *Econometrica*, Vol. 91, pp. 903–942.

Jung, Philip and Moritz Kuhn (2014) "Labour Market Institutions and Worker Flows: Comparing Germany and the US," *The Economic Journal*, Vol. 124, pp. 1317–1342.

Kohlbrecher, Britta, Christian Merkl, and Daniela Nordmeier (2016) "Revisiting the matching function," *Journal of Economic Dynamics and Control*, Vol. 69, pp. 350–374.

Lachowska, Marta, Isaac Sorkin, and Stephen A Woodbury (2022) "Firms and Unemployment Insurance Take-up,"Technical report, National Bureau of Economic Research.

Lochner, Benjamin, Stefan Seth, and Stefanie Wolter (2020) "Decomposing the large firm wage premium in Germany," *Economics Letters*, Vol. 194, p. 109368.

Mortensen, Dale T. and Christopher A. Pissarides (1994) "Job Creation and Job Destruction in the Theory of Unemployment," *The Review of Economic Studies*, Vol. 61, pp. 397–415.

Moser, Christian, Farzad Saidi, Benjamin Wirth, and Stefanie Wolter (2021) "Credit Supply, Firms, and Earnings Inequality,"Technical report, ECONtribute Discussion Paper.

Muehlemann, Samuel and Harald Pfeifer (2016) "The Structure of Hiring Costs in Germany: Evidence from Firm-Level Data," *Industrial Relations: A Journal of Economy and Society*, Vol. 55, pp. 193–218.

Mueller, Andreas I (2017) "Separations, Sorting, and Cyclical Unemployment," *American Economic Review*, Vol. 107, pp. 2081–2107.

Mukoyama, Toshihiko and Ayşegül Şahin (2006) "Costs of Business Cycles for Unskilled Workers," *Journal of Monetary Economics*, Vol. 53, pp. 2179–2193.

Petrongolo, Barbara and Christopher A. Pissarides (2001) "Looking into the Black Box: A Survey of the Matching Function," *Journal of Economic Literature*, Vol. 39, p. 390–431.

Pissarides, Christopher A. (2009) "The Unemployment Volatility Puzzle: Is Wage Stickiness the Answer?" *Econometrica*, Vol. 77, pp. 1339–1369.

Pries, Michael J. (2008) "Worker Heterogeneity and Labor Market Volatility in Matching Models," *Review of Economic Dynamics*, Vol. 11, pp. 664–678.

Ravn, Morten O and Harald Uhlig (2002) "On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations," *Review of Economics and Statistics*, Vol. 84, pp. 371–376.

Schmieder, Johannes F, Till Von Wachter, and Jörg Heining (2023) "The Costs of Job Displacement over the Business Cycle and its Sources: Evidence from Germany," *American Economic Review*, Vol. 113, pp. 1208–1254.

Shimer, Robert (2005) "The Cyclical Behavior of Equilibrium Unemployment and Vacancies," *American Economic Review*, Vol. 95, p. 25–49.

Silva, José Ignacio and Manuel Toledo (2009) "Labor Turnover Costs and the Cyclical Behavior of Vacancies and Unemployment," *Macroeconomic Dynamics*, Vol. 13, p. 76–96.

Stüber, Heiko (2017) "The Real Wage Cyclicality of Newly Hired and Incumbent Workers in Germany," *The Economic Journal*, Vol. 127, pp. 522–546.

Stüber, Heiko, Markus M. Grabka, and Daniel D. Schnitzlein (2023) "A Tale of Two Data Sets: Comparing German Administrative and Survey Data Using Wage Inequality as an Example," *Journal for Labour Market Research*, Vol. 57, p. 8.

Trenkle, Simon (2023) "Unemployment Insurance Receipt, Take-Up and Labor Market Conditions,"Technical report, Mimeo, IZA.

A Online Appendix: Data Details

A.1 Sample Selection

We restrict our observation period to 1985-2017 as the AKM effects are only estimated for this period.[21] 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 minimize variation in hours worked (which are not measured in the data). Our sample restrictions approximate those from the AKM estimation in Bellmann et al. (2020). 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. We correct for the 2011 occupational break in the data using the approach from Hansch (2025).

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).[22] Interruptions of these payments can occur for up to four weeks to six weeks due to sanctions. In those cases, we still consider the worker as unemployed to ensure the continuity of the unemployment status following Fitzenberger and Wilke (2010).

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 (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).[23] Otherwise, there may be the danger that the imputation procedure artificially affects the residual wage dispersion among high-wage groups.

Following Jung and Kuhn (2014), we construct a quarterly panel dataset based on the spell information 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-

[21] 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.

[22] As information on registered unemployment is available from 1997 onward only, the benefit-based approach is chosen to obtain a long and consistent definition of unemployment.

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

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, following Carrillo-Tudela et al. (2023), we standardize (z-score) the AKM worker/firm fixed effects to have mean 0 and standard deviation 1 in each of the different sub-periods using the distributional moments from Bellmann et al. (2020), then calculate the average z-score for each person and firm across the time intervals. This allows us to obtain a consistent (time-invariant) ranking of worker and firm unobserved heterogeneity across all time intervals. Finally, we group workers based into quartiles of AKM worker fixed effects based on the obtained worker distribution.

Table 9 gives summary statistics for 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 fixed effects, 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. Job turnover (defined as the absolute number of establishment changes per worker) drops with AKM worker FE, while education increases, as measured by an increasing share of workers with a 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 firm wage premia (Lochner et al., 2020).

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}.[24] 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.

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 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.

[24] 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.

Table 9: Summary statistics

Variable	AKM worker FE quartile				Total
	1	2	3	4	
Log real daily wage	4.12 (0.42)	4.46 (0.27)	4.61 (0.25)	4.75 (0.26)	4.48 (0.39)
Age	38.54 (11.03)	37.89 (10.97)	38.83 (10.99)	40.62 (11.13)	38.97 (11.08)
Women (%)	0.64 (0.48)	0.33 (0.47)	0.28 (0.45)	0.29 (0.45)	0.38 (0.49)
German (%)	0.84 (0.36)	0.89 (0.31)	0.93 (0.25)	0.95 (0.21)	0.90 (0.29)
Firm tenure (years)	5.93 (6.01)	7.54 (6.87)	9.15 (7.61)	9.85 (7.90)	8.12 (7.30)
Occupation tenure (years)	7.26 (6.47)	9.03 (7.18)	10.95 (7.99)	11.77 (8.38)	9.75 (7.74)
Job turnover	1.50 (2.20)	1.78 (2.43)	1.46 (2.04)	1.01 (1.57)	1.45 (2.12)
No vocational training (%)	0.27 (0.44)	0.15 (0.36)	0.08 (0.28)	0.05 (0.21)	0.14 (0.34)
Vocational training (%)	0.71 (0.46)	0.82 (0.38)	0.87 (0.33)	0.80 (0.40)	0.80 (0.40)
University degree (%)	0.03 (0.16)	0.03 (0.16)	0.04 (0.20)	0.15 (0.36)	0.06 (0.24)
Log firm size	4.07 (2.04)	4.66 (2.14)	4.93 (2.21)	4.80 (2.16)	4.61 (2.17)
AKM worker FE (z-score)	-0.90 (0.58)	-0.16 (0.11)	0.17 (0.09)	0.68 (0.31)	-0.05 (0.66)
AKM firm FE (z-score)	0.47 (0.54)	0.67 (0.44)	0.73 (0.40)	0.66 (0.45)	0.63 (0.47)
Number of observations (worker x quarter)	6105576	6105579	6105670	6105479	24422304

Note: SIAB 1985-2017. Standard deviation in parentheses. Job turnover corresponds to the average number of times that a worker changes establishments.

B Unconditional Moments across Educational Groups

Table 10 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 10: Relative, Absolute Deviations, and Means by Education

Log deviations	No voc. training	Vocational training	University degree
Separation rate	0.119	0.116	0.122
Job-finding rate	0.096	0.065	0.155
Unemployment rate	0.092	0.101	0.102
Absolute deviations	**No voc. training**	**Vocational training**	**University degree**
Separation rate	0.251	0.151	0.156
Job-finding rate	0.969	0.970	1.82
Unemployment rate	0.816	0.487	0.495
Levels (means)	**No voc. training**	**Vocational training**	**University degree**
Separation rate	2.03	1.26	1.23
Job-finding rate	9.94	15.1	13.6
Unemployment rate	9.92	4.77	4.55

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 11 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 11: Relative, Absolute Deviations, and Means by AKM Worker FE

	AKM Worker FE Quartile			
Log deviations	1	2	3	4
Separation rate	0.104	0.139	0.128	0.127
Job-finding rate	0.084	0.085	0.078	0.081
Unemployment rate	0.095	0.115	0.114	0.105
Absolute deviations	1	2	3	4
Separation rate	0.284	0.211	0.104	0.068
Job-finding rate	0.880	1.530	1.597	1.256
Unemployment rate	1.032	0.595	0.299	0.204
Means	1	2	3	4
Separation rate	2.6	1.45	0.79	0.52
Job-finding rate	10.8	18.1	20.1	15.7
Unemployment rate	11.4	5.00	2.53	1.91

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 Comovement of Previous Residual Wage with Unemployment Rate

As in Table 1, we calculate the comovement of the previous residual wage among those losing their job and the contemporaneous unemployment rate each year subsequently adding firm covariates and fixed effects. Consistent with Table 1, 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 comovement between the previous residual wage of those losing their job and aggregate unemployment.

Table 12: Cyclicality of previous residual wage among the Unemployed

Comovement with	Unemployed, measure from previous year	
	Residual wage (worker observables)	Residual wage (additionally controlling for firm covariates)
Unemployment rate	0.85*	0.52*
Observations	32	32
	Residual wage (additionally controlling for AKM worker FE)	Residual wage (additionally controlling for one-way worker FE)
Unemployment rate	0.24	0.33
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 Separation Rate Dynamics Above/Below Median

Figure 3 shows the separation rate above and below the median wage.

Figure 3: 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.

F Empirical Robustness Checks

F.1 Excluding Workers that Experience Firm Closures

As a further robustness check to our baseline analysis with firm closures, we exclude all workers that experience a plant closure event at least once in their employment biographies, re-estimate all Mincer regressions and re-calculate group-specific transition rates and cyclicalities.

Overall, excluding workers that experience a plant closure event has a negligible impact on our findings. As Table 13 shows, excluding plant closure events, separations remain more cyclical for high-wage workers by a factor of 1.96, and additionally controlling for AKM worker fixed effects eliminates the high-low differences in the separation rate cyclicality. Table 14 and Table 15 additionally show that the separation rate cyclicality is increasing with worker fixed effects, and that the comovements of the previous wage of the unemployed with aggregate unemployment are very similar to the baseline.

Table 13: Cyclicality and Level of Transition Rates by Worker Groups Excl. Workers in Firm Closures

		(I) Raw wage		(II) + Baseline controls		(III) + Firm-level controls		(IV) + AKM worker FE		(V) + One-way worker FE	
		Below	Above	Below	Above	Below	Above	Below	Above	Below	Above
Separation Rate	Cyclicality	0.45***	0.88***	0.47***	0.70***	0.48***	0.65***	0.58***	0.48**	0.52***	0.56***
	Mean	1.99	0.52	1.71	0.80	1.55	0.95	1.33	1.18	1.38	1.13
Job-Finding Rate	Cyclicality	-0.21**	-0.19**	-0.21**	-0.21**	-0.22**	-0.20**	-0.18	-0.23***	-0.15	-0.27***
	Mean	13.5	14.9	12.9	15.5	12.1	16.4	12.9	14.3	12.0	15.7
Job-to-Job Rate	Cyclicality	-0.95***	-0.67***	-0.96***	-0.71***	-0.97***	-0.81***	-0.92***	-0.86***	-0.93***	-0.85***
	Mean	2.69	1.26	2.31	1.65	2.11	1.85	2.14	1.82	2.25	1.71

Note: Following Mueller (2017), the cyclicality of the series is measured as the coefficient β in the regression $ln(x_{j,t}) = \alpha + \beta \times ln(U_t) + \epsilon_{j,t}$, where $x_{j,t}$ is the separation, job finding, or job-to-job rate of group j 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 3 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, occupation and firm tenure, gender, German nationality, education (3 categories), occupation (2-digit) and year dummies. In a second step, we add firm covariates: log establishment size, AKM firm fixed effects and dummies for labor market regions. In a third step, we add AKM worker fixed effects.For the estimation with one-way worker fixed effects, we remove the AKM firm fixed effects and control for log establishment size, 3-digit industries and labor market regions instead. SIAB 1986-2017. ***p<0.01, **p<0.05, *p<0.10

Table 14: Cyclicality of Transition Rates by AKM Worker FE Groups Excl. Workers in Firm Closures

		AKM Worker FE Quartile			
		1	2	3	4
Separation Rate	Cyclicality	0.39**	0.75***	0.85***	0.89***
	Mean	2.47	1.34	0.72	0.49
Job-Finding Rate	Cyclicality	-0.44***	-0.08	-0.05	-0.18**
	Mean	10.6	17.9	19.6	15.3
Job-to-Job Rate	Cyclicality	-1.01***	-0.76***	-0.81***	-0.70***
	Mean	2.36	2.34	1.91	1.66

Note: The cyclicality of the series is measured as the coefficient β in the regression $ln(x_{j,t}) = \alpha + \beta \times ln(U_t) + \epsilon_{j,t}$. 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 3 and 128 quarterly observations are used in the regressions. SIAB 1986-2017. ***p<0.01, **p<0.05, *p<0.10

Table 15: Cyclicality of Previous Wage among the Unemployed Excl. Workers in Firm Closures

Comovement with	Unemployed, measure from previous year	
	Raw wage	Wage Rank
Unemployment rate	1.39**	0.69**
Observations	32	32
	AKM worker fixed effect	Residual wage (additionally controlling for AKM worker FE)
Unemployment rate	2.03***	0.22
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 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

F.2 Separation Rate Dynamics for Mass-Layoff Events

In the baseline analysis, we proxy for financial constraints based on plant closures as these events can be well-identified in the SIAB, thus minimizing concerns over capturing restructuring and relabeling of firms (Hethey-Maier and Schmieder, 2013). However, focusing on plant closures may understate the importance of financial frictions to the extent that the firm does not completely shut down as a result of cyclical financial constraints. To rule out that our proxy for financial frictions based on plant closures is driving our result on the relatively low importance of cyclical cash flow constraints for aggregate dynamics, Table 16 shows the cyclical dynamics of the separation rate among EU separations that occur as a result a mass layoff, and other EU separations.

Following Davis and Von Wachter (2011) and Jarosch (2023), a mass layoff is recorded in year t if the establishment had at least 50 employees in $t-2$, employment falls by 30% to 99% between $t-2$ and t, employment in $t-2$ is not more than 130% of employment in $t-3$ and employment in $t+1$ is not more than 90% of employment in $t-2$. The conditions in the years before and after the mass layoff avoid capturing short-term firm employment fluctuations. As Table 16 shows, accounting for mass layoffs does not substantially change the pattern shown with plant closures, with EU transitions from mass-layoff events still being too small to meaningfully impact aggregate dynamics. In line with this, the separation rate cyclicality for other separations that are not due to mass layoffs is close to the baseline estimate for all separations. Thus, we have no indication that financial frictions (proxied by mass-layoff events) are a key driver for our documented empirical results.

Table 16: Separation rate cyclicality and mass-layoff events

	Separation rate concept					
	All separations (EU)		Mass layoffs only ($EU^{masslayoffs}$)		Excl. mass layoffs (EU^{other})	
	Below	Above	Below	Above	Below	Above
Cyclicality	0.48***	0.91***	0.38	1.92***	0.48***	0.86***
Mean	2.12	0.56	0.05	0.02	2.07	0.54
Observations	128	128	128	128	128	128

Note: The cyclicality of the series is measured as the coefficient β in the regression $ln(x_{j,t}) = \alpha + \beta \times ln(U_t) + \epsilon_{j,t}$. 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 3 and 128 quarterly observations are used in the regressions. SIAB 1986-2017. ***p<0.01, **p<0.05, *p<0.10

F.3 Results Based on Imputed Wages

In the SIAB data, wages are censored at the social security contribution ceiling. To predict the missing wage data, we follow Card et al. (2013), Dauth and Eppelsheimer (2020) and Dustmann et al. (2009) and impute wage observations above the social security ceiling based on a two-step procedure. In a first step, we fit Tobit wage equations separately by year and three education groups. All regressions control for gender, age and age squared interacted with an indicator for workers above 40 years of age, firm tenure and firm tenure squared, measured experience and German nationality dummy. In a second step, we repeat the Tobit wage regressions using the leave-one-out means of average log wage of each worker over time and of all workers within each establishments in a given year. Following Gartner (2005), to avoid that the correlation of imputed wages with the covariates is higher than the correlation of true unobserved wages with the covariates, we assume wages are log-normally distributed and add a normally distributed random term to the fitted values.

Table 17 shows the main results on the cyclicalities of transition rates above/below the median wage based on imputed wages. In terms of the raw wage, workers above the median have 1.84 more cyclical separations, while differences in the job-finding rate remain small. In addition, after controlling for AKM worker fixed effects, differences in the cyclicalities of the separation rate disappear, as in the baseline. Table 18 shows that separations still progressively become more cyclical in higher AKM fixed-effect groups for the imputed wage sample, while Table 19 shows that the comovement of the previous wage of the unemployed with aggregate unemployment increases a bit relative to the baseline (1.52 vs. 1.43 in the baseline), as the dispersion in the wage distribution is increased by including the upper (imputed) tail. This is also reflected in terms of a bit stronger comovement of the previous worker fixed effects of the unemployed. Still, the comovement is not statistically significant in terms of the previous residual wage when additionally controlling for AKM worker fixed effects. In short, our key empirical results are unaffected when we use imputed wages instead of excluding workers that cross the social security contribution ceiling once.

The wage imputation, while doing a fairly good job at approximating the top tail of the distribution, cannot fully compensate for the information loss due to censoring and the resulting biases. See Drechsel-Grau et al. (2022) for a detailed discussion on this and a comparison to uncensored tax data.

For the dispersion of residual wages, the imputation comes with a caveat. As imputed wages contain both the fitted value and a normally distributed random draw, the estimated dispersion of residual wages with imputed wages is likely to be larger due to the imputation method. By construction, imputed wages always contain a drawn random shock component that cannot be predicted with observed characteristics or fixed effects.

Table 17: Cyclicality and Level of Transition Rates by Worker Groups incl. Imputed Wages.

		(I) Raw wage		(II) + Baseline controls		(III) + Firm-level controls		(IV) + AKM worker FE		(V) + One-way worker FE	
		Below	Above	Below	Above	Below	Above	Below	Above	Below	Above
Separation Rate	Cyclicality	0.50***	0.95***	0.50***	0.73***	0.52***	0.66***	0.62***	0.53**	0.54***	0.62***
	Mean	1.85	0.42	1.82	0.86	1.31	0.95	1.11	1.15	1.21	1.05
Job-Finding Rate	Cyclicality	-0.21**	-0.30**	-0.26**	-0.18**	-0.29**	-0.16*	-0.23**	-0.23***	-0.18	-0.30***
	Mean	13.8	15.5	13.0	15.8	12.0	16.6	13.1	14.4	11.9	16.1
Job-to-Job Rate	Cyclicality	-0.88***	-0.59***	-0.86***	-0.64***	-0.89***	-0.73***	-0.82***	-0.67***	-0.84***	-0.74***
	Mean	2.64	1.51	2.32	1.83	2.10	2.06	2.17	1.98	2.32	1.84

Note: Following Mueller (2017), the cyclicality of the series is measured as the coefficient β in the regression $ln(x_{j,t}) = \alpha + \beta \times ln(U_t) + \epsilon_{j,t}$, where $x_{j,t}$ is the separation, job finding, or job-to-job rate rate of group j 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 3 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, occupation and firm tenure, gender, German nationality, education (3 categories), occupation (2-digit) and year dummies. In a second step, we add firm covariates: log establishment size, AKM firm fixed effects and dummies for labor market regions. In a third step, we add AKM worker fixed effects. In a fourth step, for the estimation with one-way worker fixed effects, we remove the AKM firm fixed effects and control for log establishment size, 3-digit industries and labor market regions instead. SIAB 1986-2017. ***p<0.01, **p<0.05, *p<0.10

Table 18: Cyclicality of Transition Rates by AKM Worker FE Groups incl. Imputed Wages

		AKM Worker FE Quartile			
		1	2	3	4
Separation Rate	Cyclicality	0.45**	0.82***	0.87***	1.00***
	Mean	2.41	1.15	0.58	0.39
Job-Finding Rate	Cyclicality	-0.41***	-0.04	-0.11	-0.29**
	Mean	11.6	19.2	17.9	12.6
Job-to-Job Rate	Cyclicality	-0.97***	-0.81***	-0.78***	-0.55***
	Mean	2.40	2.17	1.81	1.91

Note: The cyclicality of the series is measured as the coefficient β in the regression $ln(x_{j,t}) = \alpha + \beta \times ln(U_t) + \epsilon_{j,t}$. 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 3 and 128 quarterly observations are used in the regressions. SIAB 1986-2017. ***p<0.01, **p<0.05, *p<0.10

Table 19: Cyclicality of Previous Wage among the Unemployed incl. Imputed Wages

Comovement with	Unemployed, measure from previous year	
	Raw wage	Wage Rank
Unemployment rate	1.52*	0.66*
Observations	32	32
	AKM worker fixed effect	Residual wage (additionally controlling for AKM worker FE)
Unemployment rate	2.33***	0.25
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 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

Table 20 shows the dispersion of residual wages across worker fixed effects quartiles with imputed wages. As the random shock draw cannot be captured with covariates, the standard deviation is particularly large for the top quartile (standard deviation of 1.49 relative to the first quartile). As we believe that this larger dispersion is partly an artifact of the imputation,[25] we abstain from calibrating our model based on these residual wage numbers and follow Stüber (2017) and Bauer and Lochner (2020) by focusing on uncensored wage observations.

[25] See also Stüber et al. (2023) for a comparison of administrative wages and survey wages, specifically the deviations at the 90th percentile of the distribution.

Table 20: Residual Wage Dispersion by AKM Worker FE Groups incl. Imputed Wages

	AKM worker FE quartile			
	1	2	3	4
Std. deviation of residual wage (level)	0.261	0.163	0.186	0.389
Normalized (relative to quartile 1)	1.00	0.62	0.71	1.49

Note: the table shows the standard deviation of the level of residual wages from a Mincer-type regression controlling for a third-order polynomial in age, firm and occupational tenure, dummies for education, occupation, labor market regions, German nationality, calendar year and including AKM worker and firm fixed effects. Note: SIAB 1985-2017.

F.4 Excluding Workers with Low Turnover

The AKM model identifies separately additive firm and worker fixed effects based on a connected set of establishments that are linked by worker mobility (Abowd et al., 1999). Consequently, in the presence of lacking job mobility, there is the risk that worker fixed effects capture job attributes rather than worker time-invariant characteristics. For workers that never change establishments in the observation period, AKM worker fixed effects are imputed as the average residual wage, where the residual wage is given by the raw log daily wage net of time-varying observables and the estimated AKM firm fixed effects (Card et al., 2013).

To address this concern, we restrict the sample to workers that move at least twice in the entire observation window (1985-2017), re-run the Mincer regressions and re-calculate group-specific transition rates and cyclicalities. Full-time workers in our observation period change establishments on average 1.35 times in their employment biographies (see Table 9), such that restricting to at least two moves is quite restrictive, effectively dropping 69% of full-time workers in our sample.

Table 21 shows the levels and cyclicality of transition rates for the restricted sample of movers. In terms of the raw wage, workers above the median have 1.6 more cyclical separations with small differences in job-finding rates, while the dominant role of the worker fixed effects remains robust. The overall level of separations increases relative to the full sample, which reflects the inherent higher mobility of the restricted sample. Tables 22 and 23 show that, for the sample of workers with high job turnover, the cyclicality of the separation rate also increases with the AKM worker fixed effect, and the comovement of aggregate unemployment with the previous wage remains positive (1.32 vs. 1.43 in the baseline), and turns insignificant once adding AKM worker fixed effects. Finally, Table 24 shows that the residual wage dispersion across quartiles of worker fixed effects is comparable to that in the baseline. Overall, the results indicate that limited mobility does not impact our key conclusions.

Table 21: Cyclicality and Level of Transition Rates by Worker Groups for High Turnover Workers.

		(I) Raw wage		(II) + Baseline controls		(III) + Firm-level controls		(IV) + AKM worker FE		(V) + One-way worker FE	
		Below	Above	Below	Above	Below	Above	Below	Above	Below	Above
Separation Rate	Cyclicality	0.56***	0.90***	0.58***	0.72***	0.59***	0.69***	0.66***	0.58***	0.63***	0.63***
	Mean	3.15	0.93	2.71	1.37	2.49	1.59	2.14	1.94	2.16	1.92
Job-Finding Rate	Cyclicality	-0.30**	-0.40**	-0.30**	-0.36***	-0.33***	-0.30***	-0.24*	-0.38***	-0.24*	-0.38***
	Mean	17.8	22.2	17.5	21.6	16.9	22.0	17.9	19.5	17.5	20.1
Job-to-Job Rate	Cyclicality	-0.85***	-0.61***	-0.86***	-0.62***	-0.85***	-0.72***	-0.82***	-0.75***	-0.85***	-0.71***
	Mean	5.06	2.79	4.54	3.33	4.20	3.67	4.34	3.53	4.44	3.43

Note: Following Mueller (2017), the cyclicality of the series is measured as the coefficient β in the regression $ln(x_{j,t}) = \alpha + \beta \times ln(U_t) + \epsilon_{j,t}$, where $x_{j,t}$ is the separation, job finding, or job-to-job rate rate of group j 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 3 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, occupation and firm tenure, gender, German nationality, education (3 categories), occupation (2-digit) and year dummies. In a second step, we add firm covariates: log establishment size, AKM firm fixed effects and dummies for labor market regions. In a third step, we add AKM worker fixed effects. For the estimation with one-way worker fixed effects, we remove the AKM firm fixed effects and control for log establishment size, 3-digit industries and labor market regions instead. SIAB 1986-2017. ***p<0.01, **p<0.05, *p<0.10

Table 22: Cyclicality of Transition Rates by AKM Worker FE Groups for High Turnover Workers.

		AKM Worker FE Quartile			
		1	2	3	4
Separation Rate	Cyclicality	0.50***	0.77***	1.01***	0.94***
	Mean	3.75	2.26	1.35	0.83
Job-Finding Rate	Cyclicality	-0.60***	-0.24*	-0.08	-0.16
	Mean	14.7	22.0	26.1	23.7
Job-to-Job Rate	Cyclicality	-0.91***	-0.75***	-0.66***	-0.67***
	Mean	4.25	4.08	3.74	3.62

Note: The cyclicality of the series is measured as the coefficient β in the regression $ln(x_{j,t}) = \alpha + \beta \times ln(U_t) + \epsilon_{j,t}$. 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 3 and 128 quarterly observations are used in the regressions. SIAB 1986-2017. ***p<0.01, **p<0.05, *p<0.10

Table 23: Cyclicality of Previous Wage among the Unemployed for High Turnover Workers.

Comovement with	Unemployed, measure from previous year	
	Raw wage	Wage Rank
Unemployment rate	1.32*	0.61**
Observations	32	32
	AKM worker fixed effect	Residual wage (additionally controlling for AKM worker FE)
Unemployment rate	1.90***	0.23
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 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

Table 24: Residual Wage Dispersion by AKM Worker FE Groups for High Turnover Workers

	AKM worker FE quartile			
	1	2	3	4
Std. deviation of residual wage (level)	0.260	0.167	0.153	0.165
Normalized (relative to quartile 1)	1.00	0.64	0.59	0.63

Note: the table shows the standard deviation of the level of residual wages from a Mincer-type regression controlling for a third-order polynomial in age, firm and occupational tenure, dummies for education, occupation, labor market regions, German nationality, calendar year and including AKM worker and firm fixed effects. Note: SIAB 1985-2017.

F.5 Different Smoothing Parameter for HP Filter

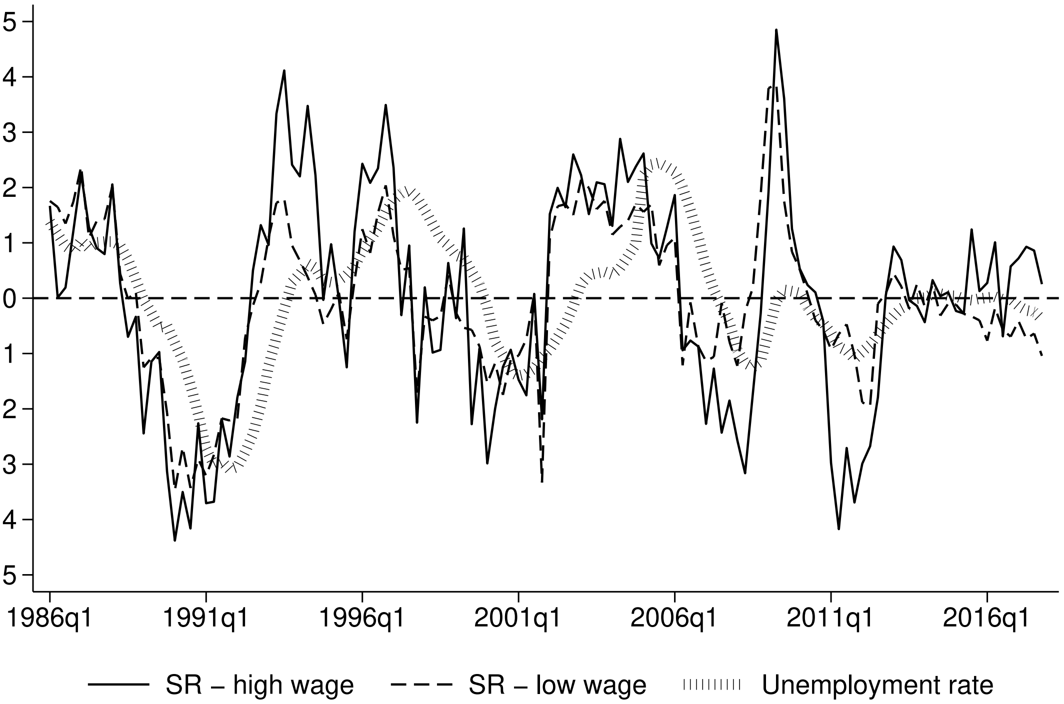
In our baseline analysis, we follow Ravn and Uhlig (2002) and use the recommended smoothing parameters, λ, of 1600 for quarterly data and 6.25 for annual data. In this Appendix, we present results based on Shimer (2005)'s values of $\lambda = 100,000$ for quarterly data and $\lambda = 100$ for annual data, as in Mueller (2017). Larger values for the smoothing parameter reduce the volatility of the cyclical component of all series, but separations remain more volatile and cyclical in relative terms for high-wage workers than for low-wage workers, while differences in the job-finding rates are small. Subsequently adding worker and firm controls, yields a similar dominant role for the worker fixed effect as in the baseline.

However, all quantitative results are somewhat less pronounced than in the main part and show less statistical significance. This can be best understood when comparing Figure 3 to Figure 4. It is visible that the key patterns are very similar. The logarithm of the separation rate for high-wage workers is clearly more volatile than for low-wage workers. However, this is not fully reflected in the estimated comovement with unemployment due to different lead-lag patterns with $\lambda = 100,000$. The time series for the previous wage behave very differently at the beginning and at the end of the sample (see Figure 5). In other words, the HP filter creates a well-known endpoint problem.[26] We consider the smoothing parameters of $\lambda = 1600$ for quarterly data and $\lambda = 6.25$ for annual data as more suitable for the German case.

Maybe most importantly, the positive comovement between the prior fixed effects of those workers losing their job and unemployment remains very robust. It is only the more noisy actual wage series that loses statistical significance. Thus, our key story remains unaffected that recessions are episodes when relatively more workers with permanently higher wages lose their job.

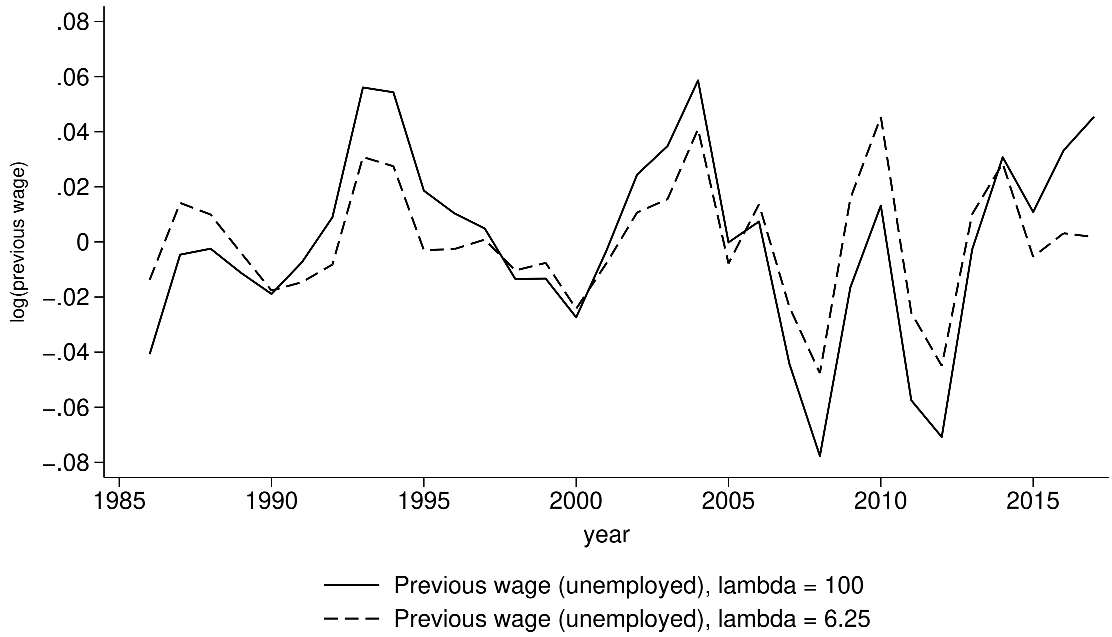
[26] For example, when removing the first and last five years in the sample (after HP-filtering), the difference in the comovement of the separation rate with unemployment (above and below the median wage) with the two smoothing parameters shrinks considerably. In this case, the separation rate cyclicality under $\lambda = 100,000$ is 0.45*** for below-median wage vs. 0.72*** above-median wage, compared to 0.44*** for below-median wage and 0.91*** for above-median wage under $\lambda = 1600$.

Figure 4: Cyclical Component of Separation Rate by Wage Group, 1986-2017 with $\lambda =$ 100,000.



Note: SIAB, 1986-2017. Series are quarterly observations, seasonally adjusted using X-13ARIMA-SEATS and HP-filtered using a smoothing parameter of 100,000 to obtain the cyclical component. Workers are grouped based on the median daily wage for full-time workers in each year.

Figure 5: Previous wage of the unemployed with $\lambda = 6.25$ and $\lambda = 100$.



Note: SIAB, 1986-2017. Each series is generated by keeping the worker observation each June 30th (in unemployment), imputing the observed workers' daily wages from the previous year, calculating the average yearly series for the unemployed and HP-filtering with different smoothing parameters.

Table 25: Cyclicality and Level of Transition Rates by Worker Groups based on HP-filter with $\lambda = 100{,}000$.

		(I) Raw wage		(II) + Baseline controls		(III) + Firm-level controls		(IV) + AKM worker FE		(V) + One-way worker FE	
		Below	Above	Below	Above	Below	Above	Below	Above	Below	Above
Separation Rate	Cyclicality	0.60***	0.80***	0.62***	0.69***	0.59***	0.73***	0.69***	0.60**	0.63***	0.65***
	Mean	2.12	0.56	1.82	0.86	1.65	1.03	1.42	1.26	1.47	1.22
Job-Finding Rate	Cyclicality	-0.13	0.01	-0.09	-0.12	-0.09	-0.10	-0.07	-0.10	-0.05	-0.13
	Mean	13.8	15.5	13.2	15.8	12.4	16.7	13.3	14.7	12.3	16.0
Job-to-Job Rate	Cyclicality	-0.86***	-0.53***	-0.82***	-0.65***	-0.84***	-0.72***	-0.78***	-0.79***	-0.80***	-0.78***
	Mean	2.82	1.32	2.42	1.72	2.21	1.93	2.24	1.91	2.35	1.80

Note: Following Mueller (2017), the cyclicality of the series is measured as the coefficient β in the regression $ln(x_{j,t}) = \alpha + \beta \times ln(U_t) + \epsilon_{j,t}$, where $x_{j,t}$ is the separation, job finding, or job-to-job rate rate of group j 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 100,000. Newey-West standard errors with lag order of 3 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, occupation and firm tenure, gender, German nationality, education (3 categories), occupation (2-digit) and year dummies. In a second step, we add firm covariates: log establishment size, AKM firm fixed effects and dummies for labor market regions. In a third step, we add AKM worker fixed effects. In a fourth step, for the estimation with one-way worker fixed effects, we remove the AKM firm fixed effects and control for log establishment size, 3-digit industries and labor market regions instead. SIAB 1986-2017. ***p<0.01, **p<0.05, *p<0.10

Table 26: Cyclicality of Transition Rates by AKM Worker FE Groups with λ = 100,000

		AKM Worker FE Quartile			
		1	2	3	4
Separation Rate	Cyclicality	0.48***	0.87***	0.95***	0.76***
	Mean	2.6	1.45	0.79	0.52
Job-Finding Rate	Cyclicality	-0.32***	-0.01	0.15	-0.26*
	Mean	10.8	18.1	20.1	15.7
Job-to-Job Rate	Cyclicality	-0.93***	-0.71***	-0.69***	-0.59***
	Mean	2.36	2.34	1.91	1.66

Note: The cyclicality of the series is measured as the coefficient β in the regression $ln(x_{j,t}) = \alpha + \beta \times ln(U_t) + \epsilon_{j,t}$. All series are seasonally-adjusted using X-13ARIMA-SEATS, detrended using an HP filter with smoothing parameter of 100,000. Newey-West standard errors with lag order of 3 and 128 quarterly observations are used in the regressions. SIAB 1986-2017. ***p<0.01, **p<0.05, *p<0.10

Table 27: Cyclicality of Previous Wage among the Unemployed based on HP-filter with $\lambda = 100$.

Comovement with	Unemployed, measure from previous year	
	Raw wage	Wage Rank
Unemployment rate	0.83	0.44**
Observations	32	32
	AKM worker fixed effect	Residual wage (additionally controlling for AKM worker FE)
Unemployment rate	1.81***	0.17
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 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 $\lambda = 100$. SIAB 1986-2017. ***p<0.01, **p<0.05, *p<0.10

F.6 Cyclicality of Sample Attrition

In the SIAB dataset, sample attrition may occur if individuals leave the labor force, become self-employed, move abroad or become civil servants in the public sector. To the extent that sample attrition is nonrandom across worker groups, the documented shifts in the pool of unemployed toward high-wage workers may be mechanically driven by a higher likelihood for low-wage workers to leave the pool of unemployed by dropping out of the sample which may as well vary over the business cycle. To assess the impact of cyclical sample attrition, we check the cyclicality of unemployment to non-participation rates (UN) across worker fixed-effect groups. In each period t, the UN rate is defined as the number of transitions from the pool of unemployment insurance recipients into out of the data, divided by the stock of unemployment insurance recipients in the previous periods $t-1$. After calculating the UN rate, we check level differences and the cyclicality across worker fixed-effect groups in Table 28.

Table 28 shows that the level of the UN rate increases with the worker fixed effect, contrary to the concern that attrition may be concentrated among low-wage earners. In addition, the cyclicality (albeit imprecisely estimated) also increases with the worker fixed effect. These patterns indicate that attrition out of the pool of unemployed is not selected toward low fixed-effect workers. To the contrary, high fixed-effect workers are more likely to leave the dataset following unemployment.

Table 28: Cyclicality of UN rate across Worker FE Groups

	AKM Worker FE Quartile			
	1	2	3	4
Cyclicality	-0.24	-0.21	-0.30*	-0.30*
Mean	9.60	9.78	11.5	14.1
Observations	128	128	128	128

Note: The cyclicality of the series is 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 3 and 128 quarterly observations are used in the regressions. SIAB 1986-2017. ***p<0.01, **p<0.05, *p<0.10

F.7 Cyclicality of Unemployment Insurance Take-Up

Unemployment insurance take-up is not necessarily given following separations among eligible workers. For Germany, Trenkle (2023) shows that, among likely eligible separators, only 73% claim unemployment insurance benefits in the first year following the separation. The share of unemployment insurance recipients increases in recessions, a pattern that is not mechanically driven by longer unemployment durations in recessions as take-up increases immediately after job loss. Similarly, for Washington state, Lachowska et al. (2022) find that about 45% of likely eligible separators in fact claim unemployment insurance.

In our baseline results, we define unemployment based on unemployment insurance benefit recipience, such that differential take-up rates across workers groups may in principle impact the documented shifts in the pool of unemployed. For example, if high-wage workers are more likely than low-wage workers to claim unemployment insurance benefits during cyclical downturns, our baseline definition of separation rates may overstate separations among high-wage workers relative to low-wage workers and consequently, the shift in the pool of unemployed toward high-wage workers.

To evaluate the impact of differential take-up behavior, we construct transition rates based on registered unemployment status, which is available in the SIAB data from 1997 onward. Under the registered-based definition, we consider a worker as unemployed whenever we observe the worker registered as unemployed, which may or may not overlap with parallel unemployment insurance benefits as benefits need to be subsequently applied for. Under the benefit-based definition, a worker is unemployed if and only if we observe receipt unemployment insurance benefits.

Table 29 shows the level and cyclicality of the separation rate under the registered unemployment definition and Table 30 under the benefit-based definition for the period 1998-2017 (80 quarters). Under both definitions, separations remain more cyclical among high-wage workers while the levels of the separation rate remain similar. At face value, the high-low difference in the separation rate cyclicality in terms of the raw wage equals 0.40 vs. 0.96 for benefit-based and 0.26 vs. 0.85 for registered unemployment. Under both definitions of the separation rate, progressively adding worker fixed effects yields an elasticity of the separation rate with respect to unemployment that is no longer more volatile for high-wage workers than for low-wage workers. Consistent with findings from Trenkle (2023), we observe that under the benefit-based definition, there is a more statistically significant comovement of the separation rate with the unemployment rate, consistent with unemployment insurance take-up being cyclical.

The observation period in this robustness check is substantially shorter than in the baseline. This leads to a fall in statistical significance. Thereby, the results have to be taken with a grain of salt. However, most importantly, our key results remain unaffected.

The separation rate for high-wage workers is larger than for low-wage workers based on raw wages. This is no longer the case once we control for worker fixed effects.

Table 29: Cyclicality and Level of Transition Rates by Worker Groups based on Registered Unemployment.

		(I) Raw wage		(II) + Baseline controls		(III) + Firm-level controls		(IV) + AKM worker FE		(V) + One-way worker FE	
		Below	Above	Below	Above	Below	Above	Below	Above	Below	Above
Separation Rate	Cyclicality	0.26	0.85***	0.32	0.47*	0.32	0.47*	0.48**	0.23	0.38*	0.36
	Mean	2.06	0.46	1.74	0.77	1.55	0.96	1.31	1.21	1.47	1.22
Job-Finding Rate	Cyclicality	-0.53***	-0.60***	-0.50***	-0.62***	-0.50***	-0.62***	-0.42***	-0.66***	-0.30***	-0.64***
	Mean	17.5	19.6	16.8	20.6	16.0	21.3	16.8	18.9	16.7	19.4
Job-to-Job Rate	Cyclicality	-1.08***	-0.82***	-1.11***	-0.85***	-1.06***	-0.86***	-1.01***	-0.91***	-1.02***	-0.89***
	Mean	2.82	1.32	2.43	1.73	2.18	1.97	2.21	1.94	2.34	1.81

Note: Following Mueller (2017), the cyclicality of the series is measured as the coefficient β in the regression $ln(x_{j,t}) = \alpha + \beta \times ln(U_t) + \epsilon_{j,t}$, where $x_{j,t}$ is the separation, job finding, or job-to-job rate rate of group j 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 2 and 80 quarterly observations are used in the regressions. Residual wages are obtained from regression controlling first for observable worker covariates: third-order polynomial in age, occupation and firm tenure, gender, German nationality, education (3 categories), occupation (2-digit) and year dummies. In a second step, we add firm covariates: log establishment size, AKM firm fixed effects and dummies for labor market regions. In a third step, we add AKM worker fixed effects. In a fourth step, for the estimation with one-way worker fixed effects, we remove the AKM firm fixed effects and control for log establishment size, 3-digit industries and labor market regions instead.SIAB 1998-2017. ***p<0.01, **p<0.05, *p<0.10

Table 30: Cyclicality and Level of Transition Rates by Worker Groups based on Benefit Recipience.

		(I) Raw wage		(II) + Baseline controls		(III) + Firm-level controls		(IV) + AKM worker FE		(V) + One-way worker FE	
		Below	Above	Below	Above	Below	Above	Below	Above	Below	Above
Separation Rate	Cyclicality	0.40*	0.96***	0.46**	0.60**	0.45**	0.58**	0.59***	0.39	0.48**	0.52*
	Mean	2.11	0.47	1.79	0.79	1.60	0.98	1.37	1.22	1.39	1.20
Job-Finding Rate	Cyclicality	-0.17	-0.22*	-0.14	-0.25**	-0.13	-0.26**	-0.07	-0.26**	-0.04	-0.30***
	Mean	13.5	17.2	13.0	16.9	12.4	17.3	12.9	14.3	13.0	15.7
Job-to-Job Rate	Cyclicality	-1.08***	-0.82***	-1.11***	-0.85***	-1.06***	-0.86***	-1.01***	-0.91***	-1.02***	-0.89***
	Mean	2.82	1.33	2.43	1.73	2.18	1.97	2.21	1.94	2.34	1.81

Note: Following Mueller (2017), the cyclicality of the series is measured as the coefficient β in the regression $ln(x_{j,t}) = \alpha + \beta \times ln(U_t) + \epsilon_{j,t}$, where $x_{j,t}$ is the separation, job finding, or job-to-job rate rate of group j 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 2 and 80 quarterly observations are used in the regressions. Residual wages are obtained from regression controlling first for observable worker covariates: third-order polynomial in age, occupation and firm tenure, gender, German nationality, education (3 categories), occupation (2-digit) and year dummies. In a second step, we add firm covariates: log establishment size, AKM firm fixed effects and dummies for labor market regions. In a third step, we add AKM worker fixed effects.In a fourth step, for the estimation with one-way worker fixed effects, we remove the AKM firm fixed effects and control for log establishment size, 3-digit industries and labor market regions instead. SIAB 1998-2017. ***p<0.01, **p<0.05, *p<0.10

G Calibration based on AKM Worker Fixed Effects

The AKM fixed effects from Bellmann et al. (2020) are estimated separately for five sub-intervals covering the period 1985-2017. To calculate the level differences in AKM worker fixed effects for the calibration, we take the distribution of AKM worker fixed effects in logs and calculate quartiles of the fixed-effects distribution separately for each time interval.[27] Finally, we take the exponent and calculate the mean fixed effect for each quartile and time interval (Table 31).

Table 31: Average worker fixed effects by time interval and worker fixed-effect quartile

AKM Worker FE Quartile	Time Interval					Average	Norm. to Q1
	1	2	3	4	5		
1	49.71	52.32	56.60	80.46	45.12	56.84	1.00
2	65.43	68.31	74.82	107.47	59.05	75.02	1.32
3	74.21	77.54	85.61	124.44	69.95	86.35	1.52
4	89.99	95.88	107.48	159.29	94.14	109.36	1.93

Note: SIAB, 1985–2017. Sample of West German full-time workers aged 20–60. The time intervals refer to 1 = 1985–1992, 2 = 1993–1999, 3 = 1998–2004, 4 = 2003–2010, 5 = 2010–2017.

H Derivation of Nash Bargaining

The Nash product is:

$$\Lambda\left(\varepsilon_{ijt}\right) = \left[J\left(\varepsilon_{ijt}\right)\right]^{1-\gamma}\left[W\left(\varepsilon_{ijt}\right) - U_{t,j}\right]^{\gamma}. \tag{23}$$

Maximizing the Nash product with respect to wages yields:

$$\begin{aligned}\frac{\partial \Lambda_t}{\partial w\left(\varepsilon_{ijt}\right)} = {} & \gamma\left(W\left(\varepsilon_{ijt}\right) - U_{t,j}\right)^{\gamma-1}\frac{\partial W\left(\varepsilon_{ijt}\right)}{\partial w\left(\varepsilon_{ijt}\right)}\left(J\left(\varepsilon_{ijt}\right)\right)^{1-\gamma} \\ & + (1-\gamma)\left(W\left(\varepsilon_{ijt}\right) - U_{t,j}\right)^{\gamma}\left(J\left(\varepsilon_{ijt}\right)\right)^{-\gamma}\frac{\partial J\left(\varepsilon_{ijt}\right)}{\partial w\left(\varepsilon_{ijt}\right)} = 0.\end{aligned} \tag{24}$$

Therefore:

$$\gamma J\left(\varepsilon_{ijt}\right) = (1-\gamma)\left(W\left(\varepsilon_{ijt}\right) - U_{t,j}\right). \tag{25}$$

When we substitute the present values from equations (16), (18), and (19) and use the one-period-forward iterated version of equation (25), we obtain:

[27] Without normalization (z-scoring) the AKM fixed effects are comparable within but not between time intervals, see Appendix A.

$$w(\varepsilon_{ijt}) = \gamma\left(a_{t,j} - \varepsilon_{ijt} + E_t p_{t+1,j}(1-\phi_{t+1})\,\delta J^I_{t+1,j}\right) + (1-\gamma)\,b_j. \tag{26}$$

I 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 Table 8).

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.

J Parameter Values in Counterfactual Exercises

In Table 8 in the main part, we show the simulation results for alternative scenarios. The tables below show the full set of changed parameter values for these three scenarios.

Table 32 shows the parameters values for the scenario where we do not target the actual flow rates from the data. Instead, we impose the flow rates from group 1 to all four groups. In addition, we keep the same scale parameter for the idiosyncratic shock distribution as in the baseline scenario.

Table 32: Parameter Values for Counterfactual with Same Flows

	1	2	3	4
Productivity	1.000	1.390	1.620	2.065
Matching efficiency	0.111	0.165	0.203	0.173
Replacement rate	$0.752a_1$	$0.894a_2$	$0.920a_3$	$0.933a_4$
Dispersion parameter	1.178	0.701	0.618	0.656
Hiring costs	$1.248a_1$	$0.514a_2$	$0.428a_3$	$0.208a_4$

Table 33 shows the parameters values for the scenario where we impose the same surplus on all groups. We do so by setting the same replacement rate, matching efficiency and hiring costs (relative to productivity).

Table 33: Parameter Values for Counterfactual with Same Surplus

	1	2	3	4
Productivity	1.000	1.390	1.620	2.065
Matching efficiency	0.111	0.111	0.111	0.111
Replacement rate	$0.752a_1$	$0.752a_2$	$0.752a_3$	$0.752a_4$
Dispersion parameter	1.178	1.638	1.908	2.433
Hiring costs	$1.248a_1$	$1.248a_2$	$1.248a_3$	$1.248a_4$

K Adjusting Separation Rate Dynamics

K.1 Targeting Comovement of Separation Rate for Lowest Productivity Group

In the calibration in the main part, we bind our hands by calibrating to the relative wage dispersion from the microeconomic data and by assuming a bargaining power, $\gamma = 0.5$. In this Appendix, we readjust the bargaining power such that the separation rate in the labor market segment with the lowest ex ante productivity comoves in the same way with aggregate unemployment as in the data (i.e., estimated coefficient of 0.42).

To reach this target, we set workers' bargaining power to 0.29 instead of 0.5. As in the main part, we target the relative residual wage dispersion from the data and keep the other labor market targets. For comparability, we keep the same productivity in each segment as in the main part.

With a lower bargaining power for workers, a smaller fraction of the idiosyncratic match-specific shock realization is handed on to workers. Thus, in order to match the relative wage dispersion, a more dispersed idiosyncratic shock can be chosen. At the same time, a lower bargaining power for workers increases firms' profits. In order to hit the same labor market targets as before, we require larger ex post hiring costs. This increases the amplification of the job-finding rate and unemployment (see Silva and Toledo (2009) and Pissarides (2009) for the underlying mechanism).

Table 34 shows the parameter values in this robustness check. Table 35 shows the cyclicalities of the job-finding rates and separation rates in responses to aggregate productivity shocks.

While the comovement of the separation rate with aggregate unemployment for group 1 is targeted, the comovement of all other groups shifts down proportionally relative to the baseline (compare Table 35 to Table 7 in the main part). Although the comovement of separation rates is now closer to the empirical facts, the robustness check comes with several caveats. First, in order to match the targets, we have to choose ex post hiring costs that are ways above the empirically observed level. Based on microeconomic data, Muehlemann and Pfeifer (2016) find that hiring costs are roughly two thirds of quarterly

Table 34: Model Parameters in Robustness Check

Quartile	1	2	3	4
Productivity	1.000	1.390	1.620	2.065
Matching efficiency	0.111	0.184	0.203	0.158
Replacement rate	$0.752a_1$	$0.791a_2$	$0.796a_3$	$0.848a_4$
Dispersion parameter	1.963	1.167	1.030	1.093
Hiring costs	$4.184a_1$	$1.959a_2$	$1.687a_3$	$1.358a_4$

Note: The table shows the parameters to match the targets.

Table 35: Cyclicality of Separation Rate and Job-Finding Rate in Data and Calibration

Wage Quartiles	1	2	3	4
Separation Rate (Simulation)	0.42	0.84	1.09	1.93
Separation Rate (Data)	0.42	0.76	0.86	0.89
Job-Finding Rate (Simulation)	-0.60	-0.82	-0.87	-0.97
Job-Finding Rate (Data)	-0.45	-0.13	-0.06	-0.21

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

wages in Germany. While the order of magnitude of hiring costs is roughly in line with the empirical number in the main part, hiring costs are several times larger in this robustness check (around 220 percent).

Second, although prior wages comove positively with aggregate unemployment, the relationship is quantitatively less pronounced than in the main part (see column "Robust." in Table 36). This is partly connected to very large hiring costs that generate powerful equilibrium effects. With large hiring costs, market tightness, job findings and unemployment fluctuate more (see Silva and Toledo (2009) and Pissarides (2009)). This affects the comovement of the separation rate with aggregate unemployment via two channels: i) Unemployment gets more volatile relative to the prior wages. ii) As market tightness fluctuates more and these fluctuations feed into Nash bargaining as part of the future net present value of a job (see model equations 7 and 20), wages in each labor market segment become a lot more procyclical in this robustness check.

The latter effect generates substantially stronger comovements of group-specific wages with aggregate unemployment. This dampens the positive comovement of prior wages with aggregate unemployment. To understand this mechanism, it is important to remember the underlying reason for the positive comovement between prior wages and aggregate unemployment. Although wages in each group fall in recessions, more high-wage workers enter the pool of unemployed. When group-specific wages become more procyclical (i.e., larger wage cuts in recessions), this countervails the composition effect across groups.

Table 36: Estimated Comovement of Prior Wages and Fixed Effects with Unemployment

Comovem. with U	Data	Robust.	Targ. Wages	Same Surplus	Same Surplus & Targ. Wages
Prior Wage of Un.	1.43	0.37	0.98	-0.89	-0.53
Fixed Effect of Un.	2.09	1.46	1.46	0	0

Note: The table shows the estimated comovement of the prior wage and fixed effects of those who lost their job ("Un.") with aggregate unemployment in data and simulation. The column "Robust." shows the results for the robustness check. In addition, the column "Targ. Wages" shows results when the empirically observed wage cyclicality is targeted in allocationally non-relevant manner. The last two columns show the scenario where the surplus is the same relative to productivity for all groups. The column "Same Surplus" imposes the same surplus on all groups as in the main part, using standard Nash bargaining. The column "Same Surplus & Wages" imposes the same surplus and targets wage cyclicalities to the values estimated from the data. In analogy with the empirical data, aggregated annual simulated data is HP-filtered with smoothing parameter 6.25.

To show the role of wage dynamics, we estimate the wage cyclicality of incumbent workers in each worker fixed effect quartile and impose this cyclicality in allocationally irrelevant manner in the simulation. Following Bils (1985), we estimate a standard empirical model at the quarterly frequency separately for each quartile of the AKM worker fixed effects distribution:

$$ln(w_{i,t}) = \beta_0 + \beta_1 u_t + \beta_2 NH_{i,t} + \beta_3 (NH_{i,t} \times u_t) + \gamma X_{i,t} + \delta_i + \epsilon_{i,t} \tag{27}$$

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. β_1 gives the estimated wage cyclicality among incumbent workers. 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 quarters or changes occupations (2-digit) within firms (Stüber, 2017; Bauer and Lochner, 2020). Table 37 shows the estimation results. Interestingly, the empirical comovement of incumbent workers' wages with aggregate unemployment is substantially lower for high-wage workers than for low-wage workers. These patterns are consistent with Figueiredo (2022) for the United States who finds lower wage cyclicalities for good matches.

Table 36 shows that the positive comovement of prior wages with aggregate unemployment increases from 0.37 to 0.98 when we impose the empirically observed comovement of wages from Table 37 (see column "Targ. Wages"). Note that for comparability reasons, we impose the wage cyclicality in an allocationally irrelevant way. In other words, job-finding and separation rate dynamics are exactly the same as in the robustness check. However, we assume that wages for those who lose their job follow the empirically ob-

Table 37: Wage Cyclicality among incumbent workers by AKM Worker FE Groups

	AKM Worker FE Quartile			
	1	2	3	4
Wage Cyclicality of Incumbent Workers	-1.23***	-0.69***	-0.65***	-0.35***
Observations	5893955	5934458	5922989	5878714
Adjusted R-Squared	0.68	0.60	0.63	0.69

Note: The table shows the estimated wage cyclicality for incumbent workers, namely, coefficient β_1 from equation 27. 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

served dynamics (i.e., wages in recessions drop less than under Nash bargaining).

In short, the robustness check shows that the model version that is targeted to the separation rate cyclicality of the lowest groups continues to deliver a positive comovement of prior wages with aggregate unemployment. However, the estimated coefficient drops relative to the baseline, as this model version delivers too cyclical wages. Once we fix the wage cyclicality issue, the simulation numbers are close to the data again.

The last two columns in Table 36 show what happens when we set the same surplus relative to productivity and the same flow rates for all four groups (in the same way as in the main part). As in the main part, the comovement between the fixed effect and unemployment drops to zero, as the separation rate dynamics in all groups is the same. Furthermore, the comovement between the prior wage and unemployment becomes negative (see column "Same Surplus"). When imposing the empirically relevant wage cyclicality, the comovement of the prior wage and unemployment remains negative (see column "Same Surplus & Targ. Wages"). This shows once more the importance of the interaction of ex ante heterogeneity with the idiosyncratic match-specific shock distribution that generates more cyclical separations for high-wage workers.

K.2 Different Wage Dispersion Scenarios

In a second robustness check, we provide an accounting exercise that replicates the comovement of the separation rate with aggregate unemployment for all four groups. We use the same common parameters as in Section K.1 and readjust the group-specific parameter values. Most importantly, instead of targeting the dispersion of the relative wage dispersion and the average aggregate replacement rate, we target the comovement of group-specific separation rates with aggregate unemployment. We set the group-specific parameters to match the same steady states as in the baseline.

In order to obtain the empirically observed comovement of separations with unemployment, we have to drop the target for the relative residual wage dispersion. Table 38 shows the parameter values for this second robustness check. Table 39 shows that the cyclicality of the separation rate is matched.

Table 38: Model Parameters in Robustness Check

Quartile	1	2	3	4
Productivity	1.000	1.390	1.620	2.065
Matching efficiency	0.111	0.184	0.203	0.158
Replacement rate	$0.673a_1$	$0.713a_2$	$0.697a_3$	$0.680a_4$
Dispersion parameter	2.588	1.606	1.528	2.294
Hiring costs	$5.805a_1$	$2.900a_2$	$2.741a_3$	$3.546a_4$

Note: The table shows the parameter values to match the targets in robustness check 2.

Table 39: Cyclicality of Separation Rate and Job-Finding Rate in Data and Calibration

Wage Quartiles	1	2	3	4
Separation Rate (Simulation)	0.42	0.76	0.86	0.89
Separation Rate (Data)	0.42	0.76	0.86	0.89
Job-Finding Rate (Simulation)	-0.79	-1.03	-1.04	-0.99
Job-Finding Rate (Data)	-0.45	-0.13	-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 robustness check allows us to understand how much less dispersed wages would have to be in relative terms to match the separation rate cyclicality from the data. Table 40 compares the relative wage dispersion parameters (normalizing the first group to 1) and the relative wage dispersion from the baseline calibration, from Section 27 and from this section.

It is visible that the dispersion parameters in robustness check 1 from Appendix K.1 are basically a rescaled version of the baseline calibration. The absolute values are smaller in robustness check 1 than in the baseline (1.963 vs. 1.178 for group 1), as a smaller fraction of match-specific idiosyncratic shocks is handed to due to the lower bargaining power. However, in relative terms, everything remains the same. Thereby, the wage dispersion relative to group 1 is the same in the baseline calibration and in robustness check 1 (see Table 40).

In contrast, in order to match the separation rate cyclicality from the data for all four groups, more dispersed wages are required. Table 40 shows (see rows with "Robustness 2") that the scaling parameter for the distribution and the wage dispersion would have to be around 60 percent larger in group 4 in order to match the cyclicalities from the data. The gap is smaller for groups 2 and 3.

Table 40: Relative Wage Dispersion and Dispersion Parameters

Quartile	1	2	3	4
Dispersion Parameter (Baseline)	1.00	0.59	0.52	0.56
Dispersion Parameter (Robustness 1)	1.00	0.59	0.52	0.56
Dispersion Parameter (Robustness 2)	1.00	0.62	0.59	0.89
Wage Dispersion (Baseline)	1.00	0.62	0.55	0.59
Wage Dispersion (Robustness 1)	1.00	0.62	0.55	0.59
Wage Dispersion (Robustness 2)	1.00	0.64	0.62	0.94

Note: The table shows the conditional wage dispersion and the distributional parameter relative to group 1. "Baseline" denotes the calibration from the main part. "Robustness 1" denotes the version from Appendix K.1, where the separation rate cyclicality for group 1 is targeted. "Robustness 2" denotes the accounting exercise, where the separation rate cyclicalities of all four groups are targeted.

L Simulation Results with Exogenous Separations

While separations where completely endogenous in the main part, this Appendix shows results for a model with partly exogenous separations, denoted by σ_j, and partly endogenous separation. We start by showing the key modified equations and then describe the quantitative results.

The job-creation condition:

$$\frac{\kappa_j}{q_{t,j}} + h_j = E_t \left[(1 - \sigma_j)(1 - \phi_{t,j}) J^I_{t,j} \right], \tag{28}$$

with the modified future value of a job:

$$J^I_{t,j} = a_t - \bar{w}_{t,j} - H(\tilde{\varepsilon}_{ijt}) + E_t (1 - \sigma_j)(1 - \phi_{t+1,j}) \delta J^I_{t+1,j}. \tag{29}$$

Furthermore, the exogenous separation rate also shows up in the equation for the cutoff point:

$$\tilde{\varepsilon}_{ijt} = a_{t,j} - w(\tilde{\varepsilon}_{ijt}) + E_t (1 - \sigma_{j,t})(1 - \phi_{t+1}) \delta J^I_{t+1,j}. \tag{30}$$

The modified Nash wage is:

$$w(\varepsilon_{ijt}) = \gamma \left(a_{t,j} - \varepsilon_{ijt} + E_t p_{t+1,j} (1 - \sigma_j)(1 - \phi_{t+1,j}) \delta J^I_{t+1,j} \right) + (1 - \gamma) b_j. \tag{31}$$

As we calibrate the exogenous separation to job-to-job-transitions, we assume that workers who separate exogenously immediately move to a different job. Thus, the employment dynamics equation remains unaffected.

This Appendix shows results with a uniform exogenous separation rate $\sigma_j = 0.021$ for all four groups, corresponding to the average aggregate job-to-job transition rate in our sample. Table 41 shows the parameter values for this scenario. Note that we follow the same calibration strategy with the same targets as in the main part.

Table 41: Parameter Values for $\sigma_j = 0.021$

	1	2	3	4
Productivity	1.000	1.353	1.569	1.996
Matching efficiency	0.111	0.184	0.2026	0.157
Replacement rate	$0.740a_1$	$0.802a_2$	$0.811a_3$	$0.855a_4$
Dispersion parameter	0.922	0.548	0.484	0.513
Hiring costs	$0.745a_1$	$0.288a_2$	$0.235a_3$	$0.033a_4$

Table 44 shows the parameters for scenario where we do not target the actual wage dispersion from the data. Instead, we impose the same flow rates on all groups.

Table 42: Cyclicality of Separations and Job-Finding Rate in Data and Calibration

Wage Quartiles	1	2	3	4
Separation Rate (Simulation)	0.64	1.26	1.67	2.85
Separation Rate (Data)	0.42	0.76	0.86	0.89
Job-Finding Rate (Simulation)	-0.30	-0.40	-0.43	-0.43
Job-Finding Rate (Data)	-0.45	-0.13	-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.

Table 43: Estimated Comovement of Prior Wages and Fixed Effects with Unemployment: Four Scenarios

Comovem. with U	Data	Baseline	Same Flows	And Same Surplus
Wage	1.45	1.52	0.80	-0.57
Fixed Effect	2.18	2.18	1.02	0.00

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

Table 45 shows the scenario where we do not target the actual wage dispersion from the data and we set the same flow rates for all four groups. Instead, impose the same surplus on all groups, by setting the same hiring costs (relative to productivity), the same replacement rate and the same matching efficiency.

Table 44: Alternative Parameter Values: All Groups Same Flows

	1	2	3	4
Productivity	1.000	1.353	1.569	1.996
Matching efficiency	0.111	0.160	0.187	0.161
Replacement rate	$0.740a_1$	$0.886a_2$	$0.913a_3$	$0.927a_4$
Dispersion parameter	0.922	0.548	0.484	0.513
Hiring costs	$0.745a_1$	$0.288a_2$	$0.235a_3$	$0.033a_4$

Table 45: Alternative Parameter Values: All Groups Same Surplus

	1	2	3	4
Productivity	1.000	1.353	1.569	1.996
Matching efficiency	0.111	0.111	0.111	0.111
Replacement rate	$0.740a_1$	$0.740a_2$	$0.740a_3$	$0.740a_4$
Dispersion parameter	0.922	1.247	1.446	1.839
Hiring costs	$0.745a_1$	$0.745a_2$	$0.745a_3$	$0.745a_4$