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Wage and Employment Cyclicalities at the Establishment Level*

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Abstract

Although the quantitative relationship between employment cyclicality and wage cyclicality is central for the dynamics of macroeconomic models, there is little empirical evidence on this topic. We use the German AWFP dataset to document that wage cyclicalities are very heterogeneous across establishments. Based on this heterogeneity, we estimate the relationship between employment cyclicality and wage cyclicality at the establishment level. We use this micro-estimate as a calibration target for a macro labor market flow model with heterogeneous wage dynamics that nests the standard search and matching model. Based on this micro-macro linkage, we provide a new quantitative benchmark for the role of wage rigidity in search and matching models. Furthermore, we show that acyclical and countercyclical wage establishments are key drivers for stronger labor market reactions in recessions than in booms.

JEL classification: *E32, E24, J64.*

Keywords: Wage Cyclicality, Employment Cyclicality, Labor Market Flow Model, Labor Market Dynamics, Establishments, Administrative Data.

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1 Introduction

The question of how real wages evolve over the business cycle has been a central topic in macroeconomics for many decades.[1] In search and matching models, more rigid wages lead to a stronger response of the job-finding rate and unemployment in response to aggregate shocks (e.g., Shimer, 2005; Hall, 2005; Hall and Milgrom, 2008; Christiano et al., 2021). Against this background, there is a growing empirical literature on how cyclical the wages of newly hired workers are (e.g., Carneiro et al., 2012; Martins et al., 2012; Haefke et al., 2013; Kudlyak, 2014; Basu and House, 2016; Stüber, 2017; Schaefer and Singleton, 2019; Gertler et al., 2020). In addition, there is an emerging literature that documents the impact of downward nominal wage rigidity on labor market flows at the establishment level. Ehrlich and Montes (2023) find a meaningful connection between DNWR and labor market flows using linked employer-employee data for Germany.[2] However, there is an important gap in the existing literature. If wage rigidity plays a significant role in amplifying labor market fluctuations, this must be evident in terms of the empirical link between employment dynamics and wage dynamics at the establishment level. Due to the lack of sufficiently rich panel data, there is little empirical evidence on this issue.[3]

Our paper fills this gap by investigating whether there is a meaningful empirical relationship between employment cyclicality and wage cyclicality at the establishment level. Using the Administrative Wage and Labor Market Flow Panel (AWFP), we exploit the establishment-specific heterogeneity of wage cyclicality. Our analysis reveals that about two-thirds of German establishments exhibit procyclical wages, while the remaining third exhibits countercyclical wages. We are the first to document a meaningful and robust negative relationship between employment cyclicality and wage cyclicality at the establishment level (after controlling for potential compositional effects). We propose a labor market flow framework and calibrate it to the cross-sectional dispersion of wages and the empirical relationship between employment cyclicality and wage cyclicality. We perform several counterfactual exercises to determine the extent to which wage cyclicality matters for the dynamics of the aggregate labor market. We show that acyclical and countercyclical wage establishments are key drivers for aggregate amplification of the labor market and for asymmetric labor market reactions over the business cycle.

Figure 1 illustrates the empirical key result. The left panel shows that the 20 percent

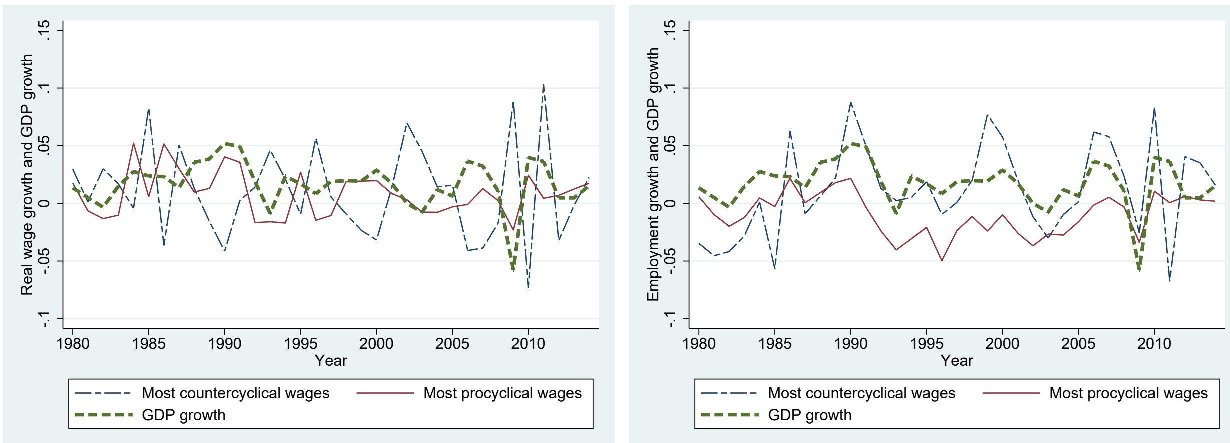
[1] See, e.g, Bils (1985); Blanchard and Fischer (1989); Mankiw (1989); Beaudry and DiNardo (1991); Solon et al. (1994); Pissarides (2009).

[2] For the United States, see Kurmann and McEntarfer (2019).

[3] A notable exception is Carlsson and Westermark (2022) who show that the cyclicality of incumbents' wages matters for the dynamics of the separation rate.

of establishments with the most procyclical wages have a clearly visible positive correlation of real wage growth with real GDP growth, while the correlation is negative for the most countercyclical establishments. The right panel illustrates that more procyclical wage establishments show less volatile employment movements.

Figure 1: Mean Real Daily Wage Growth and Mean Employment Growth of the Establishments with the Most Procyclical and Most Countercyclical Wages



1.1: Mean Real Daily Wage Growth

1.2: Mean Employment Growth

Note: West Germany (excluding Berlin), 1979–2014. Establishments with the most procyclical (countercyclical) wage are those equal to or above (below) the 80^{th} (20^{th}) percentile of our wage cyclicality measure α_{1i} in the given year (see Section 2.2). α_{1i} are estimated using the number of aggregated full-time employment as the business cycle indicator, using the full universe of establishments (employment weighted results; extreme outliers dropped, see Footnote 13).

Beyond this illustration, we document wage cyclicality, employment cyclicality, and their connection at the establishment level. We take several steps to control for potential composition effects. In our baseline estimations, we use sector-specific employment as business cycle indicator. We control for establishment fixed effects and changes in mean worker characteristics.[4]

We also discuss possible causes for the heterogeneity of wage cyclicalities across establishments. To this end, we link the AWFP to the IAB Establishment Panel (see Ellguth et al., 2014). We find that the share of establishments participating in collective bargaining is lower for establishments with strongly procyclical and strongly countercyclical wages than for other establishments.

In order to connect micro-data with macroeconomic outcomes, we propose a random search model with heterogeneous wage cyclicalities. We assume that establishments select

[4]Furthermore, our results are not driven by heterogeneities between sectors or by small establishments. Our results also remain robust when we exclude the Great Recession from our regressions (where the adjustment in hours per worker was large) or when we exclude short-lived establishments.

a certain fraction of applicants based on their idiosyncratic match-specific training costs (in the spirit of Chugh and Merkl, 2016). Following Merkl and van Rens (2019), we show that the homogeneous version of our model (i.e., without heterogeneous wage cyclicality) can be made observationally equivalent to the standard search and matching model under certain parameterizations.

To make quantitative statements, we fit our model to two important dimensions from the data, namely, the heterogeneity of wage cyclicality across establishments and the impact of wage cyclicality on employment cyclicality. This disciplines the effects of our counterfactual exercises. We show, for example, that if all establishments followed standard Nash bargaining, labor market responses to aggregate shocks would decline by more than two-thirds. In addition, we contribute to the debate on labor market asymmetries in search and matching models. Petrosky-Nadeau et al. (2018) and Petrosky-Nadeau and Zhang (2021) emphasize the importance of wage rigidity in the search and matching model to generate labor market asymmetries. We provide complementary evidence on the role of wage cyclicalities for labor market asymmetries.

The paper proceeds as follows. Section 2 presents the AWFP dataset. Section 3 documents the heterogeneity of real wage cyclicalities and employment cyclicalities across establishments. Section 4 estimates the relationship between employment cyclicalities and wage cyclicalities at the establishment level (including various robustness checks). Section 5 derives the model, calibrates it against the empirical results, and shows counterfactual results. Section 6 concludes.

2 Data

2.1 Administrative Wage and Labor Market Flow Panel

The Administrative Wage and Labor Market Flow Panel (AWFP, see Stüber and Seth, 2018) aggregates German administrative (register) data from the worker to the establishment level for the years 1975 to 2014. The underlying administrative microeconomic data source is mainly the Employment History (Beschäftigtenhistorik, BeH) of the Institute for Employment Research (IAB). The BeH contains information on each worker subject to social security contributions in Germany. Before aggregating the data to the establishment level, several corrections and imputations were performed at the micro level.

The AWFP provides a long time series for wages and labor market flows for each establishment in Germany. This is a major advantage compared to existing datasets and it allows us to exploit time variation at the establishment level. One drawback of the AWFP, or register data in Germany more generally, is that it does not provide information on the exact number of hours worked. Therefore, in order to have a homogeneous reference group, we restrict ourselves to full-time workers. Wages are defined as mean real daily wages (deflated by the CPI, in 2010 prices) of all employed full-time workers in a given establishment. Daily wages include the base salary, all bonuses and special payments (such as performance bonuses, holiday pay, or Christmas allowance), fringe benefits, and other monetary compensations received throughout the year (or the duration of the employment spell). Therefore, daily wages are a measure of total compensation rather than a daily base wage. Because establishments are sometimes able to circumvent wage rigidity by adjusting fringe (non-wage) benefits (e.g., Lebow et al., 1999; Grigsby et al., 2021), this wage concept offers significant advantages in studying the relationship between wage and employment cyclicalities (e.g., Ehrlich and Montes, 2023). Daily wages of workers above the contribution assessment ceiling are imputed according to Card et al. (2015) before aggregating the data to the establishment level.

We use the AWFP at the annual frequency and restrict the data to West German establishments (excluding Berlin) and the years 1979–2014 to avoid the break caused by German reunification.[5] We chose the annual frequency due to the nature of the data. Wages in the AWFP are calculated based on individuals' employment spells. If an employment spell lasts for the entire calendar year, we would get no quarter-level variation over time in that year. Variations at the quarterly level thus result only from shorter employment spells. We also drop all establishments that change industry or state. Since we control for establishment fixed effects in our regressions, we do not need to control for industry and state.[6] More detailed information about the AWFP can be found in Appendix A.1.1.

2.2 Baseline Sample

In our baseline regressions, we only include establishments that have an average of at least ten full-time workers and for which we have at least five observations. This choice is motivated by several considerations: First, we want to ensure that our results are not affected by very small establishments that may not be relevant for the overall economy. Second, newly founded establishments are very volatile. Therefore, they may introduce noise in our estimations. According to Brixy et al. (2006), establishments in Germany can be considered mature or established after five years. After that, they no longer differ significantly from older

[5]All stocks are calculated using an "end-of-period" definition. Using the annual frequency, this is December 31^{st} of each year. For more details see Appendix A.1.1.

[6]Since our analysis is based on wage growth and employment growth, we cannot consider establishment creation and closure, as we cannot calculate meaningful growth rates for these cases.

establishments in terms of wage levels and working conditions.[7] Third, employee dismissal protection in Germany depends on the number of employees. The statutory protection against dismissal does not apply to employees in small businesses.[8] This is another reason why we exclude small establishments, which are subject to other institutional regulations. Fourth, from a statistical point of view, our employment cyclicality and wage cyclicality measures can be very imprecisely estimated for short-lived establishment with only a few observations. We want to prevent our results from being affected by these establishments.

Table 1: Descriptive Statistics

Variable	AWFP	Baseline sample
Worker-year observations	539,002,807	432,171,298
	100%	80.2%

Note: AWFP restricted to all West German establishments (excluding Berlin) with at least one full-time (regular) worker.

In summary, we expect our sample restrictions to yield more representative and stable results. Despite our restrictions, our baseline sample still covers on average 80.2% of all full-time worker-year observations (see Table 1), with the proportion varying between 76.8% and 82.7% over the years 1979–2014. In addition, our baseline sample covers 74.5% of all hires. Aggregated time series of selected variables for West Germany (excluding Berlin) constructed using the entire AWFP and our baseline sample, as well as further statistical information on the baseline sample, can be found in Appendix A.1.1. The aggregate dynamics of our baseline sample and the entire AWFP are very similar. The robustness of our baseline results and the choice of our baseline sample are discussed in Section 4.3.

3 Wage and Employment Cyclicalities

In this section, we first estimate the comovement of establishments' wage growth with sector-specific employment growth. We show that there is substantial heterogeneity across establishments. Typically, worker-specific wages are regressed on aggregate unemployment (growth), e.g., Martins et al. (2012); Haefke et al. (2013); Card et al. (2015); Stüber (2017); Gertler et al. (2020). We deviate from this practice: we use the number of full-time workers, N_t^j, as our business cycle indicator. It can be calculated for different sub-aggregation groups

[7] Fackler et al. (2019) also use this threshold and identify establishments as incumbent establishments if they are five years or older. Since we demand at least five observations and use wage and employment growth, we also only consider establishments five years and older.

[8] Over the years, the number of employees from which the statutory protection against dismissal takes effect has changed. Until the end of 2003 it was over five employees, since 2004 it is over ten employees.

(such as sectors j) from our dataset. In addition, this definition is in line with our wage definition, which is also based on full-time workers, while unemployment and GDP refer to all workers. It is also important to note that we use growth rates instead of levels in our regressions, as we are interested in the heterogeneity over the business cycle. In addition, by first differencing, we prevent spurious regressions with non-stationary variables.[9] Second, we estimate the comovement of establishments' employment growth with a sector-specific employment growth. Here, we also find substantial heterogeneity across establishments. In Section 4, we then analyze the relationship between the employment and wage cyclicalities of establishments.

3.1 Establishments' Wage Cyclicality

We are interested in the heterogeneous reaction across establishments to sectoral business cycle fluctuations. To this end, we estimate the following employment-weighted high-dimensional fixed effects regression:[10]

$$\Delta \ln w_{ijt} = \alpha_0 + \alpha_{1i} \Delta \ln N_t^j + \alpha_2 t + \alpha_3 t^2 + \alpha_4^{'} \mathbf{C}_{it} + \mu_i^w + v_{ijt}^w, \tag{1}$$

where $\Delta \ln w_{ijt}$ is the growth rate of mean real daily wages of establishment i in (industry) sector j in year t and $\Delta \ln N_t^j$ is the growth rate of full-time workers in sector j. α_{1i} shows how strongly the wage growth of establishment i (in sector j) reacts to changes in the (sectoral) business cycle indicator N_t^j (full-time employment), indicating how procyclical or countercyclical a certain establishment is. μ_i is the establishment-fixed effect, and $\mathbf{C}_{it}$ is a vector of control variables including the changes in education shares and gender shares at the establishment level, as well as changes in the average age, tenure, and tenure squared of the workers within the establishment. We include changes in these control variables instead of levels to better control for changes in the workforce composition of the establishments. In addition, we include a linear and quadratic time trend.[11]

Equation (1) yields over 356 thousand coefficients α_{1i}, which correspond to the number of establishments in our baseline specification.[12] Thus, each establishment i has an estimated $\hat{\alpha}_{1i}$ that is fixed for the entire life span. Since we use the raw aggregated AWFP, we drop

[9] As a robustness check, we estimate the average wage cyclicality using the baseline sample and show that our results are comparable to results using individual worker data (see Appendix A.2 and A.3).

[10] Using the Stata package reghdfe written by Correia (2018). For unweighted results, analogous to Tables 2 and 2, see Appendix A.7.

[11] When we exclude the time trend from our regressions, both the heterogeneity of wage cyclicalities and their impact on establishment-specific employment change very little. The same is true if we include year dummies instead of time trends.

[12] Goodness of fit measures of the regression: observations: 7,259,116; R^2: 0.24; within R^2: 0.12.

extreme outliers for our analysis of the connection between wage and employment cyclicalities (see Section 4).[13] To be consistent, the results presented in Tables 2 and 3 exclude these outliers.[14]

Table 2: Wage Cyclicality at Different Disaggregation Levels

Estimated coefficients: $\hat{\alpha}_{1i}$	31 Sectors	National level
Cyclicality at 10^{th} percentile	-0.69	-0.89
Cyclicality at 20^{th} percentile	-0.27	-0.34
Cyclicality at 30^{th} percentile	-0.06	-0.05
Cyclicality at 40^{th} percentile	0.09	0.16
Cyclicality at 50^{th} percentile	0.22	0.34
Cyclicality at 60^{th} percentile	0.35	0.52
Cyclicality at 70^{th} percentile	0.49	0.72
Cyclicality at 80^{th} percentile	0.69	1.00
Cyclicality at 90^{th} percentile	1.06	1.51
Observations	344, 537	344, 396

Note: We drop extreme outliers before the calculation of this table (see Footnote 13).

Table 2 shows that there is substantial heterogeneity in wage cyclicalities across establishments. The second column of Table 2 reports percentiles for the estimated $\hat{\alpha}_{1i}$ for our baseline regression using the sectoral business cycle indicator. The median establishment has about the same cyclicality as the average establishment (see Table A.2): A 1% larger sectoral employment growth is associated with a 0.22% larger wage growth for the median establishment. While establishments at the 80th percentile show strongly procyclical real wages (0.69), establishments at the 20th percentile show countercyclical real wages (-0.27). Our estimation reveals that about 66 percent of all establishments have procyclical wage setting ($\alpha_{1i} > 0$), while nearly 34 percent of all establishments have a countercyclical wage movement. Our paper is the first to document these facts, since the AWFP offers long time series for wages for each establishment.

The third column in Table 2 reports the estimated $\hat{\alpha}_{1i}$ for different percentiles, using national employment growth as the business cycle indicator instead of sectoral employment growth (the correlation of these two differently estimated wage cyclicality measures is 0.70). The dispersion of wage cyclicalities increases somewhat at the higher aggregation level. Regardless of the level of aggregation, there is a substantial degree of heterogeneity. Thus, our

[13] In all our regressions, tables, and figures, we omit observations with estimated $\hat{\alpha}_{1i}$ (see Section 3.1) and $\hat{\beta}_{1i}$ (see Section 3.2) below the 1^{th} or above the 99^{th} percentile of the corresponding distribution.

[14] Therefore, Regressions (1) and (2) estimate over 356 thousand coefficients but about 344 thousand coefficients are presented in Tables 2 and 3. Since we exclude outliers for two different measures, the number of remaining observations differs slightly and depends on the aggregation level of the business cycle indicator.

results on heterogeneous wage cyclicalities are mainly driven by heterogeneities of establishments within sectors.[15]

It is important to note that in the context of this article, an establishment with procyclical wage movement is one for which an increase in sectoral employment growth is associated with an increase in establishment wage growth.[16] In contrast, an establishment with countercyclical wage growth is one in which an increase in sectoral employment growth is associated with a decrease in establishment wage growth.

It may come as a surprise that such a large share of establishments exhibit a countercyclical real-wage trend over the business cycle. Three comments are in order: First, countercyclical real wages have traditionally been considered a typical feature of Keynesian models (e.g., Bils, 1985; Beaudry and DiNardo, 1991; Solon et al., 1994). Second, it is important to remember that the wage in the AWFP is a measure of total compensation. It contains, inter alia, bonuses[17] and payments made in excess of the collectively agreed minimum. These features provide (some) establishments with the flexibility to make real wage cuts in sufficiently severe recessions and stronger wage increases in boom times. Furthermore, Elsby and Solon (2019) provide evidence that nominal wage cuts are a fairly common phenomenon. Third, even though we refer to countercyclical real wages, this does not necessarily imply that establishments reduce real wages. As we show in Section 4.2.1, countercyclical wage establishments tend to have a larger fixed effect on their average wage growth. Therefore, in a boom, many of them deviate negatively from the higher average real wage growth.

3.2 Establishments' Employment Cyclicality

Analogous to Equation (1), we estimate the cyclicality of employment β_{1i} for each establishment:

$$\Delta \ln n_{ijt} = \beta_0 + \beta_{1i} \Delta \ln N_t^j + \beta_2 t + \beta_3 t^2 + \beta_4^{'} \mathbf{C}_{it} + \mu_i^n + v_{ijt}^n, \tag{2}$$

where each establishment i has an estimated $\hat{\beta}_{1i}$ that is fixed for the entire life span. The $\hat{\beta}_{1i}$ show how strongly the employment growth of establishment i (in sector j) reacts to changes in the sectoral business cycle indicator N_t^j (full-time employment). They indicate how procyclical or countercyclical a certain establishment is in terms of its employment. As for wage cyclicality, we estimate this regression employment-weighted.

[15] As a robustness check, we also run the regressions separately for the 31 sectors (see Appendix A.4).

[16] Because upswings and downswings in manufacturing may be very different compared to service sectors, we have chosen sectoral business cycle indicators. However, the key message that wage cyclicalities are highly heterogeneous at the establishment level also applies for other indicators such as national GDP. Results are available on request.

[17] According to the German Statistical Office, in 2012 bonus payments were 9% of gross earnings for firms with more than ten employees.

Table 3: Employment Cyclicality at Different Disaggregation Levels

Estimated coefficients: $\hat{\beta}_{1i}$	31 Sectors	National level
Cyclicality at 10^{th} percentile	-2.12	-2.94
Cyclicality at 20^{th} percentile	-0.87	-1.20
Cyclicality at 30^{th} percentile	-0.23	-0.30
Cyclicality at 40^{th} percentile	0.23	0.29
Cyclicality at 50^{th} percentile	0.64	0.82
Cyclicality at 60^{th} percentile	1.09	1.39
Cyclicality at 70^{th} percentile	1.65	2.11
Cyclicality at 80^{th} percentile	2.50	3.16
Cyclicality at 90^{th} percentile	4.20	5.13
Observations	$344,537$	$344,396$

Note: We drop extreme outliers before the calculation of this table (see Footnote 13).

Table 3 shows that there is (substantial) heterogeneity in employment cyclicalities across establishments.[18] As for wage cyclicality (Table 2), we present results for our baseline specification — using sectoral employment as the business cycle indicator (column 2) — and using national employment as business cycle indicator (column 3). About 65% of all establishments exhibit procyclical employment movements ($\beta_{1i} > 0$). Again, the dispersion increases somewhat at the higher aggregation level. Regardless of the level of aggregation, however, there is a substantial degree of heterogeneity. Thus, our results on heterogeneous employment cyclicalities are also mainly due to heterogeneities of establishments within sectors.

4 Relationship of Employment and Wage Cyclicalities

In this section, we analyze the relationship between employment and wage cyclicalities at the establishment level. First, we show that establishments with more procyclical wages exhibit less procyclical employment adjustment. Second, we analyze possible reasons for different wage cyclicalities across establishments. Third, we document the robustness of our results along several dimensions.

4.1 Effect of Wage Cyclicality on Employment Cyclicality

We have estimated a measure of wage cyclicality ($\hat{\alpha}_{1i}$, see Section 3.1) and a measure of employment cyclicality ($\hat{\beta}_{1i}$, see Section 3.2) for each establishment i. This allows us to

[18]Goodness of fit measures of the regression: observations: 7,259,116; R^2: 0.33; within R^2: 0.14. Please be reminded that we drop extreme outliers (see Footnote 13). Therefore Regression (2) estimates over 356 thousand coefficients but only about 344 thousand coefficients are presented in Table 3.

analyze the relationship between these two measures. We regress $\hat{\alpha}_{1i}$ for each establishment on $\hat{\beta}_{1i}$ of that establishment, weighting by mean establishment size:

$$\hat{\beta}_{1i} = \gamma_0 + \gamma_1 \hat{\alpha}_{1i} + v_{it}^{\hat{\beta}}. \tag{3}$$

Note that Equation (3) is a cross-sectional regression since each establishment has one value for wage cyclicality and one value for employment cyclicality for the observation period. Table 4 shows that there is a negative relationship between the cyclicality of wages and the cyclicality of employment at the establishment level. Establishments whose wages comove more procyclically with sector-specific employment show a less procyclical comovement of their employment with sector-specific employment. Therefore, establishments for which an increase in sectoral employment growth is associated, on average, with an increase in their wage growth are also establishments for which an increase in sectoral employment growth is associated with a decrease in their employment growth.[19]

Table 4: Effect of Wage Cyclicality on Employment Cyclicality

Estimated coefficient $\hat{\gamma}_1$	-0.460^{***}
R^2	0.01
Observations	344,537

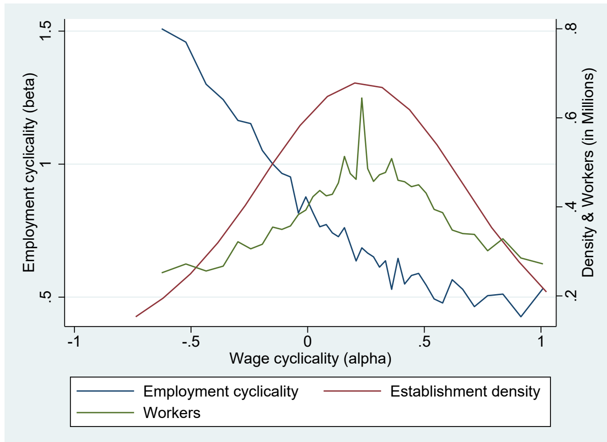
Note: *** indicates statistical significance at the 1 percent level. We drop extreme outliers before running the regression (see Footnote 13). Regressions are weighted by mean establishment size.

Figure 2 illustrates our result graphically, with the wage cyclicality measure ($\hat{\alpha}_{1i}$) on the horizontal axis and the employment cyclicality measure ($\hat{\beta}_{1i}$) on the vertical axis. We divide establishments into 50 bins according to their $\hat{\alpha}_{1i}$ (with the most countercyclical wage establishments on the left and the most proyclical wage establishments on the right) and calculate the mean $\hat{\beta}_{1i}$ for each bin. Each bin contains 1/50 of all establishments. Therefore, we use narrow bins in areas of the wage cyclicality distribution where we observe many establishments, and then gradually expand the bins in sparser parts of the distribution. As can be seen from the density function, the bin range increases with the absolute value of $\hat{\alpha}_{1i}$. In other words, we observe far more establishments with acyclical or moderately cyclical wages than establishments with strongly procyclical or countercyclical wages. In addition, the number of employees (in millions) per bin is shown in the graph (right-hand side axis).

Figure 2 shows a negative relationship between wage cyclicality and employment cyclicality, which flattens out in the positive part of wage cyclicality. The figure illustrates the

[19] Although we have used the sector-specific employment growth rate as a business cycle indicator in our regressions, the response may vary from sector to sector. To check this, we run the same regressions at the sectoral level. The coefficients are negative in most of the 31 sectors (see Appendix A.4).

Figure 2: Mean of Employment Cyclicality Measure Along the Wage Cyclicality Measure Distribution



Note: We divide the range of the wage cyclicality measure ($\hat{\alpha}_{1i}$, see Section 3.1) into 50 bins. Each bin contains 1/50 of all observations, showing the mean. We drop extreme outliers (see Footnote 13). The figure is showing results for mean $\hat{\alpha}_{1i} \geq$ the 10th percentile and $\hat{\alpha}_{1i} \leq$ the 90th percentile of the estimated $\hat{\alpha}_{1i}$ (see Table 2).

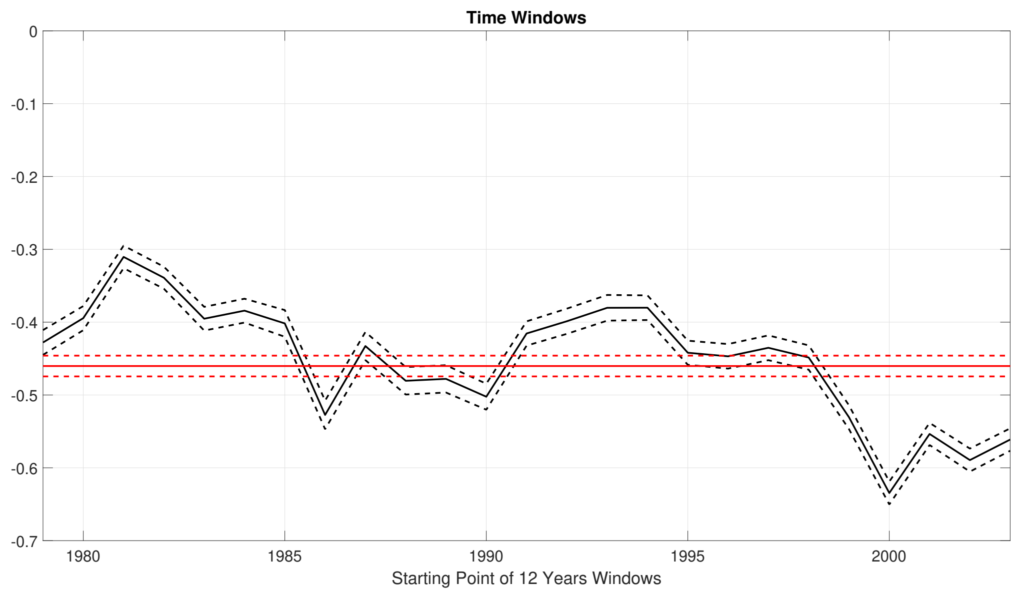
estimated regression coefficient from Equation (3): more countercyclical wage establishments are associated with less procyclical employment cyclicalities. The negative relationship flattens for strongly procyclical establishments.

What is the underlying economic intuition for the negative relationship between employment cyclicality and wage cyclicality? Imagine two establishments in a boom. Our results suggest that the establishment with a larger upward adjustment of real wages increases employment by less than the establishment with a smaller positive (or even negative) real wage movement. Although this result appears very intuitive, it is important to emphasize that we are the first to show this relationship between wage and employment cyclicalities based on establishment-level estimates. The previous literature was limited by a lack of suitable datasets for such a link.

Why is this link between wage and employment cyclicalities so important? Our empirical approach provides a quantitative benchmark for various quantitative models. In principle, it would be possible that different wage dynamics represent insurance contracts and therefore do not have a significant impact on labor market dynamics. However, our results suggest that wage cyclicalities matter for establishment-level employment cyclicalities.

Since we estimate a time-invariant indicator for each establishment, we used a long time horizon for our estimations. However, these measures may be unstable over time. From an institutional perspective, we expect wage cyclicalities to be relatively stable over time (i.e., a procyclical wage establishment remains procyclical), as establishments inherit habits and institutions from the past (e.g., the unionization of the workforce or the establishment's culture).

Figure 3: Stability over Time



Note: The black solid curve shows the estimated connection between employment cyclicality and wage cyclicality for rolling 12 year time windows (from 1979–1990 to 2003–2014). The black dashed curves show 95 percent confidence intervals. The red line is the average estimate for the entire sample (with dashed confidence bands).

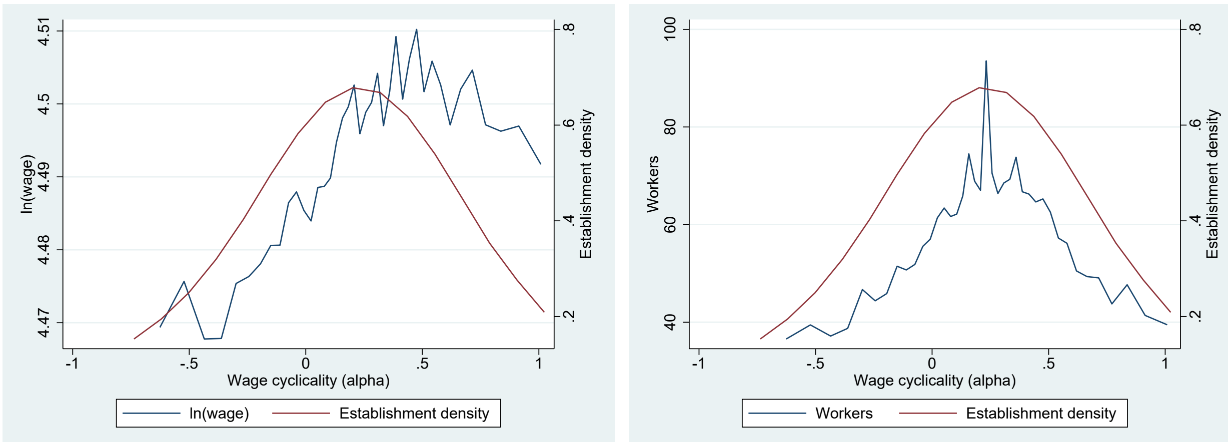
To check the robustness of our results in the time dimension, we estimate the effect of wage cyclicality on employment cyclicality using 25 rolling 12-year windows (1979–1990 to 2003–2014). Figure 3 shows that the quantitative results are very robust over time. The estimated relationship between employment cyclicality and wage cyclicality is statistically significant at the 1 percent level in all cases.

4.2 Potential Drivers

So far, we have documented the heterogeneity of wage cyclicalities across establishments and its impact on the employment cyclicalities. Before checking the robustness of our results, we will discuss potential underlying drivers. The AWFP does not contain any information on unionization or institutional details on wage formation. Therefore, we first document the relationship between establishment wage levels, establishment size, and establishment fixed effects with wage cyclicality (based on the baseline sample). We then link a subsample of the AWFP to the IAB Establishment Panel, which contains information on institutional details.

4.2.1 Characteristics of Establishments

Figure 4: Mean Daily Wages and Mean Stock of Full-Time Workers Along the Wage Cyclicality Measure Distribution



4.1: Mean ln(Mean Real Daily Wage) 4.2: Mean Stock of Full-Time Workers

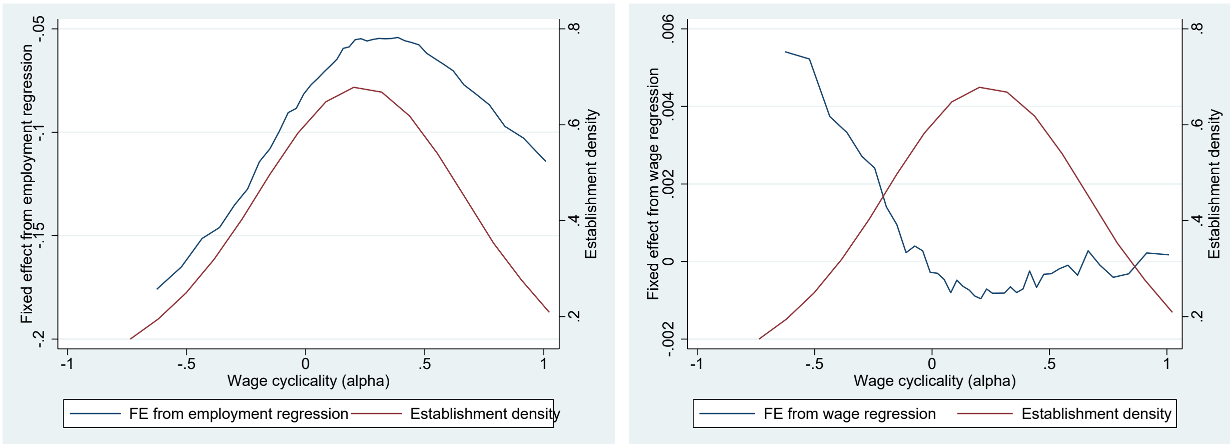
Note: We divide the range of the wage cyclicality measure ($\hat{\alpha}_{1i}$, see Section 3.1) into 50 bins. Each bin contains 1/50 of all observations, showing the mean. We drop extreme outliers (see Footnote 13). The figure is showing results for mean $\hat{\alpha}_{1i} \geq$ the 10th percentile and $\hat{\alpha}_{1i} \leq$ the 90th percentile of the estimated $\hat{\alpha}_{1i}$ (see Table 2).

Figures 4 and 5 sort establishments according to their wage cyclicalities into 50 bins. Figure 4.1 shows the mean real wage of full-time workers for each bin. Mean wages are slightly higher for establishments with acyclical or procyclical wage cyclicality than for countercyclical establishments. However, these wage differences do not appear to be economically relevant. The lowest value is about 4.48 and the highest about 4.51, i.e., there is only a difference of 3% or less than € 3 gross per worker and day.

Figure 4.2 shows the mean number of full-time workers for each bin. The picture reveals a nonlinear pattern. Strongly procyclical and countercyclical wage establishments are similar in size. In contrast, moderately procyclical wage establishments (in the middle of the distribution) are larger in size. Note that a similar qualitative picture emerges when the sampling restrictions are removed. Obviously, this fact may be related to the industrial relation regime. It is well known that larger establishments are more likely to be involved in collective bargaining (see Section 4.2.2 for details).

In Appendix A.5, we present some statistics for pro- and countercyclical establishments ($\hat{\alpha}_{1i} > 0$ and $\hat{\alpha}_{1i} < 0$, respectively) as well as for strongly countercyclical ($\hat{\alpha}_{1i} \leq$ 20th percentile), strongly procyclical establishments ($\hat{\alpha}_{1i} \leq$ 80th percentile), and acyclical and moderately cyclical establishments (20th percentile $< \hat{\alpha}_{1i} <$ 80th percentile). Statistics for the baseline sample itself are presented in Table A.1 in Appendix A.1.1.

Figure 5: Establishment Fixed Effects from the Employment and Wage Regression Along the Wage Cyclicality Measure Distribution



5.1: Fixed Effects from the Employment Regression (μ_i^n)

5.2: Fixed Effects from the Wage Regression (μ_i^w)

Note: We divide the range of the wage cyclicality measure ($\hat{\alpha}_{1i}$, see Section 3.1) into 50 bins. Each bin contains 1/50 of all observations, showing the mean. We drop extreme outliers (see Footnote 13). The figure is showing results for mean $\hat{\alpha}_{1i} \geq$ the 10th percentile and $\hat{\alpha}_{1i} \leq$ the 90th percentile of the estimated $\hat{\alpha}_{1i}$ (see Table 2).

In addition to linking the measure of wage cyclicality to descriptives, we show the relationship with the estimated establishment fixed effects. Figure 5.1 shows the relationship between wage cyclicality and the establishment fixed effect (μ_i^n) from the employment cyclicality regression (Equation (2)). The establishment fixed effect is largest for establishments with moderately procyclical wages. A larger establishment fixed effect means that an establishment has a larger average employment growth rate. This can be connected to Figure 4.2. Establishments with the highest average employment growth rate (over a long time horizon) are those with the largest size.

Figures 5.2 provides a link between the wage cyclicality of establishments and their establishment fixed effect (μ_i^w) from the wage regression (Equation (1)). This figure reveals an insightful relationship for countercyclical wage establishments. A more countercyclical wage is associated with a larger establishment fixed effect. In other words: In establishments with (strongly) countercyclical wages, average real wage growth is greater than in procyclical establishments. Recall that we found that a large fraction of establishments has countercyclical real wages. Accounting for the establishment fixed effects puts this result into perspective. Countercyclical wage establishments do not necessarily lower real wages in booms, but merely show a negative deviation from their average positive real wage growth.

4.2.2 Industrial Relations

We are not in a position to provide a definitive to the causes of heterogeneity in the wage cyclicalities. Instead, we are the first to document these heterogeneities and their implications. However, this subsection links the AWFP to the IAB Establishment Panel (EP). In this way, we can provide some anecdotal evidence (at the cost of losing about 95% of our observations).[20] The IAB EP is an annual survey of establishments in Germany that has been conducted since 1993. It targets a representative sample of about $15,000$ to $16,000$ establishments per year. It covers various topics, such as the business performance and strategies, and institutional information (e.g., works councils, collective agreements, ownership structure) among others (see Ellguth et al. (2014) and Appendix A.1.2).

Table 5 shows the fraction of establishments (weighted by size) in different bargaining regimes for five quintiles of wage cyclicalities. We determine the wage cyclicality quintile using our AWFP baseline sample results and using the survey answers (if available).[21] Note that we sort the quintiles from the most countercyclical group (quintile 1) to the most procyclical group (quintile 5).

Table 5: Wage Bargaining Regime and Works Council

	Quintile of wage cyclicalities				
	1	2	3	4	5
Wage bargaining regime					
Collective bargaining	50.3	62.6	70.0	68.5	56.1
Firm level bargaining	9.4	8.7	7.4	7.6	7.8
Works council (in %)					
Yes	47.4	58.9	68.5	67.7	55.5

Note: We determine the wage cyclicality quintile with the full AWFP sample and use the (min-mode) survey answers (if available) of the IAB Establishment Panel. Quintile 1 (5) are the most countercyclical (procyclical) wage establishments. Results are weighted by establishment size.
Source: AWFP linked to the IAB Establishment Panel for the years 1993–2014.

In this way, clear patters can be demonstrated. A larger share of establishments in quintiles 3 and 4 (i.e., those with acyclical and moderately procyclical wages) are part of the collective bargaining agreement. In addition, a larger share of these establishments have a works council (see Table 5).[22] It seems entirely plausible to us that both collective

[20] Information on the wage bargaining regime is available for 17,508 establishments of our baseline sample and information on the existence of works councils for 18,003 establishments.

[21] The patterns are very similar whether we use a specific base year in the survey or an average of the answers (since the bargaining regime or the existence of a works council may change over time). The results in Table 5 are obtained by using the response mode of an establishment.

[22] Works councils are the elected worker representation at the establishment level who have a say in certain important decisions such as dismissals.

bargaining and works councils are associated with more moderate real wage movements over the business cycle. Collective bargaining agreements represent only constitute minimum wage payments (i.e., higher wage increases are possible). However, it can be assumed that collective agreements are an important anchor for the wage formation of establishments that have chosen to participate in the agreement.[23] Although works councils do not play a formal role in wage negotiations, their existence is known to be correlated with wage outcomes (see, e.g., Addison et al., 2010). It is thus in line with our expectations that a higher share of works councils are associated with more moderate real wage cyclicalities.[24]

In short, establishments with moderately procyclical wages tend to be larger, are covered by a collective bargaining agreement, and are more likely to have a works council. From a theoretical perspective, these facts are straightforward to explain. Being part of a collective bargaining means that wages tend to be adjusted in line with the sector-specific business cycle. In contrast, based on our dataset, we cannot provide an explanation for why some establishments exhibit strongly procyclical wages and others exhibit countercyclical wages, even though they appear comparable in terms of the observable characteristics shown, such as size or collective bargaining.

Using the IAB EP, we also checked whether an additional control for the presence of a works council or for establishments' participation in collective bargaining affects our regression results. In both cases, the introduction of the new control variable has virtually no effect on the effect of wage cyclicality on employment cyclicality ($\hat{\gamma}_1$). Results are available upon request.

4.3 Further Robustness Checks

In what follows, we perform several robustness checks. First, we show that our baseline sample restrictions lead to more representative and stable results by restricting and relaxing the restrictions on mean workers and the number of observations. Second, we discuss and analyze the role of newly hired versus incumbent workers. Third and fourth, we discuss composition effects and working time effects, respectively.

4.3.1 Establishment Size and Short-Lived Establishments

To analyze the role of establishment size, we run our regressions using the entire AWFP (i.e., including establishments of all sizes) and for a sample of establishments with on average at

[23]Of course, this may also apply to some establishments that are not formally part of the collective agreement. However, these can undermine the collective conditions.

[24]In the IAB Establishment Panel, larger establishments are overrepresented (see Ellguth et al., 2014). This means that the share of collective bargaining is overrepresented compared to all establishments.

least 20 full-time workers. Table 6 shows that the estimated coefficient $\hat{\gamma}_1$ increases when we exclude smaller establishments from the sample. This confirms our conjecture that small establishments are noisier because they may have zero full-time workers in certain periods. In addition, small size may generate extreme growth rates. Moreover, it shows that our results are not driven by small establishments (which would be worrisome). In contrast, we obtain a stronger correlation the larger the establishments are.

Table 6: Effect of Wage Cyclicality on Employment Cyclicality — Altering the Mean Establishment Size

Mean size	all	10	20
Estimated coefficient $\hat{\gamma}_1$	-0.292^{***}	$\mathbf{-0.460}^{***}$	-0.500^{***}
R^2	0.01	0.01	0.01
Observations	2,298,507	344,537	177,151

Note: *** indicates statistical significance at the 1 percent level. Baseline regression result in bold. We drop extreme outliers before running the regression (see Footnote 13). Regressions are weighted by mean establishment size.

To analyze the role of short-lived establishments, we run our baseline regressions without restrictions on the number of observations in the sample and with a least ten and 15 observations, respectively. Table 7 shows that the estimated coefficient converges to a level of around −0.46 with a least five observations and remains at this level, or slightly higher.

Table 7: Effect of Wage Cyclicality on Employment Cyclicality — Altering the Minimal Number of Required Observations per Establishment

Required observations	2	5	10	15
Estimated coefficient $\hat{\gamma}_1$	-0.312^{***}	$\mathbf{-0.460}^{***}$	-0.542^{***}	-0.530^{***}
R^2	0.00	0.01	0.02	0.02
Observations	405,060	344,537	270,426	214,191

Note: *** indicates statistical significance at the 1 percent level. Baseline regression result in bold. We drop extreme outliers before running the regression (see Footnote 13). Regressions are weighted by mean establishment size.

Overall, these results are consistent with our conjecture that small establishments and short-lived establishments may add noise to the regressions. Based on these results, we consider the sample restrictions for our baseline regressions to be appropriate.

4.3.2 Newly Hired versus Incumbents Workers

Pissarides (2009) and Haefke et al. (2013) show that in search and matching models, wages for newly hired workers are relevant for job creation, not wages for incumbent workers. In all of our regressions, we use the wages of all full-time employees, not just those of newly hired workers. Why do we think this is a good strategy?

First of all, Stüber (2017) shows based on individual-level regressions that wage cyclicalities of newly hired workers over the business cycle in Germany are fairly similar to the wage cyclicalities for incumbent workers (i.e., incremental effects are either very small or statistically insignificant). Thus, the distinction between entrants and incumbents is less of an issue for Germany than for other countries.

Second, in Appendix A.3, we estimate the wage cyclicality with respect to unemployment. While Stüber (2017) estimates it at the individual full-time worker level, our wage cyclicality is estimated at the establishment level for full-time workers. At the worker level, Stüber (2017) finds coefficients of -1.26. At the establishment level, we estimate a coefficient of -1.16. The estimated elasticities are remarkably similar, which reassures us that our establishment dataset replicates the same cyclicality patterns as worker-level datasets. The slightly lower coefficient at the establishment level is in line with Solon et al. (1994). They argue that using aggregated data instead of microeconomic data leads to an underestimation of wage cyclicality due to a composition bias.

Finally, for econometric reasons (non-stationarity and trends), we have opted for an estimation in first differences. Note that the wage growth for entrants at the establishment level is not a well-defined concept. In our dataset, we do not know an individual's wage in the previous job or the previous employment spell of the entrant. Thus, we would have to compare the average entrant wages of this period to the previous period (at the establishment level). In this case, composition issues would play a much larger role than for the entire workforce (compositional issues are discussed later in the next section). While the stock of employed workers changes over time, most workers remain from the previous period. By contrast, there are different entrants in each period.

4.3.3 Composition Effects and Incumbent Workers

There may be a concern that our results may be affected by reverse causality due to compositional effects. Imagine an establishment with procyclical employment and completely fixed (acyclical) wages for two worker types: w_l for low-qualified workers and w_h for high-qualified workers, with $w_l < w_h$. If the establishment hires workers during a boom and the proportion of low-qualified and high-qualified workers in the establishment remains constant, the mean wage of the establishment would not change. However, we would observe a countercyclical mean wage if the establishment increases the share of low-qualified workers. Its mean wage would decrease due to a pure composition effect (since $w_l < w_h$ and the share of workers receiving w_l increases).

It is important to emphasize that we take several steps to prevent this type of reverse causality from affecting our results. First, we use full-time workers as our reference group. This group is certainly more homogeneous than total establishment employment, which may include jobs with a small number of hours that can vary widely (e.g., so called mini-jobs). Second, we use the sector-specific employment growth rate as business cycle indicator. Workforces within a sector are expected to be more similar than across sectors in terms of observable and unobservable characteristics. Third, in the first stage of our regressions, we control for time-invariant heterogeneity and changes in various observables (e.g., change of education composition). However, change in unobservable characteristics may still be an influential factor that we have not fully controlled for.

To check for the robustness of the results, we replace the wage growth for all full-time workers with the wage growth of incumbent workers, i.e., employment relationships that already existed in the previous period. The stock of incumbents is more stable in composition than newly hired workers. Therefore, potential composition biases are less of an issue.[25] Table 8 shows that the estimated effect ($\hat{\gamma}_1^{\text{incumbents}}$) is even larger than in our baseline estimation ($\hat{\gamma}_1$). This is further evidence that composition effects are not the key driver for our results (see Appendix A.6 for further illustrative evidence).

Table 8: Effect of Wage Cyclicality of Incumbent Workers on Employment Cyclicality

Estimated Coefficient	$\hat{\gamma}_1^{\text{incumbents}}$	$\hat{\gamma}_1$
Coefficient	-0.648^{***}	$\mathbf{-0.460}^{***}$
R^2	0.03	0.01
Observations	257,470	344,537

Note: *** indicates statistical significance at the 1 percent level. Baseline regression result in bold. We drop extreme outliers before running the regression (see Footnote 13). Regressions are weighted by mean number of incumbent workers and mean establishment size, respectively.

Finally, Appendix A.5 shows the estimated distribution of wage cyclicality at different percentiles within establishments (i.e., using the 25th and the 75th percentile instead of the mean daily wage of the establishment). Interestingly, the estimated distribution of wage cyclicality at the 25th and 75th percentiles looks very similar to the average wage. Moreover, the estimated relationship between employment and wage cyclicality for these two percentiles is also negative and statistically significant. This is further evidence that composition is not the key driver for our results.

[25] We owe this idea to Pedro Martins.

4.3.4 Working Time Effects

Our dataset does not contain information on the number of hours worked. Could the fluctuation of hours generate spurious results? We take several steps to rule out the possibility that hours worked could be driving our results. First, we restrict our analysis to full-time workers. Second, we control for time-varying observable variables and time-invariant unobserved heterogeneity in estimating our establishment-level wage regressions.

In addition, it is worth noting that the extensive margin of labor adjustment is usually much more important than the intensive margin in Germany. Merkl and Wesselbaum (2011) show that the extensive margin can explain more than 80% of aggregate hours fluctuations in Germany (from the 1970s to the Great Recession). However, during the Great Recession, the intensive margin was by far the dominant adjustment mechanism (see Burda and Hunt, 2011). Therefore, we exclude the Great Recession from our regressions (i.e., we run the regressions up to 2006, see Table 9). Compared to the baseline regression result, the quantitative results for the comovement measure become only slightly smaller. Therefore, we believe that intensive margin adjustments cannot be the key driver for our results.

Table 9: Effect of Wage Cyclicality on Employment Cyclicality — Excluding the Great Recession

Estimated Coefficient	$\hat{\gamma}_1^{\leq 2006}$	$\hat{\gamma}_1$
Coefficient	-0.436^{***}	$\mathbf{-0.460}^{***}$
R^2	0.01	0.01
Observations	298,054	344,537

Note: *** indicates statistical significance at the 1 percent level. Baseline regression result in bold. We drop extreme outliers before running the regression (see Footnote 13). Regressions are weighted by mean establishment size.

In addition, the adjustment of hours was particularly important in the manufacturing sector during the Great Recession. The manufacturing sector made greater use of measures as short-time work than the service sector. However, looking at the sectoral level, the effects of different wage cyclicalities on employment are very similar for manufacturing and services (see Table A.4 in Appendix A.4).

5 Heterogeneous Wage Cyclicalities: Theory

The previous sections showed that there is substantial cross-sectional heterogeneity in wage cyclicalities in Germany and that these heterogeneities matter for employment cyclicalities at the establishment level. Given that these results are based on reduced-form regressions, they do not allow us to analyze how much wage cyclicalities matter in aggregate (and not just at the establishment level). Thus, this section looks at the empirical patterns through the lens of a structural model.

We derive a labor market flow model that allows us to match three important facts from the data. First, we want to ensure that the coexistence of wage cyclicalities and hiring at any point in time can be replicated. For establishments with more than ten employees, the number varies between 92 and 98 percent. For establishments with more than 50 employees, at least 99 percent hire in any given year. Second, we calibrate our model to the wage cyclicality heterogeneity in the data. Third, we target the estimated effect of wage cyclicality on employment cyclicality at the establishment level. Matching these three facts allows us to make meaningful statements on the role of wage cyclicalities and heterogeneities based on counterfactual exercises.

5.1 Theoretical Model

We require a model that allows for heterogeneous wage cyclicalities over the business cycle and the possibility that establishments hire at any point in time. A possible choice would be a segmented labor market framework, as in Barnichon and Figura (2015). However, we find substantial heterogeneity in wage cyclicalities independently of the disaggregation level (national or 31 sectors). Thus, market segmentation is not the key driver for different wage cyclicalities in Germany and we need to model different wage cyclicalities within a labor market segment.

We assume that each establishment obtains an undirected flow of applicants, which is determined by a degenerate contact function. Once workers and establishments get in contact with one another, each worker-establishment pair draws a realization from the same idiosyncratic training cost distribution. Establishments choose an optimal cutoff point and thereby decide about the fraction of workers they want to hire (labor selection). The cutoff point and the hiring rate depend on the wage cyclicality. Hiring will be different (but will not necessarily be shut down) if the wage cyclicality is different from other establishments in the economy.[26]

Our model setup is similar to Chugh and Merkl (2016). The key difference is that we allow for heterogeneous wage cyclicalities across establishments. Under certain assumptions, the homogeneous version of our model delivers globally equivalent job-finding rate and unemployment dynamics as the standard search and matching model (see Appendix A.13 for details, which is based on Merkl and van Rens (2019)). In our quantitative exercise, we

[26]We abstract from vacancies because they are not included in the AWFP (where we only have stocks, flows, and wages).

will impose this equivalence property. This will allow us to connect to the Shimer (2005) puzzle debate. By setting the wage cyclicality of all groups to the same number, we obtain a homogeneous version of our model.[27]

5.1.1 Heterogeneous Groups and Matching

In our model economy, there is a continuum of establishments that differ in terms of their wage formation over the business cycle.[28] Workers can either be searching or employed. Employed workers are separated with an exogenous probability ϕ. In each period, searching workers send their application to one random establishment (i.e., search is random and undirected). Thus, each establishment receives a certain fraction of searching workers in the economy, where the number of overall contacts in the economy is equal to the number of searching workers in the period. This corresponds to a degenerate contact function.

Establishments produce with a constant returns technology with labor as the only input. They maximize the following intertemporal profit function (with discount factor δ):

$$E_0 \left\{ \sum_{t=0}^{\infty} \delta^t \left[a_t n_{it} - w_{it}^I (1-\phi) n_{i,t-1} - c_{it} s_t \eta(\tilde{\varepsilon}_{it}) \left(\frac{\bar{w}^E(\tilde{\varepsilon}_{it})}{\eta(\tilde{\varepsilon}_{it})} + \frac{H(\tilde{\varepsilon}_{it})}{\eta(\tilde{\varepsilon}_{it})} + h \right) \right] \right\}, \tag{4}$$

subject to the evolution of the establishment's employment stock in every period:

$$n_{it} = (1-\phi) n_{it-1} + c_{it} s_t \eta(\tilde{\varepsilon}_{it}), \tag{5}$$

where a_t is aggregate productivity, which is subject to aggregate shocks, w_{it}^I is the wage for incumbent workers (who do not require any training). We assume that a certain fraction, c_{it}, of searching workers, s_t, applies randomly at establishment i. Note that $c_{it} s_t$ is exogenous to establishment i.

Applicants who apply at establishment i draw an idiosyncratic match-specific training cost shock from a stable density function $f(\varepsilon)$. Establishments of type i will only hire a match below a certain threshold $\varepsilon_{it} \preceq \tilde{\varepsilon}_{it}$, i.e., only workers with favorable characteristics will be selected. This yields the selection rate for establishment i: $\eta(\tilde{\varepsilon}_{it}) = \int_{-\infty}^{\tilde{\varepsilon}_{it}} \varepsilon f(\varepsilon) d\varepsilon$. The term in brackets on the right hand side of Equation (4) shows how much the establishment has to pay for the average new hires, namely the average wage for an entrant, $\bar{w}^E(\tilde{\varepsilon}_{it})/\eta(\tilde{\varepsilon}_{it})$, the average training costs, $H(\tilde{\varepsilon}_{it})/\eta(\tilde{\varepsilon}_{it})$, both conditional on being hired. In addition, there is a fixed

[27] In Appendix A.11, we also derive a search and matching model with decreasing returns to labor, which allows for the coexistence of heterogeneous wage cyclicalities and hiring at any point in time. This framework is unable to match the quantitative connection between wage cyclicalities and employment cyclicalities.

[28] We abstract from establishment entry, i.e., the number of establishments is fixed.

hiring cost component h. We define $\bar{w}^E(\tilde{\varepsilon}_{it}) = \int_{-\infty}^{\tilde{\varepsilon}_{it}} w^E(\varepsilon) f(\varepsilon) d\varepsilon$ and $H(\tilde{\varepsilon}_{it}) = \int_{-\infty}^{\tilde{\varepsilon}_{it}} \varepsilon f(\varepsilon) d\varepsilon$.

Existing worker-establishment pairs are homogeneous and have the following present value:

$$J_{it} = a_t - w_{it}^I + E_t \delta (1 - \phi) J_{it+1}. \tag{6}$$

Solving the maximization problem (see Appendix A.8) yields the evolution of the establishment-specific employment stock and the optimal selection condition:

$$n_{it} = (1 - \phi) n_{it-1} + c_{it} s_t \eta(\tilde{\varepsilon}_{it}), \tag{7}$$

$$\tilde{\varepsilon}_{it} = a_t - w^E(\tilde{\varepsilon}_{it}) - h + E_t \delta (1 - \phi) J_{it+1}. \tag{8}$$

Establishments are indifferent between hiring and not hiring at the cutoff point $\tilde{\varepsilon}_{it}$. An establishment of type i will select all applicants below the hiring threshold, namely:

$$\eta(\tilde{\varepsilon}_{it}) = \int_{-\infty}^{\tilde{\varepsilon}_{it}} f(\varepsilon) d\varepsilon. \tag{9}$$

Given that establishments are homogeneous (except for their wage cyclicality), in steady state, they all have the same selection rate η. The selection rate over the business cycle depends on the wage formation mechanism.

5.1.2 Wage Formation

Our paper does not provide a theoretical foundation for different wage cyclicalities. In reality, they may be driven by different labor market institutions or price setting behavior. However, our dataset does not allow us to isolate the driving forces. We believe that it is reasonable to assume that establishments inherit their wage formation mechanisms from the past (e.g., due to the degree of unionization or the culture of the establishment).[29] Therefore, we treat the wage cyclicality over the business cycle as exogenous in our model. We take different wage cyclicalities as given, which we change in our counterfactual exercises.

In spirit of Blanchard and Galí (2007), we choose a simple wage formation mechanism to model different wage cyclicalities:

$$w_{it} = \kappa_i (a_t w^{norm}) + (1 - \kappa_i) w^{norm}, \tag{10}$$

where κ_i is the establishment-specific degree of wage cyclicality over the business cycle and

[29] Knoppik and Beissinger (2009) show for 12 EU countries (including Germany) that the variation in national degrees of downward nominal wage rigidity cannot convincingly be explained by institutional factors such as, e.g., union density or bargaining coverage.

w^{norm} is the wage norm, where the economy converges to in the long run. Note that in our calibration, we will set w^{norm} to the steady state level of a Nash bargaining solution (such that the wage fluctuates around this reference point, which is bilaterally efficient). Thus, all establishments have the same wage in steady state. An establishment with $\kappa_i = 1$ comoves one to one with aggregate productivity, i.e., it is strongly procyclical. By contrast, for $\kappa_i < 0$, the establishment shows a countercyclical real wage behavior.

Note that the wage in group i is the same for all workers (i.e., $w_{it} = w_{it}^E = w_{it}^I$). The same wage for all workers can also be rationalized based on bargaining if training costs are sunk (as, e.g., assumed by Pissarides, 2009).

5.1.3 Aggregation

In order to establish an equilibrium, we have to aggregate across all establishments. The aggregate selection rate is

$$\eta_t = \frac{\sum_{i=1}^{E} c_{it} \eta \left(\tilde{\varepsilon}_{it} \right)}{\sum_{i=1}^{E} c_{it}}, \tag{11}$$

where E is the number of establishments. The aggregate employment rate is

$$n_t = \left(1 - \phi\right) n_{t-1} + s_t c_t \eta_t, \tag{12}$$

where the second term on the right hand side denotes the number of new matches, namely all workers who were searching for a job (s_t), who got in contact (c_t) with an establishment and who got selected (η_t). The aggregated contact rate is simply the sum of all establishment-specific contact rates,[30] $c_t = \sum_{i=1}^{E} c_{it}$.

All workers who search for a job and who are unable to match are defined as unemployed.

$$u_t = s_t \left(1 - c_t \eta_t\right), \tag{13}$$

i.e., those who lost their job exogenously in period t and those searching workers who did not find a job in the previous period.

In addition, unemployed workers and employed workers add up to 1:

$$n_t = 1 - u_t. \tag{14}$$

We assume that each searching worker gets in contact with one establishment in each period, i.e., there is a degenerate contact function where the overall number of contacts is

[30] We assume that there cannot be more than one contact per worker and per period.

equal to the number of searching workers. This means that in aggregate the probability of a worker to get in contact with an establishment is 1 ($\sum_{i=1}^{E} c_{it} = 1$).

Aggregate output in the economy is aggregate productivity multiplied with aggregate employment minus the average training costs:

$$y_t = a_t n_t - \sum_{i=1}^{E} \left(c_{it} \eta\left(\tilde{\varepsilon}_{it}\right) s_t \left(\frac{H_{it}}{\eta\left(\tilde{\varepsilon}_{it}\right)} + h \right) \right). \tag{15}$$

Note that we will choose five establishment types in our baseline simulation (see Appendix A.10 for a robustness check) below and we will assign exogenous contact rates according to their average empirical size. The establishment type will be our disaggregation level because all establishments of the same type behave in the same way.

5.2 Calibration

5.2.1 Parameter Values

In order to analyze the effects of different wage cyclicalities at the establishment level, we parameterize and simulate the model. Due to the quarterly frequency of our simulation, we set the discount factor to $\delta = 0.99$. In line with the average quarterly flow rates from the AWFP, the exogenous quarterly separation rate is set to $\phi = 0.07$ (see Bachmann et al., 2021, for quarterly statistics).

Aggregate productivity is normalized to 1. We assume that productivity is subject to aggregate shocks, with a first-order autoregressive process. The aggregate productivity shock is drawn from a normal distribution with mean zero. The first-order autocorrelation coefficient is set to 0.8. The standard deviation of the shock is normalized to 0.01.

We assume that the w^{norm} is equal to the steady state value of Nash bargaining with bargaining power 0.5 (see Appendix A.8.2 for the analytical derivation of this reference point) and a value of unemployment benefits of 0.65. Under this parameterization, we obtain a steady state wage of 0.95.

In order to target the distribution of wage cyclicalities from the data, we discretize our model economy into five different wage cyclicality groups. As establishments in different quintiles of our distribution have different sizes (see Table A.6 in the Appendix A.5 for details), we assume different exogenous contact rates for each group, namely $c_i = [0.14, 0.21, 0.27, 0.23, 0.15]$.[31]

[31] The alternative would be to assume different productivities and thereby different endogenous selection rates. However, Table A.6 shows that wage levels in these different quintiles are very similar. Therefore, we abstain from this solution.

In order to obtain comparability with the standard search and matching model, following Merkl and van Rens (2019), we use an inverse Pareto distribution for the idiosyncratic training cost distribution (see Appendix A.13 for the equivalence proof).[32] In line with Kohlbrecher et al. (2016) and other matching function estimations, we set the elasticity of the underlying matching function with respect to unemployment to $\psi = 0.65$.

We target the steady state selection rate to 0.45 to obtain the average unemployment rate from 1979–2014 (0.08). To reach this target, we set the fixed ex-post hiring costs to $hc = -0.22$ (the sum of fixed and average idiosyncratic training costs is 0.06 in steady state). In order to target the estimated effects of wage cyclicalities on employment cyclicalities ($\hat{\gamma}_1 = -0.46$), we set the distributional parameter for the cumulative distribution function $\eta_t = \left(\frac{\tilde{\varepsilon}_t}{\chi}\right)^{\frac{1-\psi}{\psi}}$ to $\chi = 3.58$. As our estimation is performed based on annual data, we explain in Appendix A.12 how we do the aggregation from quarterly simulated to annual data to ensure comparability. The next subsection contains a detailed discussion of how the micro estimation affects the macroeconomic outcomes.

To determine the wage cyclicality parameters κ_i, we match the 10th, 30th, 50th, 70th, and 90th percentile from Table A.2, by setting $\kappa_i = [-0.26, -0.02, 0.08, 0.18, 0.39]$. Under our chosen calibration, we do not hit the bargaining bounds in any of the simulations (i.e., neither workers nor establishments have an incentive to end the employment relationship). Thus, our model does not run afoul of the Barro (1977) Critique.

5.2.2 Connection between Micro Estimation and Macro Simulation

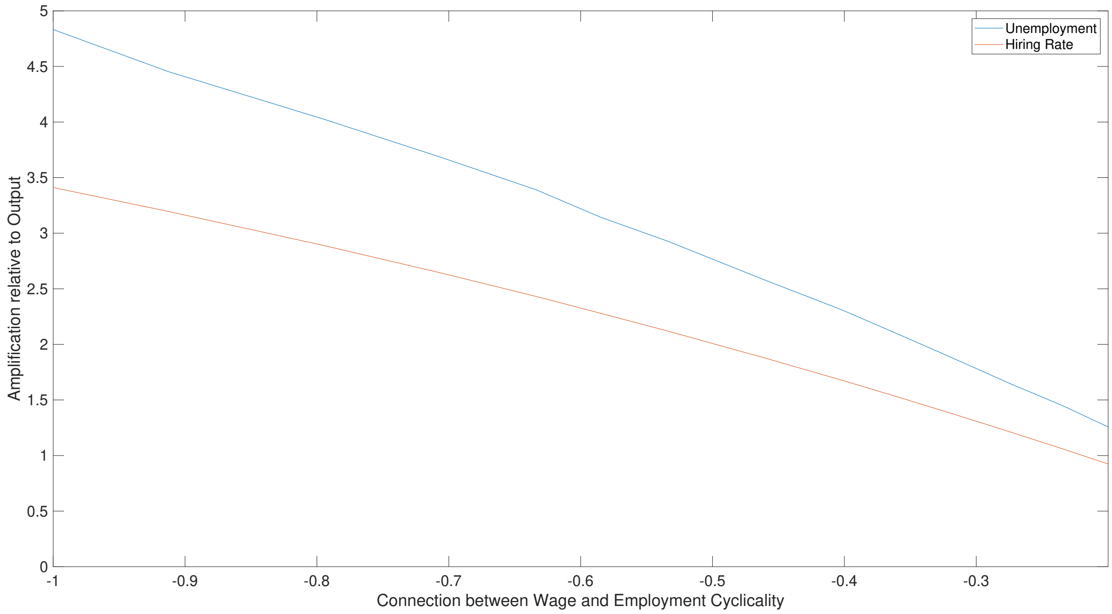
In our calibration strategy, we have chosen the parameter χ of the inverse Pareto distribution such that we obtain $\hat{\gamma}_1 = -0.46$ from simulated data. This choice matters for the quantitative performance of the model.

Intuitively, a less dispersed distribution leads to a stronger reaction in response to establishment-level and aggregate changes. Why? A less dispersed distribution means that there is more density mass around the cutoff point. Thereby, a given change in the cutoff point leads to a relatively large change in the selection rate and thereby labor adjustment.

Thus, the larger $\hat{\gamma}_1$ in our empirical micro-estimations, the less dispersed will be the distribution and the more mass will be around the cutoff point. This will lead to a more pronounced reaction of the model economy to aggregate shocks (and thereby more amplification). Figure 6 shows different targeted $\hat{\gamma}_1$ (in a range from -1.0 to -0.2, with the same targeted steady state) on the horizontal axis and the relative standard deviation of the hiring rate and unemployment relative to output on vertical axis: A larger $\hat{\gamma}_1$ leads to more

[32] As five groups is an arbitrary number, we use ten groups in a robustness check in Appendix A.10. All key results are unaffected by this larger number of groups.

Figure 6: Connection between Microeconomic Estimate and Macroeconomic Amplification



Note: The horizontal axis shows different targets for $\hat{\gamma}_1$. The vertical axis shows the amplification of the hiring rate and unemployment relative to output.

amplification.

The results from our micro estimations are decisive for how strongly our model economy reacts to aggregate shocks. In combination with the estimated wage cyclicalities, this pins down the aggregate role of wage cyclicalities in counterfactual exercises. Thereby, our quantitative exercise is different from many other counterfactual exercises in the literature. We bind our hands based on our microeconomic results.

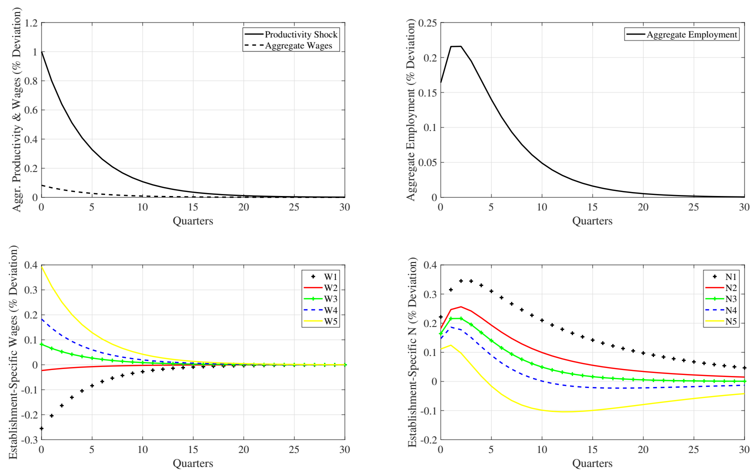
5.3 Model Performance

Figure 7 shows the impulse response functions of the model economy in reaction to a positive aggregate productivity shock.[33] In aggregate, average wages and employment respond procyclically to the aggregate productivity shock (see the upper two panels). However, establishments react very differently to the aggregate productivity shock depending on their wage cyclicality group (see the lower two panels). Real wages at the most countercyclical wage group (denoted by W1) decline, while they increase at the most procyclical wage group (denoted by W5). Employment shows the inverted behavior. It increases for the most coun-

[33] For the counterfactual exercises, we linearize the model. For a nonlinear analysis, see subsection 5.4.2.

tercyclical wage group (denoted by N1), while it falls (after some quarters) for the most procyclical wage group (denoted by N5).

Figure 7: Impulse Response Functions to a Positive Aggregate Productivity Shock



Note: The figure shows aggregate (upper two panels) and group-specific (lower two panels) reactions to a positive aggregate productivity shock. The most countercyclical wage group is denoted by a 1 and the most procyclical wage group is denoted by a 5.

In our model, both the most countercyclical and the most procyclical establishments show a larger volatility of real wages than establishments in the middle of the distribution. Although we did not target this U-shape of wage volatility, this pattern can also be found in the data.[34]

Why does employment increase in the immediate aftermath of the shock for the most procyclical wage group but decrease later on? Under our chosen calibration strategy, the net present value of a job also increases for the most procyclical wage group in response to a positive productivity shock. In other words, the productivity increase is larger than the wage increase. Thus, even the most procyclical establishments have an incentive to increase their selection rate (i.e., the share of applicants they choose). See Equations (8) and (9) for details. However, the new present values (and thereby the selection rate) increase more for the most countercyclical establishments. As aggregate employment increases due to the aggregate shock, the pool of available searching workers and thereby the number of applicants per establishment declines. After some quarters, this equilibrium effect dominates for the most procyclical wage establishments.

[34]Therefore, it is important that our measure of wage cyclicality from Equation (1) takes into account the direction of the wage movement. A measure of wage cyclicality based on the wage volatility would be misleading.

Before we use the model for counterfactual exercises, we look at its aggregate performance. Table 10 shows the standard deviations of the aggregate hiring rate (hr),[35] employment rate (n), and unemployment rate (u) relative to the standard deviation of real GDP, both in data and model simulations. For equivalent empirical statistics based on different filters and time frequencies, see Appendix A.12.2. The hiring rate and unemployment are more volatile than aggregate GDP. Thus, our model amplifies aggregate productivity shocks. For the hiring rate and unemployment, the model generates about one-half of the aggregate volatility from the data. For employment, there is a somewhat larger gap between the volatility in the data and the simulation.[36]

Table 10: Standard Deviations of Hiring Rate, Number of Full-Time Employment, and Unemployment Rate (all Relative to Real GDP)

	hr	n	u
Data	3.84	0.87	5.05
Simulation	1.88	0.22	2.58

Note: Observation period is 1979–2014. Hiring rate and employment are aggregated from the AWFP and deseasonalized with X-12-ARIMA. All variables are expressed in logs and as deviations from the Hodrick-Prescott filter (with a smoothing parameter of 1600).

Keep in mind that we have not targeted aggregate labor market amplification in our calibrated model. Instead, we have targeted the heterogeneities of wage cyclicalities and the effect of different wage cyclicalities on employment cyclicalities (and thereby disciplined the parameterization of the idiosyncratic shock dispersion).

Moreover, we have simulated our model using only aggregate productivity shocks. In reality, other aggregate shocks also play a role and thereby potentially create additional labor market amplification. Against this background, our simulated model does a remarkably good job by replicating about one-half of the observed amplification for the hiring rate and unemployment.

Table 11 shows that our model generates the right signs for the correlations between various aggregate variables. In addition, for most variables, we also obtain the right quantitative dimension. The reasonable match for amplification and correlations of aggregate variables puts us in a position to use our model for counterfactual exercises.

[35] The establishment-specific hiring rate is defined as the number of matches divided by the average number of employed workers in this and the previous quarter.

[36] This larger gap may be related to worker churn (see Bachmann et al. (2021)), which we do not model in our theoretical framework and which may increase the volatility of employment in the data.

Table 11: Correlations between Hiring Rate, Number of Full-Time Employment (both Aggregated from the AWFP), and Unemployment Rate

	corr(hr,n)	corr(hr,GDP)	corr(n,GDP)	corr(hr,u)	corr(u,GDP)
Data	0.33	0.60	0.55	-0.51	-0.55
Simulation	0.32	0.64	0.93	-0.32	-0.93

Note: All variables are expressed in logs and as deviations from the Hodrick-Prescott filter (with a smoothing parameter of 1600).

5.4 Counterfactual Exercises

5.4.1 Heterogeneity and Labor Market Amplification

We use our labor market flow model with heterogeneous wage cyclicalities for two purposes. We analyze whether heterogeneous wage cyclicalities matter for aggregate dynamics. In addition, we analyze the quantitative role of aggregate wage cyclicality for aggregate labor market amplification. These exercises are disciplined by our micro-estimates, as we targeted the connection between employment cyclicality and wage cyclicality to these empirical results.

In the first set of counterfactual exercises, we impose a symmetric wage cyclicality on all establishments. If all establishments behave as the median establishment (namely, $\kappa_i = 0.08$ for i = [1,5]), labor market amplification barely changes relative to the baseline scenario (see the second column in Table 12). The intuition is straightforward: in this scenario, about one-half of establishments are less procyclical than in the baseline, and the other half are more procyclical than in the baseline. These two effects almost cancel out, as wage cyclicalities are pretty symmetric around the median (see Table 2).

Analogously to Krusell and Smith (1998), these heterogeneities leave aggregate dynamics relatively unaffected. However, this quantitative result does not mean that heterogeneities in wage cyclicalities do not matter. Next, we show that the results from aggregate wage regressions would lead to different conclusions than our first counterfactual exercise based on the median establishment. Further, we show that the volatility of wages may be a misleading indicator for aggregate wage rigidity in the presence of both pro- and countercyclical wage establishments. In addition, we show in the next subsection that countercyclical wage establishments are a key driver for asymmetric labor market responses to large aggregate shocks.

In order to run an aggregate wage regression, we aggregate our own micro-data. Based on these time series, we estimate an aggregate wage growth-employment growth elasticity. We obtain an estimated coefficient of 0.29, which is larger than the coefficient for the median

Table 12: Counterfactual Exercises

	Exercises with Homogeneous Wage Cyclicality				Heterogeneous	
	All median	All agg. average	All Nash	All countercyc.	No procyc. wages	No countercyc. wages
u	0.1	-2.1	-69.8	30.6	11.4	-3.8
n	0.1	-2.0	-69.3	29.3	11.0	-3.7
w	-0.8	27.4	925.8	196.2	-51.7	49.8
u to w	-7.6	-7.7	-7.5	15.6	-22.0	-7.6

Note: The table shows the percentage change of the standard deviation of simulated unemployment and employment relative to the baseline (in logarithms, normalized by the standard deviation of output, and HP filtered). The last row shows the relative change of the standard deviation of unemployment to the standard deviation of wages (in percent). The second column imposes the median wage cyclicality on all establishments (median), the third column sets all establishments to a wage cyclicality to replicate the number from an aggregate wage regression (average), the fourth column imposes Nash bargaining, the fifth column imposes the 10th percentile (all countercyc.) from Table 2. The last two columns set all procyclical wage establishments (no procyc.) and countercyclical establishments (no countercyc.) to zero.

(0.22).[37] This would be the reference point for aggregate wage cyclicality if an applied econometrician does not have access to microeconomic data. When imposing this target (namely, $\kappa_i = 0.11$), the standard deviation of wages increases by 27 percent and labor market amplification drops by 2 percent (see third column in Table 2). Thus, while our analysis based on the median establishment suggests that aggregate dynamics are almost unaffected by heterogeneous wage cyclicalities, an analysis based on aggregate numbers would lead to different results.

The differences between the median and the average wage cyclicality become even more extreme when we replace the wage from our dataset with a publicly available real hourly wage time series[38] in the wage regression. Such a regression yields a small positive and statistically insignificant connection between aggregate wage growth and aggregate employment growth. It would tell the researcher that average wages in Germany are acyclical. Setting wages to an acyclical value increases labor market amplification (see Appendix A.9 for a discussion and details).

Standard search and matching models typically assume Nash bargaining (see Shimer (2005)). It is well known that this assumption generates very procyclical wages and thereby dampens labor market amplification. To understand the difference between actual wage formation and Nash bargaining, we set the wage cyclicality of all groups to Nash bargaining.

[37]Keep in mind that the procyclical wage groups are somewhat larger in size than the countercyclical wage groups, leading to a more procyclical wages in the counterfactual. In addition, the estimated elasticity comes from an aggregate regression without fixed effect and without compositional controls.

[38]Source: WSI, `https://www.wsi.de/data/wsi_vm_loehne_laender.xlsx`.

In this case, labor market amplification drops by close to 70 percent.[39] Under Nash bargaining, the procyclicality of wages increases more than in a scenario where we set the wage cyclicality of all establishments to the 10th percentile of procyclical wages (see Appendix A.9 for details). While the qualitative effects of different wage cyclicalities in search and matching models are well understood (e.g., Hall, 2005; Shimer, 2005; Hall and Milgrom, 2008), our paper adds a new quantitative contribution to the literature. Remember that we have disciplined our exercise by the quantitative connection between employment cyclicality and wage cyclicality (see Section 5.2.2) through our microeconometric estimations.

When we impose a countercyclical wage on all establishments (namely, $\kappa_i = -0.26$), the labor market reacts by roughly 30 percent more to aggregate shocks. This exercise shows that countercyclical wage establishments are important amplifiers for the labor market.

Finally, we impose an asymmetric wage cyclicality distribution on the model economy. First, we do not allow for proyclical establishments any more and impose $\kappa_i = [-0.26, -0.02, 0, 0, 0]$. This increases labor market amplification by around 11 percent. Second, we eliminate countercyclical wage establishments ($\kappa_i = [0, 0, 0.08, 0.18, 0.39]$). This reduces labor market amplification by around 4 percent. The key insight of this exercise is that policy interventions that affect the cross-sectional flexibility of wage adjustment may matter substantially for aggregate labor market amplification. Examples of such policy interventions are procyclical minimum wage policies or making collective bargaining agreements universally applicable. Reich (2009) shows, for example, for the United States that minimum wages typically increase in times of growing employment. Procyclical minimum-wage policies may prevent countercyclical wage adjustments. On the contrary, collectively bargained wages in Germany are typically less procyclical over the business cycle than actual economy-wide wages. They are negotiated on a centralized level and typically set in a staggered manner.[40] Thus, if economic policy declares collective-bargaining agreements universally applicable (which was done on the sectoral level in the past),[41] this may prevent wage cuts in recessions (i.e., prevent a procyclical adjustment).

In addition, the last row in Table 12 shows that the aggregate connection between the standard deviation of wages and the standard deviation of unemployment depends very much on the underlying policy exercise. When making procyclial wage establishments acyclical (see column 'no procyc. wages'), the relative reaction of the standard deviation of unemployment to the standard deviation of wages (last row) is much larger than in all other exercises

[39] For quantitatively similar implications for Nash bargaining for the United States, see recent work by Knowles and Lupoli (2023).

[40] For the role and effects of fixed-wage contracts in Sweden, see Björklund et al. (2019).

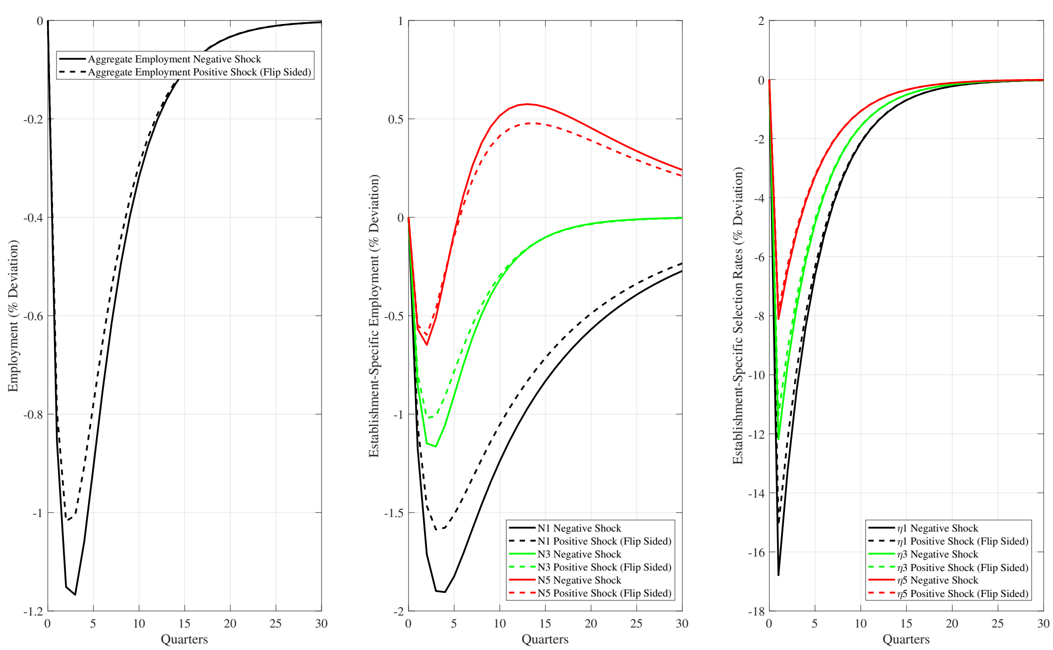
[41] In this case, collective bargaining agreements are not only relevant for those inside the collective bargaining agreement, but for all workers in the sector.

(-22 percent instead of around -8 percent). When imposing countercyclical wages on all establishments, a larger standard deviation of wages is even associated with a larger standard deviation of unemployment (see the positive sign in the last row in Table 12). In both cases, aggregate wages turn from procyclical to countercyclical. Therefore, just looking at the standard deviation of wages is a misleading indicator for wage rigidity in the presence of heterogeneous wage cyclicality.

5.4.2 Wage Heterogeneity and Labor Market Asymmetries

To gain further insights on the role of heterogeneity in wage cyclicality, we analyze the implications of large business cycle shocks. For this purpose, we solve the full nonlinear model structure to a 5 percent negative aggregate productivity shock (in analogy to the order of magnitude of GDP decline during the Great Recession) and to a symmetric 5 percent positive aggregate productivity shock.

Figure 8: Nonlinear Model Response to a Positive Aggregate and Negative Productivity Shock



Note: The figure shows aggregate (left panel) and group-specific (middle and right panel) reactions to a 5 percent positive and a 5 percent aggregate productivity shock. The most countercyclical wage group is denoted by a 1 and the most procyclical wage group is denoted by a 5. The employment and selection rate responses to the positive aggregate shock are flip sided for better visibility.

Figure 8 shows the nonlinear model response to these large aggregate shocks (for better visibility, the employment and the selection rate reactions to the positive aggregate shock are flip sided). The most countercyclical wage groups (denoted by N1) and the acyclical wage groups (denoted by N3) show much larger asymmetries in response to aggregate shocks than procyclical wage establishments (denoted by N5). Thus, these groups drive the asymmetric reaction of the labor market in response to aggregate shocks. These asymmetric reactions are in line with empirical evidence. Abbritti and Fahr (2013) show that labor markets react more strongly in recessions than in booms. The job-finding rate is an important driver for this phenomenon. The right panel in Figure 8 shows that establishment-specific selection rates are more asymmetric over the the business cycle for countercyclical wage establishments than for procyclical wage establishments. This is driven by the curvature of the underlying training cost density function, which is pinned down by the equivalence with the matching function (see Section 5.2.1 and Appendix A.13). Countercyclical wage establishments show the largest cutoff point movements in response to aggregate shocks. Thereby, in recessions, their cutoff point moves into a part of the idiosyncratic distribution with higher density and the selection rate reacts more than in booms.[42]

In order to make the case more convincing that wage cyclicalities are a key driver of asymmetric (un)employment reactions, we connect our theoretical results to three pieces of empirical evidence based on our micro-data. First, in the empirical part, it is visible that the wage cyclicality distribution is fairly symmetric (see Table 2), while at the same time, the employment cyclicality distribution shows strong asymmetries in the cross-sectional distribution (see Table 3). The most procyclical employment establishments are much farther away from the median than the most countercyclical employment establishments. Second, Figure 2 shows the nonlinear cross-sectional relationship between employment and wage cyclicality. The quantitative connection between employment cyclicality and wage cyclicality is larger for countercyclical establishments than for procyclical establishments. This is in line with the nonlinear model reaction in Figure 8. Third, Figure 3 shows the time-varying connection between employment cyclicality and wage cyclicality. Due to asymmetries, we expect a much larger employment reaction from countercyclical wage establishments in episodes of economic crisis. When we calculate the average real GDP growth over the same time windows and correlate it with the estimated connection between employment cyclicality and wage cyclicality, as expected, we obtain a positive correlation of approximately 0.5. The estimated connection between employment and wage cyclicality is particularly large during periods of large employment fluctuations for countercyclical establishments (around the time

[42]For more details on the nonlinear model mechanism in selection models, see Kohlbrecher and Merkl (2022), although they do not analyze the role of wage rigidity. They also show that the empirical job-finding rate in the United States reacts in skewed fashion over the business cycle.

of the Great Recession and afterwards). See Figure 1 for a visual inspection of employment fluctuations for the most countercyclical establishments. They are particularly large at the end of the sample when the connection between employment cyclicality and wage cyclicality is largest.

Our results on the interaction of wage cyclicality and labor market asymmetries are closely related to Petrosky-Nadeau et al. (2018) and Petrosky-Nadeau and Zhang (2021). They show the importance of the interaction between wage inertia and trading externality for asymmetric labor market reactions in the search and matching model.[43] While they compare their model outcomes to aggregate data from a panel of countries, we complement their work by showing that nonlinear model reactions are supported by several dimensions in our rich administrative microeconomic dataset in Germany. As the homogeneous version of our model nests the standard search and matching model, a similar model mechanism is at work, as in their paper.

5.5 Connection to Cyclical Earnings Risk

Our empirical and theoretical results allow us to connect to the cyclical earnings risk literature. Guvenen et al. (2017) show for the United States that the earnings of poor workers are more reactive to the aggregate business cycle than the earnings of workers in the middle of the distribution.[44] Kramer (2022) shows a quantitatively very similar connection for Germany.

We do our empirical analysis based on an establishment data set (AWFP), and therefore we have only limited knowledge of person characteristics. However, we can connect to the findings by Kramer (2022) who shows for Germany that the heterogeneity in earnings risk over the business cycle is mainly driven by a different relative reaction of the job-finding rate over the business cycle. Low-earnings individuals have on average much lower job-finding rates, which in relative terms move a lot more over the business cycle. This is the key driver for differences of earnings risks over the business cycle.

We have shown that countercyclical wage establishments show the largest employment reactions in recessions. Thus, they can be expected to be important drivers for the pattern identified by Kramer (2022). Although countercyclical wage establishments provide more insurance to their incumbent workers in recessions, the number of newly created jobs drops more substantially in recessions than at procyclical establishments. This could be a major

[43] By contrast, Abbritti and Fahr (2013) use an asymmetric wage adjustment mechanism over the cycle.

[44] Busch et al. (2022) show for the United States, Germany, Sweden, and France that income growth is strongly procyclical in all countries. This fact also holds for full-time workers, which is the unit of observation that we use in our empirical analysis.

driver for the decline of job-finding prospects for low-earnings workers.[45]

6 Conclusion

Using the Administrative Wage and Labor Market Flow Panel (AWFP), we show that the average real wage behavior masks that establishments have very different wage cyclicalities. Around one-third of establishments exhibits a countercyclical wage over the business cycle. Due to the linkage of the AWFP with the IAB Establishment Panel, we are able to show that acyclicality is associated with a higher share of establishments within collective bargaining. In addition, these establishments are on average larger relative to all other groups. By contrast, strongly countercyclical wage establishments tend to have a larger average real wage growth than the average in the economy.

Furthermore, we are able to show that differences in real wage cyclicalities have meaningful implications for employment cyclicalities. Establishments with more procyclical wages have a less procyclical employment behavior. This is in line with our proposed theoretical framework. In counterfactual exercises, we show the quantitative importance of wage rigidities for aggregate amplification. Furthermore, we show that acyclical and countercyclical establishments are important drivers for asymmetric labor market reactions over the business cycle. We also discuss the connection to the earnings risk literature. A deeper investigation would require further linkages between establishment and worker data, which we leave for future research.

By showing that establishments' wage rigidity does affect their employment dynamics, our paper provides support for quantitative theories where different wage cyclicalities affect employment. Our paper looks at the effects of wage cyclicality through the lens of a model with random search. Thereby, we present one possible mechanism that is in line with the pattern in the data. However, we consider our paper as a starting point that establishes empirical facts that are relevant for various other streams of the literature. Our wage cyclicality measures are not structural but in a reduced form and can easily be compared to other simulated models, e.g., to directed search models (e.g., Julien et al., 2009), to New Keynesian frameworks with infrequent wage adjustments, or to medium-scale dynamic stochastic general equilibrium models (e.g., Christiano et al., 2005; Smets and Wouters, 2007).

[45] We leave a more detailed analysis of how low-earnings workers are affected by countercyclical wage establishments for future research. When we look at the composition of workers at different wage cyclicality establishments, we find no meaningful differences in terms of the average wage or skill composition between countercyclical and procyclical wage establishments (see Table A.1 in the Appendix A.1.1). However, the AWFP does not provide information on the position in the earnings distribution.

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A Appendix for Online Publication

A.1 Datasets

A.1.1 The Administrative Wage and Labor Market Flow Panel

The Administrative Wage and Labor Market Flow Panel (AWFP) aggregates German administrative wage, labor market flow, and stock information to the establishment level for the years 1975–2014. All data are available at an annual and quarterly frequency (see Stüber and Seth, 2018, 2019).

The underlying administrative microeconomic data source is mainly the Employment History (Beschäftigtenhistorik, BeH) of the Institute for Employment Research (IAB). The BeH comprises all individuals who were at least once employed subject to social security since 1975.[46] Some data packages — concerning flows from or into unemployment — use additional data from the Benefit Recipient History (Leistungsempfängerhistorik, LeH). The LeH comprises, inter alia, all individuals that receive benefits in accordance with Social Code Book III (recorded from 1975 onwards). Before aggregating the data to the establishment level, several corrections and imputations were conducted at the micro level.

For coherency, we focus on wages and flows for "regular workers". In the AWFP a person is defined as a "regular worker" when he/she is full-time employed and belongs to person group 101 (employee s.t. social security without special features), 140 (seamen) or 143 (maritime pilots) in the BeH. Therefore, all (marginal) part-time employees, employees in partial retirement, interns etc. are not accounted for as regular workers.

Wages are defined as the mean real daily wages (in 2010 prices) of all employed full-time (regular) workers in a particular establishment.[47] The daily wages include the base salary, all bonuses and special payments (such as performance bonuses, holiday pay, or Christmas allowance), fringe benefits, and other monetary compensations received throughout the year (or the duration of the employment spell). Therefore, the daily wages correspond more to a measure of total compensation than to a daily base wage. Workers' daily wages above the contribution assessment ceiling are imputed following Card et al. (2015) before aggregating the data to the establishment level.[48]

In the AWFP, stocks and flows are calculated using an "end-of-period" definition:

- The stock of employees of an establishment in year t equals the number of full-time workers on the last day of year t.

[46] The BeH also comprises marginal part-time workers employed since 1999.
[47] Deflated using the CPI.
[48] For details see Appendix 8.2 of Schmucker et al. (2016).

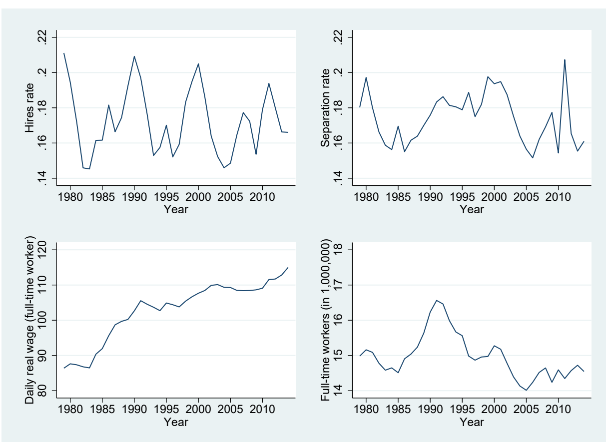
- Inflows of employees into an establishment for year t equal the number of full-time workers who were regularly employed on the last day of year t but not so on the last day of the preceding year, t-1.

- Outflows of employees from an establishment for year t equal the number of full-time workers who were regularly employed on the last day of the preceding year (t-1) but not so on the last day of year t.

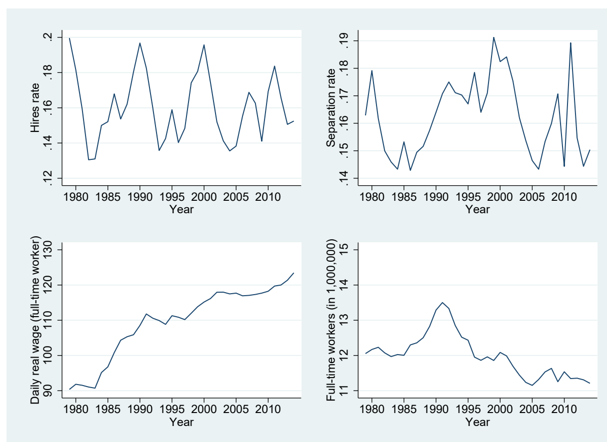
For more detailed information on the AWFP please refer to Stüber and Seth (2018).

We use the AWFP at the annual frequency and restrict the data to West German establishments (excluding Berlin) and the years 1979–2014. The dataset contains more than 3.3 million establishments. For illustration purposes Figure A.1.1 shows the time series for the aggregated hiring rate, separation rate, mean daily real wage per full-time worker (in 2010 prices), and the number of full-time workers. Hires (separation) rate is calculated as the sum of all hires (separations) divided by the average number of full-time workers in t and t-1.

Figure A.1: Aggregated time series for West Germany



A.1.1: AWFP



A.1.1: Baseline sample

Note: West Germany (excluding Berlin), 1979–2014.
Baseline sample restrictions: Only establishments with on average at least ten full-time workers are included. Further, the establishment must be observed at least five times.

For our baseline sample we restrict the AWFP data as follows. We consider only establishments with on average at least ten full-time workers. Further we only keep establishments for which we have at least five observations.[49] It covers on average 80.2% of all full-time workers. Over the years 1979–2014 the share varies between 76.8% and 82.7%. In Section 2.2 we motivate our baseline selection criteria in detail. Analog to illustration Figure A.1.1,

[49]Since we analyze wage growth and employment growth, this means that we need to observe the establishments for at least six years in the AWFP.

Figure A.1.2 shows the time series for our baseline sample. Some descriptive statistics for the baseline sample are presented in Table A.1. In Appendix A.5, we present some statistics for pro- and countercyclical establishments ($\hat{\alpha}_{1i} > 0$ and $\hat{\alpha}_{1i} < 0$, respectively) as well as for strongly countercyclical ($\hat{\alpha}_{1i} \leq$ 20th percentile), strongly procyclical establishments ($\hat{\alpha}_{1i} \leq$ 80th percentile), and acyclical and moderately cyclical establishments (20th percentile $< \hat{\alpha}_{1i} <$ 80th percentile).

Table A.1: Descriptive Statistics Baseline Sample (I)

Variable	Mean	Std. Dev.
Establishment size	52.06	233.50
workers log(daily wage)	4.64	0.30
Low-skilled workers	14.30%	14.17
Medium-skilled workers	73.42%	17.75
High-skilled workers	12.27%	15.92
Male workers	70.64%	23.30
Mean tenure	23.95	9.88
Mean age	39.69	3.63

Note: This table shows descriptive statistics for the baseline sample. Before calculating the statistics, extreme outliers are removed (see footnote 13). Results are based on a sample of 344,537 establishments. For these establishments, we have 7,157,705 establishment-year observations, considering 427,008,993 person-year observations. The sample thus covers 18% of all establishment-year observations and over 79% of all person-year observations. Statistics weighted by mean establishment size.

A.1.2 The IAB Establishment Panel

The IAB Establishment Panel is an annual survey of establishments located in Germany which has been conducted since 1993 (Fischer et al., 2009; Ellguth et al., 2014) and it can be linked to the AWFP. The survey information is collected mostly in face-to-face interviews. The survey aims for a representative sample of about 15,000 to 16,000 establishments each year.

The IAB Establishment Panel contains information on the establishments which is not available in the administrative data which is used to generate the AWFP. It covers various topics such as the business performance and strategies, investment and innovation activities, vocational/further training, recruitment and layoff behaviour, working time issues and structural information (e.g., works councils, collective agreements, ownership structure) among others.

The sampling frame of the IAB Establishment Panel comprises all establishments in

Germany with at least one employee who is fully liable to social security on June 30th of the previous year. Establishments that exclusively have workers in marginal part-time employment are excluded from the sampling frame. The survey sample is disproportionately stratified in three dimensions: First, the sample is stratified by 16 federal states. Second, the survey sample is stratified by ten establishment size classes as the population is very much skewed towards small establishments. Third, the survey sample is stratified by industries to allow for differentiated analyses in this respect.

A.2 Average Wage Cyclicality

Our regression equation for quantifying the average cyclicality of mean real daily wage growth at the establishment level is

$$\Delta \ln w_{ijt} = \alpha_0 + \alpha_1 \Delta \ln N_t^j + \alpha_2 t + \alpha_3 t^2 + \alpha_4^{'} \mathbf{C}_{it} + \mu_i + \varepsilon_{ijt}, \tag{A.1}$$

where $\Delta \ln w_{ijt}$ is the growth rate of mean real daily wages of establishment i in (industry) sector j in year t and $\Delta \ln N_t^j$ is the growth rate of full-time workers in sector j. μ_i is the establishment-fixed effect, and $\mathbf{C}_{it}$ is a vector of control variables including the changes of education shares and gender shares at the establishment level as well as changes in the average age, tenure, and tenure squared of the workers within the establishment. We include changes in these control variables instead of levels to better control for changes in the work force composition of the establishments. In addition, we include a linear and quadratic time trend.[50]

As the business cycle indicator in our baseline specification, we use the aggregate employment growth rate at the industry level using 31 sectors (see Appendix A.4 for details). By using the sector level, we want to make sure that our results are not driven by heterogeneity between sectors, e.g., different exposures to the aggregate business cycle.

Table A.2 shows that the estimated coefficient $\hat{\alpha}_1$ for aggregate employment growth is positive and statistically significant. A 1% larger sectoral employment growth is associated with a 0.2% larger wage growth on average. This confirms results from earlier studies that the average wage growth is procyclical (e.g., Solon et al., 1994, for the United States or Stüber, 2017, for Germany).

Appendix A.3 shows that a regression in levels — using the aggregated unemployment rate as the business cycle indicator — delivers a result that is comparable with regressions

[50]When we exclude the time trend from our regressions, both the heterogeneity of wage cyclicalities and their impact on establishment-specific employment change very little. The same is true if we include year dummies instead of time trends.

Table A.2: Average Wage Cyclicality

Estimated coefficient $\hat{\alpha}_1$	0.218***
Controls	Changes in education shares, gender share, mean age, mean tenure, and mean tenure^2. Establishment fixed effects, year, and year^2
R^2 | within R^2	0.17 | 0.13
Observations	7,259,116

Note: *** indicates statistical significance at the 1 percent level. Weighted by establishment size.

results on the worker level (see also Section 4.3.2). This confirms that our establishment-level approach delivers similar results as the typical worker-level approach. Given that we are ultimately interested in the interaction between wage and employment cyclicalities, the establishment level is relevant, as this is where employment is determined.

A.3 Comparison with Worker Level Regressions

This Appendix shows that our establishment-level dataset generates a similar result to the existing literature on wage cyclicalities for Germany. There are two key differences from the existing literature. First, the papers use worker-level data. Second, generally they use level-regressions instead of difference equations.[51] For comparability reasons, we estimate the following regression using the AWFP data:

$$\ln w_{it} = \alpha_0 + \alpha_1 u_t + \alpha_2 t + \alpha_3 t^2 + \alpha_4^{'} \mathbf{C}_{it} + \mu_i + \varepsilon_{it}, \tag{A.2}$$

where w_{it} is the mean real daily wage of all full-time workers at establishment i in year t. u_t is the aggregate unemployment rate for West Germany. We include a linear and a quadratic time trend as well as establishment fixed effects, μ_i, to control for time-invariant heterogeneity. C contains a vector of control variables, education shares at the establishment level, gender, the mean age of workers in the establishment, their mean tenure and squared mean tenure, and dummies for sectors and federal states. For comparability reasons with the existing literature, which is based on the worker level, we weight our regressions with the size of the establishment.

Our estimated coefficient, using the baseline sample (see Table A.3), is well in line with the results of Stüber (2017).[52] He estimates the sensitivity of ln(real daily wages) to unemployment at the worker (and not the establishment) level and finds coefficients of -1.26 for

[51] We have decided to estimate a first-difference equation because we are interested in the heterogeneity of wage cyclicalities and we want to prevent spurious results due to trends.

[52] Using the entire AWFP instead of the baseline sample, yields a similar coefficient: -1.17^{***}.

all workers.[53]

Table A.3: Weighted Wage Regression using the Baseline Sample

Estimated coefficient $\hat{\alpha}_1$	-1.16^{***}
Controls	Education shares, gender share, mean age, mean tenure, mean tenure^2, establishment fix effects, sector dummies, federal state dummies, year, year^2
R^2 | within R^2	0.95 | 0.62
Observations	7,259,116

Note: *** indicates statistical significance at the 1 percent level. Weighted by establishment size.

The coefficient estimated by Stüber (2017) for all workers is slightly larger than the coefficients in our regressions. This is in line with Solon et al. (1994), who argue that using aggregated time series data instead of longitudinal microeconomic data leads to an underestimation of wage cyclicality due to a composition bias. Although they compare microeconomic data to highly aggregated data (e.g., on the national level), the argument also applies to our analysis, where we use numbers that are aggregated from the worker level to the establishment level.

A.4 Results for 31 Industry Sectors

Each establishment in Germany belongs to one of 31 (industry) sectors (see note under Table A.4) according to the German Classification of Economic Activities (edition 1993, WZ 93). At the sector level, between 38.2% and 77.6% of establishments in a given sector have procyclical wage movements (PWS; $\alpha_{1i} \geq 0$). The larger dispersion — compared to the baseline results — is mainly driven by some special sectors.[54] Between 48.1% and 74.8% of establishments in a given sector have procyclical employment movements (PES; $\beta_{1i} \geq 0$). Here as well, the larger dispersion is mainly driven by some special sectors.[55]

[53] Stüber (2017) estimates a coefficient for newly hired workers of -1.33. This means that the incremental effect is economically small in Germany.

[54] The lower values are sector 10 (manufacturing of coke, refined petroleum products and nuclear fuels) with 38.2%, sector 30 (private households with employed persons) with 42.6%, and sector 19 (electricity, gas and water supply) with 47.6% PWS. The upper values are sector 9 (manufacturing of pulp, paper and paper products; publishing and print) with 77.6%, 15 (manufacturing of machinery and equipment – not elsewhere classified) with 77.4%, sectors 20 (construction) with 77.1% PWS.

[55] The lower values are sector 30 (private households with employed persons) with 48.1%, sector 7 (manufacturing of leather and leather product) with 57.2%, and sector 10 (manufacturing of coke, refined petroleum products and nuclear fuel) with 59.0% PES. The upper values are sector 15 (manufacturing of machinery and equipment – not elsewhere classified) with 74.8%, sector 16 (manufacturing of electrical and optical equipment) with 73.0%, and sector 24 (financial intermediation) with 72.4% PES.

Table A.4: Effect of Wage Cyclicality on Employment Cyclicality for Industry Sectors

Sector	1	2	3	4
Estimated coefficient $\hat{\gamma}_1$	-0.663^{***}	-4.226^{*}	0.581^{**}	-1.931^{***}
N	3,100	16	314	1,122
Sector	5	6	7	8
Estimated coefficient $\hat{\gamma}_1$	-0.500^{***}	-0.965^{***}	-1.091^{***}	-0.150^{**}
N	9,911	5,425	846	3,013
Sector	9	10	11	12
Estimated coefficient $\hat{\gamma}_1$	-0.444^{***}	1.684^{***}	-0.8207^{***}	-0.286^{***}
N	7,622	182	2,932	4,976
Sector	13	14	15	16
Estimated coefficient $\hat{\gamma}_1$	-0.708^{***}	-0.082^{***}	-0.168^{***}	0.040
N	3,931	16,106	12,178	10,106
Sector	17	18	19	20
Estimated coefficient $\hat{\gamma}_1$	-0.141	-0.391^{***}	0.061	-0.298^{***}
N	2,305	4,676	2,551	41,254
Sector	21	22	23	24
Estimated coefficient $\hat{\gamma}_1$	-0.516^{***}	-0.918^{***}	-0.518^{***}	-0.218^{***}
N	70,288	10,257	24,847	10,291
Sector	25	26	27	28
Estimated coefficient $\hat{\gamma}_1$	-0.577^{***}	-0.226^{***}	-0.792^{***}	-0.413^{***}
N	45,144	13,013	5,699	21,254
Sector	29	30	31	all
Estimated coefficient $\hat{\gamma}_1$	-0.605^{***}	0.100	0.348	-0.460^{***}
N	10,742	84	324	344,537

Note: 1) Agriculture, hunting and forestry; 2) Fishing; 3) Mining and quarrying of energy producing materials; 4) Mining and quarrying, except of energy producing materials; 5) Manufacturing of food products, beverages, and tobacco; 6) Manufacturing of textiles and textile products; 7) Manufacturing of leather and leather products; 8) Manufacturing of wood and wood products; 9) Manufacturing of pulp, paper and paper products; publishing and print; 10) Manufacturing of coke, refined petroleum products and nuclear fuel; 11) Manufacturing of chemicals, chemical products and man-made fibers; 12) Manufacturing of rubber and plastic products; 13) Manufacturing of other non-metallic mineral products; 14) Manufacturing of basic metals and fabricated metal products; 15) Manufacturing of machinery and equipment (not elsewhere classified); 16) Manufacturing of electrical and optical equipment; 17) Manufacturing of transport equipment; 18) Manufacturing (not elsewhere classified); 19) Electricity, gas and water supply; 20) Construction; 21) Wholesale and retail; repair of motor vehicles, motorcycles and personal and household goods; 22) Hotels and restaurants; 23) Transport, storage, and communication; 24) Financial intermediation; 25) Real estate, renting, and business activities; 26) Public administration and defense; compulsory social security ; 27) Education; 28) Health and social work; 29) Other community, social and personal service activities; 30) Private households with employed persons; 31) Extra-territorial organizations and bodies. According to the industry classification 1993.

***, **, and * indicate statistical significance at the 1, 5, and 10 percent level.

We drop extreme outliers before running the regression (see Footnote 13). Weighted by mean establishment size.

Although we have used the sector-specific employment growth rate as the business cycle indicator in our baseline regressions (see Section 4), the reaction may be different from sector to sector. In order to check this, we additionally run the regressions on the sectoral level. Table A.4 shows that the estimated coefficient is negative in most of the 31 industry sectors. As expected, there is some heterogeneity between the industry sectors.

We observe five sectors with positive coefficients: (3) mining and quarrying of energy producing materials, (10) manufacturing of coke, refined petroleum products and nuclear fuel, (16) manufacturing of electrical and optical equipment, (19) electricity, gas and water supply, (30) private households with an employed persons, (31) extra-territorial organizations and bodies. All these sectors have in common that they are either really small and/or very regulated as Sector (19), or they are very special sectors, such as the last two. Sector 16 stands out somewhat — but here the coefficient is not statistically significant. We also observe two very negative coefficients for sectors 2 and 4, but again the sectors are rather small.

A.5 Wage Cyclicality at Different Percentiles

Table A.5 shows descriptive statistics for countercyclical and procyclical wage establishments. Procyclical establishments are on average somewhat larger than countercyclical establishments. However, in terms of most other statistics (e.g. share of skills or mean age), procyclical and countercyclical wage establishments resemble one another pretty much.

Table A.5: Descriptive Statistics for Pro- and Countercyclical Establishments of the Baseline Sample

Variable	Counter-cyclical	Pro-cyclical
Establishments	115,429	229,108
Mean establishment size	41.65	57.31
log(daily wage)	4.60	4.64
Low-skilled workers	12.46%	14.97%
Medium-skilled workers	74.13%	73.16%
High-skilled workers	13.40%	11.86%
Male workers	69.09%	71.21%
Mean tenure	19.83	25.46
Mean age	39.38	39.80

Note: The table shows statistics for establishments with countercyclical and procyclical wages. Statistics for the baseline sample are presented in Table A.1. Weighted by mean establishment size.

Table A.6 shows the same descriptive statistics for quintiles of the wage cyclicality distribution. It reveals an inverted U-shape for the mean establishment size. Both strongly countercyclical ($\leq$ 20th percentile) and strongly procyclical establishments ($\leq$ 80th percentile) are smaller than moderately cyclical establishments.

Table A.6: Descriptive Statistics for Quintiles of the Wage Cyclicality Distribution of the Baseline Sample

Variable	$\leq 20^{th}$ percentile	$\left]20^{th}, 40^{th}\right[$ percentile	$\left[40^{th}, 60^{th}\right]$ percentile	$\left]60^{th}, 80^{th}\right[$ percentile	$\geq 80^{th}$ percentile
Establishments	68,907	68,908	68,907	68,908	68,907
Mean establishment size	35.71	54.32	70.67	61.24	38.39
log(daily wage)	4.60	4.61	4.64	4.64	4.65
Low-skilled workers	11.52%	14.02%	15.49%	15.19%	13.68%
Medium-skilled workers	73.91%	74.31%	73.65%	73.27%	71.55%
High-skilled workers	14.57%	11.67%	10.86%	11.54%	14.78%
Male workers	68.07%	70.43%	72.04%	70.67%	70.70%
Mean tenure	17.16	23.86	27.35	26.27	20.42
Mean age	39.27	39.55	39.86	39.86	39.67

Note: The table shows statistics for establishments in the quintiles of the wage cyclicality distribution. Statistics for the baseline sample are presented in Table A.1. Weighted by mean establishment size.

Table A.7 shows the wage cyclicality patterns for establishments at different percentiles of the wage cyclicality distribution. In addition to estimating the cyclicality of the average wage ($\hat{\alpha}_{1i}$), we also estimate the cyclicality at the 25th and 75th percentile. The cyclicality patterns at different percentiles are fairly similar to the average.

Finally, Table A.8 shows the estimated relationship between wage cyclicality and employment cyclicality at different percentiles. The estimated connection is negative and statistically significant for the 25th and 75th percentile (although somewhat weaker for the 75th percentile). This is another sanity check that composition is not the key driver for our results.

Table A.7: Wage Cyclicality at Different Percentiles

Estimated coefficients:	$\hat{\alpha}_{1i}^{p25}$	$\hat{\alpha}_{1i}$	$\hat{\alpha}_{1i}^{p75}$
Cyclicality at 10^{th} percentile	-0.99	-0.69	-0.82
Cyclicality at 20^{th} percentile	-0.42	-0.27	-0.32
Cyclicality at 30^{th} percentile	-0.15	-0.06	-0.07
Cyclicality at 40^{th} percentile	0.04	0.09	0.10
Cyclicality at 50^{th} percentile	0.19	0.22	0.24
Cyclicality at 60^{th} percentile	0.34	0.35	0.39
Cyclicality at 70^{th} percentile	0.53	0.49	0.55
Cyclicality at 80^{th} percentile	0.79	0.69	0.79
Cyclicality at 90^{th} percentile	1.30	1.06	1.25
Observations	344,036	$344,371$	344,410

Note: We drop extreme outliers before the calculation of this table (see Footnote 13).

Table A.8: Effect of Wage Cyclicality on Employment Cyclicality for Different Percentiles

Estimated Coefficient	$\hat{\gamma}_1^{p25}$	$\hat{\gamma}_1$	$\hat{\gamma}_1^{p75}$
Coefficient	$-.325^{***}$	$\mathbf{-0.460}^{***}$	$-.292^{***}$
R^2	0.01	0.01	0.01
Observations	344,036	344,293	344,410

Note: *** indicates statistical significance at the 1 percent level. Baseline regression result in bold. We drop extreme outliers before running the regression (see Footnote 13). Weighted by mean establishment size.

A.6 Worker Composition and Wages

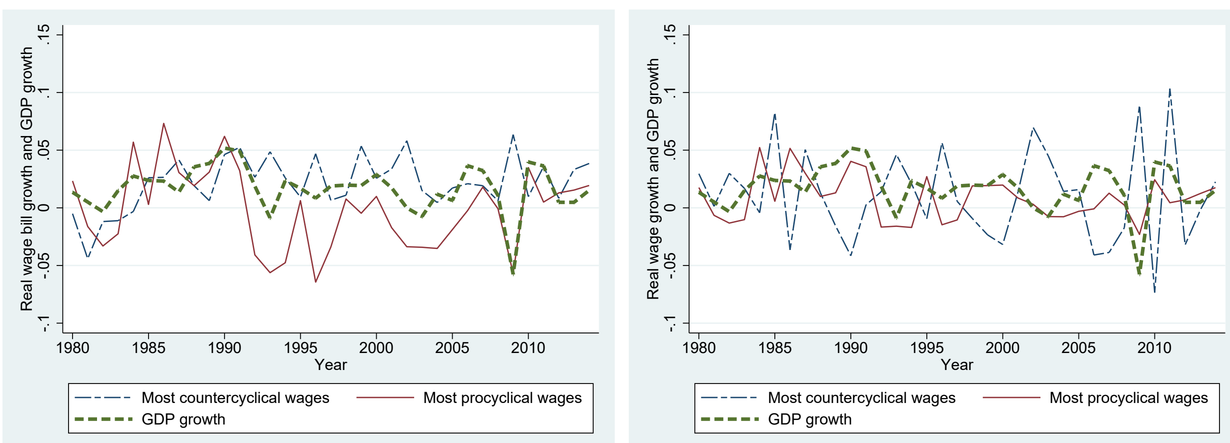
Take the example from Section 4.3.3: An establishment with procyclical employment and completely fixed (acyclical) wages for two worker types: w_l for low-qualified workers and w_h for high-qualified workers, with $w_l < w_h$. If the establishment hires workers in a boom, keeping the share of low- and high-qualified workers in the establishment constant, the establishments' mean wage would not change. However, we would observe a countercyclical mean wage if the establishment increases the share of low-qualified workers in a boom. This scenario appears realistic because the unemployment rate of low-qualified workers is more volatile than for high-qualified workers in Germany (see, e.g., Röttger et al., 2019).

Let us assume the following scenario: a procyclical employment establishment (A) fires low-qualified workers in recessions and a countercyclical employment establishment (B) hires those workers. In this case, the mean wage (w_{it}) of establishment A would increase in recessions and the mean wage of establishment B would decrease due to the composition effect. However, in that case, the wage sum ($w_{it}n_{it}$) of establishment A would decrease in recessions (due to fewer workers n_{it}) and the wage sum of establishment B would increase (due to more workers). Hence, we would expect an inverted (or at least strongly dampened) cyclicality of the wage sum in comparison to the cyclicality of the mean wage if the composition effect is of first order importance.

In order to check whether the composition effect could be the key driving force, Figure A.2.1 therefore shows the mean growth rate of the wage bill ($w_t n_t$ instead of w_t, see Figure A.2.2)[56] for the most procyclical and the most countercyclical establishments.

The mean growth rate of the wage bill continues to be procyclical in the first group and countercyclical in the last group, although both cyclicality patterns are a bit less pronounced for the entire wage bill than for the establishments' mean wage. Since the dampening of the cyclicality is not strong, we see this as an additional evidence that the above described composition effect is not the key driver of our results.

Figure A.2: Mean Wage Sum and Mean Real Daily Wage Growth of the Establishments with the Most Procyclical and Most Countercyclical Wages



A.2.1: Mean Real Wage Sum Growth

A.2.2: Mean Real Daily Wage Growth

Note: West Germany (excluding Berlin), 1979-2014. Establishments with the most procyclical (countercyclical) wage are those equal to or above (below) the 80^{th} (20^{th}) percentile of our wage cyclicality measure α_{1i} in the given year (see Section 2.2). α_{1i} are estimated using the number of national full-time workers as the business cycle indicator (employment weighted results; extreme outliers dropped, see Footnote 13)

[56] Figure A.2.2 is identical to Figure 1.1 from Section 1.

A.7 Selection of Unweighted Results

Table A.9: Wage Cyclicality at Different Disaggregation Levels

Estimated coefficients: $\hat{\alpha}_{1i}$	31 Sectors	National level
Cyclicality at 10^{th} percentile	-0.78	-1.01
Cyclicality at 20^{th} percentile	-0.32	-0.41
Cyclicality at 30^{th} percentile	-0.09	-0.09
Cyclicality at 40^{th} percentile	0.07	0.14
Cyclicality at 50^{th} percentile	0.20	0.32
Cyclicality at 60^{th} percentile	0.34	0.51
Cyclicality at 70^{th} percentile	0.49	0.73
Cyclicality at 80^{th} percentile	0.71	1.04
Cyclicality at 90^{th} percentile	1.12	1.61
Observations	$344,293$	$344,126$

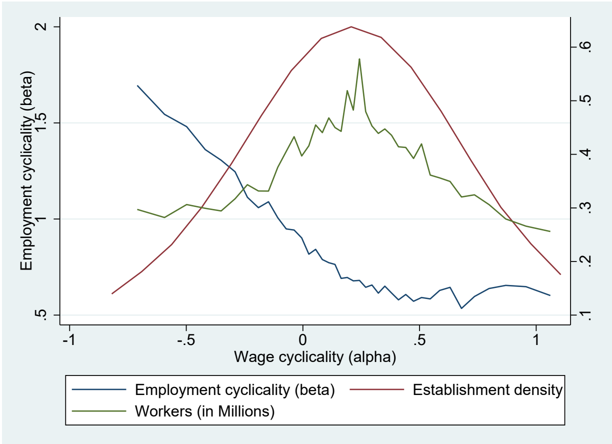
Note: We drop extreme outliers before the calculation of this table (see Footnote 13).

Table A.10: Employment Cyclicality at Different Disaggregation Levels

Estimated coefficients: $\hat{\beta}_{1i}$	31 Sectors	National level
Cyclicality at 10^{th} percentile	-2.40	-3.51
Cyclicality at 20^{th} percentile	-0.98	-1.39
Cyclicality at 30^{th} percentile	-0.30	-0.45
Cyclicality at 40^{th} percentile	0.19	0.19
Cyclicality at 50^{th} percentile	0.63	0.77
Cyclicality at 60^{th} percentile	1.12	1.43
Cyclicality at 70^{th} percentile	1.78	2.28
Cyclicality at 80^{th} percentile	2.80	3.56
Cyclicality at 90^{th} percentile	4.94	6.23
Observations	$344,293$	$344,126$

Note: We drop extreme outliers before the calculation of this table (see Footnote 13).

Figure A.3: Mean of Employment Cyclicality Measure Along the Wage Cyclicality Measure Distribution



Note: We divide the range of the wage cyclicality measure ($\hat{\alpha}_{1i}$, see Section 3.1) into 50 bins. Each bin contains 1/50 of all observations, showing the mean. We drop extreme outliers (see Footnote 13). The figure is showing results for mean $\hat{\alpha}_{1i} \geq$ the 10th percentile and $\hat{\alpha}_{1i} \leq$ the 90th percentile of the estimated $\hat{\alpha}_{1i}$ (see Table 2).

A.8 Model Derivation

A.8.1 Establishment Maximization

Establishments maximize profits

$$E_0 \left\{ \sum_{t=0}^{\infty} \delta^t \left[a_t n_{it} - w_{it}^I (1-\phi) n_{i,t-1} - c_{it} s_t \eta(\tilde{\varepsilon}_{it}) \left(\frac{\bar{w}^E(\tilde{\varepsilon}_{it})}{\eta(\tilde{\varepsilon}_{it})} + \frac{H(\tilde{\varepsilon}_{it})}{\eta(\tilde{\varepsilon}_{it})} + h \right) \right] \right\}, \tag{A.3}$$

subject to the evolution of establishments' employment stock in every period:

$$n_{it} = (1-\phi) n_{it-1} + c_{it} s_t \eta(\tilde{\varepsilon}_{it}). \tag{A.4}$$

Let $\delta^t \lambda_t$ denote the Lagrange multiplier and take the first order derivative with respect to λ_t, $\tilde{\varepsilon}_{it}$, and n_{it}:

$$n_{it} = (1-\phi) n_{it-1} + c_{it} s_t \eta(\tilde{\varepsilon}_{it}), \tag{A.5}$$

$$-c_{it} s_t \left(\frac{\partial \bar{w}^E(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} + \frac{\partial H(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} + \frac{\partial \eta(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} h \right) + \lambda_t c_{it} s_t \frac{\partial \eta(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} = 0, \tag{A.6}$$

$$a_t - \lambda_t + (1-\phi)\delta E_t \left(\lambda_{t+1} - w_{it+1}^I \right) = 0. \tag{A.7}$$

Isolating the Lagrange multiplier in Equation (A.6) yields:

$$\lambda_t = \frac{\frac{\partial \bar{w}^E(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} + \frac{\partial H(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} + \frac{\partial \eta(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} h}{\frac{\partial \eta(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}}}. \tag{A.8}$$

Keep in mind the three definitions:

$$\eta(\tilde{\varepsilon}_{it}) = \int_{-\infty}^{\tilde{\varepsilon}_{it}} f(\varepsilon) d\varepsilon, \tag{A.9}$$

$$\bar{w}^E(\tilde{\varepsilon}_{it}) = \int_{-\infty}^{\tilde{\varepsilon}_{it}} w_t^E(\varepsilon) f(\varepsilon) d\varepsilon, \tag{A.10}$$

$$H(\tilde{\varepsilon}_{it}) = \int_{-\infty}^{\tilde{\varepsilon}_{it}} \varepsilon f(\varepsilon) d\varepsilon. \tag{A.11}$$

This allows us to simplify Equation (A.8), using the Fundamental Theorem of Calculus:

$$\lambda_t = \frac{w^E(\tilde{\varepsilon}_{it}) f(\tilde{\varepsilon}_{it}) + \tilde{\varepsilon}_{it} f(\tilde{\varepsilon}_{it}) + f(\tilde{\varepsilon}_{it}) h}{f(\tilde{\varepsilon}_{it})} \tag{A.12}$$

$$= w^E(\tilde{\varepsilon}_{it}) + \tilde{\varepsilon}_{it} + h. \tag{A.13}$$

When we substitute this Lagrange multiplier into Equation (A.7), we obtain the selection condition:

$$\tilde{\varepsilon}_{it} = a_t - w^E(\tilde{\varepsilon}_{it}) - h + (1-\phi)\delta E_t \left(w^E(\tilde{\varepsilon}_{it+1}) + \tilde{\varepsilon}_{it+1} + h - w_{it+1}^I \right) \tag{A.14}$$

Iterating $\tilde{\varepsilon}_{it}$ one period forward, substituting it into the right hand side of the equation and using the definition for

$$J_{it} = a_t - w_{it}^I + E_t \delta \left(1-\phi\right) J_{it+1}, \tag{A.15}$$

yields the selection condition, as shown in Equation (8) in the main part:

$$\tilde{\varepsilon}_{it} = a_t - w^E(\tilde{\varepsilon}_{it}) - h + E_t \delta \left(1-\phi\right) J_{it+1}. \tag{A.16}$$

A.8.2 Derivation of the Nash Wage

The Nash product is

$$\Lambda_t = \left(W_t - U_t\right)^{\nu} \left(J_t\right)^{1-\nu}, \tag{A.17}$$

with

$$W_t - U_t = w_t - b + E_t\delta\left(1-\phi-\eta_{t+1}\right)\left(W_{t+1} - U_{t+1}\right), \tag{A.18}$$

and

$$J_t = a_t - w_t + E_t\delta\left(1-\phi\right) J_{t+1}. \tag{A.19}$$

Maximization of the Nash product with respect to the wage yields

$$\frac{\partial \Lambda_t}{\partial w_t} = \nu J_t \frac{\partial W_t}{\partial w_t} + \left(1-\nu\right)\left(W_t - U_t\right)\frac{\partial J_t}{\partial w_t} = 0, \tag{A.20}$$

$$\nu J_t = \left(1-\nu\right)\left(W_t - U_t\right). \tag{A.21}$$

After substitution:

$$\nu\left(a_t - w_t + E_t\delta\left(1-\phi\right)J_{t+1}\right) = \left(1-\nu\right)\left[w_t - b + E_t\delta\left(1-\phi-\eta_{t+1}\right)\left(W_{t+1}-U_{t+1}\right)\right]. \tag{A.22}$$

Using Equation (A.21):

$$\nu\left(a_t - w_t + E_t\delta\left(1-\phi\right)J_{t+1}\right) = \left(1-\nu\right)\left[w_t - b + E_t\delta\left(1-\phi-\eta_{t+1}\right)\frac{\nu}{\left(1-\nu\right)}J_{t+1}\right], \tag{A.23}$$

$$w_t = \nu\left(a_t + \delta\eta_{t+1}J_{t+1}\right) + \left(1-\nu\right)b. \tag{A.24}$$

A.9 Numerical Robustness: 5 Groups

Table A.11 shows further counterfactual exercises based on five different wage cyclicality groups.

When we set the wage cyclicality of all groups to the most procyclical wage group (namely, $\kappa_i = 0.39$ for establishments), labor market amplification is reduced by roughly 30 percent (see the second column in Table A.11). In other words, if all establishments had a wage cyclicality as the establishment at the 90th percentile of the distribution, the labor market would react much less to aggregate shocks. Thus, it matters that a substantial fraction of establishments have acyclical or even countercyclical wages. This sort of heterogeneity amplifies the response of the labor market to aggregate shocks.

An acyclical wage for all establishments results in 7 to 8 percent more amplification (see the second column in Table A.11). Actually, this corresponds to a scenario where the researcher imposes results from a macro-regression with real hourly aggregate wage growth[57] and aggregate employment growth (from our data). Such an aggregate regression delivers a

[57] Source: WSI, `https://www.wsi.de/data/wsi_vm_loehne_laender.xlsx`.

Table A.11: Counterfactual Exercises: Further Exercises

	All 90th percentile	All acyclical
u	-29.9	7.7
n	-29.4	7.4
w	27.4	-100

Note: The table shows the percentage change of the standard deviation of simulated unemployment and employment relative to the baseline (in logarithms, normalized by the standard deviation of output, and HP filtered). The second column imposes the 90th percentile on all establishments, and the second column imposes an acyclical wage.

small and statistically insignificant coefficient for the elasticity between aggregate wages and employment. Hourly wages from the National Accounts show different aggregate dynamics than average earnings for full-time workers. This may partly related to part-time jobs, which are not included in our sample.

A.10 Numerical Robustness: 10 instead of 5 Groups

In the main part, we calibrated the model economy to five different groups (from the most countercyclical to the most procyclical). The number of groups is arbitrary. Therefore, we check in this section whether the quantitative results change in a meaningful way when we move from five to ten groups.

We calibrate the wage cyclicality to the median within each of the ten groups (see Table A.12). In all other dimensions, we follow exactly the same calibration strategy as for the baseline. We set $c_i = [0.06, 0.08, 0.09, 0.11, 0.13, 0.14, 0.13, 0.11, 0.09, 0.06]$ to match the size to those ten groups.

The labor market statistics are basically the same in the baseline calibration. The standard deviation of labor market variables remains unchanged up to the second digit (see Table A.13).

Table A.14 compares different scenarios with five and ten groups. In addition, we also set the wage cyclicality to the 95th percentile and 5th percentile in the distribution.

Three results are worth mentioning: First, it can be seen in Table A.14 that all our key results are very similar, independently of the number of groups.

Second, when we set the wage cyclicality of all groups to the median wage cyclicality, the quantitative effects are a bit larger with ten groups than with five groups. The standard deviation of unemployment increases, for example, by 0.2 percent instead of 0.1 percent. The underlying reason is that with ten groups the skewness of the wage cyclicality distribution at its extremes can be captured more accurately. Eliminating this skewness depresses the

Table A.12: Wage Cyclicality at Different Disaggregation Levels

Estimated coefficients: $\hat{\alpha}_{1i}$	31 Sectors
Cyclicality at 5^{th} percentile	-1.18
Cyclicality at 15^{th} percentile	-0.43
Cyclicality at 25^{th} percentile	-0.15
Cyclicality at 35^{th} percentile	0.02
Cyclicality at 45^{th} percentile	0.16
Cyclicality at 55^{th} percentile	0.28
Cyclicality at 65^{th} percentile	0.42
Cyclicality at 75^{th} percentile	0.58
Cyclicality at 85^{th} percentile	0.84
Cyclicality at 95^{th} percentile	1.52
Observations	344,537

Note: We drop extreme outliers before the calculation of this table (see Footnote 13).

Table A.13: Standard Deviations of Hiring Rate, Employment and Unemployment Rate (all Relative to Real GDP)

	hr	n	u	w
Simulation (5 Groups)	1.88	0.22	2.58	0.07
Simulation (10 Groups)	1.88	0.22	2.58	0.07

Note: All variables are expressed in logs and as deviations from the Hodrick-Prescott filter (with smoothing parameter 1600).

aggregate wage cyclicality by -3.0 percent instead of -0.8 percent and thereby generates larger aggregate effects. However, the aggregate effects are still relatively small.

Third, when we set all wage cyclicalities equal to the 95th and 5th percentiles, unsurprisingly, we obtain larger effects than at the 90th and 10th percentiles. Interestingly, even establishments at the 95th percentile are less procyclical than under the standard Nash bargaining protocol.

A.11 Search and Matching with Decreasing Returns

In Section 2.2, we have shown that the wage cyclicalities across establishments are very heterogeneous. At the same time, at least 99 (90%) of all establishments with more than 50 (10) employees hire in any given year. In order to be in line with these stylized facts, we have chosen a selection model where different applicants have a different suitability (i.e., some have low training costs, while others have high training costs). Thus, establishments with less cyclical wages will hire a larger fraction of workers in a boom than establishments with more cyclical wages.

Table A.14: Counterfactual Exercises: 10 Groups

	Homogeneous Counterfactual						Heterogeneous	
	All median	All 95th perc.	All 90th perc.	Nash	All 10th perc	All 5th perc.	No procyc.	No countercyc.
u	0.2 (0.1)	-47.0 (-)	-29.8 (-29.9)	-69.7 (-69.8)	30.9 (30.6)	46.4 (-)	11.9 (11.4)	-4.1 (-3.8)
n	0.2 (0.1)	-46.3 (-)	-29.2 (-29.4)	-69.2 (-69.3)	29.5 (29.3)	44.1 (-)	11.5 (11.0)	-4.0 (-3.7)
w	-3.0 (-0.8)	605.3 (-)	382.9 (394.1)	902.6 (925.8)	189.5 (196.2)	382.3 (-)	-49.2 (-51.7)	52.4 (49.8)

Note: The table shows the percentage change of the standard deviation of simulated unemployment, employment, and wages relative to the baseline (in logarithms, normalized by the standard deviation of output, and HP filtered). The results from the model with five groups are in brackets. Compare to Table 2.

Would it be possible in the standard search and matching (SaM) model of the Mortensen and Pissarides (1994) type to have heterogeneous wage cyclicalities across establishments, while almost all establishments (above a certain size) hire in every period? Obviously, this is possible if establishments with different wage cyclicalities act in different labor market segments, as for example in Barnichon and Figura (2015). But can the standard SaM model explain this in a given labor market segment? Imagine that establishments with different wage cyclicalities act in the same labor market segment and that they are hit by the same aggregate shock. Imagine further that the economy moves into a boom and establishment A's wage increases by more than establishment B's wage. In this case, establishment B would face a higher expected present value than establishment A. Given that the market tightness, the worker-finding rate and thereby the hiring costs are a market outcome, only establishment B would be posting vacancies and hire, while establishment A would shut down its vacancy posting and hiring activity.[58] Thus, the standard random SaM model could not yield the outcome we find in the data.

In order to reconcile the SaM model with the stylized facts above, we assume decreasing returns to labor. In such a world, an establishment with lower wages will hire more and the marginal product of labor will fall. Due to the compensating effect of the marginal product of labor, establishments with different wage cyclicalities may hire at the same time. We derive this type of model and analyze its quantitative implications.

A.11.1 Model Derivation

Establishments maximize the following intertemporal profit condition

$$E_0 \sum_{t=0}^{\infty} \left(a_t n_{it}^{\alpha} - w_{it} n_{it} - \chi v_{it} \right), \tag{A.25}$$

where $\alpha < 1$ denotes the curvature of the production function and n_{it} is the establishment-specific employment stock. χ are vacancy posting costs and v_{it} is the number of vacancies at the establishment level. Establishments maximize profits subject to the employment dynamics equation:

$$n_{it} = (1-\phi)\, n_{it-1} + v_{it} q\left(\theta_t\right). \tag{A.26}$$

[58] The standard search and matching's job-creation condition is $\frac{\kappa}{q(\theta_t)} = a_t - w_t + E_t \delta \left(1-\phi\right) \frac{\kappa}{q(\theta_{t+1})}$. Given that $\frac{\kappa}{q(\theta_t)}$ is market-determined, only the most profitable establishments will hire. Thus, different wage cyclicalities and joint hiring cannot coexist.

The first-order conditions with respect to n_{it} and v_{it} are:

$$\left(\alpha a_t n_{it}^{\alpha-1} - w_{it}\right) - \lambda_{it} + \beta E_t \lambda_{it+1} (1-\phi) = 0, \tag{A.27}$$

$$-\chi + \lambda_{it} q(\theta_t) = 0, \tag{A.28}$$

where λ is the Lagrange multiplier.

Combining these two equations, we obtain the establishment-specific job-creation conditions:

$$\frac{\chi}{q(\theta_t)} = \left(\alpha a_t n_{it}^{\alpha-1} - w_{it}\right) + \beta E_t (1-\phi) \frac{\chi}{q(\theta_{t+1}).} \tag{A.29}$$

Under decreasing returns to labor, standard Nash bargaining does not work. Therefore, we impose the same ad-hoc wage formation rule as in the main part of the paper:

$$w_{it} = \kappa_i \left(a_t w^{norm}\right) + (1-\kappa_i) w^{norm}, \tag{A.30}$$

When we set $\kappa_i = 1$, wages comove one to one with productivity. When we set $\kappa_i < 1$, wages are less procyclical over the business cycle. As in the main part, we assume that there is a discrete number of different groups of establishments with different wage cyclicalities.

In order to establish an equilibrium, we have to aggregate across all firm types. The aggregate number of vacancies and the aggregate employment are

$$v_t = \sum_{i=1}^{E} v_{it}, \tag{A.31}$$

$$n_t = \sum_{i=1}^{E} n_{it}, \tag{A.32}$$

the sum of vacancies/employment over all groups.

The aggregate job-finding rate for an unemployed worker is a function of the aggregate market tightness because we assume a Cobb-Douglas constant returns matching function, namely $m_t = \varkappa s_t^{\psi} v_t^{1-\psi}$. Thus: $p(\theta_t) = \varkappa \theta_t^{1-\psi}$ and $q(\theta_t) = \varkappa \theta_t^{\psi}$, with $\theta_t = v_t / s_t$.

Employed workers are defined as those who remain employed from the previous period and the new matches:

$$n_t = (1-\phi) n_{t-1} + s_t p_t. \tag{A.33}$$

All workers who search for a job and who are unable to match are defined as unemployed:

$$u_t = s_t (1 - p_t), \tag{A.34}$$

A.11.2 Calibration and Numerical Results

We remain as close as possible to the calibration in the main part. We set the discount factor to $\delta = 0.99$ and the exogenous separation rate to $\phi = 0.07$. The aggregate productivity shock is drawn from a normal distribution with mean zero and the standard deviation is normalized to 1. The first-order autocorrelation coefficient is set to 0.8.

Due to the matching function and the decreasing returns, we require some additional parameters. We set the weight on vacancies in the matching function to $\psi = 0.65$. The curvature of the production function is set to $\alpha = 0.67$ and the steady state wage is normalized to 0.95 to be comparable to the value in the selection model ($\nu = 0.95$). Vacancy posting costs are normalized to 1 ($\chi = 1$) and the matching efficiency is chosen to fix the steady state unemployment rate of 0.08 ($\varkappa = 0.54$).

Independently, how we set κ_i, we obtain a $\hat{\gamma}_1 \simeq -3.2$ in our simulated model. In other words, the connection between wage cyclicalities and hiring rate cyclicalities is a lot larger than in the data (where $\hat{\gamma}_1 \simeq -0.46$). We will explain in the next subsection that this is related to the curvature of the production function. When we set a smaller value for α, we obtain a smaller $\hat{\gamma}_1$. However, it would have to be implausibly small in order to obtain the target from the data.

A.11.3 Some Analytics

The key equation is the steady state job-creation condition:

$$\frac{\chi}{q(\theta)} (1 - \beta (1 - \phi)) = \alpha a n_i^{\alpha - 1} - w_i, \tag{A.35}$$

where the marginal product of labor is equal to $mpl = \alpha a n_i^{\alpha-1}$.

Given our calibration, we can plug in the numerical values:

$$\frac{\chi}{q(\theta)} (1 - \beta (1 - \phi)) = 0.67 n_i^{-0.33} - w_i. \tag{A.36}$$

The left-hand side of the equation is purely market determined (i.e., exogenous to the individual establishment). Now assume two establishments with different wage cyclicalities. In establishment A, the wage does not move, while in establishment B, the wage goes up by 1%. How do these two establishments react to a 1% increase of aggregate productivity? In equilibrium, the right hand side of the equation has to adjust such that it is the same for all establishments, i.e., the adjustment of the marginal product of labor has to compensate for the wage differential.

Let's assume for illustration purposes that $mpl \approx w$. In this case, an one percent differential in the wage movement can roughly be compensated by a 3% differential in the establishment-specific employment movement. This is due to the typical calibration for the production function ($\alpha = 0.67$), which leads to an exponent of -0.33 for the mpl in Equation (A.36). Thus, the estimated coefficient can be expected to be around -3.

What do we learn from this exercise? Under decreasing returns to scale, different wage cyclicalities can coexist. However, from a quantitative perspective, under the typical curvature of the production function, different wage movements lead to much stronger differences in employment movements than estimated in the data. The reason is that the adjustment happens via the marginal product of labor, which requires a sufficiently strong employment adjustment. This mechanism is absent in the selection model that we use in the main part where the adjustment happens via heterogeneous training costs. Thereby, the latter generates quantitative results that are closer to the estimations from the data.

A.12 Aggregation and Comparability of Data

A.12.1 Aggregation of Simulated Data

Due to the nature of our microeconomic data (i.e. wage information is only available for the entire year if the employment spell lasts the entire year), we use annual data in our microeconomic estimations. However, as usual, we simulate our model economy at the quarterly frequency, using the same number of periods as in the empirical data.

When we target $\hat{\gamma}_1 = -0.46$ in our calibration exercises, we aggregate the simulated data to an annual level to ensure comparability. We do so in line with the nature of the data.

In the dataset, establishment-level employment 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.

In the dataset, wages are defined as the average daily wage over four quarters (if the employment spell lasts for four quarters). Therefore, we also define the wage based on four quarters.

Based on these coherent definitions between data and model, we use these aggregated annual time series and estimate the connection between employment and wage cyclicality (based on log-differences of the annual time series). The distributional parameter χ is set such that we obtain the same estimated coefficient from our baseline regression based on simulated data as in the data ($\hat{\gamma}_1 = -0.46$).

A.12.2 Data Moments at Different Frequencies

Typically, business cycle moments are reported at the quarterly level and the much of the Shimer (2005) debate was using the Hodrick-Prescott filter. As we use an annual dataset in the empirical analysis, Figure A.15 shows the standard deviation of the hiring rate and the unemployment rate relative to the standard deviation of output based on different time frequencies and filtering techniques. Independently of the time frequency and the filtering technique, the amplification effects have a similar order of magnitude.

Table A.15: Standard Deviations of Hiring Rate, Job-Finding Rate and Unemployment (all Relative to Real GDP)

	hr	u
Quarterly Data (HP Filter)	3.84	5.05
Annual Data (HP Filter)	4.66	4.69
Quarterly Data (First Differences)	4.68	4.04
Annual Data (First Differences)	4.57	5.71

Note: Observation period is 1979–2014. All variables are expressed in logs. The cyclical component is either calculated as log-differences or as deviations from the Hodrick-Prescott filter (with smoothing parameter 1600).

A.13 Equivalence between Selection and Search & Matching Model

This Appendix shows that the homogeneous version of the selection model used in our paper can be made equivalent to the standard search and matching model. Under certain distributional assumptions, which we use in the main part of the paper, there is global equivalence.[59] Thus, the insights from our model quantitative exercise are not only relevant for the used selection model, but also for the more widely used class of search models with a matching function.

The proof in this section is based on Merkl and van Rens (2019). Assume a dynamic search and matching model with constant returns matching function:

$$m_t = v_t^{1-\psi} s_t^{\psi},$$

where α is the elasticity of the matching function with respect to searching workers.

[59] For a more general class of distributions, the dynamics of the job-finding rate dynamics in the homogeneous version of the selection model is equivalent to the job-finding rate dynamics in the search and matching model up to a first-order approximation (results are available on request).

Furthermore, there are linear ex-ante vacancy posting costs, χ, and ex-post hiring costs, h. Given that vacancies are posted up to the point where the expected return of a vacancy equals the expected hiring costs, the following equation holds:

$$\frac{\chi}{q_t} = E_t \sum_{t=0}^{\infty} \delta^t \left(1-\phi\right)\left(a_t - w_t\right) - h, \tag{A.37}$$

where the left-hand side is the average value of ex-ante hiring costs (with $q_t = m_t/v_t$) and the right-hand side are the expected discounted value of profits minus the ex-post hiring costs.

In a selection model, the job-creation condition is:

$$\tilde{\varepsilon}_t = E_t \sum_{t=0}^{\infty} \delta^t \left(1-\phi\right)\left(a_t - w_t\right) - h, \tag{A.38}$$

where the left-hand side is the cutoff point of training costs up to which hiring takes place and the right-hand side is the equivalent discounted stream of profits.

Combining equations (A.37) and (A.38), we obtain the condition under which two models are globally equivalent:

$$\tilde{\varepsilon}_t = \frac{\chi}{q_t}. \tag{A.39}$$

In the search and matching models, the job-finding rate can be expressed as a function of market tightness (with $\theta_t = v_t/s_t$):

$$\eta_t = \theta_t^{1-\psi}. \tag{A.40}$$

Combining equations (A.39) and (A.40), we obtain:

$$\frac{\chi}{q_t} = \chi \eta_t^{\frac{\psi}{1-\psi}} = \tilde{\varepsilon}_t. \tag{A.41}$$

Thus, we have global equivalence for the job-finding rate if:

$$\eta_t = \left(\frac{\tilde{\varepsilon}_t}{\chi}\right)^{\frac{1-\psi}{\psi}}. \tag{A.42}$$

We use this functional form for the cumulative distribution function (i.e. an inverse Pareto distribution) in the main part of the paper to have a selection model that provides globally equivalent dynamics of the job-finding rate and unemployment to a search and matching model.

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