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Christian Merkl, Heiko Stüber

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Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
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Wage and Employment Cyclicalities at the Establishment Level

Abstract

We document substantial cross-sectional heterogeneity of German establishments' real wage cyclicality over the business cycle. While wages of the median establishment are moderately procyclical, 36 percent of establishments have countercyclical wages. We estimate a negative connection between establishments' wage cyclicality and their employment cyclicality, thereby providing a benchmark for quantitative macroeconomic models. We propose and calibrate a labor market flow model to match various empirical facts and to perform counterfactual exercises. If all establishments behaved as the most procyclical ones, labor market amplification would drop by one-third. If all followed Nash bargaining, it would drop by more than two-thirds.

JEL-Codes: E320, E240, J640.

Keywords: wage cyclicality, employment cyclicality, labor market flow model, labor market dynamics, establishments, administrative data.

*Christian Merkl**
Chair of Macroeconomics
Friedrich-Alexander-Universität
Erlangen-Nürnberg
Lange Gasse 20
Germany – 90403 Nürnberg
Christian.Merkl@fau.de

Heiko Stüber
Institute for Employment Research (IAB)
Nuremberg / Germany
heiko.stueber@iab.de

*corresponding author

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1 Introduction

The question how real wages move over the business cycle has been crucial in macroeconomics for many decades, although macroeconomic benchmark models have changed over time (e.g., Bils, 1985; Blanchard and Fischer, 1989; Mankiw, 1989; Beaudry and DiNardo, 1991; Solon et al., 1994; Pissarides, 2009). In recent literature, the cyclicality of real wages plays a key role in solving the Shimer (2005) puzzle in search and matching models. With less procyclical wages, job creation and (un)employment are more volatile over the business cycle (e.g., Hall, 2005; Hall and Milgrom, 2008; Christiano et al., forthcoming). This brings the search and matching model closer in line with time series properties of labor market data.

Against this background, there is a growing empirical literature on the question how cyclical wages (of newly hired workers)[1] are (e.g., Carneiro et al., 2012; Martins et al., 2012; Haefke et al., 2013; Stüber, 2017; Gertler et al., 2020). There is also an emerging literature that documents the effects of downward nominal wage rigidity (DNWR) on labor market flows at the establishment level (for the United States, e.g., Kurmann and McEntarfer, 2017). For establishments in Germany, Ehrlich and Montes (2020) find a meaningful connection between DNWR and labor market flows using linked employer-employee data. They show that an establishment with the sample-average level of DNWR has a lower quit rate, a higher layoff rate, and a lower hire rate than an establishment with no measured DNRW.

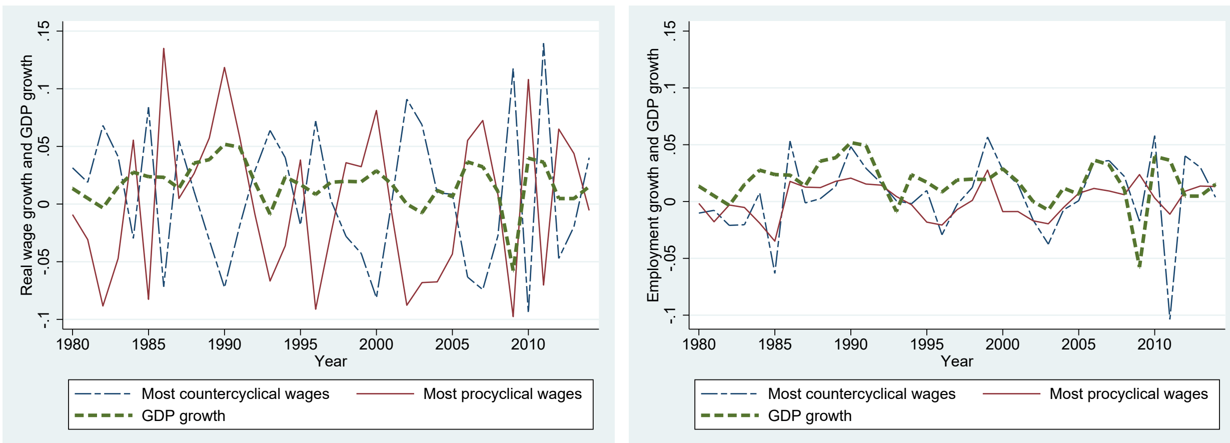
However, the existing literature is missing one important empirical connection. If real wage rigidity is an important amplifier for the labor market, there should be a meaningful empirical connection between wage dynamics and employment dynamics at the firm level. Using the Administrative Wage and Labor Market Flow Panel (AWFP), which comprises the universe of German establishments, we attempt to fill this research gap in three steps. First, we document a substantial cross-sectional heterogeneity of wage cyclicalities and employment cyclicalities across establishments.[2] Second, we estimate the quantitative connection between

[1] Or more generally, the allocative wage, e.g., approximated by the user cost of labor (e.g., Kudlyak, 2014; Basu and House, 2016).

[2] Germany offers an unique environment for analyzing the effects of heterogeneous wage cyclicalities on

wage cyclicality and employment cyclicality at the establishment level. Finally, we move from the establishment level to the aggregate level and use a macroeconomic labor market model to analyze the macroeconomic implications of the observed wage cyclicalities.

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.

Our paper shows that economy-wide average wage cyclicality over the business cycle masks that establishments have heterogeneous wage cyclicalities. We find that the majority of establishments behaves in a procyclical manner over the business cycle and thereby drives the average procyclicality. However, nearly 36 percent of establishments behave in a countercyclical manner, some of them strongly. Figure 1.1 illustrates this key result by showing the mean real daily wage growth for establishments with the most procyclical and for establishments with the most countercyclical wages.[3] The former show a clearly visible positive comovement with real GDP, while it is negative for the latter. For illustration purposes, consider the Great Recession in 2009, where German GDP dropped by around 5 percent. Establishments with the most procyclical wages saw a decline of real wages in a similar order

establishments' employment cyclicalities because wage formation is very diverse.

[3]The definition of the most procyclical (countercyclical) establishments is provided under Figure 1.

of magnitude. By contrast, establishments with the most countercyclical wages faced a real wage increase.

Furthermore, our paper documents and estimates the effects of different real wage cyclicalities on employment cyclicalities: more procyclical wage establishments have less procyclical employment cyclicalities. Figure 1.2 illustrates this result. Consider again the Great Recession in 2009: establishments with the most procyclical wages, i.e., those that cut real wages, increased their average employment slightly. By contrast, establishments with the most countercyclical wages faced a decline in average employment. This illustrates that real wage cyclicalities have an effect on employment dynamics.

While Figure 1 shows purely descriptive results, our paper estimates these effects at the establishment level, taking various steps to prevent that our empirical results are driven by composition effects. In our baseline specifications, we use sectoral employment as a sector-specific business cycle indicator.[4] We control, inter alia, for establishment fixed effects and changes in mean worker characteristics. Very importantly, our results are not driven by heterogeneities between sectors. They even remain robust when we run regressions for sectors separately. They also remain robust when we exclude the Great Recession from our regressions, where the intensive margin of labor adjustment was particularly important.

The paper contains various additional robustness checks. Our findings are, e.g., not driven by small establishments. When we restrict our sample to larger establishments, the estimated connection between wages and employment increases. The results are also robust to excluding short-lived establishments. Regarding compositional concerns, we use incumbents' wage growth (instead of the wage growth of all workers). The result is very similar to our baseline result. We also discuss and show why establishment-specific revenue shocks cannot be the key driver of our results (see Appendices A.5 and A.7). To test for the robustness of our wage cyclicality measures over time, we suggest alternative measures to estimate the connection between (relative) wage growth and (relative) employment growth.

[4] By contrast, Figures 1.1 and 1.2 are based on aggregated full-time employment as business cycle indicator. This allows us to show graphical results on the aggregate level that can be compared to GDP.

The results confirm the robustness of our baseline specification (see Appendix A.6).

We also discuss potential underlying drivers of the heterogeneity of wage cyclicalities across establishments and the implications for employment cyclicalities. Given that the AWFP is an administrative dataset, we do not have any direct evidence on the unionization of the workforce or the bargaining regime chosen by establishments. However, we can link the AWFP to the IAB Establishment Panel (see Ellguth et al., 2014). Using this linked data, we find a nonlinear pattern between wage cyclicality quintiles and bargaining regimes. The share of establishments that is part of the collective bargaining regime is smaller both for establishments with strongly procyclical and strongly countercyclical wages than for other establishments. However, when we re-estimate the connection between employment and wage cyclicalities controlling for these institutional factors in this subsample, our results remain robust.

All our empirical results can be used as a benchmark and input for quantitative theoretical models. It has to be kept in mind that they are estimated at the establishment level. In order to make statements how much these heterogeneous cyclicalities matter in aggregate, a macroeconomic model of the labor market is required. We propose a model with labor market flows and heterogeneous wage cyclicalities. We use a simple mechanism where establishments select a certain fraction of applicants based on their idiosyncratic match quality (in the spirit of Chugh and Merkl, 2016). Different wage cyclicalities are bilaterally efficient, as wages in our simulations are between workers' and establishments' reservations wages. Thus, our model does not run afoul of the Barro (1977) Critique.[5]

In order to make quantitative statements on the role of heterogeneities and wage cyclicalities for aggregate labor market amplification, we fit our model to several important dimensions from the data, namely the heterogeneity of wage cyclicalities across establishments and the effects of wage cyclicality on employment cyclicality. This disciplines the effects of our

[5]According to the Barro (1977) Critique, a wage rigidity is bilaterally inefficient in a neoclassical demand-supply framework because both parties would be better off without this rigidity, i.e., there is money left on the table.

three counterfactual exercises. First, when we set the wage cyclicality of all establishments to the one of the median establishment, aggregate amplification changes very little relative to our baseline scenario. In this counterfactual exercise one half of establishment becomes more procyclical and the other half becomes less procyclical. Given that the empirical wage cyclicality distribution is relatively symmetric, these two effects cancel out. Second, when we set the wage cyclicality of all establishments to the one of the most procyclical establishments from the data, one third of labor market amplification gets lost. Thus, the heterogeneity of wage cyclicalities matters, as a large fraction of establishment are either ayclical or even countercyclical. These establishments amplify the reaction of the German labor market to aggregate shocks. Third, when we assume that all establishments follow standard Nash bargaining (instead of their observed wage cyclicalities), the standard deviations of the hires rate and unemployment drop by more than two thirds of their initial level. In different words, we show that a major share of German labor market amplification is due the observed wage cyclicalities, which is much less procyclical than under Nash bargaining.

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 from the data. However, we consider our paper as a starting point that establishes empirical facts, which 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., directed search models (e.g., Julien et al., 2009) or to medium-scale dynamic stochastic general equilibrium models (e.g., Christiano et al., 2005; Smets and Wouters, 2007).

The paper proceeds as follows. Section 2 presents the AWFP dataset and explains the sample selection for our baseline regression. Section 3 documents the heterogeneity of real wage cyclicalities and employment cyclicalities across establishments. Section 4 estimates the connection between wage and employment cyclicalities at the establishment level (including various robustness checks). Section 5 derives a model of heterogeneous wage cyclicalities across establishments and calibrates the model to the empirical results. The counterfactual exercises show the role of wage cyclicality for aggregate amplification. 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 level to the establishment level for the years 1975–2014. 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 in Germany who is subject to social security. Before aggregating the data to the establishment level, several corrections and imputations were conducted 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 use the time variation at the establishment level. One disadvantage of the AWFP (or register data in Germany more generally) is that it does not provide information on the exact number of hours worked.[6] To have a homogeneous reference group, we therefore restrict ourselves to full-time workers.[7] Wages are defined as mean real daily wages (in 2010 prices) of all employed full-time workers in a particular establishment.[8] 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 are a measure of total compensation rather than a daily base wage. Since companies are some-

[6]It is important to note that the extensive margin of labor — the adjustment over the business cycle — is a lot more important than the intensive margin in Germany (e.g., Reicher, 2012).

[7]More precisely, we use "regular workers" according to the definition of the AWFP (see Appendix A.1.1).

[8]We deflate daily wages using the German CPI.

times able to circumvent wage rigidity by adjusting non-wage benefits (e.g., Lebow et al., 1999; Grigsby et al., 2019), the BeH wage concept offers considerable advantages when investigating the relationship between wage and employment cyclicalities (Ehrlich and Montes, 2020). Workers' daily wages above the contribution assessment ceiling are imputed following Card et al. (2015) before aggregating the data to the establishment level.

We use the AWFP at the annual frequency[9] and restrict the data to West German establishments (excluding Berlin) and the years 1979–2014.[10] Note that we have opted for 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 year, we would not obtain any time variation at the quarterly level in this given year. Thus, time variation on the quarterly level only comes from shorter employment spells. Further we drop all establishments that change the industry sector or the federal state. As we control for establishment fixed effects in our regressions, we do not need to control for the industry sector and the federal state.[11] For more detailed information on the AWFP see Appendix A.1.1.

2.2 Baseline Sample

In our baseline regressions, we only included establishments that have on average 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 make sure that our results are not driven by very small establishments that may not be relevant for the entire economy. Second, newly founded establishments are very volatile. Thus, they may generate noise in our estimations. According to Brixy et al. (2006), establishments in Germany can be seen as mature or incumbent establishments after five years. Afterwards, they do not substantially differ from

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

[10] We chose these restrictions for data quality reasons and to circumvent the break by German unification.

[11] Since our analysis relies on wage and employment growth, we cannot consider the birth and death of establishments as we cannot calculate meaningful growth rates for these occasions.

older establishments concerning wage levels and working conditions.[12] Third, employees' protection against dismissal in Germany depends on the number of employees. The statutory protection against dismissal does not apply to employees of small businesses.[13] This is another reason why we exclude small establishments, which are subject to different institutional rules. Fourth, from a statistical perspective our wage and employment cyclicality measures may be estimated very imprecisely for short-lived establishment with only a few observations. We want to prevent that our results are driven 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 a nutshell, we expect more representative and more stable results from our sample restrictions. Despite our restrictions, our baseline sample still covers on average 80.2% of all worker-year observations of full-time workers (see Table 1).[14] Aggregated time series of selected variables for West Germany (excluding Berlin) — generated using the entire AWFP and our baseline sample — and further sample statistics are provided in Appendix A.1.1. The robustness of our baseline results and the choice of our baseline sample are discussed in Section 4.3.

3 Wage and Employment Cyclicalities

There is a growing empirical literature on the question how flexible or rigid wages are over the business cycle (e.g., Martins et al., 2012; Haefke et al., 2013; Card et al., 2015; Stüber,

[12]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.

[13]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.

[14]Over the years 1979–2014 the share varies between 76.8% and 82.7%.

2017; Gertler et al., 2020). Typically, worker-specific wages are regressed on aggregate unemployment (growth). We deviate from this practice in an important way. 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 (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.

In this section, we first estimate the average wage cyclicality using the baseline sample and show that our results are comparable to results using individual worker data. Second, we estimate the comovement of establishments' wage growth with a sector-specific employment growth. There is substantial heterogeneity across establishments. Third, we estimate the comovement of establishments' employment growth with a sector-specific employment growth. Here, we also find substantial heterogeneity across establishments.

3.1 Average Wage Cyclicality

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

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

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.[15]

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.3 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 2: Average Wage Cyclicality

Estimated coefficient $\hat{\alpha}_1$	0.195^{***}
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	0.15 | 0.12
Observations	7,259,116

Note: *** indicates statistical significance at the 1 percent level.

Table 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.4 shows that a regression in levels — using the aggregated unemployment rate as the business cycle indicator — delivers a result that is comparable with regressions results on the worker level.[16] 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.

[15]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.

[16]See also Section 4.3.2 and Footnote 34.

3.2 Establishments' Wage Cyclicality

The estimated coefficient in the previous subsection represents the average wage reaction to sectoral business cycle fluctuations. However, in this paper, we are interested in the heterogeneous reaction across establishments. For this purpose, we estimate the following high-dimensional fixed-effects regression (see Correia, 2018):

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

where α_{1i} shows how strongly the wage growth of establishment i (in sector j) reacts to changes of the (sectoral) business cycle indicator N_t^j (full-time employment), indicating how procyclical or countercyclical a certain establishment is. Equation (2) generates over 356 thousand coefficients α_{1i}, which correspond to the number of establishments in our baseline specification.[17] So 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 extreme outliers for our analysis of the connection between wage and employment cyclicalities (see Section 4).[18] To be consistent, the results presented in Tables 3 and 4 exclude these outliers.[19]

Table 3 shows that there is substantial heterogeneity of wage cyclicalities across establishments. The second column of Table 3 contains 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 2). While establishments at the 80th percentile show strongly procyclical real wages (0.71), establishments at the 20th percentile show countercyclical real wages (-0.32). Our estimation reveals that nearly 36 percent of all establishment have a countercyclical real wage movement. Our paper is the first to document these facts, as the AWFP offers long time series for wages for each

[17] Goodness of fit measures of the regression: observations: 7,259,116; R^2: 0.20; within R^2: 0.11.

[18] In all our regressions, tables, and figures, we drop observations with estimated $\hat{\alpha}_{1i}$ (see Section 3.2) and $\hat{\beta}_{1i}$ (see Section 3.3) below the 1^{th} or above the 99^{th} percentile of the corresponding distribution.

[19] Therefore, Regressions (2) and (3) estimate over 356 thousand coefficients but about 344 thousand coefficients are presented in Tables 3 and 4. As we drop outliers for two different measures, the number of remaining observations differs slightly and depends on the aggregation level of the business cycle indicator.

Table 3: 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	0.13
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, 127

Note: We drop extreme outliers before the calculation of this table (see Footnote 18).

establishment.

About 64% of all establishments have procyclical wage setting (PWS; $\alpha_{1i} \geq 0$). Looking at the state level, the share of establishments with PWS hardly differs between the states.[20] Thus, it appears that wage cyclicality is not a matter of location. In different words, it appears that the substantial heterogeneity of wage cyclicality can be found in all West German states. At the sector level, using the 31 sectors, the dispersion of the share of PWS is larger. Between 38% and 76% of establishments in a given sector have PWS. However, the large dispersion is mainly driven by some special sectors.[21]

The third column in Table 3 shows the estimated $\hat{\alpha}_{1i}$ at different percentiles using national employment growth as the business cycle indicator instead of sectoral employment growth. The dispersion of wage cyclicalities increases somewhat at the higher aggregation level. However, there is a substantial degree of heterogeneity independently of the aggregation level. Thus, our results on heterogeneous wage cyclicalities are mainly driven by heterogeneities of

[20] Between 61% and 67% of establishments in a given state have PWS.

[21] The lower values are sector 10 (manufacturing of coke, refined petroleum products and nuclear fuels) with 38%, sector 19 (electricity, gas and water supply) with 42%, and sector 30 (private households with employed persons) with 43% PWS. The upper values are sector 15 (manufacturing of machinery and equipment – not elsewhere classified) with 76%, sectors 20 (construction), 9 (manufacturing of pulp, paper and paper products; publishing and print;), and 14 (manufacturing of basic metals and fabricated metal products) with 75% PWS.

establishments within sectors.[22]

It may appear surprising that such a large fraction of establishments shows a countercyclical real wage movement over the business cycle. Three comments are in order: First, traditionally countercyclical real wages were considered as a typical feature of Keynesian models (e.g., Bils, 1985; Beaudry and DiNardo, 1991; Solon et al., 1994). Second, keep in mind that the wage in the AWFP is a measure of total compensation. It contains, inter alia, bonus payments[23] and payments that are made above the minimum required from collective bargaining agreements. These features provide flexibility for (some) establishments to implement real wage cuts in sufficiently strong recessions and stronger wage increases in booms. Further, Elsby and Solon (2019) document that nominal wage cuts are a quite common phenomenon. Third, even though we refer to countercyclical real wages, it does not necessarily mean that establishments decrease real wages. As we will show in Section 4.2.1, countercyclical wage establishment tend to have a larger fixed effect for their average wage growth. Thus, in a boom, many of them deviate negatively from an on average larger real wage growth.

3.3 Establishments' Employment Cyclicality

Analogous to Equation (2), we estimate the cyclicality of employment β_{1i} for each establishment:

$$\Delta \ln n_{ijt} = \beta_0 + \beta_{1i} \Delta \ln N_t^j + \beta_2 t + \beta_3 t^2 + \beta_4' \mathbf{C}_{it} + \mu_i^n + v_{ijt}^n, \tag{3}$$

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 of 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.

[22] As a robustness check, we also run the regressions separately for the 31 sectors (see Appendix A.3).

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

Table 4 shows that there is (substantial) heterogeneity of employment cyclicalities across establishments.[24] As for wage cyclicality (Table 3), we present results for our baseline specification — using the sectoral employment as business cycle indicator (second column) — and using national employment as business cycle indicator (third column). Again, the dispersion increases somewhat at the higher aggregation level. However, there is a substantial degree of heterogeneity independently of the aggregation level. Thus, our results on heterogeneous employment cyclicalities are also mainly driven by heterogeneities of establishments within sectors.

Table 4: 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	$344,293$	$344,127$

Note: We drop extreme outliers before the calculation of this table (see Footnote 18).

As for wage cyclicality, about 64% of all establishments have procyclical employment setting (PES; $\beta_{1i} \geq 0$). Looking at the state level, the share of establishments with PES hardly differs between the states.[25] Thus, it appears that also employment cyclicality is not a matter of location. It seems that a substantial heterogeneity of wage and employment cyclicality can be found in all West German states. At the sector level, using the 31 sectors, the dispersion of the share of PES is somewhat larger, but not as large as for PWS. Between 54% and 75% of establishments in a given sector have PES. Here as well, the dispersion is

[24]Goodness of fit measures of the regression: observations: 7,259,116; R^2: 0.22; within R^2: 0.08. Please be reminded that we drop extreme outliers (see Section Footnote 18). Therefore Regression (3) estimates over 356 thousand coefficients but only about 344 thousand coefficients are presented in Table 4.

[25]Between 62% and 65% of establishments in a given state have PES.

mainly driven by some special sectors.[26]

4 Connection between Establishments' Wage and Employment Cyclicality

In this section we analyze the connection between establishments' wage and employment cyclicality. First, we show that establishments with more procyclical wages have a less procyclical employment adjustment. Second, we analyze potential driving sources for different wage cyclicalities across establishments. Third, we document the robustness of our results in various dimensions.

4.1 The Effect of Wage Cyclicality on Employment Cyclicality

We estimated a wage cyclicality ($\hat{\alpha}_{1i}$, see Section 3.2) and an employment cyclicality ($\hat{\beta}_{1i}$, see Section 3.3) measure for each establishment i. This allows us to analyze the connection between these two. We regress $\hat{\alpha}_{1i}$ for each establishment on $\hat{\beta}_{1i}$ of the respective establishment:

$$\hat{\beta}_{1i} = \gamma_0 + \gamma_1 \hat{\alpha}_{1i} + v_{it}^{\hat{\beta}}. \tag{4}$$

Note that Equation (4) is a cross-sectional regression, as each establishment has one wage cyclicality value and one employment cyclicality value for the entire observation period. Table 5 shows that there is a negative connection between the cyclicality of wages and the cyclicality of employment at the establishment level.

[26]The lower values are sectors 26 (public administration and defense; compulsory social security) and 30 (private households with employed persons) with 54%, sector 19 (electricity, gas and water supply) with 56%, sectors 10 (manufacturing of coke, refined petroleum products and nuclear fuels) and 29 (other community, social and personal service activities) with 58%, and sector 9 (manufacturing of pulp, paper and paper products; publishing and print) with 59% PWS. The upper values are sector sector 2 (fishing) with 75%, sector 15 (manufacturing of machinery and equipment – not elsewhere classified) with 73%, and sector 13 (manufacturing of other non-metallic mineral products) with 72% PWS.

Table 5: Effect of Wage Cyclicality on Employment Cyclicality

Estimated coefficient $\hat{\gamma}_1$	-0.452^{***}
R^2	0.01
Observations	344,293

Note: *** indicates statistical significance at the 1 percent level. We drop extreme outliers before running the regression (see Footnote 18).

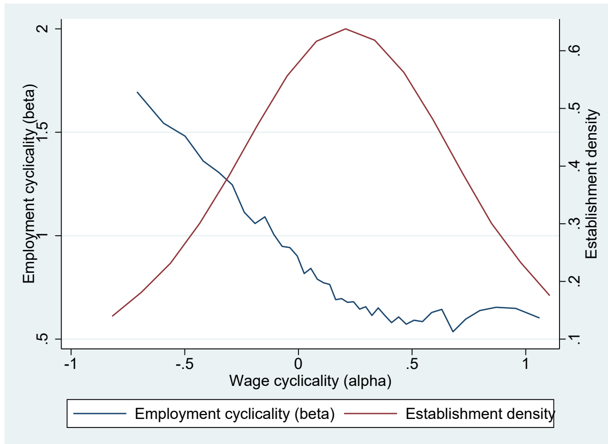
Although we have used the sector-specific employment growth rate as business cycle indicator in our regressions, the reaction may be different from sector to sector. In order to check this, we run the same regressions on the sectoral level. The coefficients are negative in most of the 31 sectors (see Appendix A.3).

Figure 2 illustrates our baseline sample 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 classify 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. Hence, we use narrow bins in areas of the wage cyclicality distribution where we observe many establishments and then gradually widen bins in thinner parts of the distribution. As can be seen from the density function, the bin rage is increasing 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 pro- or countercyclical wages.

Figure 2 shows a negative connection between wage cycliality and employment cyclicality, which flattens out in the positive part of wage cyclicality. The figure illustrates the estimated regression coefficient from Equation (4): more countercyclical wage establishments are associated with less procyclical employment cyclicalities. The negative relationship is flattening for very procyclial establishments.

What is the underlying economic intuition for the negative connection between employment cyclicality and wage cyclicality? Imagine two establishments in a boom. Our results suggest that the establishment with a stronger upward adjustment of real wages increases

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

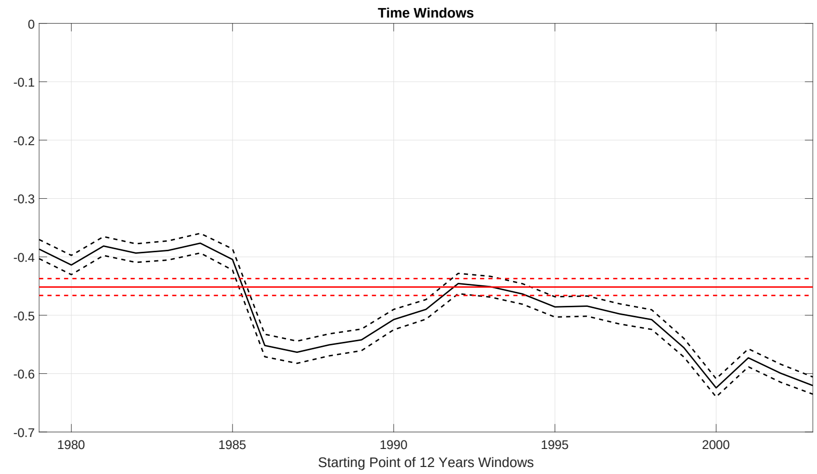


Note: We divide the range of the wage cyclicality measure ($\hat{\alpha}_{1i}$, see Section 3.2) into 50 bins. Each bin contains 1/50 of all observations, showing the mean. We drop extreme outliers (see Footnote 18). The figure is showing results for mean $\hat{\alpha}_{1i} \geq$ the 10th percentile and $\hat{\alpha}_{1i} \leq$ the 90th percentile of the estimated $\hat{\alpha}_{1i}$ (see Table 3).

employment by less than the establishment with a smaller positive (or even negative) real wage movement. While this result appears very intuitive, it has to be emphasized that we are the first to show this link between wage and employment cyclicalities based on estimations at the establishment level. The existing literature was limited by a lack of appropriate datasets to provide such a linkage.

Why is this link between wage and employment cyclicalities important? As mentioned in the introduction, our empirical approach provides a quantitative benchmark for different quantitative models. In principle, it could be possible that different wage dynamics represent insurance contracts and thereby do not have much of an effect on labor market dynamics. However, our results indicate the wage cyclicalities matter for employment cyclicalities at the establishment level.

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).

As we estimate one time-invariant indicator for each firm, 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 firms inherit habits and institutions from the past (e.g., the unionization of the workforce or the establishment's culture).

To test for the robustness of our results in the time dimension, 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 connection between employment and wage cyclicality is statistically significant at the 1 percent level in all cases.[27]

[27] To further test for the robustness of our results in the time dimension, we propose in Appendix A.6 alternative measures to estimate the connection between (relative) wage growth and (relative) employment growth. These measures define the growth relative to all other establishments in a given year and sector.

4.2 Potential Drivers

So far, we have documented the heterogeneity of wage cyclicalities across establishments and the implications for employment cyclicalities. Before we proceed to check the robustness of our results, we will discuss potential underlying drivers. Unfortunately, the AWFP does not contain any information on unionization or institutional details on wage formation. Therefore, we start by documenting the connection between establishments' wage level, establishment size as well as fixed effects with wage cyclicality (based on the baseline sample). Afterwards, we link a subsample of the AWFP to the IAB Establishment Panel, which contains information on institutional details.

4.2.1 Establishments' Characteristics

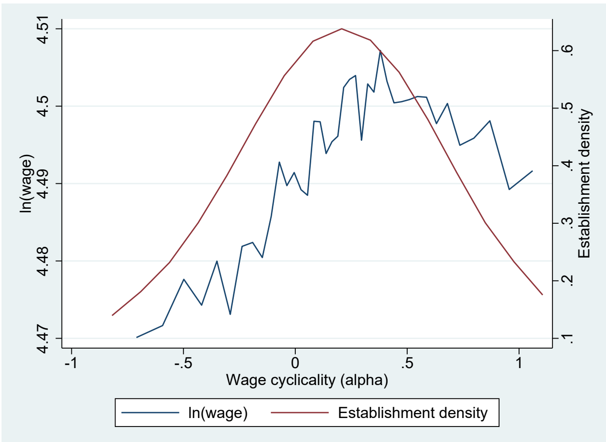
Figures 4 and 5 sorts establishments according to their wage cyclicalities into 50 bins.[28] Figure 4.1 shows the mean real wage of full-time workers for each bin. Mean wages are slightly higher for establishments with acyclical or procyclical wage cyclicality than for countercyclical establishments. 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 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. By contrast, moderately procyclical wage establishments (in the middle of the distribution) are larger in size. Note that a similar qualitative picture arises when we remove the sample restrictions. Obviously, this fact may be connected to the industrial relation regime. It is well known that larger establishments are more likely to be part of the collective bargaining agreement (see Section 4.2.2 for details).

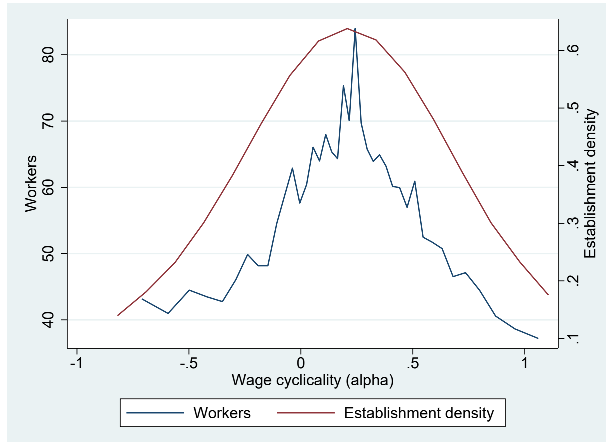
In Appendix A.2, we present some statistics for pro- and countercyclical establishments ($\hat{\alpha}_{1i} > 0$ and $\hat{\alpha}_{1i} < 0$, respectively) as well as for strongly countercyclical ($\hat{\alpha}_{1i} \leq$ 20th

[28] As in in Fig. 2, we sort from most countercyclical on the left to most procyclical on the right.

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

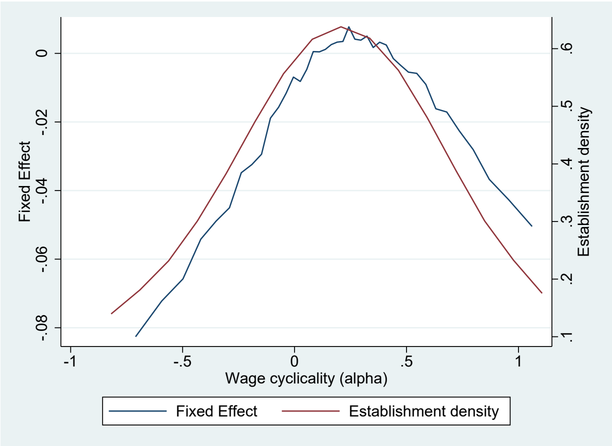
Note: We divide the range of the wage cyclicality measure ($\hat{\alpha}_{1i}$, see Section 3.2) into 50 bins. Each bin contains 1/50 of all observations, showing the mean. We drop extreme outliers (see Footnote 18). The figure is showing results for mean $\hat{\alpha}_{1i} \geq$ the 10th percentile and $\hat{\alpha}_{1i} \leq$ the 90th percentile of the estimated $\hat{\alpha}_{1i}$ (see Table 3).

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.

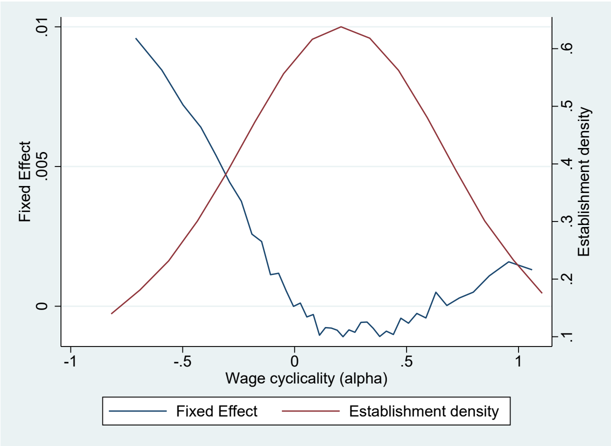
In addition to linking the wage cyclicality measure to descriptives, we show the connection to the estimated establishment fixed effects. Figure 5.1 shows the connection between wage cyclicality and the establishment fixed effect (μ_i^n) from the employment cyclicality regression (Equation (3)). The 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 largest average employment growth rate (over a long time horizon) are those with the largest size.

Figures 5.2 connects establishments' wage cyclicality to their establishment fixed effect (μ_i^w) from the wage regression (Equation (2)). This figure reveals an insightful connection for countercyclical wage establishments. A more countercyclical wage is associated with a larger

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 3.2) into 50 bins. Each bin contains 1/50 of all observations, showing the mean. We drop extreme outliers (see Footnote 18). 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 3).

establishment fixed effect. In different words, establishments with very countercyclical wages show an average real wage growth that is larger than at other establishments. Remember that we found that a large fraction of establishments shows countercyclical real wages. Taking into account the establishment fixed effects puts this finding into perspective. Countercyclical wage establishments do not necessarily cut real wages in booms, but only show a negative deviation from their average positive real wage growth.

4.2.2 Industrial Relations

We are unable to provide a definitive answer concerning the underlying sources of the heterogeneity of 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). Thereby, we can provide some first anecdotal evidence (at the cost of losing at least 99% of our observations).[29] The EP is an annual survey of establishments located in Germany which has been conducted since 1993. It aims for a representative sample of about 15,000 to 16,000 establishments each 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 6 shows the share of establishments within 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).[30] Note that we sort the quintiles from the most countercyclical group (quintile 1) to the most procyclical group (quintile 5).

Table 6: Wage Bargaining Regime and Works Council

	Quintile of wage cyclicalities				
	1	2	3	4	5
Wage bargaining regime					
Collective bargaining	51.5	64.5	70.4	66.7	53.9
Firm level bargaining	9.7	8.4	7.2	7.8	8.3
Works council (in %)					
Yes	49.9	61.0	68.6	65.3	52.6

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.
Source: AWFP linked to the IAB Establishment Panel for the years 1995–2014.

This exercise allows us to document clear-cut patterns. A larger share of establishments in quintiles 3 and 4 (i.e., those with acylical and moderately procyclical wages) are part of the collective bargaining agreement. In addition, a larger share of these establishments has a works council (see Table 6).[31] It appears completely reasonable to us that both collective bargaining and works councils are associated with more moderate real wage movements over

[29]Information on the wage bargaining regime is available for 17,525 establishments of our baseline sample and information on the existence of works councils for 18,019 establishments.

[30]The patterns are very similar independently if we use one particular base year in the survey or an average of the answers (as the bargaining regime or the existence of a works council may change over time). Results in Table 6 are obtained by using the mode answer of an establishment.

[31]Works councils are the elected worker representation at the establishment level, which co-determines certain important decisions such as firing.

the business cycle. Collective bargaining agreements only constitute minimum wage payments (i.e., higher wage increases are possible). However, it can be expected that collective agreements are an important anchor for the wage formation of those establishments that decided to be part of the agreement.[32] Although works councils do not have a formal role in wage negotiations, their existence is known to be correlated with wage outcomes (see, e.g., Addison et al., 2010). Thus, it is in line with our expectations that a higher share of works councils is associated with more moderate real wage cyclicalities.[33]

In a nutshell, establishments with moderately procyclical wages tend to be larger, within 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 the collective bargaining means that wages are typically adjusted in line with the sector-specific business cycle. By contrast, based on our dataset, we cannot offer an explanation why some establishments show strongly procyclical wages and others show countercyclical wages, although they appear comparable in terms of the shown observable characteristics such as size or collective bargaining.

Finally, we check whether controlling for labor market institutions changes our key results. Table 7 re-estimates equation (4) based on the AWFP-IAB Establishment Panel linkage. Comparing column 2 and 3 shows that the estimated coefficient is somewhat larger (in absolute terms) than in the AWFP baseline sample. The results remain robust when we control for collective bargaining (column 5) and having a works council (column 6), using dummy variables. As not all establishment provide answers to these questions, we also show the estimated coefficient for a comparable sample without these controls (see columns 4 and 6).

[32]This may obviously also be true for some establishments that are formally not member of the collective agreement. However, those can undercut the collective conditions.

[33]The IAB Establishment Panel oversamples larger establishments (see Ellguth et al., 2014). Thus, the share of collective bargaining is over-represented with respect to all establishments.

Table 7: Effect of Wage Cyclicality on Employment Cyclicality — Baseline merged with EP

Estimated Coefficient	$\hat{\gamma}_1$	$\hat{\gamma}_1^{EP}$	$\hat{\gamma}_1^{EP_{CB}}$	$\hat{\gamma}_1^{EP_{CB}}$	$\hat{\gamma}_1^{EP_{WC}}$	$\hat{\gamma}_1^{EP_{WC}}$
Coefficient	$\mathbf{-0.452}^{***}$	-0.586^{***}	-0.558^{***}	-0.559^{***}	-0.602^{***}	-0.597^{***}
Collective bargaining				-0.024		
Works council						0.265^{***}
R^2	0.01	0.02	0.01	0.01	0.02	0.02
Observations	344,293	14,435	9,765	9,765	14,101	14,101

Note: *** indicates statistical significance at the 1 percent level. Baseline regression result in bold. We drop extreme outliers before running the regression (see Footnote 18).

4.3 Further Robustness Checks

In the following we perform several robustness checks. First, we show that our baseline sample restrictions result in more representative and more stable results by restricting and loosening the restrictions concerning mean workers and number of observations. Second, we discuss and analyze the role of newly hired versus incumbent workers. Third and forth, we discuss composition effects and working time effects, respectively. Finally, Appendix A.6 provides an alternative measure, which also allows us to discuss the potential role for establishment-specific revenue cycles (see Appendix A.7).

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 least 20 full-time workers. Table 8 shows that the estimated coefficient $\hat{\gamma}_1$ increases with the mean size of establishments. This confirms our conjecture that small establishments are more noisy. In addition, it shows that our results are not driven by small establishments (which would be worrisome). By contrast, we obtain a stronger connection, the larger establishment are.

Table 8: Effect of Wage Cyclicality on Employment Cyclicality — Altering the Mean Establishment Size

Mean size	all	10	20
Estimated coefficient $\hat{\gamma}_1$	-0.181^{***}	$\mathbf{-0.452}^{***}$	-0.598^{***}
R^2	0.01	0.01	0.01
Observations	2,297,544	344,293	177,027

Note: *** indicates statistical significance at the 1 percent level. Baseline regression result in bold. We drop extreme outliers before running the regression (see Footnote 18).

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 9 shows that the estimated coefficient converges to a level of around -0.45 with a least five observations and remains at this level.

Table 9: Effect of Wage Cyclicality on Employment Cyclicality — Altering the Minimal Number of Required Observations per Establishment

Required observations	2	5	10	15
Estimated coefficient $\hat{\gamma}_1$	-0.328^{***}	$\mathbf{-0.452}^{***}$	-0.458^{***}	-0.473^{***}
R^2	0.00	0.01	0.01	0.01
Observations	404,914	344,293	270,179	213,987

Note: *** indicates statistical significance at the 1 percent level. Baseline regression result in bold. We drop extreme outliers before running the regression (see Footnote 18).

Overall, these results are in line 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 as appropriate.

4.3.2 Newly Hired versus Incumbents Workers

Pissarides (2009) and Haefke et al. (2013) show that wages for new jobs (newly hired) are relevant for job creation in search and matching models and not wages for incumbent workers. In all our regressions, we have used the wages for all full-time workers and not just those that are newly matched. Why do we think that this is a valid 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.4, 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. Nevertheless, the estimated elasticities are remarkably similar, which reassures us that our establishment dataset replicates the same cyclicality patterns as worker-level datasets.[34]

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 a person's wage in the previous job or the previous entrant spell. 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

A major concern is that our results may be driven by reverse causality through composition 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 in a boom, keeping the share

[34] At the worker level, Stüber (2017) finds coefficients of -1.26. We estimate, at the establishment level, a coefficient of -1.16. 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.

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. 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).[35]

It is worthwhile emphasizing that we have taken several steps to prevent that this sort of reverse causality drives our results. First, we have used full-time workers as our reference group. This group is certainly more homogeneous than the entire employment at establishments, which also includes jobs with a small number of hours (e.g., so called minijobs) that may be very different. Second, we have used the sector-specific employment growth rate as business cycle indicator. It can be expected that workforces within sectors are more similar in terms of observable and unobservable characteristics than across sectors. Third, we have controlled for time-invariant heterogeneity and changes in various observables (skill, gender, age, etc.) in the first stage of our regressions (e.g., change of education composition). However, the change of unobservable characteristics may still be an important driver that we have neglected.

To test for the robustness of results, we replace the wage growth for all full-time worker by the incumbents' wage growth, i.e., worker relationships that already existed in the previous period. The stock of incumbents is more stable in terms of composition than new hires. Thus, potential composition biases are less of an issue.[36] Table 10 shows, that the estimated effect ($\hat{\gamma}_1^{\text{incumbents}}$) is very similar to our baseline estimation ($\hat{\gamma}_1$). This provides another piece of evidence that composition effects are not the key driver for our results.[37]

Finally, Appendix A.2 shows the estimated wage cyclicality distribution at different percentiles within the establishments (i.e., using the 25th and the 75th percentile instead of the mean daily wage of the establishment). Interestingly, the estimated wage cyclicality

[35] Vice versa, we would observe a procyclical wage (due to a pure composition effect) if the establishment would increase it share of high-qualified workers due to hiring in the boom.

[36] We owe this idea to Pedro Martins.

[37] In Appendix A.5, we provide a further illustrative robustness check to illustrate that composition effects cannot be the key driver of our result.

Table 10: Effect of Wage Cyclicality of Incumbent Workers on Employment Cyclicality

Estimated Coefficient	$\hat{\gamma}_1^{\text{incumbents}}$	$\hat{\gamma}_1$
Coefficient	-0.561^{***}	$\mathbf{-0.452}^{***}$
R^2	0.02	0.01
Observations	264,843	344,293

Note: *** indicates statistical significance at the 1 percent level. Baseline regression result in bold. We drop extreme outliers before running the regression (see Footnote 18).

distribution looks very similar at the 25th and 75th percentile than for the average wage. In addition, the estimated connection between employment and wage cyclicality is also negative and statistically significant for these two percentiles.

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 have taken several steps to exclude that working hours can be the driving force for our results. First, we have constrained ourselves to full-time workers.[38] Second, when estimating our wage regressions at the establishment level, we have controlled for time-variant observables and time-invariant unobserved heterogeneity.

In addition, it is worth mentioning that in usual times the extensive margin of labor adjustment is far more important in Germany than the intensive margin. 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). During the Great Recession, the intensive margin was however by far the dominant adjustment mechanism (see Burda and Hunt, 2011). Therefore, we exclude the Great Recession episode from our regressions (i.e., we rerun the regressions up to 2006, see Table 11). Compared to the baseline regression result, our quantitative results becomes only slightly smaller for the comovement measure. Therefore, we believe that intensive margin adjustments cannot be the key driver for our results.

[38] Table A.2 in Appendix A.1.1 provides an overview on the share of full-time (regular) workers and the share of all workers employed in establishments of our baseline sample.

Table 11: Effect of Wage Cyclicality on Employment Cyclicality — Excluding the Great Recession

Estimated Coefficient	$\hat{\gamma}_1^{\leq 2006}$	$\hat{\gamma}_1$
Coefficient	-0.387^{***}	$\mathbf{-0.452}^{***}$
R^2	0.01	0.01
Observations	297,825	344,293

Note: *** indicates statistical significance at the 1 percent level. Baseline regression result in bold. We drop extreme outliers before running the regression (see Footnote 18).

Furthermore, hours adjustment during the Great Recession was particularly important in the manufacturing sector. The manufacturing sector used measures such as short-time work more than the service sector. However, when we look at the sectoral level, the effects of different wage cyclicalities on employment are very similar for manufacturing and services (see Table A.6 in Appendix A.3).

5 Heterogeneous Wage Cyclicalities: Theory

The previous two sections showed that there is a substantial cross-sectional heterogeneity of 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.[39] Second, we calibrate our model to the wage cyclicality heterogeneity from the data. Third, we target the estimated interaction between wages cyclicality and employment cyclicality. Matching these three facts allows us to make meaningful statements on the role of wage cyclicalities and heterogeneities based on

[39] For establishments with more than ten employees, the number varies in between 92 and 98 percent. For establishments with more than 50 employees, at least 99 percent hire in any given year.

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.[40] An 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 hires 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.[41]

Our model setup is similar to Chugh and Merkl (2016). The key difference is that we allow for heterogeneous wage cyclicalities across establishments. Kohlbrecher et al. (2016) show that a model setup with labor selection generates an equilibrium Cobb-Douglas constant returns comovement between matches on the one hand and unemployment and vacancies on the other hand. This means that a homogeneous version of our model yields observationally equivalent labor market dynamics to a search and matching model with constant returns. We will exploit this fact in Section 5.4, where we set the wage cyclicality of all groups to the

[40] Given that the aggregation level in our empirical analysis is the establishment level, we also refer to establishments instead of firms in our theoretical model.

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

most procyclical group and thereby obtain a homogeneous version of our model. This allows us to contribute to the Shimer (2005) puzzle debate.

In Appendix A.9, 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. However, it turns out that (for a reasonable parameterization) this framework is unable to match the quantitative connection between wage cyclicalities and employment cyclicalities.

5.1.1 Heterogeneous Groups and Matching

In our model economy, there is a continuum of establishments that are completely homogeneous, except for their wage formation over the business cycle.[42] Workers can either be unemployed (searching) or employed. Employed workers are separated with an exogenous probability ϕ. In each period, unemployed workers send their application to one random establishment (i.e., search is completely undirected). Thus, each establishments receives an equal 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.[43]

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

$$E_0 \left\{ \sum_{t=0}^{\infty} \delta^t \left[a_t n_{it} - w_{it}^I (1-\phi) n_{i,t-1} - c_{it} s_t \eta(\tilde{\varepsilon}_{it}) \left(\frac{\bar{w}^E(\tilde{\varepsilon}_{it})}{\eta(\tilde{\varepsilon}_{it})} + \frac{H(\tilde{\varepsilon}_{it})}{\eta(\tilde{\varepsilon}_{it})} + h \right) \right] \right\}, \tag{5}$$

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

$$n_{it} = (1-\phi) n_{it-1} + c_{it} s_t \eta(\tilde{\varepsilon}_{it}), \tag{6}$$

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

[43] In Appendix A.9, we derive a search and matching model, where establishments act along the vacancy margin instead of the selection margin. In this model, workers are also randomly assigned to establishments.

where a_t is productivity, which is subject to aggregate productivity 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.

The applicants who apply at establishment i draw an idiosyncratic match-specific training cost shock (or more generally a match-specific productivity 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 (5) 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 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:

$$J_{it} = a_t - w_{it}^I + E_t \delta (1-\phi) J_{it+1}. \tag{7}$$

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

$$n_{it} = (1-\phi) n_{it-1} + c_{it} s_t \eta(\tilde{\varepsilon}_{it}), \tag{8}$$

$$\tilde{\varepsilon}_{it} = a_t - w^E(\tilde{\varepsilon}_{it}) - h + E_t \delta (1-\phi) J_{it+1}. \tag{9}$$

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:

$$\eta\left(\tilde{\varepsilon}_{it}\right)=\int_{-\infty}^{\tilde{\varepsilon}_{it}} f\left(\varepsilon\right)d\varepsilon. \tag{10}$$

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).[44] 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:

$$w_{it}=\kappa_i\left(a_t w^{norm}\right)+\left(1-\kappa_i\right)w^{norm}, \tag{11}$$

where κ_i is the establishment-specific degree of wage cyclicality over the business cycle and 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[45] (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 $\kappa_i<0$,

[44]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.

[45]See Appendix A.8.2 for the analytical derivation.

the establishment shows a countercyclical real wage behavior.

Note that the wage in group i is the same for all worker (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

$$\eta_t = \frac{\sum_{i=1}^{E} \eta\left(\tilde{\varepsilon}_{it}\right)}{E}, \tag{12}$$

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

$$n_t = (1-\phi)\, n_{t-1} + s_t c_t \eta_t, \tag{13}$$

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,[46] $c_t = \sum_{i=1}^{E} c_{it}$.

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

$$u_t = s_t\left(1 - c_t \eta_t\right), \tag{14}$$

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:

$$n_t = 1 - u_t. \tag{15}$$

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

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 equal to the number of searching workers.[47] This means that in aggregate the probability of a worker to get in contact with an establishment is 1 ($c_t = 1$). Thus, the contact probability with an establishment of type i is

$$c_{it} = \frac{1}{E}, \tag{16}$$

where E is the number of establishments or establishment types (depending on the disaggregation level).

Note that we will choose five establishment types in our simulation below. The establishment type will be our disaggregation level because all establishments of the same type behave in the same way.

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

$$y_t = a_t n_t - \sum_{i=1}^{E} \left(\frac{\eta\left(\tilde{\varepsilon}_{it}\right)}{E} s_t \frac{H_{it}}{\eta\left(\tilde{\varepsilon}_{it}\right)} + h \right). \tag{17}$$

5.2 Simulation-Based Effects

5.2.1 Calibration

In order to analyze the effects of different wage cyclicalities at the establishment level, we parametrize and simulate the model. We set the discount factor to $\delta = 0.99$, given that our simulation is performed at the quarterly frequency. 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). This also pins down the economy wide hires rate (matches/employment), which must be equal to the separation rate in steady state.

[47]This is similar to Chugh and Merkl (2016) who show how the model can be extended to multiple applications per period.

The 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.[48] Further, 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), which corresponds to a steady state wage of 0.95.

For tractability, we use a logistic distribution for the idiosyncratic training distribution with mean zero. We set the the linear hiring costs $h = 0.77$ such that we obtain the average unemployment rate from 1979–2014 (0.08), conditional on the distributional training cost parameter, which will be explained below.

Finally, we set the wage cyclicality parameters κ_i and the dispersion parameter z jointly such that we match two targets. First, we target the wage cyclicality from the data. Second, we target the effects of wage cyclicalities on employment cyclicalities. Obviously, κ_i and z interact. However, for illustration purposes, we explain the mechanisms separately below.

In order to target the distribution of wage cyclicalities from the data, we discretize our model economy into five different wage cyclicality groups. Remember that the parameter κ_i determines the wage cyclicality ($w_{it} = \kappa_i \left(a_t w^{norm}\right) + \left(1 - \kappa_i\right) w^{norm}$), i.e., whether establishments are procyclical or countercyclical. We set κ_i such that the wage cyclicality in our model is in line with the data. To determine κ_i, we match the 10th, 30th, 50th, 70th, and 90th percentile from Table 2, by setting $\kappa_i = [-0.29, -0.03, 0.07, 0.18, 0.41]$. We have two groups with negative values for κ. This means that their real wages increase in a recession, i.e., they are countercyclical. Two comments are in order. First, a countercyclical real wage is unusual in a real model of the economy. In reality, it may for example be the result of nominal rigidities. Since our dataset does not allow us to analyze the causes of this cyclicality (e.g., establishments' price setting behavior), we simply impose this pattern in our

[48]This number is both in line with the autocorrelation of labor productivity (per employed worker) in Germany from 1979–2014 and the estimated autocorrelation of productivity shocks in Smets and Wouters (2007).

model (i.e., as a constraint for establishments). Second, although separations are exogenous in our model, it has to be checked whether a worker's value of employment becomes smaller than the value of unemployment.[49] However, under our chosen calibration, we do not hit the bargaining bounds in any of the simulations (i.e., neither workers nor establishment have an incentive to end the employment relationship).

As a second target, we replicate the connection between wage cyclicalities and employment cyclicalities. More precisely, we ensure that our simulated model generates the same estimation result as in Table 5, namely $\hat{\gamma}_1 = -0.45$.[50] The target is reached by setting the dispersion parameter of the idiosyncratic logistic training cost distribution to $z = 0.74$.

The dispersion parameter z is both key for the amplification of the labor market in response to aggregate shocks and for the effect of wage cyclicalities on employment. A smaller dispersion means that there is more density around the cutoff point for training costs. Whenever the economy is hit by a positive aggregate shock, the cutoff point $\tilde{\varepsilon}_{it}$ increases, i.e., establishments are less selective and hire workers with larger training costs. With more density around the cutoff point, the hires rate and thereby employment increases by more. In different words, a smaller z leads to stronger aggregate amplification and a stronger quantitative connection between wage cyclicality and employment cyclicality. This tight connection disciplines our quantitative exercise: The estimated connection between employment and wages pins down the dispersion of the training cost distribution and thereby the reaction of employment to aggregate productivity shocks (i.e., by replicating $\hat{\gamma}_1$ from the estimation, we bind our hands how strongly our model amplifies aggregate shocks).

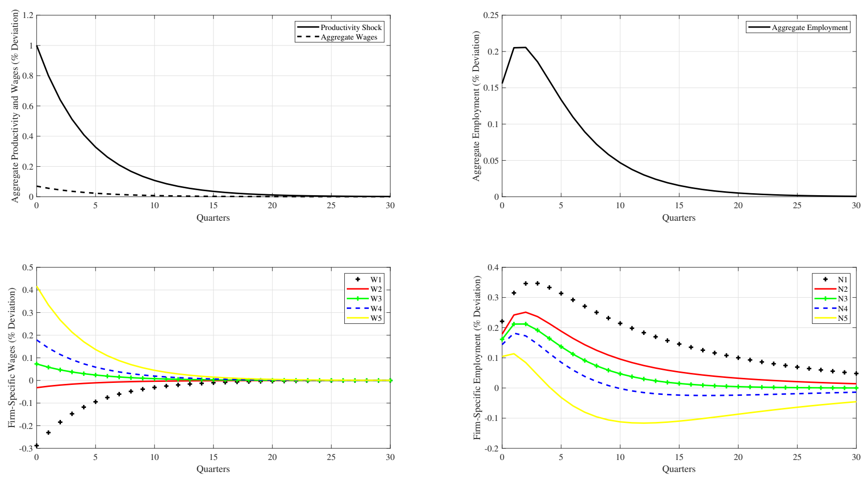
[49] Assume a business cycle downturn. In this case, a match with a procyclical wage establishment becomes less attractive for the worker due to the wage decrease. If the value of employment was smaller than the value of unemployment, the worker would quit the job.

[50] For this purpose, we simulate our model, aggregate the simulated quarterly data to the annual level and estimate the same annual regression as for Table 5.

5.3 Model Performance

We have calibrated our model to match two important facts from the data: i) the degree of heterogeneity across plants in terms of wage cyclicality, ii) the effect of these different wage cyclicalities on employment cyclicalities.

Figure 6: 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 with a 1, the most procyclical wage group is denoted with a 5.

Figure 6 shows the impulse response functions of the model economy in reaction to a positive aggregate productivity shock. In aggregate, average wages and employment respond procyclically to the aggregate productivity shock (see upper two panels). However, firms react very differently to the aggregate productivity shock depending on their wage cyclicality group (see lower two panels). 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 a flip-sided behavior. It increases for the most countercyclical wage group (denoted by N1), while it falls (after some quarters) for the most procyclical wage group (denoted by N5).

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 increases for the most procyclical wage group in response to a positive productivity shock. In different 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). 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 contacts with firms declines. After some quarters, this effect dominates for the most procyclical wage establishments, as they increase their selection rate less than other establishments.

Before we use the model for counterfactual exercises, we look at its aggregate performance. Table 12 shows the standard deviations of the aggregate hires rate (hr), employment rate (n), and unemployment rate (u) relative to the standard deviation of real GDP. The hires rate and unemployment are more volatile than aggregate GDP. Thus, our model amplifies aggregate productivity shocks. For the hires 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 in the simulation. This larger gap may be related to worker churn,[51] which we do not model in our theoretical framework and which may increase the volatility of employment in the data.

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 parametrization of the idiosyncratic shock dispersion).

In addition, we have simulated our model with aggregate productivity shocks only. 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 hires rate and

[51] Bachmann et al. (2021) show that there is substantial worker churn in Germany.

unemployment.

Table 12: Standard Deviations of Hires Rate, Number of Full-Time Employment (both Aggregated from the AWFP and Deseasonalized with X-12-ARIMA) and Unemployment Rate (all Relative to Real GDP)

	hr	n	u
Data	3.88	0.88	5.38
Simulation	2.00	0.23	2.73

Note: Observation period is 1979–2014. All variables are expressed in logs and as deviations from the Hodrick-Prescott filter (with smoothing parameter 1600).

Table 13 shows that our model generates the right signs for the correlations between various aggregate variables. For most variables, we do not only obtain the sign right, but also the right quantitative dimension. The absolute value of the correlation between (un)employment and GDP is larger in the model simulation than in the data. This is unsurprising given that productivity is the only aggregate shock in our model.

Table 13: Correlations between Hires 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	0.56	0.59	-0.52	-0.57
Simulation	0.32	0.68	0.91	-0.32	-0.91

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

Overall, our model generates realistic aggregate labor market amplification and it replicates the sign of important correlations from the data. This puts us into a position to use our model for counterfactual exercises.

5.4 Counterfactual Exercises

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. We have proposed a selection model that allows for heterogeneous wage cyclicalities in the cross section. Note that this model in its homogeneous version was shown to generate observationally equivalent labor market dynamics to a standard search and matching model (Kohlbrecher et al., 2016). Given that a standard search and matching model with constant returns to scale cannot replicate the empirical feature that establishments have heterogeneous wage cyclicalities and hire in (almost) any period.[52] Thus, it is natural to use our proposed framework for counterfactual analysis.

In a first counterfactual exercise, we set the wage cyclicality parameter for all establishments equal to one of the intermediate group ($\kappa_1 = ... = \kappa_5 = 0.07$). In this scenario, the standard deviations of the hires rate and unemployment barely change relative to the baseline scenario. The intuition is straightforward: If all establishments behaved like the median establishment, one half of establishments would be less procyclical than in the baseline and the other half would be more procyclical than in the baseline. These two effects basically cancel out, as wage cyclicalities are pretty symmetric around the median (see Table 3). However, this does not mean that heterogeneities of wage cyclicalities do not matter.

Table 14: Counterfactual Exercises

	Calibrated baseline	All intermediate group	All most procyclical group	All Nash Bargaining
Hires rate	2.00	1.99	1.35	0.60
Employment	0.23	0.23	0.16	0.07
Unemployment	2.73	2.72	1.82	0.80

Note: The Table shows the standard deviation of the logarithm of simulated the unemployment, the hires rate and employment.

To see that heterogeneities of wage cyclicalities do matter, we set the wage cyclicality of all groups to the most procyclical wage group (namely, $\kappa_1 = ... = \kappa_5 = 0.42$) in a second counterfactual exercise. Table 14 shows that labor market amplification would be reduced by roughly one-third in this case. In different words, if all establishments had a wage cyclicality as the establishment at the 90th percentile of the distribution, the labor market would react

[52]The selection framework has the advantage that we can target the connection between wage and employment cyclicality. We show in Appendix A.9 that this is not the case in a search and matching model, even with decreasing returns to labor.

much less to aggregate shocks. Thus, it matters that a substantial fraction of establishments has acyclical or even countercyclical wages. This sort of heterogeneity amplifies the response of the labor market to aggregate shocks.

Third, we assume that all five groups follow standard Nash bargaining.[53] In this scenario (see Table 14), the amplification drops by more than two-thirds relative to the baseline scenario. Under Nash bargaining, wages are a lot more procyclical than observed for nearly all establishments in Germany. Wages move roughly one to one with aggregate productivity in this scenario, i.e., the incentives for establishments to create extra jobs in a boom are small. This exercise directly addresses the Shimer (2005) puzzle. It shows that the observed wage cyclicalities in the German labor market lead to a labor market response that is three times larger than under standard Nash bargaining.

Overall, our counterfactual exercises point to powerful effects of different wage cyclicalities for aggregate labor market fluctuations. The qualitative connection between wage cyclicalities and employment cyclicalities is well established in the existing theoretical literature. The novel contribution of our paper is of quantitative nature, as we have targeted the connection between wage cyclicality and employment cyclicality, which we estimated from German establishment data. One key parameter for labor market amplification is the standard deviation of the training cost distribution, which we have disciplined by the quantitative connection between wage and employment cyclicalities. We have shown that if all establishments behaved like the most procyclical wage establishments or followed Nash bargaining, the labor market would react by one-third and two-thirds less to aggregate shocks, respectively.

[53] We set the bargaining power for workers and firms to 0.5. See Appendix A.8.2 for derivation of standard Nash bargaining.

6 Conclusion

Using the new Administrative Wage and Labor Market Flow Panel (AWFP), we show that the average real wage behavior masks that establishments have very different wage cyclicalities. Nearly 36 percent of establishments have 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 moderate cyclicality is associated with a higher share of establishments within collective bargaining. In addition, moderately procyclical establishments are on average larger relative to all other groups. In addition, 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 (or even countercyclical) 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. By contrast, the heterogeneities between establishments matters very little for aggregate amplification.

By showing that establishments' wage rigidity does affect their employment dynamics, our paper provides support for quantitative theories where different wage cyclicalities affect employment. The regression results establish a quantitative benchmark for different theoretical frameworks such as random search and matching models, directed search models or New Keynesian frameworks with infrequent wage adjustments.

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A Appendices 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.[54] 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 receipt 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.[55] 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

[54] The BeH also comprises marginal part-time workers employed since 1999.

[55] Deflated using the CPI.

(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.[56]

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.
- 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).

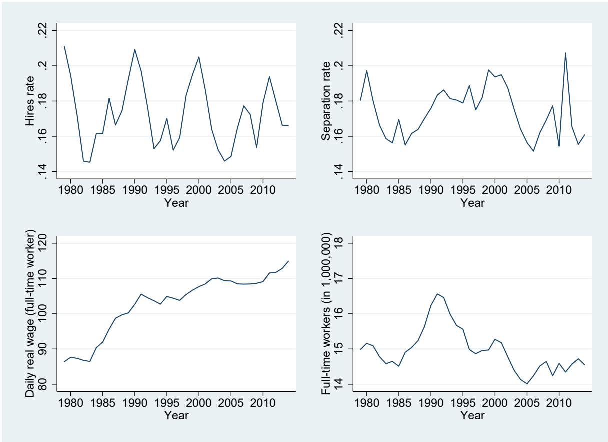
We use the AWFP at the annual frequency and restrict the data to West German establishments (excluding Berlin) and the years 1979–2014. The dataset contains more than 3.3 million establishments. For illustration purposes Figure A.1.1 shows the time series for the aggregated hires rate, separation rate,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

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.[57] It covers on average 80.2% of all full-time workers. Over the years 1979–2014 the share varies between 76.7% and 82.8% (see Table A.2).

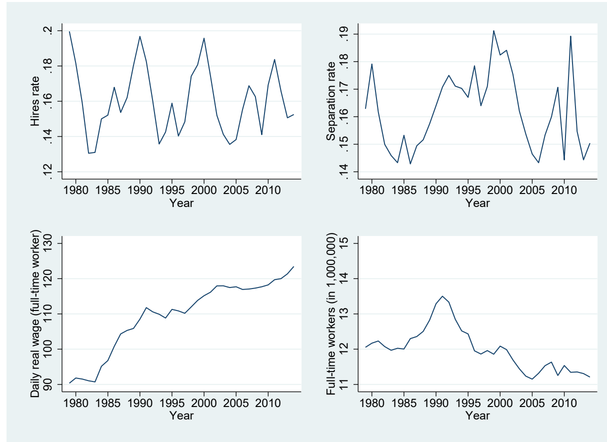
[56] For details see Appendix 8.2 of Schmucker et al. (2016).

[57] 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: 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 worker are included. Further, the establishment must be observed at least five times.

In Section 2.2 we motivate our baseline selection criteria in detail. Analog to illustration Figure A.1.1, 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.2, 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	51.64	231.55
log(daily wage)	4.49	0.31
Low-skilled workers	12.25%	14.61
Medium-skilled workers	78.16%	19.27
High-skilled workers	9.59%	16.23
Male workers	67.88%	26.68
Mean tenure	20.08	9.12
Mean age	38.99	4.28

Note: This table shows descriptive statistics for the baseline sample. We drop extreme outliers before calculating the statistics (see Footnote 18). We end up with a sample of 344,293 establishments.

Table A.2: Descriptive Statistics Baseline Sample (II)

Year	Establishments	Regular workers	All workers
1979	172,426	12,053,666	14,104,759
	(0.18)	(0.80)	(0.79)
1980	177,254	12,170,256	14,270,880
	(0.19)	(0.80)	(0.78)
1981	182,467	12,232,449	14,394,221
	(0.18)	(0.816)	(0.79)
1982	186,943	12,073,482	14,285,913
	(0.18)	(0.82)	(0.80)
1983	191,287	11,968,938	14,218,885
	(0.19)	(0.82)	(0.80)
1984	192,126	12,026,331	14,338,996

Continued on next page

Table A.2 – continued from previous page

Year	Establishments	Regular workers	All workers
	(0.19)	(0.82)	(0.80)
1985	192,870	12,004,817	14,398,980
	(0.19)	(0.83)	(0.81)
1986	194,097	12,299,813	14,758,248
	(0.19)	(0.83)	(0.81)
1987	196,061	12,358,750	14,828,063
	(0.18)	(0.82)	(0.80)
1988	198,083	12,504,151	14,968,380
	(0.18)	(0.82)	(0.80)
1989	200,173	12,825,136	15,325,426
	(0.18)	(0.82)	(0.80)
1990	202,775	13,288,262	15,854,546
	(0.18)	(0.82)	(0.80)
1991	205,566	13,502,468	16,111,380
	(0.18)	(0.82)	(0.80)
1992	207,454	13,335,613	15,951,159
	(0.18)	(0.81)	(0.79)
1993	208,349	12,850,421	15,413,267
	(0.18)	(0.80)	(0.79)
1994	209,248	12,519,426	15,039,370
	(0.18)	(0.80)	(0.78)
1995	209,706	12,433,178	14,969,168
	(0.18)	(0.80)	(0.78)
1996	209,770	11,953,238	144,93,189

Continued on next page

Table A.2 – continued from previous page

Year	Establishments	Regular workers	All workers
	(0.18)	(0.80)	(0.78)
1997	211,586	11,862,866	14,523,758
	(0.18)	(0.80)	(0.78)
1998	212,338	11,961,060	14,764,045
	(0.19)	(0.80)	(0.78)
1999	212,652	11,857,680	16,290,442
	(0.18)	(0.79)	(0.73)
2000	213,259	12086894	16,727,956
	(0.18)	(0.79)	(0.73)
2001	212,827	11,987,569	16,715,708
	(0.18)	(0.79)	(0.73)
2002	211,145	11,693,959	16,393,323
	(0.18)	(0.79)	(0.73)
2003	209,212	11,442,399	16,319,699
	(0.18)	(0.80)	(0.73)
2004	208,153	11,236,116	16,267,626
	(0.18)	(0.80)	(0.72)
2005	206,735	11,150,808	16,311,917
	(0.18)	(0.80)	(0.72)
2006	207,126	11,317,956	16,640,935
	(0.18)	(0.79)	((0.72)
2007	207,954	11,532,627	17,041,642
	(0.18)	(0.79)	(0.72)
2008	209,141	11,633,257	17,264,342

Continued on next page

Table A.2 – continued from previous page

Year	Establishments	Regular workers	All workers
	(0.18)	(0.79)	(0.72)
2009	208,413	11,254,611	17,014,384
	(0.18)	(0.79)	(0.72)
2010	207,876	11,537,020	17,368,564
	(0.18)	(0.79)	(0.72)
2011	202,940	11,343,968	17,557,388
	(0.19)	(0.79)	(0.71)
2012	198,445	11,354,680	17,462,040
	(0.18)	(0.78)	(0.70)
2013	193,704	11,308,163	17,386,924
	(0.18)	(0.77)	(0.69)
2014	188,955	11,209,270	17,209,078
	(0.18)	(0.77)	(0.69)
1979–2014	7259,116	432,171,298	566,984,601
	(0.18)	(0.80)	(0.76)

Note: Shares on all West German establishments (excluding Berlin) with at least one regular worker in parentheses.

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 (see Stüber et al., 2020). 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 of all establishments in Germany with at least one employee who is fully liable to social security at June 30th of the previous year. Establishments that have exclusively 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 stratifies by industries to allow for differentiated analyses in this respect.

A.2 Wage Cyclicality at Different Percentiles

Table A.3 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. The table further shows that the size differences show an inverted U-shape. Both strongly countercyclical ($\leq$ 20th percentile) and strongly procyclical establishments ($\leq$ 80th percentile) are smaller than the moderately cyclical establishments.

Table A.4 checks whether the wage cyclicality patterns changes at different percentiles of the wage distribution within establishments. 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.

Table A.3: Descriptive Statistics for Pro- and Countercyclical Establishments of the Baseline Sample

Variable	Counter-cyclical	Pro-cyclical	$\leq 20^{th}$ percentile	$]20^{th}, 80^{th}[$ percentile	$\geq 80^{th}$ percentile
Establishments	121,547	222,746	68,858	206,577	68,858
Mean establishment size	44.84	55.35	38.65	60.35	38.50
log(daily wage)	4.48	4.50	4.47	4.50	4.49
Low-skilled workers	11.62%	12.60%	11.41%	12.44%	12.54%
Medium-skilled workers	77.69%	78.41%	76.67%	79.19%	76.56%
High-skilled workers	10.69%	8.99%	11.92%	8.37%	10.90%
Male workers	65.28%	69.30%	63.94%	69.28%	67.63%
Mean tenure	18.05	21.19	15.88	22.31	17.58
Mean age	38.88	39.05	38.75	39.17	38.68

Note: The table shows statistics for establishments with countercyclical and procyclical wages (column 2 and 3) and for establishments within different percentiles of the wage cyclicality distribution (column 4–6). Statistics for the baseline sample are presented in Table A.1.

Table A.4: Wage Cyclicality at Different Percentiles

Estimated coefficients:	$\hat{\alpha}_{1i}^{p25}$	$\hat{\alpha}_{1i}$	$\hat{\alpha}_{1i}^{p75}$
Cyclicality at 10^{th} percentile	-1.14	-0.78	-0.92
Cyclicality at 20^{th} percentile	-0.50	-0.32	-0.37
Cyclicality at 30^{th} percentile	-0.19	-0.09	-0.11
Cyclicality at 40^{th} percentile	0.01	0.07	0.07
Cyclicality at 50^{th} percentile	0.18	0.20	0.22
Cyclicality at 60^{th} percentile	0.34	0.34	0.37
Cyclicality at 70^{th} percentile	0.54	0.49	0.55
Cyclicality at 80^{th} percentile	0.83	0.71	0.81
Cyclicality at 90^{th} percentile	1.41	1.12	1.32
Observations	343,947	$344,293$	344,156

Note: We drop extreme outliers before the calculation of this table (see Footnote 18).

Finally, Table A.5 shows the estimated connection between employment cyclicality and wage 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.5: Effect of Wage Cyclicality on Employment Cyclicality for Different Percentiles

Estimated Coefficient	$\hat{\gamma}_1^{p25}$	$\hat{\gamma}_1$	$\hat{\gamma}_1^{p75}$
Coefficient	$-.443^{***}$	$\mathbf{-0.452}^{***}$	$-.190^{***}$
R^2	0.02	0.01	0.00
Observations	343,947	344,293	344,156

Note: *** indicates statistical significance at the 1 percent level. Baseline regression result in bold. We drop extreme outliers before running the regression (see Footnote 18).

A.3 Results for 31 Industry Sectors

Each establishments in Germany belongs to one of 31 (industry) sectors (see note under Table A.6) according to the German Classification of Economic Activities (Edidition 1993, WZ 93). Although we have used the sector-specific employment growth rate as business cycle indicator in our 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.6 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 three sectors with positive coefficients: (19) electricity, gas and water supply, (26) public administration and defense; compulsory social security, and (30) private households with employed person. All these sectors have in common that they are either really small and/or are very regulated as Sector (19), or they are very special sectors such as the last two.

Table A.6: Effect of Wage Cyclicality on Employment Cyclicality for Industry Sectors

Sector	1	2	3	4
Estimated coefficient $\hat{\gamma}_1$	-0.534^{***}	-1.056^{*}	-0.363	-0.464^{***}
N	3,097	17	311	1,125
Sector	5	6	7	8
Estimated coefficient $\hat{\gamma}_1$	-0.689^{***}	-0.926^{***}	-1.362^{***}	-0.597^{***}
N	9,902	5,422	845	3,016
Sector	9	10	11	12
Estimated coefficient $\hat{\gamma}_1$	-0.399^{***}	-0.476	-0.077	-0.607^{***}
N	7,612	183	2,921	4,973
Sector	13	14	15	16
Estimated coefficient $\hat{\gamma}_1$	-0.488^{***}	-0.336^{***}	-0.270^{***}	-0.342^{***}
N	3,929	16,093	12,172	10,090
Sector	17	18	19	20
Estimated coefficient $\hat{\gamma}_1$	-0.508^{***}	-0.447^{***}	0.158^{*}	-0.230^{***}
N	2,307	4,679	2,547	41,239
Sector	21	22	23	24
Estimated coefficient $\hat{\gamma}_1$	-0.410^{***}	-0.837^{***}	-0.364^{***}	-0.047
N	70,245	10,268	24,812	10,299
Sector	25	26	27	28
Estimated coefficient $\hat{\gamma}_1$	-0.378^{***}	0.255^{***}	-0.863^{***}	-0.914^{***}
N	45,102	12,998	5,704	21,247
Sector	29	30	31	all
Estimated coefficient $\hat{\gamma}_1$	-0.382^{***}	1.167^{**}	-1.904^{***}	-0.452^{***}
N	10,734	84	326	344,293

Notes:
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 18).

We also estimated sectoral regression for our alternative relative measures (see Section A.6) separately for each sector. Results are very robust: all estimated coefficients are negative and statistically significant (results available on request).

A.4 Comparison with Worker Level Regressions

This Appendix shows that our establishment-level dataset generates a similar result as the existing literature on wage cyclicalities for Germany. There are two key differences to the existing literature. First, the papers use worker-level data. Second, generally they use level-regressions instead of difference equations.[58] For comparability reasons, we estimate the following regression using the AWFP data:

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

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.7), is well in line with the results of Stüber (2017).[59] 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 all workers.[60]

Stüber (2017) coefficient for all workers is somewhat larger than the ones 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

[58]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.

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

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

Table A.7: 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.

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.

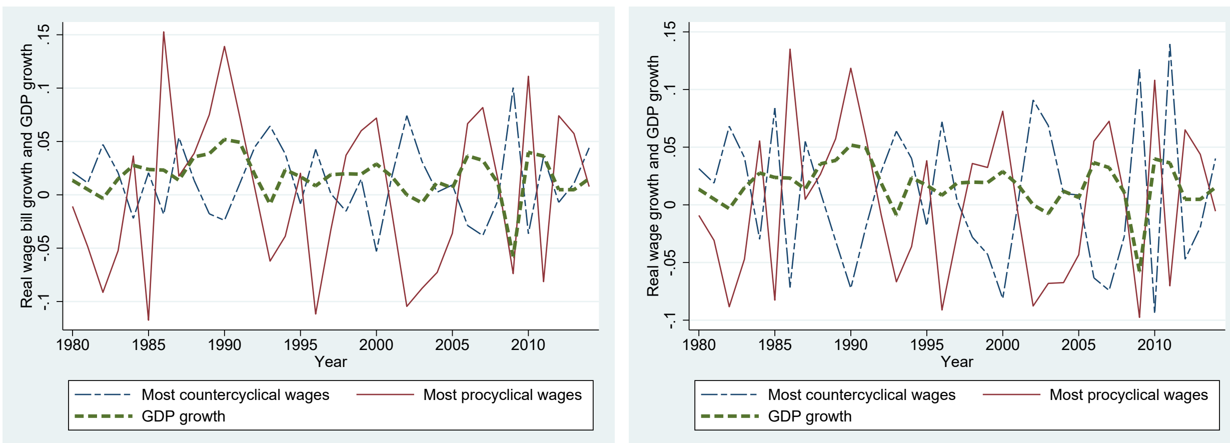
A.5 Worker Composition and Wages

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)[61] for the most procyclical and the most countercyclical establishments.

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.

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.

In Appendix A.7, we estimate the potential role of establishment-specific revenue cycles based on an alternative measure. The latter is introduced in the next section.

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

A.6 Alternative Measure

Our wage and employment cyclicality measures from the main part have the advantage that the establishment-specific wage and employment movement are connected to the sector-specific business cycle. As we estimate one time-invariant indicator for each firm, we require a long time horizon for our estimations. Thus, the key disadvantage of this measure is that it may be unstable over time. As discussed in Section 1, we expect wage cyclicalities to be relatively stable over time (i.e., a procyclical wage establishment remains procyclical), as firms inherit habits and institutions from the past (e.g., the unionization of the workforce or the establishment's culture).

Although we already tested for the robustness of our results, by using time windows, this section provides a further robustness check. We propose alternative measures to estimate the connection between (relative) wage growth and (relative) employment growth. These measures define the growth relative to all other establishments in a given year and sector.

$\triangle \ln w^r_{ijt}$ is defined as a relative wage growth measure:

$$\triangle \ln w^r_{ijt} = \triangle \ln w_{ijt} - \frac{\sum_{i=1}^{E} \triangle \ln w_{ijt}}{E_{jt}}, \tag{A.2}$$

where E_{jt} is the number of establishments in sector j in year t. $\triangle \ln w_{ijt}$ is the wage growth of establishment i in sector j in year t. Thus, $\triangle \ln w^r_{ijt}$ is the relative wage growth of establishment i compared to all other establishments in a given sector and year.[62] A positive (negative) number indicates a wage growth above (below) average.

The key advantage of this relative wage growth measure is its flexibility (compared to the measure in Section 4, which establishes a connection to a business cycle indicator). Assume that an establishment behaves differently in the first part and the second part of our sample period, e.g., procyclical in the first part and countercyclical in the second. In this case, the relative wage measure would show a positive relative wage growth in a boom in the first part

[62]We use the same sectoral definition as in the previous subsections, with 31 sectors.

of the sample and a negative relative wage measure in a boom in the second part.

We are interested in the effects of establishments' wage growth on the establishment-specific employment. Thus, we also need to define a relative employment growth measure (in analogy to our relative wage growth measure):

$$\triangle \ln n^r_{ijt} = \triangle \ln n_{ijt} - \frac{\sum_{i=1}^{E} \triangle \ln n_{ijt}}{E_{jt}}, \tag{A.3}$$

which denote establishment-specific employment growth ($\triangle \ln n^r_{ijt}$) relative to the mean in a given sector and year.

Given that we define our employment growth measure in the same flexible way as our wage growth measure, we are able to estimate period-by-period effects. To determine the connection between relative wage growth and relative employment growth, we estimate the following regression:[63]

$$\triangle \ln n^r_{ijt} = \alpha_o + \alpha_1 \triangle \ln w^r_{ijt} + \alpha_2^{'} \mathbf{C}_{it} + \mu_t + \mu_i + \varepsilon_{ijt}, \tag{A.4}$$

where μ_t are time fixed effects, μ_i are establishment fixed effects, and C_{it} is vector of control variables (same controls as in the baseline regression).

A.6.1 Baseline Results for the Alternative Measure

Table A.8 shows that our estimation delivers a negative and statistically significant coefficient. Intuitively, a wage growth above the median level in the sector is associated with an employment growth below the median level.

It is worthwhile mentioning that in case of completely stable wage cyclicalities over time (i.e., a procyclical wage establishment remains procyclical), the estimation results from Section 2.2 and this Section should deliver the same results.[64] Since the estimated coefficients

[63] Since we use the raw aggregated data, we drop — analogous to our baseline regression — extreme outliers. In all our regressions, tables, and figures, we drop the 1st and 99th percentile for the relative wage and the relative employment cyclicality measure to ensure that our results are not driven by extreme outliers.

[64] We can show this based on our theoretical simulations. Results are available on request.

are quantitatively very close to one another ($\hat{\gamma}_1 = -0.45, \hat{\alpha}_1 = -0.50$), it confirms the robustness of our baseline results.

As in Section 4.3.3, we also run the regressions for the alternative measure based on incumbents' wage growth. As column 3 of Table A.8 shows, the result remains very close to the baseline specification.

Table A.8: Effect of Relative Wage Growth on Relative Employment Growth

Estimated Coefficient	$\hat{\alpha}_1$	$\hat{\alpha}_1^{\text{incumbents}}$
Coefficient	-0.503^{***}	-0.524^{***}
R^2	0.19	0.16
Observations	7,015,517	5,586,215

Note: *** indicates statistical significance at the 1 percent level. To estimate $\hat{\alpha}_1^{n,\text{incumbents}}$, we consider the wage of incumbent workers instead the wage of all workers in Equation A.2. We drop, analogous to our baseline regression (see Footnote 18), extreme outliers. We drop the 1st and 99th percentile for the relative wage and the relative employment cyclicality measure.

A.7 Establishment-Specific Revenue Cycles

Using the alternative relative measure from the previous section, we discuss and estimate whether our empirical results could be driven by establishment-specific revenue cycles. Imagine two establishments with the same wage cyclicality. Imagine that establishment A's revenues and thereby wages go up in a boom, while establishment B's revenues and thereby wages go down in a boom. The way we measure wage cyclicality, we would identify establishment A as procyclical (due to the positive comovement of the wage with the business cycle) and establishment B as countercyclical. Note, however, that in such an environment establishment A (with the supposedly procyclical wage) would increase the employment stock in the boom, while establishment B (with the supposedly countercyclical wage) would reduce the employment stock in the boom. This is the opposite of what we find in our regressions: procyclical wage establishments increase employment by less in booms than countercyclical wage establishments. Thus, establishment-specific revenue cycles are unlikely to be the key driver of our results.

In the AWFP, we do not have any information on revenues at the establishment level. However, as shown in Section 4.2.2, we can link the AWFP to the IAB Establishment Panel. This allows us to calculate an establishment-specific value added measure.[65] As the IAB Establishment Panel is only available from the beginning of the 1990s, we are unable to analyze the interaction value-added movements and our baseline wage cyclicality measures (which are based on long time series for each establishment, starting in 1979). However, we can use the flexible period-by-period measures from Section A.6.

In a first step, we re-estimate equation (A.4) for the connection between the AWFP and the IAB Establishment Panel for the years 1994–2014 to see whether results differ from the baseline specification. The estimated coefficient, see column 2 of Table A.9, is very similar to the coefficient obtained using the AWFP baseline sample ($\hat{\alpha}_1 = -0.50$).

In a second step, we add relative firm-specific value added as an additional control variable to the regression equation (A.4) to see whether our baseline regressions suffer from an omitted variable bias. The relative value added is calculated analogously to the other relative measures, namely:

$$\triangle \ln va^r_{ijt} = \triangle \ln va_{ijt} - \frac{\sum_{i=1}^{E} \triangle \ln va_{ijt}}{E_{jt}}. \tag{A.5}$$

The estimated coefficient for wages, see column 3 of Table A.9, is barely affected by adding value added to the regression. Thus, our previous regressions are not seriously biased by an omitted variable. The estimated coefficient for value added turns out to be relatively small.

To illustrate the connection between value added and wages further, we estimate the comovement between idiosyncratic value added and wages. We estimate the comovement between relative wages and relative value added, adding the same controls as in the previous specifications:

[65] We approximate value added as: business volume * (1 - share of intermediate inputs).

$$\triangle \ln w^r_{ijt} = \alpha_o + \alpha^{va}_1 \triangle \ln va^r_{ijt} + \alpha_2^{'} \mathbf{C}_{it} + \mu_t + \mu_i + \varepsilon_{ijt}. \tag{A.6}$$

Column 4 of Table A.9 shows that there is a positive comovement between wages and value added. However, it is economically small. A 1% larger value added growth at the establishment level is associated with 0.004% larger wage growth. Thus, establishment-specific idiosyncratic value added movements appear to be quantitatively very little connected to wage movements at the establishment level. This is another piece of evidence that our key results are very unlikely to be driven by establishment-specific revenue fluctuations that are different from the sector-specific cycle.

Table A.9: Effect of Relative Wage Growth and Value Added Growth on Relative Employment Growth, and the Effect of Relative Value Added Growth on Relative Wage Growth

Independent variable	$\triangle \ln n^r_{ijt}$	$\triangle \ln n^r_{ijt}$	$\triangle \ln w^r_{ijt}$
Estimated coefficient $\hat{\alpha}_1$	-0.383^{***}	-0.391^{***}	
Estimated coefficient $\hat{\alpha}^{va}_1$		0.015^{***}	0.004^{***}
Controls	Changes in education shares, gender share, mean age, mean tenure, mean tenure^2. Establishment fix effects and year dummies		
R^2	0.27	0.27	0.15
Observations	20,822	20,822	20,822

Note: *** indicates statistical significance at the 1 percent level. We drop, analogous to our baseline regression (see Footnote 18), extreme outliers. We drop the 1st and 99th percentile for the relative wage and the relative employment cyclicality measure.

Overall, our robustness checks show that the estimated effects of wages on employment is unaffected by including value added into the regressions. In addition, the quantitative connection between establishment-specific value added variation and establishment-specific wage variation is small. All of this gives support to the conclusion that our estimated connection between wage cyclicalities and employment cyclicalities is not driven by establishment-specific value-added cycles.

A.8 Model Derivation

A.8.1 Establishment Maximization

Establishments maximize profits

$$E_0 \left\{ \sum_{t=0}^{\infty} \delta^t \left[a_t n_{it} - w_{it}^I (1-\phi) n_{i,t-1} - c_{it} s_t \eta(\tilde{\varepsilon}_{it}) \left(\frac{\bar{w}^E(\tilde{\varepsilon}_{it})}{\eta(\tilde{\varepsilon}_{it})} + \frac{H(\tilde{\varepsilon}_{it})}{\eta(\tilde{\varepsilon}_{it})} + h \right) \right] \right\}, \tag{A.7}$$

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

$$n_{it} = (1-\phi) n_{it-1} + c_{it} s_t \eta(\tilde{\varepsilon}_{it}). \tag{A.8}$$

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}:

$$n_{it} = (1-\phi) n_{it-1} + c_{it} s_t \eta(\tilde{\varepsilon}_{it}), \tag{A.9}$$

$$-c_{it} s_t \left(\frac{\partial \bar{w}^E(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} + \frac{\partial H(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} + \frac{\partial \eta(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} h \right) + \lambda_t c_{it} s_t \frac{\partial \eta(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} = 0, \tag{A.10}$$

$$a_t - \lambda_t + (1-\phi) \delta E_t \left(\lambda_{t+1} - w_{it+1}^I \right) = 0. \tag{A.11}$$

Isolating the Lagrange multiplier in Equation (A.10) yields:

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

Keep in mind the three definitions:

$$\eta(\tilde{\varepsilon}_{it}) = \int_{-\infty}^{\tilde{\varepsilon}_{it}} f(\varepsilon) d\varepsilon, \tag{A.13}$$

$$\bar{w}^E(\tilde{\varepsilon}_{it}) = \int_{-\infty}^{\tilde{\varepsilon}_{it}} w_t^E(\varepsilon) f(\varepsilon) d\varepsilon, \tag{A.14}$$

$$H(\tilde{\varepsilon}_{it}) = \int_{-\infty}^{\tilde{\varepsilon}_{it}} \varepsilon f(\varepsilon) d\varepsilon. \tag{A.15}$$

This allows us to simplify Equation (A.12), using the Fundamental Theorem of Calculus:

$$\lambda_t = \frac{w^E(\tilde{\varepsilon}_{it}) f(\tilde{\varepsilon}_{it}) + \tilde{\varepsilon}_{it} f(\tilde{\varepsilon}_{it}) + f(\tilde{\varepsilon}_{it}) h}{f(\tilde{\varepsilon}_{it})} \tag{A.16}$$

$$= w^E(\tilde{\varepsilon}_{it}) + \tilde{\varepsilon}_{it} + h. \tag{A.17}$$

When we substitute this Lagrange multiplier into Equation (A.11), we obtain the selection condition:

$$\tilde{\varepsilon}_{it} = a_t - w^E(\tilde{\varepsilon}_{it}) - h + (1-\phi)\delta E_t \left(w^E(\tilde{\varepsilon}_{it+1}) + \tilde{\varepsilon}_{it+1} + h - w^I_{it+1} \right) \tag{A.18}$$

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

$$J_{it} = a_t - w^I_{it} + E_t \delta \left(1-\phi\right) J_{it+1}, \tag{A.19}$$

yields the selection condition, as shown in Equation (9) in the main part:

$$\tilde{\varepsilon}_{it} = a_t - w^E(\tilde{\varepsilon}_{it}) - h + E_t \delta \left(1-\phi\right) J_{it+1}. \tag{A.20}$$

A.8.2 Derivation of the Nash Wage

The Nash product is

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

with

$$W_t - U_t = w_t - b + E_t\delta\left(1 - \phi - \eta_{t+1}\right)\left(W_{t+1} - U_{t+1}\right), \tag{A.22}$$

and

$$J_t = a_t - w_t + E_t\delta\left(1 - \phi\right)J_{t+1}. \tag{A.23}$$

Maximization of the Nash product with respect to the wage yields

$$\frac{\partial \Lambda_t}{\partial w_t} = \nu J_t \frac{\partial W_t}{\partial w_t} + \left(1 - \nu\right)\left(W_t - U_t\right)\frac{\partial J_t}{\partial w_t} = 0, \tag{A.24}$$

$$\nu J_t = \left(1 - \nu\right)\left(W_t - U_t\right). \tag{A.25}$$

After substitution:

$$\nu\left(a_t - w_t + E_t\delta\left(1 - \phi\right)J_{t+1}\right) = \left(1 - \nu\right)\left[w_t - b + E_t\delta\left(1 - \phi - \eta_{t+1}\right)\left(W_{t+1} - U_{t+1}\right)\right]. \tag{A.26}$$

Using Equation (A.25):

$$\nu\left(a_t - w_t + E_t\delta\left(1 - \phi\right)J_{t+1}\right) = \left(1 - \nu\right)\left[w_t - b + E_t\delta\left(1 - \phi - \eta_{t+1}\right)\frac{\nu}{\left(1 - \nu\right)}J_{t+1}\right], \tag{A.27}$$

$$w_t = \nu\left(a_t + \delta\eta_{t+1}J_{t+1}\right) + \left(1 - \nu\right)b. \tag{A.28}$$

A.9 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.

Would it be possible in a standard search and matching 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, such as for example in Barnichon and Figura (2015). But can a standard search and matching 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.[66] Thus, the standard random search and matching model could not yield the outcome we find in the data.

In order to reconcile the search and matching 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

[66]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.

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.9.1 Model Derivation

Establishments maximize the following intertemporal profit condition

$$E_0 \sum_{t=0}^{\infty} \left(a_t n_{it}^{\alpha} - w_{it} n_{it} - \chi v_{it}\right), \tag{A.29}$$

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:

$$n_{it} = (1-\phi)\, n_{it-1} + v_{it} q\left(\theta_t\right). \tag{A.30}$$

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

$$\left(\alpha a_t n_{it}^{\alpha-1} - w_{it}\right) - \lambda_{it} + \beta E_t \lambda_{it+1} \left(1-\phi\right) = 0, \tag{A.31}$$

$$-\chi + \lambda_{it} q\left(\theta_t\right) = 0, \tag{A.32}$$

where λ is the Lagrange multiplier.

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

$$\frac{\chi}{q\left(\theta_t\right)} = \left(\alpha a_t n_{it}^{\alpha-1} - w_{it}\right) + \beta E_t \left(1-\phi\right) \frac{\chi}{q\left(\theta_{t+1}\right).} \tag{A.33}$$

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:

$$w_{it} = \kappa_i \left(a_t w^{norm}\right) + \left(1 - \kappa_i\right) w^{norm}, \tag{A.34}$$

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

$$v_t = \sum_{i=1}^{E} v_{it}, \tag{A.35}$$

$$n_t = \sum_{i=1}^{E} n_{it}, \tag{A.36}$$

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 $m_t = \varkappa u_t^{1-\psi} v_t^{\psi}$. Thus: $p\left(\theta_t\right) = \varkappa \theta_t^{\psi}$ and $q\left(\theta_t\right) = \varkappa \theta_t^{1-\psi}$, with $\theta_t^{1-\psi} = v_t / u_t$.

Unemployment workers and employed workers have to add up to 1:

$$n_t = 1 - u_t. \tag{A.37}$$

A.9.2 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 $\psi = 0.5$. 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 ($\nu = 0.95$). The matching efficiency is normalized to 1 ($\varkappa = 1$) and the vacancy posting costs are chosen to fix the steady state unemployment rate of 0.08 ($\chi = 0.54$).

Independently, how we set κ_i, we obtain a $\hat{\gamma}_1 \simeq -3.3$ in our simulated model. In different words, the connection between wage cyclicalities and hires rate cyclicalities is a lot larger than in the data (where $\hat{\gamma}_1 \simeq -0.45$). 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.9.3 Some Analytics

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

$$\frac{\chi}{q(\theta)}(1-\beta(1-\phi)) = \alpha a n_i^{\alpha-1} - w_i, \tag{A.38}$$

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:

$$\frac{\chi}{q(\theta)}(1-\beta(1-\phi)) = 0.67 n_i^{-0.33} - w_i. \tag{A.39}$$

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, a 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.39). 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.

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