Wage Cyclicalities and Labor Market Dynamics at the Establishment Level: Theory and Evidence

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Abstract

Using the new AWFP dataset covering all German establishments, we document a substantial cross-sectional heterogeneity of establishments' mean real wages over the business cycle. While the median establishments' real wages are procyclical, there is a large fraction of establishments with countercyclical real wages. We show that establishments with more procyclical wages have a less procyclical hires rate and employment behavior. We propose a labor market flow model, calibrate it to the heterogeneity of wage cyclicalities and obtain similar patterns for labor market dynamics as in the data. When we set the wage cyclicalities of all establishments equal to the most procyclical establishments, labor market volatilities drop by more than 60 percent. Our counterfactual exercise thus quantifies the importance of wage dynamics for labor market amplification.

JEL classification: *E32, E24, J64.*

Keywords: Wage Cyclicality, Labor Market Flow Model, Labor Market Dynamics, Establishments, Administrative Data, Job and Worker Flows.

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1 Introduction

The question whether real wages are procyclical or countercyclical over the business cycle is of key importance for macroeconomics. The answer to this question has been used to discriminate between different macroeconomic frameworks (e.g. Beaudry and DiNardo 1991, Bils 1985, and Solon et al. 1994). A theory in the spirit of Keynes (1936) implies countercyclical real wages. By contrast, classical theories (e.g. real business cycle theory) imply procyclical wages.[1] Based on aggregate data, macroeconomists argued for a long time that real wages show weak cyclicality (e.g. Blanchard and Fischer 1989 and Mankiw 1989). Solon et al. (1994) showed that these aggregate results are due to a composition bias, while real wages are actually procyclical over the business cycle based on microeconomic data.

In the more recent literature, the cyclicality of real wages plays a key role in solving the Shimer (2005) puzzle in search and matching models. When wages become less procyclical over the business cycle (e.g. Hall 2005, Hall and Milgrom 2008), job creation and (un)employment become more volatile. This brings the search and matching model closer in line with the time series properties of labor market data. There is a growing empirical literature on the question how cyclical wages are (e.g. Carneiro et al. 2012, Martins et al. 2012, Haefke et al. 2013, Gertler et al. 2016, Stüber 2017). However, there is not a single paper that analyzes whether establishment-specific differences in real wage cyclicalities actually affect hiring and employment behavior over the business cycle. If wage rigidity is a solution for the Shimer (2005) puzzle, it is not only important to find some degree of wage rigidity in the data. It is also important that different wage cyclicalities actually have an effect on the hiring and employment behavior of establishments in the data.

We consider this a substantial gap in the literature. Our paper fills this gap by using the newly created Administrative Wage and Labor Market Flow Panel (AWFP) dataset, which aggregates German administrative worker data to the establishment level (see Stüber and Seth 2017a). The dataset comprises the entire universe of German establishment for the years 1975–2014. The AWFP contains, inter alia, detailed wage[2] information, employment stocks, job flows, and worker flows for more than 3 million establishments. This allows us to analyze the quantitative effects of real wage cyclicality on job and workers flows.

Our paper documents a substantial heterogeneity of real wage cyclicalities across establishments. We find that the majority of establishments indeed behaves in a procyclical manner over the business cycle and thereby drive the average procyclicality. However, more

[1] For a modern discussion of this issue see Galí (2013) who emphasizes that (in contrast to traditional Keynesian models) the real wage is not necessarily countercyclical in a New Keynesian framework (depending on the degree of price stickiness).

[2] Wages/salaries including all bonuses.

than 40 percent of establishments behave in a countercyclical manner, some of them very strongly. Our paper shows that the average wage cyclicality over the business cycle masks the fact that establishments have very different wage dynamics.

Figure 1 illustrates this key result by showing the mean real wage growth for establishments with the most procyclical and for establishments with the most countercyclical wages.[3] 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 of magnitude. By contrast, establishments with the most countercyclical wages faced a real wage increase.

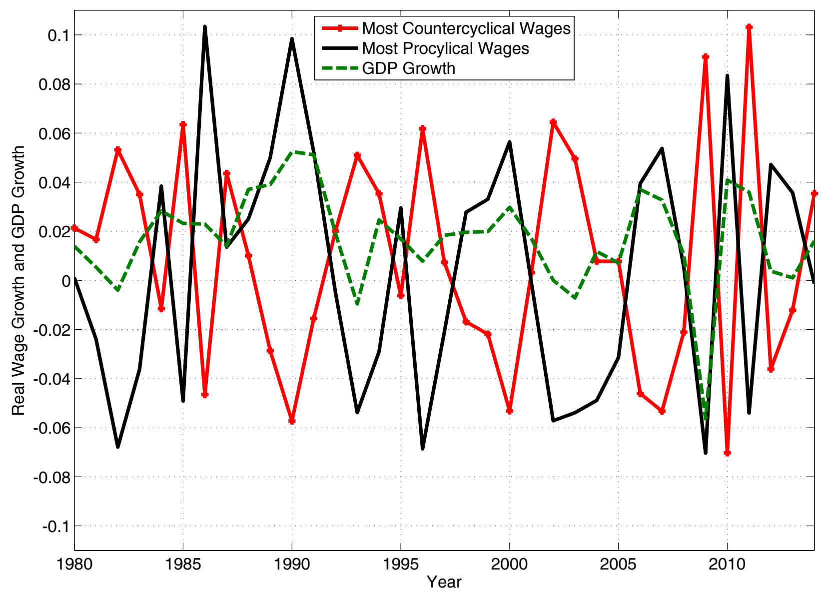

Figure 1: The figure shows the real GDP growth, the mean real wage growth for the establishments with the most procyclical wages and for the establishments with the most countercyclical wages. Real wages are defined as wages/salaries per full-time workers (including all bonuses).

Furthermore, our paper documents and estimates the effects of different real wage cyclicalities on job and worker flows. We find that wage dynamics matter for labor market flow dynamics. More procyclical wage establishments have less procyclical employment dynamics. Figure 2 illustrates this result. Consider again the Great Recession in 2009: the establishments with the most procyclical wages, i.e. those that cut real wages, increased their average

[3] We define establishments with the most procyclical (countercyclical) wage as 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 3.1). In contrast to our baseline regressions, Figures 1 and 2 are based on the national full-time workers as business cycle indicator for determining α_{1i}. This allows us to show easily interpretable graphical results on the aggregate level.

employment (job flows). By contrast, establishments with the most countercyclical wages faced a strong decline in average employment. This illustrates that real wage cyclicalities have a strong effect on labor market dynamics. Our paper takes a closer look at these effects at the establishment level.

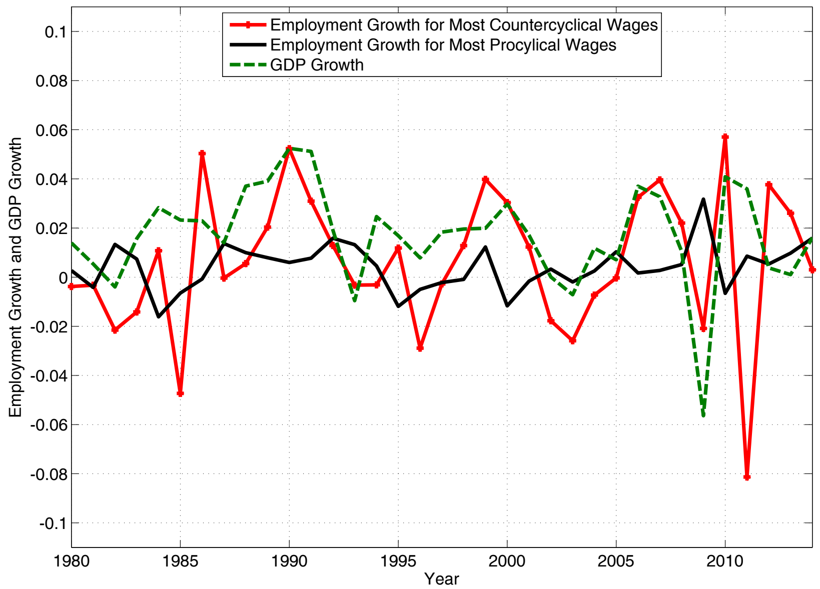

Figure 2: The figure shows the real GDP growth, the mean employment growth (job flows) for the establishments with the most procyclical wages and for the establishments with the most countercyclical wages.

While Figures 1 and 2 show purely descriptive results, we have taken various steps to prevent that our empirical results are driven by composition effects. In our regressions, we control for establishment fixed effects, mean age, tenure, and many other observables. Very importantly, our results are not driven by heterogeneities between sectors. First, in our baseline specifications, we use a sector-specific business cycle indicator. Second, our results remain robust when we run regressions for different sectors separately. In addition, our results are robust to excluding small establishments, short-lived establishments, or the Great Recession (when the intensive margin of labor adjustment was more important). Furthermore, we run our main regressions on the connection between wage cyclicality and employment cyclicality for ongoing jobs (instead of all jobs) as a further robustness check regarding compositional concerns. The results are very similar to our baseline results. In addition, all our results are based on wages, stocks, and flows for full-time workers to capture adjustments of the extensive margin. We show in a quantitative exercise why the intensive margin of labor adjustment cannot be the driving source for our results. We also discuss why establishment-specific revenue shocks cannot be the key driver of our results.

Germany offers an unique environment for analyzing the effects of heterogeneous wage cyclicalities for establishments' hiring and employment dynamics because wage formation is very diverse. Establishments may choose to be part of a collective bargaining agreement at the sectoral level, where wages are bargained between trade unions and employers' associations. It is important to know that such agreements allow establishments to pay higher wages than fixed in the agreement. Alternatively, they may choose to bargain with a union at the establishment level. As a third option, wages may be determined without the involvement of unions as individual contracts (see Section 3 in Hirsch et al. 2014, for institutional details and descriptives). In practice, the wage formation mechanism is affected by establishment characteristics (e.g. the size of the establishment), institutional details (e.g. the existence of a works council, although it does not have an official role in wage formation, see e.g. Addison et al. 2010), explicit or implicit actions by employees (such as the unionization of the workforce) and the reaction by the establishment.

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 our dataset to the IAB-Establishment Panel survey (see Ellguth et al. 2014). We find a highly nonlinear pattern between wage cyclicality quintiles and bargaining regimes. The share of establishments that is part of the collective bargaining regime is much smaller for establishments with strongly procyclical and strongly countercyclical wages than for the average establishment. By contrast, the fraction of establishments with collective bargaining agreement is above average for acyclical and moderately procyclical establishment. Although the collective bargaining agreement only constitutes minimum wage payments (i.e. more generous pay is possible), it appears reasonable that real wage fluctuations are more moderate for establishments within the collective bargaining agreement.

There is a small emerging literature that documents the effects of downward nominal wage rigidity on labor market flows at the establishment level (Kurmann and McEntarfer 2017 for the United States and Ehrlich and Montes 2017 for Germany). These two papers use linked employer-employee data. Therefore, the cross-sectional and time dimension is much smaller than in our paper. By contrast, we use the entire universe of establishments for more than three decades. This allows us to analyze the comovement of wages with sector-specific business cycle indicators. Thus, our work is highly complementary to theirs.[4]

In order to interpret the effects of different wage cyclicalities on labor market flow dy-

[4]Elsby (2009) shows that there is a connection between downward nominal wage rigidity and wage cyclicality. He shows that firms compress both wage increases and wage cuts in the presence of downward nominal wage rigidity. While this is a very interesting channel, we believe that there are potentially many other channels that drive the cyclicality of real wages over the business cycle (e.g. labor market institutions or price setting behavior).

namics and to be able to perform counterfactual exercises, 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). In line with the data, for reasonable aggregate shock sizes, all establishments hire in every time period in our model, despite having different wage cyclicalities. In addition, 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] The model allows us to make qualitative and quantitative predictions on the expected effects of different wage cyclicalities on job and worker flows. It is well known that a lower procyclicality of real wages leads to more amplification in standard search and matching models. One important insight from our model with heterogeneous wage cyclicalities is that volatility-based measures are not suitable for measuring the effects of these wage heterogeneities on hiring and employment dynamics. When we compare procyclical real wage establishments to countercyclical wage establishments, the latter does not necessarily show a larger standard deviation of employment over the business cycle than the former. Our model shows that procyclical wage establishments may actually show a countercyclical employment behavior, i.e. their employment may move into the opposite direction compared to the one for countercyclical wage establishments and may show a similar absolute movement. Against this background, our wage cyclicality measures in the empirical estimations take into account the direction of the wage and employment movements.

As mentioned earlier, our paper also contributes to the literature that discusses the role of wage rigidities in search and matching models (e.g. Hall 2005, Hall and Milgrom 2008) for solving the Shimer (2005) puzzle. If wage rigidity is a solution for the Shimer (2005) puzzle, it is not only important to find some degree of wage rigidity in the data. It is also important that different wage cyclicalities actually have an effect on the hiring behavior of establishments in the data. In principal, rigid real wages could simply represent an insurance of risk neutral establishments for risk averse workers. Such an insurance would prevent wage cuts during recessions and dampen wage increases in booms. If worker-establishment pairs find a commitment mechanism such that workers have to pay for this insurance in booms, the present value of a match and thereby the hiring behavior may not be affected much by the wage cyclicality over the business cycle. A less volatile income stream could simply represent insurance payments from risk neutral (unconstrained) establishments to risk averse

[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.

(or credit constrained) workers, without any (or not much of an) effect on hiring. However, our empirical analysis shows that different wage cyclicalities affect job and worker flows in a quantitatively similar way as in our model where insurance considerations play no role.

The quantitative similarities between simulation and empirical results allow us to perform counterfactual exercises. When we set the wage cyclicality of all establishments equal to the wage cyclicality of the most procyclical establishments, the standard deviations of the job-finding rate and unemployment drop by around two thirds to three quarters of their initial level. Thus, we can show that a large fraction of the amplification on the labor market is due to wage cyclicality, in particular, due to establishments with ayclical and countercyclical real wages over the business cycle.

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. We consider our paper as a starting point that establishes stylized 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 or Smets and Wouters 2003).

The rest of the paper proceeds as follows. Section 2 presents the AWFP dataset and documents the heterogeneous real wage cyclicalities of establishments over the business cycle. Section 3 estimates the connection between wage cyclicalities and labor market flow dynamics. Section 4 derives a model of heterogeneous wage cyclicalities across establishments. We calibrate the model, show quantitative results and perform counterfactual exercises. Section 5 concludes.

2 Heterogeneous Wage Cyclicalities: Empirical Evidence

This section proceeds in two steps. First, we provide a brief description of the AWFP data. Second, we estimate how strongly wages at the establishment level comove with sector-specific employment and we show that there is substantial heterogeneity across establishments.

2.1 Dataset and Flow Definition

The Administrative Wage and Labor Market Flow Panel (AWFP) 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. We are able to identify the establishment at which workers are employed at any given point in time and we know when they move to a new establishment or into non-employment.

The AWFP aggregates all worker level information to the establishment level (in terms of wages, stocks, and worker and job flows). As the dataset contains the universe of establishments, we do not have to work with sample weights (as usual in establishment surveys). In addition, we have long time series for wages and labor market flows for each establishment. This is a major advantage compared to existing datasets.

One disadvantage of the AWFP is that we do not have information on the exact number of hours worked.[6] To have a homogenous reference group, we therefore restrict ourselves to full-time workers.[7] Wages are defined as the mean wages/salary subject to social security (including bonus pay) of all employed full-time workers in a particular establishment. Workers' wages above the contribution assessment ceiling are imputed following Card et al. (2015) before aggregating the data to the establishment level.[8] Before aggregating the data to the establishment level, several corrections and imputations were conducted at the micro data. For more detailed information on the AWFP see Appendix A.1 or Stüber and Seth (2017a). Following Davis et al. (2006), we define the hires rate (hr_{it}) as new full-time hires in an establishment i divided by the average number of full-time workers in year t and $t-1$.[9]

We use the AWFP at the annual frequency 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. Therefore, we use the data on the annual level.

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

[7] More precisely we focus on "regular workers" according to the definition used in the AWFP (see Appendix A.1).

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

[9] Stocks and flows are calculated using the "end-of-period" definition (see Appendix A.1). Since we use the raw aggregated data we decided to drop a few extreme outliers for all analysis. We calculate for each establishment i in industry sector j in each year t the growth rate of real wage ($\Delta \ln w_{ijt}$) and the growth rate of full-time workers ($\Delta \ln n_{it}$), and drop establishment-year observations below the 1^{st} and above the 99^{th} percentile of the two measures.

[10] We chose these restrictions for data quality reasons.

2.2 Wage Cyclicalities

In this section we analyze how mean wages of establishments comove with aggregate business cycle indicators. Do all establishments behave in a procyclical fashion or does a substantial fraction have countercyclical wages? How large is the heterogeneity across establishments? To answer these questions, we first estimate the average wage cyclicality over the business cycle. Second, we estimate establishment-specific wage cyclicalities to show the heterogeneity across establishments. Afterwards, we link the AWFP with the IAB-Establishment Panel to identify how our wage cyclicality measure correlates with bargaining regimes and the existence of works councils.

2.2.1 Heterogeneities across Establishments

There is a growing empirical literature on the question how wages move over the business cycle (e.g. Carneiro et al. 2012, Martins et al. 2012, Haefke et al. 2013, Gertler et al. 2016, Stüber 2017). Typically, worker-specific wages are regressed on aggregate unemployment (changes). We deviate from this practice in an important way. We use the number of full-time workers, N_t^j, as our aggregate state. This number can be calculated for different sub-aggregation groups (such as sectors j) from our own 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. We are interested in the heterogeneity over the business cycle and thereby in growth rates rather than levels. In addition, by first differencing, we prevent spurious regressions with non-stationary variables.

Our regression equation for quantifying the average cyclicality of real 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 real wage of establishment i in industry j in year t and $\Delta \ln N_t^j$ is the growth rate of full-time workers in the industry sector j. μ_i is a establishment-fixed effect, and $\mathbf{C}_{it}$ is a vector of control variables including education shares and gender shares at the establishment level as well as the average age, tenure, and tenure squared of the workers within the establishment. We also include federal state and industry sector dummies. In addition, we include a linear and quadratic time trend. When we exclude the time trend from our regressions, both the heterogeneity of wage cyclicalities and their impact on establishment-specific labor market flows change very little.

We choose the aggregate employment growth rate at a sectoral level with 31 different categories (see Appendix A.3 for details) as our business cycle indicator in our baseline specification. By using the sectoral 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 1 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 0.12% 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 B.1 shows that regressions in levels — using the aggregated unemployment rate as the business cycle indicator — deliver results that are comparable with regressions on the worker level. 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 cyclicalities and labor market dynamics, we remain at the establishment level, where hiring and employment are determined.

Table 1: Average Wage Cyclicality

Dependent Variable:	$\Delta \ln w_{ijt}$
Estimated coefficient: α_1	0.124^{***}
Controls	Education shares, gender share, mean age, mean tenure, mean tenure^2, establishment fix effects, industry dummies, federal state dummies, year, year^2
R^2 | within R^2	0.09 | 0.01
Observations	39,049,783

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

As a next step, we quantify the heterogeneous reaction of establishments with respect to the sectoral business cycle indicator. We estimate the following high-dimensional fixed effects regression (see Correia 2014):

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

Equation (2) generates more than three million coefficients α_{1i}, which corresponds to the number of establishments in our analysis. So each establishment i has an estimated $\hat{\alpha}_{1i}$ that is fixed for the entire life span. The α_{1i} show how strongly the wage growth of establishment i in industry j reacts to changes of the business cycle indicator N_t^j — they tell us how procyclical or countercyclical a certain establishment is.[11]

[11] Goodness of fit measures of the regression: observations: 39,049,783; R^2: 0.20; within R^2: 0.01.

The right column of Table 2 contains percentiles for all estimated $\hat{\alpha}_{1i}$ at the sectoral level. It shows that wage cyclicalities are very heterogeneous across establishments. The dispersion across establishments appears surprisingly large given that we already control for time-invariant heterogeneity at the establishment level, establishment characteristics and aggregate time trends.

Table 2: Cyclicality at Different Disaggregation Levels

$\hat{\alpha}_{1i}$	National level	10 Sectors	31 Sectors
Cyclicality at 30^{th} percentile	-0.75	-0.63	-0.56
Cyclicality at 40^{th} percentile	-0.21	-0.17	-0.15
Cyclicality at 50^{th} percentile	0.20	0.15	0.13
Cyclicality at 60^{th} percentile	0.60	0.48	0.42
Cyclicality at 70^{th} percentile	1.14	0.94	0.84
Observations	3,388,708	3,388,708	3,388,708

Although the median establishment has a procyclical comovement of wages with aggregate employment (0.13), establishments at the 40^{th} percentile have a countercyclical movement with aggregate full-time employment in the respective sector (-0.15). Establishments at the 30^{th} percentile are strongly countercyclical (-0.56). By contrast, establishments at the 60^{th} percentile are strongly procyclical ($+0.42$). Our estimations show that although the median establishment is procyclical, more than 40 percent of all establishment have a countercyclical real wage movement. Our paper is the first to document this fact.

It may appear surprising that such a large fraction of establishments show a countercyclical real wage movement over the business cycle. Two comments are in order: First, traditionally countercyclical real wages were considered as a typical feature of Keynesian models (e.g. Beaudry and DiNardo 1991, Bils 1985, and Solon et al. 1994). Second, keep in mind that the wage payments in the AWFP also contain bonus payments[12] and payments that are made above the minimum required from collective bargaining agreements. These features may provide enough 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.

Table 2 also shows the estimated $\hat{\alpha}_{1i}$ at different percentiles for Equation (2) where more aggregated business cycle measures are used (national or 10 industry sectors). The dispersion of wage cyclicalities increases somewhat with higher aggregation levels. However, there is a

[12]According to the German Statistical Office, in 2012 bonus payments were 9% of gross earnings for firms with more than 10 employees.

substantial degree of heterogeneity independently of the aggregation level. Thus, our results on heterogenous wage cyclicalities are mainly driven by heterogeneities of establishments within sectors.

Nearly 55% 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.[13] At the industry level, using the 31 industry sectors, the dispersion of the share of PWS is somewhat larger. Between 45% and 65% of establishments in a given sector have PWS. However, the large dispersion is mainly driven by some outliers.[14]

2.2.2 Bargaining Regimes and Works Councils

As the AWFP contains no information on the degree of unionization, bargaining regimes or presence of works councils, we are unable to provide a definitive answer for the underlying sources of the heterogeneity of wage cyclicalities. Instead, we are the first to document these heterogeneities and their implications.

However, given that we can link the AWFP to the IAB Establishment Panel (see Ellguth et al. 2014), we can provide some first anecdotal evidence (at the cost of losing far at least 99% of our observations)[15]. Table 3 shows the share of establishments within different bargaining regimes for five quintiles of wage cyclicalities.[16] Note that we sort the quintiles from the most countercyclical group (quintile 1) to the most procyclical group (quintile 5).

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) compared to the other quintiles are part of the collective bargaining agreement. In addition, a larger share of these establishments has a works council (see Table 3).[17] It appears completely reasonable to us that both collective bargaining and works councils are associated with more moderate real wage movements over the business cycle. Collective bargaining agreements only constitute minimum wage payments (i.e. higher wage increases are possible). However,

[13]Between 54% and 56% of establishments in a given state have PWS

[14]The lower outliers are sector 10 (manufacturing of coke, refined petroleum products and nuclear fuels) with 45%, sector 19 (electricity, gas and water supply) with 50% and sector 30 (private households with employed persons) with 51% PWS. The upper outliers are sector 12 (manufacturing of rubber and plastic products) with 62%, sector 26 (public administration and defense, compulsory social security) with 63%, and sector 15 (manufacturing of machinery and equipment not elsewhere classified) with 65% PWS.

[15]Information on the wage bargaining regime is available for 33,564 establishments and information on works council for 24,921 establishments.

[16]We determine the wage cyclicality quintile with the full AWFP sample and use the survey answers (if available). 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 3 are obtained by using the mode answer of an establishment.

[17]Works councils are the elected worker representation at the establishment level. While they do not have a formal role in terms of wage bargaining, they co-determine certain important decisions.

Table 3: Wage Bargaining Regime and Works Council

	Quintile of Wage Cyclicalities				
Wage Bargaining Regime (in %)	1	2	3	4	5
Collective Bargaining	35.8	48.7	61.6	55.2	36.0
Firm Level Bargaining	4.1	6.2	6.7	5.1	4.2
Other	60.1	45.0	31.8	39.7	59.8
Works Council (in %)	1	2	3	4	5
Yes	14.5	31.3	51.3	40.8	15.5

Note: We determine the wage cyclicality quintile with the full AWFP sample and use the (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.

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.[18] Although works councils do not have a formal role in wage negotiations, their existence is known to be correlated with wage outcomes. Thus, it is in line with our expectations that a higher share of works councils is associated with more moderate real wage cyclicalities.[19]

2.2.3 Hiring Behavior

Interestingly, despite the strong heterogeneity in real wage growth across establishments over the business cycle, almost all establishments in the AWFP above a certain size hire at any point in time. For establishments with more than 50 employees, at least 99 percent hire in any given year. For establishments with more than 10 employees, the number varies in between 90 and 96 percent. Thus, the data shows a coexistence between very heterogeneous wage cyclicalities within sectors and hiring at any point in time. To our knowledge, this stylized fact has also been unknown so far. Our theoretical model in Section 4 is able to replicate both facts.

[18]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.

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

3 Wage Cyclicalities and Labor Market Dynamics: Evidence

This section analyzes how different wage cyclicalities at the establishment level affect the flow and stock cyclicalities. First, we estimate how much establishment-specific employment and the hires rate comove with the sectoral business cycle. Based on these measures, we estimate the comovement between the cyclicality of wages and the cyclicality of the hires rate and employment at the establishment level. Second, to check for robustness of our results, we propose a "relative measure". This measure is more flexible than our comovement measure. Third, we present several robustness checks.

3.1 Comovement with the Aggregate State

We start by estimating our employment and hires rate[20] cyclicality measures for each establishment in analogy to Equation (2) from the Section 2.2[21]:

$$\Delta \ln n_{ijt} = \beta_0^n + \beta_{1i}^n \Delta \ln N_t^j + \alpha_2 t + \alpha_3 t^2 + \beta_3^{'} \mathbf{C}_{it} + \mu_i + v_{ijt}^n, \tag{3}$$

$$\Delta hr_{ijt} = \beta_0^{hr} + \beta_{1i}^{hr} \Delta \ln N_t^j + \alpha_2 t + \alpha_3 t^2 + \beta_3^{'} \mathbf{C}_{it} + \mu_i + v_{ijt}^{hr}. \tag{4}$$

To estimate the quantitative interdependence between wage dynamics and labor market flow dynamics, we regress the employment and hires cyclicality measure for each establishment on the wage cyclicality measure of the respective establishment (estimated as described in Section 2.2):

$$\hat{\beta}_{1i}^n = \gamma_0 + \gamma_1^n \hat{\alpha}_{1i} + v_{it}^{\hat{\beta}^n}, \tag{5}$$

$$\hat{\beta}_{1i}^{hr} = \gamma_0 + \gamma_1^{hr} \hat{\alpha}_{1i} + v_{it}^{\hat{\beta}^{hr}}. \tag{6}$$

Note that Equations (5) and (6) are cross-sectional regressions, as each establishments has one wage cyclicality value for the entire observation period. Table 4 shows that there is a negative connection between the cyclicality of wages and the cyclicality of the hires rate and employment at the establishment level. Our regressions show that more procyclical wage establishments tend to be less procyclical in terms of their employment and hires rate. Imagine two establishments in a boom. Our results suggest that the establishment with a stronger upward adjustment of real wages increases employment by less than the

[20]Note that we do not use the logarithm for the hires rate because it is already a rate normalized between 0 and 2.

[21]Results of regressions in analogy to Equation (1) are presented in Appendix A.2.

establishment with a smaller positive (or even negative) real wage movement. In different words, our regressions show a very intuitive price-quantity trade-off. Establishments that adjust their wages by a lot in a boom do not adjust employment by that much.

Table 4: Effect of Wage Cyclicality on Employment and Hires Rate Cyclicality

Estimated Coefficient	γ_1^n	γ_1^{hr}
Coefficient	-0.254^{***}	-0.658^{***}
R^2	0.02	0.01
Observations	3,388,708	3,388,708

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

While this result appears very intuitive, it has to be emphasized that we are the first to show this link between wage cyclicalities and labor market flow dynamics in the data. The existing literature was limited by a lack of appropriate datasets to provide such a linkage. As the AWFP contains the entire universe of German establishments, we were not limited by data issues.

Why is this link between wage cyclicalities and labor market dynamic important? As mentioned in the introduction, our empirical approach provides a test laboratory 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 dynamics matter for employment dynamics at the establishment level. Our empirical results can be used to analyze whether different models are in line with the data. We will make a first attempt in this direction in Section 4 and analyze how important real wage dynamics are for solving the Shimer (2005) puzzle.

It is worthwhile discussing whether our empirical results could be driven by establishment-specific revenue cycles.[22] 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 above. Procyclical wage establishments increase employment by less in booms than countercyclical wage establishments. Thus, establishment-specific revenue

[22]Unfortunately, we cannot observe revenue cycles at the establishment level in the AWFP.

cycles cannot be the key driver of our results.

Overall, our results show that a more procyclical wage movement in the data (relative to the aggregate state) is associated with a less procyclical (or even countercyclical) hires rate and employment movement. The clear advantage of our comovement measures is the estimated connection between establishment-specific wage, employment, hires rate movement and the aggregate state, i.e. we really measure cyclicality and not something else. However, it has the disadvantage that it is somewhat inflexible: we assign the same cyclicality measure to an establishment for its entire life span (up to 36 years). Thus, we check for robustness using a more flexible measure in the next section.

3.2 Relative Measures

As a robustness check, this section uses very flexible wage, employment and hires measures to determine the connection between (relative) wage growth and (relative) employment growth or hires rate. 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 measure:

$$\triangle \ln w^r_{ijt} = \triangle \ln w_{ijt} - \frac{\sum_{i=1}^{E} \triangle \ln w_{ijt}}{E_{jt}}, \tag{7}$$

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. A positive (negative) number indicates a wage growth above (below) average.

We are interested in the effects of the wage growth rate on the establishment-specific employment and labor market flow dynamics. Thus, we further define:

$$\triangle \ln n^r_{ijt} = \triangle \ln n_{ijt} - \frac{\sum_{i=1}^{E} \triangle \ln n_{ijt}}{E_{jt}}, \tag{8}$$

$$\triangle hr^r_{ijt} = \triangle hr_{ijt} - \frac{\sum_{i=1}^{E} \triangle hr_{ijt}}{E_{jt}}, \tag{9}$$

which denote establishment-specific employment growth ($\triangle \ln n^r_{ijt}$) and hires rate change ($\triangle hr^r_{ijt}$) relative to the mean in a given sector[23] and year.

These specifications are more flexible than the approach in the previous section, where each establishment has one wage cyclicality indicator for the entire observation period. If

[23] We use the same sectoral definition as in the previous subsection, with 31 industry sectors.

an establishment has an above mean wage growth in one period of a boom, but switches to a below mean wage growth in the next period of the boom, the relative measures take this into account.

To determine the connection between relative wage growth and relative employment growth or hires rate, we estimate the following regression equations:

$$\triangle \ln n_{ijt}^{r} = \alpha_o + \alpha_1^{n} \triangle \ln w_{ijt}^{r} + \alpha_2^{'}\mathbf{C}_{it} + \mu_t + \mu_i + \varepsilon_{ijt}^{n^r}, \tag{10}$$

$$\triangle hr_{ijt}^{r} = \alpha_o + \alpha_1^{hr} \triangle \ln w_{ijt}^{r} + \alpha_2^{'}\mathbf{C}_{it} + \mu_t + \mu_i + \varepsilon_{ijt}^{hr^r}, \tag{11}$$

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 previous section).

Table 5 shows that our estimation results deliver negative and statistically significant results. Interestingly, the estimated coefficients in this and the previous section are quantitatively similar. This shows that our results are robust.

Table 5: Relative Measures — Employment and Hires Rate

Independent Variable:	$\triangle \ln n_{ijt}^{r}$	$\triangle hr_{ijt}^{r}$
Estimated coefficient: $\alpha_1^{n} \mid \alpha_1^{hr}$	-0.369^{***}	-0.484^{***}
Controls	Education shares, gender share, mean age, mean tenure, mean tenure^2, establishment fix effects, industry dummies, federal state dummies, year dummies	
R^2	0.13	0.18
Observations	39,049,783	39,049,783

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

Although we have already defined our relative measure in comparison to the sector, the reaction may be different from sector to sector. In order to check this, we run the same regression on the sectoral level. The results (see Appendix A.3) are very similar in each of the 31 sectors.

3.3 Further Robustness Checks

In this section, we present further robustness checks using the comovement measure (see Section 3.1) and relative measure (see Section 3.2).

Entrants, Incumbents, and Composition: Haefke et al. (2013) and Pissarides (2009) argue that wages for new jobs (entrants) 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). This is a remarkable difference to the United States, where the wage cyclicality of new hires is much larger than for incumbent workers. Thus, the distinction between entrants and incumbents is much less of an issue for Germany.

Second, in Appendix B.1, we estimate the wage cyclicality with respect to unemployment at the establishment level. While Stüber (2017) estimates at the individual 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.

Third, in Appendix B.2, we estimate the aggregate cyclicality of wages for ongoing jobs within establishments (i.e. those that already existed in the previous year). The stock of ongoing jobs is more stable in terms of composition than new hires. Thus, potential composition biases are less of an issue.[24] We can document that the average cyclicality of real wages is very similar for ongoing jobs and all jobs (0.124 for all jobs versus 0.152 for ongoing jobs). Furthermore, we estimate the connection between wage cyclicality and employment cyclicality for ongoing jobs. The estimated effects are very similar to our baseline estimations ($\hat{\gamma}_1^n = -0.307$, compare to Table 4; $\hat{\alpha}_1^n = -0.302$, compare to Table 5). This provides another piece of evidence that composition effects are not the key driver for our results.

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 entrant wages of this period to the previous period (at the establishment level). In this case, composition issues play a much larger role than for the entire workforce (compositional issues are discussed later in this 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.

Business cycle measure: We have chosen the sectoral full-time employment within an industry sector as our business cycle indicator. When we choose a more aggregated industry

[24]We owe this idea to Pedro Martins.

definition or aggregate employment instead, all our key results carry over.[25]

Establishment size: The major share of German establishments is small. Given that we are (also) interested in the aggregate effects of wage cyclicalities, it would be disturbing if our results were exclusively driven by small establishments. However, the opposite is the case. When we rerun all regressions of Sections 3.1 and 3.2 for establishments with 10 or more employees, the estimated effects of wage cyclicalities on employment/hiring increase ($\hat{\gamma}_1^n = -1.015$, $\hat{\gamma}_1^{hr} = -0.885$, compare to Table 4; $\hat{\alpha}_1^n = -0.461$, $\hat{\alpha}_1^{hr} = -0.535$, compare to Table 5).

Long-lived establishments: A large fraction of establishment is short-lived. This may potentially lead to spurious results and conflate the standard errors. Therefore, we estimated all results of Sections 3.1 and 3.2 for establishments that existed for at least 20 years. The key results remain very similar to the baseline estimations ($\hat{\gamma}_1^n = -0.426$, $\hat{\gamma}_1^{hr} = -0.412$, compare to Table 4; $\hat{\alpha}_1^n = -0.455$, $\hat{\alpha}_1^{hr} = -0.548$, compare to Table 5).

Real versus nominal wage cyclicalities: It would be insightful to know whether real or nominal wage rigidities are the driving source for the patterns that we detect. Unfortunately, our dataset is not suitable for this issue. We do not have any establishment-specific pricing information (as our data comes from administrative social security records). When we use nominal wages instead of real wages for our regressions, the results for the effects of wage cyclicalities on employment are literally the same. The reason is that all real wages in a given year are multiplied with the same deflator. When first differencing, the relative position of wage growth is unaffected.[26]

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. Second, when estimating our wage regressions at the establishment level, we have controlled for time-variant observables und 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. Therefore, we exclude the Great Recession episode from our regressions (i.e. we rerun the

[25]Results are available on request.

[26]Although we have a real model (without inflation), for illustration purposes, we have multiplied real wages in our model with a constant or a procyclical deflator to obtain hypothetical nominal wages. The estimated results in our simulated model are also almost the same as with the real wage.

regressions up to 2006). Compared to the entire sample, our quantitative results become smaller for the comovement measure, but remain similar for the relative measure. However, when we limit ourselves to establishments with 10 or more employees, the estimated results become even larger than in the baseline regressions. Therefore, we believe that intensive margin adjustments cannot be the key driver for our results.

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 hiring/employment are very similar for manufacturing and services (see Table 11 in Appendix A.3).

Composition in terms of unobservables: Note that Figure 1 (in Section 1) shows the mean wage growth rate for the most procyclical and the most countercyclical establishments. Could the cyclicality pattern be driven by a composition effect that generates reverse causality in our regressions? Assume that an establishment employs high-effort workers (with higher wages) and low-effort workers (with lower wages). Assume further that the establishment fires the low-effort workers in a recession. This would lead to a decline of employment and an increase of the establishments' mean wage due to a pure composition effect.[27]

In order to check whether this effect could be the key driving force, Figure 3 shows the mean growth rate of the wage bill ($w_t n_t$ instead of w_t) for the most procyclical and the most countercyclical group (in analogy to Figure 1).

Interestingly, 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 somewhat less pronounced for the entire wage bill than for the establishments' mean wage. This shows that the above described composition effect cannot be the key driver of our results.[28]

Beyond this simple illustration, we have taken several steps to prevent reverse causality due to composition effects in our regressions. In contrast to Figures 1 and 3, in our empirical analysis, we have controlled for time-invariant heterogeneity and various observables (skill, gender, age, etc.). Furthermore, we have used the sector-specific employment growth rate as an indicator for the aggregate state of the economy. It can be expected that workforces within industry sectors are more similar in terms of observable and unobservable characteristics, the more we disaggregate in terms of the sectors. Furthermore, we have shown that our regression

[27] Assume that low-effort workers earn w and high-effort workers earn $2 \cdot w$. Assume further that the establishment employs an equal number of workers from each type in booms and only the high-effort workers in recessions. In this case, the mean wage would increase from $1.5 \cdot w$ to $2 \cdot w$ during the recession.

[28] In the example from the previous footnote, the entire wage bill would drop from $3 \cdot w$ in the boom to $2 \cdot w$ in the recession, i.e. it would be procyclical.

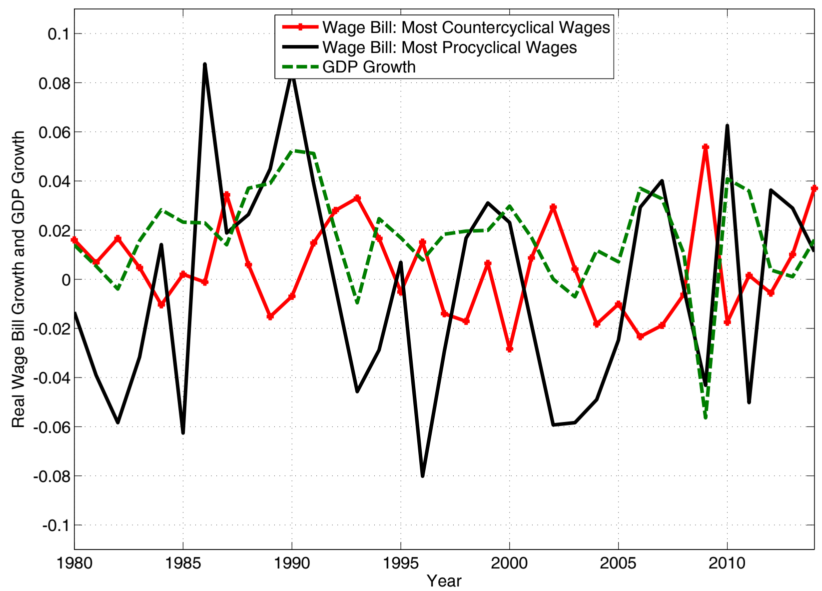

Figure 3: Mean growth rate of the wage bill ($w \cdot n$) for the most procyclical and the most countercyclical establishments.

results are very similar for ongoing jobs within an establishment (where composition is less of an issue) compared to all jobs.

4 Heterogeneous Wage Cyclicalities: Theory

This section contrasts our empirical results with a simple theoretical model. We choose this approach for several reasons. First, we can analyze whether the model can deliver similar qualitative results. In addition, the model provides a structural mechanism for the discovered reduced-form results. Second, we can analyze whether the quantitative relationships in the simulated model are in a similar order of magnitude as in the data. Given that this is the case, we can use our model for counterfactual exercises in order to analyze the importance of wage cyclicalities for aggregate dynamics.

4.1 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.[29] An obvious choice would be a segmented labor market framework, as in Barnichon and Figura (2015). However, we

[29]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.

find substantial heterogeneity in wage cyclicalities independently of the disaggregation level (national, 10 or 31 industry 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. In our model, we do not have different sectors.

We assume that each establishment obtains an undirected flow of applicants, which is determined by a degenerate contact function. Once workers and establishments get in contact with one another, each worker-establishment pair draws a realization from the same idiosyncratic training cost distribution. Establishments choose an optimal cutoff point and thereby decide about the fraction of workers they want to hire (labor selection). The cutoff point and the hiring rate depend on the wage cyclicality. Hiring will be different (but will not necessarily be shut down) if the wage cyclicality is different from other establishments in the economy.[30]

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 homogenous 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 4.3, where we set the wage cyclicality of all groups to the most procyclical group and thereby obtain a homogenous version of our model. This allows us to contribute to the Shimer (2005) puzzle debate.

In Appendix B.4, we derive a search and matching model with decreasing returns to labor, which can also replicate the stylized facts from Section 2. However, it turns out that our framework delivers outcomes that are quantitatively closer to the empirical results.

4.1.1 Heterogeneous Groups and Matching

In our model economy, there is a continuum of establishments that are completely homogenous, except for their wage formation over the business cycle.[31] 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

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

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

a degenerate contact function.[32]

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

$$E_0 \left\{ \sum_{t=0}^{\infty} \delta^t \left[a_t n_{it} - w_{it}^I (1-\phi) n_{i,t-1} - c_{it} s_t \eta(\tilde{\varepsilon}_{it}) \left(\frac{\bar{w}^E(\tilde{\varepsilon}_{it})}{\eta(\tilde{\varepsilon}_{it})} + \frac{H(\tilde{\varepsilon}_{it})}{\eta(\tilde{\varepsilon}_{it})} + h \right) \right] \right\}, \tag{12}$$

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

$$n_{it} = (1-\phi) n_{it-1} + c_{it} s_t \eta(\tilde{\varepsilon}_{it}), \tag{13}$$

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 (12) 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 workers-establishment pairs are homogenous and have the following present value:

$$J_{it} = a_t - w_{it}^I + E_t \delta (1-\phi) J_{it+1}. \tag{14}$$

Solving the maximization problem (see Appendix B.3) yields the evolution of the establishment-specific employment stock and the optimal selection condition:

$$n_{it} = (1-\phi) n_{it-1} + c_{it} s_t \eta(\tilde{\varepsilon}_{it}), \tag{15}$$

[32] In Appendix B.4, 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.

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

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:

$$\eta_{it} = \int_{-\infty}^{\tilde{\varepsilon}_{it}} f(\varepsilon)\, d\varepsilon. \tag{17}$$

Given that establishments are homogenous (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.

4.1.2 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.[33] 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). Therefore, we treat the wage cyclicality over the business cycle as exogenous in our model.[34] Therefore, we take different wage cyclicalities as given and analyze their impact on hiring and employment. To embed the different wage cyclicalities into our model, we derive the Nash bargaining solution as a benchmark for completely flexible (procyclical) wages. We assume that the steady state wage is equal to the Nash bargaining solution. However, the actual wage over the business cycle deviates from this Nash solution. Thus, in a first step, we derive the Nash wage that would prevail in the absence of different wage cyclicalities. In the second step, we impose that establishments deviate from the Nash wage in the short run. This is imposed and exogenous for establishments.

We assume that the idiosyncratic training costs and hiring costs are sunk at the time of bargaining and production.[35] Thus, all worker establishment-pairs have the same flow value, namely J_{it} from Equation (14), and thereby have the same wage within the establishment. The establishments' fallback option in case of disagreement is 0.

Workers' flow value in case of a match is

[33] See Appendix A.4 for characteristics of establishment with different wage cyclicalities.

[34] 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.

[35] This is in line with Pissarides (2009). Thus, the wage does not depend on the idiosyncratic component. This assumption is without loss of generality.

$$W_t = w_t + E_t \delta (1 - \phi) W_{t+1} + E_t \delta \phi U_{t+1}. \tag{18}$$

Workers' fallback option is the value of unemployment:

$$U_t = b + E_t \delta (1 - c_{t+1} \eta_{t+1}) U_{t+1} + E_t \delta \eta_{t+1} W_{t+1}, \tag{19}$$

where η_{t+1} is the aggregate probability of making a match in the next period.

Thus, the standard Nash product is

$$\Lambda_t = (W_t - U_t)^{\nu} (J_t)^{1-\nu}. \tag{20}$$

Maximization with respect to wages yields the following Nash bargaining result:[36]

$$w_t = \nu (a_t + E_t \delta c_{t+1} \eta_{t+1} J_{t+1}) + (1 - \nu) b, \tag{21}$$

where b are unemployment benefits that workers receive in case of unemployment.

If all establishment types followed the Nash bargaining solution, they would all have the same wage cyclicality. However, we exogenously impose different wage cyclicalities on different establishments. Note that the real wage dynamics for ongoing jobs and new matches is exactly the same in our model (in line with the empirical evidence that incremental effects are very small in Germany, see Section 3.3).

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

$$w_{it} = \kappa_i w_t + (1 - \kappa_i) w^{norm}, \tag{22}$$

where κ_i is the establishment-specific degree of wage cyclicality over the business cycle. The wage norm is the steady state value of the Nash bargain ($w^{norm} = w = \nu (a + \delta c \eta J) + (1 - \nu) b$). Thus, all establishments have the same wage in steady state. An establishment with $\kappa_i = 1$ immediately implements the Nash bargaining solution. By contrast, for $\kappa_i \neq 1$, the establishment converges to the Nash bargaining solution with a certain delay.

4.1.3 Aggregation

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

[36] See Appendix B.3.2 for the derivation.

$$\eta_t = \frac{\sum_{i=1}^{E} \eta_{it}}{E}, \tag{23}$$

where E is the number of establishments.

The aggregate employment rate is

$$n_t = (1 - \phi)\, n_{t-1} + s_t c_t \eta_t, \tag{24}$$

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

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

$$u_t = s_t \left(1 - c_t \eta_t\right), \tag{25}$$

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.

$$n_t = 1 - u_t. \tag{26}$$

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.[38] 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

$$c_{it} = \frac{1}{E}, \tag{27}$$

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.

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

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

4.2 Simulation-Based Effects

4.2.1 Calibration

In order to analyze the effects of different wage cyclicalities at the establishment level, we parametrize and simulate the model. There is a set of parameters that is absolutely standard. We set the discount factor to $\delta = 0.99$, given that our simulation will be performed on the quarterly level. 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. 2017 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.

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 and the standard deviation is normalized to 0.01. The first-order autocorrelation coefficient is set to 0.8.[39] As common in the literature, we parametrize the bargaining power of workers to $\nu = 0.5$.

In addition, we have to determine the set of parameters that is specific to our model, namely the linear hiring costs h and the properties of the idiosyncratic training shock distribution. For tractability, we use a logistic distribution for the idiosyncratic training distribution with mean zero ($\mu = 0$). We set the dispersion parameter of the idiosyncratic training cost distribution to $z = 1$.[40] We target the average unemployment rate from 1979–2014 (0.08) and thereby fix the linear hiring costs to $h = 0.8$.

Finally, we need to pin down the degree of heterogeneity of real wage growth. We discretize our economy in five different wage cyclicality groups. Remember that the parameter κ_i determines the wage cyclicality ($w_{it} = \kappa_i w_t + (1 - \kappa_i)\, w^{norm}$), i.e. how quickly establishments converge to or diverge from the Nash solution and thereby how strongly wages comove with aggregate productivity in our model.

We set κ_i such that the wage cyclicality in our model is in line with the data. We classify the estimated $\hat{\alpha}_{1i}$ — which we estimated for each establishment — into five quintiles and calculate the average real wage growth per full-time worker at the establishment level for each of these groups. To determine κ_i, we run the following regression: $\Delta \ln w_{qt} = \alpha_o + \alpha_{1q} \Delta \ln N_t + \alpha_q + v_{qt}$,[41] where $\Delta \ln w_{qt}$ corresponds to the mean growth rate of the

[39] 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 (2003).

[40] Note that this parameter is difficult to determine. However, none of our qualitative results is affected by this parameter. When we reduce z, the quantitative connection between wage cyclicalities and employment cyclicalities becomes stronger.

[41] In contrast to the empirical regressions, we use the aggregate employment here because we calibrate a

real wage of establishments within the respective quantile q and α_q are the quintiles' fixed effect. Table 6 shows the estimated comovement of the real wage growth with aggregate employment (α_{1q}) for the quintiles ($q = 1, \ldots, 5$).

Table 6: Comovement of Average Real Wage Growth with Aggregate Employment Growth for Quintiles

Comovement with quintile (q) ...	1	2	3	4	5
Employment Growth (α_{1q})	-2.00	-0.31	0.25	0.80	2.51

Note: Quintile 1 (5) are the most countercyclical (procyclical) wage establishments.

We match the α_{1q} displayed in Table 6, by setting $\kappa_i = [-0.71, -0.11, 0.09, 0.29, 0.90]$. We have two groups with negative values for κ. This means that their real wages increase in a recession, i.e. they are countercyclical. Note that we obtain countercyclical groups independently how we estimate and classify these groups. Several 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) and since we are interested in the consequences of different wage cyclicalities, we simply impose this pattern in our model (i.e. as a constraint for establishments). Second, our theoretical model is stable in terms of economics dynamics. Third, 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. 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. However, under our chosen calibration, we do not hit the bargaining bounds in any of the simulations.

4.2.2 Numerical Results and Implications

Figure 4 shows how the five different wage cyclicality types react in the model simulation to aggregate productivity shocks. Establishment 1 (with $\kappa_1 = -0.71$) has the most countercyclical wage, while establishment 5 (with $\kappa_5 = 0.9$) has the most procyclical wage over the business cycle.[42] Due to a series of positive aggregate productivity shocks, we see an

model for the entire economy (with aggregate employment as business cycle indicator). However, the key insights are the same when we use a different aggregation level.

[42]For better visibility, we only show thirty quarters, although the actual simulation is longer.

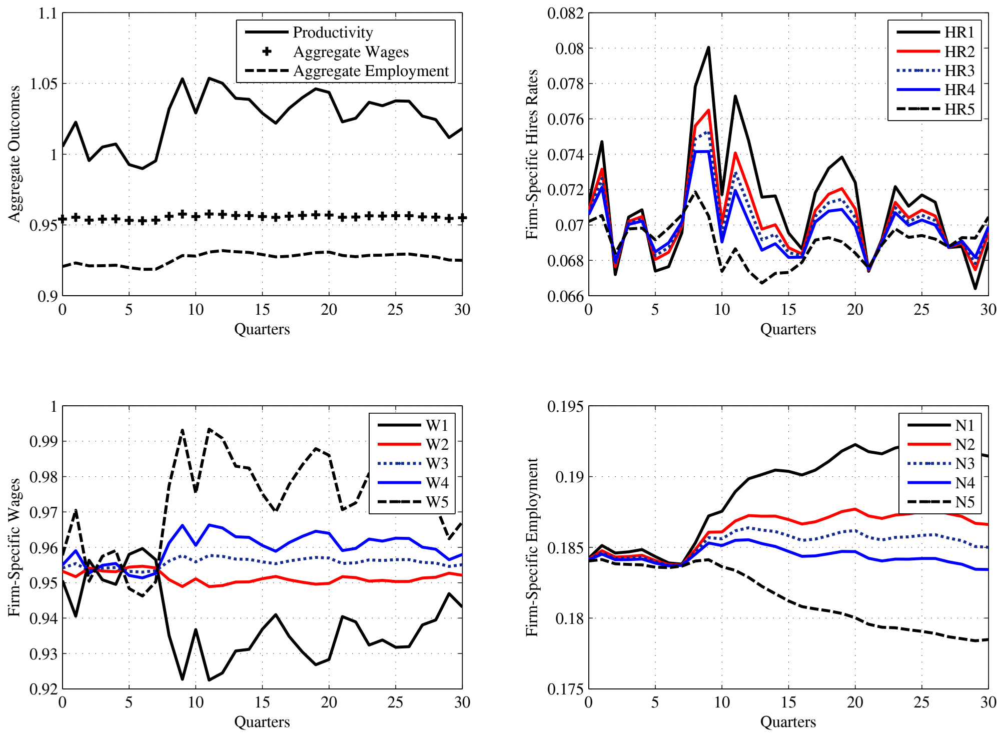

Figure 4: The upper left panel shows aggregate variables. The lower left panel shows the real wage movement of the five different groups (group 1 is the most countercyclical wage group). The upper right panel shows the hires rate and the lower right panel the employment stock.

increase of aggregate employment (see upper left panel).[43] The different wage dynamics for all establishment types are depicted in the lower left panel. Due to our calibration, wages go up for types 3,4,5 in a boom, while they drop for type 1 & 2 establishments. Under our calibration, all establishments have an incentive to hire a larger share of their applicants in a boom because the present value of a match increases. This means that the selection rate (not depicted in the Figure 4) in Equation (17) goes up for each establishment type in an economic upturn.[44] However, the establishment-specific hires rate (defined as establishment-specific matches divided by the employment stock, see upper right panel) does not necessarily increase for all groups in a boom. In some episodes, the hires rate drops for establishments of type 5 (with the most procyclical wages), although aggregate productivity is above average and the economy is in an upturn (see for example periods 10–15 in the upper right panel). This leads to a decline of the establishment-specific employment stock for establishments of

[43] We show levels instead of growth rates in Figure 4. Our explanations would be unaffected if we showed growth rates (as in the regression) instead. However, levels are more useful for illustration purposes.

[44] Although the wage of two groups is countercyclical, the present value in Equation (14) has a strong positive correlation with aggregate productivity for all five establishment types.

type 5 (see lower right panel). The decline of the hires rates and employment stock for procyclical wage establishments in booms is due to an equilibrium effect. The aggregate stock of searching workers goes down due to the boom in the economy. Therefore, all establishments obtain a smaller number of applicants. But given that establishments of type 5 increase their selection rate by the least, their hires rate and employment stock may actually decline in a boom.

This is an important observation when analyzing the effect of wage cyclicalities on establishment-specific employment, which we took into account when proposing appropriate measures for our empirical analysis above. In aggregate search and matching models, a lower procyclicality of wages leads to stronger amplification (i.e. larger volatilities of (un)employment). This is also true in our model for the entire economy (see Section 3.3). However, the standard deviation (or more generally any type of volatility measure) would not be suitable for a cross-sectional analysis of the effects of different wage cyclicalities on establishment-specific employment. While wage cyclicalities matter for hires and employment in our model, they do not have a monotonic effect on the standard deviations of establishment-specific hires rates and employment stocks. In Figure 4, establishments of type 1 and 5 both have a larger standard deviation of employment than establishments of type 3. However, their employment stocks move into different directions. This key insight from our model is very important.

4.2.3 Model Based Regression Results

Comovement with the Aggregate State

In order to see whether our quantitative model generates similar results as the data, we simulate the same number of observation periods, aggregate them to the annual frequency (to make them comparable to the data) and estimate regressions based on the simulated data. We have calibrated κ_i in order to obtain the same estimated cyclicality coefficients for real wages as in the data (see Section 4.2.1).

Analogy to our empirical exercise (see Section 3.1), we estimate the following wage regression[45],

$$\Delta \ln w_{it} = \alpha_0 + \alpha_{1i} \Delta \ln N_t + \alpha_2 t + \alpha_3 t^2 + \mu_i + v_{it}^w, \tag{28}$$

[45]In contrast to the regression in the empirical section, we do not have to control for observables because the model does not have any heterogeneities except for the wage cyclicality. As usual, we have simulated our model on the quarterly frequency. Given that we use annual data from the AWFP, for comparability reasons, we aggregate the simulated data to the annual frequency before we run regressions (coherent with the data definitions).

and the cyclicality of hires and employment:

$$\Delta \ln n_{it} = \beta_0^n + \beta_{1i}^n \Delta \ln N_t + \alpha_2 t + \alpha_3 t^2 + \mu_i + v_{it}^n, \tag{29}$$

$$\Delta hr_{it} = \beta_0^{hr} + \beta_{1i}^{hr} \Delta \ln N_t + \alpha_2 t + \alpha_3 t^2 + \mu_i + v_{it}^{hr}. \tag{30}$$

These three regressions tell us how strongly the establishment-specific wage, employment, or hires rates comove with aggregate employment.

The simulation results in Figure 4 suggest that a more procyclical wage movement leads to less procyclical employment and hires — as found in the empirical exercise. To determine the quantitative magnitude, we estimate — as in Section 3.1 — the following two regressions:

$$\hat{\beta}_{1i}^n = \gamma_0 + \gamma_1^n \hat{\alpha}_{1i} + v_{it}^{\hat{\beta}^n}, \tag{31}$$

$$\hat{\beta}_{1i}^{hr} = \gamma_0 + \gamma_1^{hr} \hat{\alpha}_{1i} + v_{it}^{\hat{\beta}^{hr}}. \tag{32}$$

Table 7 shows that there is a negative comovement between $\hat{\beta}_{1i}^n$ and $\hat{\alpha}_{1i}$ as well as between $\hat{\beta}_{1i}^{hr}$ and $\hat{\alpha}_{1i}$. As in the data, an establishment with a more procyclical wage movement shows a less procyclical employment and hires rate movement. The estimated coefficients are statistically significant at the 1% level, although we only have five cross-sectional observations in our simulation.

Table 7: Effect of Wage Cyclicality on Employment and Hires Cyclicality (Model)

Estimated Coefficient	γ_1^n	γ_1^{hr}
Coefficients	-0.382^{***}	-0.487^{***}
R^2	1.00	1.00
Observations	5	5

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

The order of magnitude of the estimated coefficients in Table 7 is remarkably similar to the results from the data. The estimated γ_1^n is somewhat larger than in the data-based regression (where $\hat{\gamma}_1^n = -0.254$, see Table 4). By contrast, the estimated γ_1^{hr} is somewhat smaller than in the data (where $\hat{\gamma}_1^{hr} = -0.657$).

Overall, the model-based coefficients and the empirical results are quantitatively remarkably close. How can it be possible that the job flow (employment change) reacts less strongly than in the model, while the worker flow (hires rate) reacts more strongly than in the model?

Remember that we have exogenous separations in the model. In reality, the separation margin is endogenous due to establishment-initiated firings or worker-initiated quits. Bachmann et al. (2017) show that worker churn is procyclical, i.e. growing establishments (with positive job flows) lose more workers in booms than in recessions. These margins are absent in our model.

Relative Measures

In order to check the robustness of results, we also use the relative measure, as in our empirical exercise (see Section 3.2). Using the simulated data, we calculate $\triangle \ln n_{it}^{r}$, $\triangle \ln n_{it}^{r}$, and $\triangle \ln n_{it}^{r}$ (see Equations 7–9 in Section 3.2) and estimate the following two regression equations[46]:

$$\triangle \ln n_{it}^{r} = \alpha_o + \alpha_1^n \triangle \ln w_{it}^{r} + \mu_i + \mu_i + \varepsilon_{it}^{n^r}, \tag{33}$$

$$\triangle hr_{it}^{r} = \alpha_o + \alpha_1^{hr} \triangle \ln w_{it}^{r} + \mu_t + \mu_i + \varepsilon_{it}^{hr^r}. \tag{34}$$

Table 8 shows that an establishment with a wage growth that is 1 percent above the average is associated with an employment growth that is 0.4 percent below the average and a hires rate that is 0.5 percentage points below the average. All estimated coefficients are statistically significant at the 1% level. Overall, the relative measures are quantitatively similar to the comovement based measures (where $\alpha_1^n = -0.369$ and $\alpha_1^{hr} = -0.484$).

Table 8: Relative Measures — Employment and Hires Rate (Model)

Dependent Variable:	$\triangle \ln n_{it}^{r}$	$\triangle hr_{it}^{r}$
Estimated coefficient: $\alpha_1^n \mid \alpha_1^n$	-0.386^{***}	-0.472^{***}
Time Dummies	Yes	Yes
R^2	0.53	0.94
Observations	175	175

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

Our simulation allows us to compare the outcomes from the comovment based measure and the relative measure. Tables 7 and 8 show that in an environment where wage cyclicalities do not change over time, these two measures yield almost the same quantitative results.

[46]In contrast to the regressions in the empirical section, we do not have to control for observables because the model does not have any heterogeneities except for the wage cyclicality (see also Footnote 45).

4.3 Counterfactual Exercises

The similarity between our empirical and simulation-based regression results puts us into a position to use our model for counterfactual exercises. While the qualitative effects of different wage cyclicalities in search and matching models are well understood (e.g. Hall 2005, Hall and Milgrom 2008, or Shimer 2005), our paper adds a new quantitative contribution to this stream of the literature. We have proposed a selection model that allows for heterogeneous wage cyclicalities in the cross-section. Note that this model in its homogenous 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. Thus, it is natural to use our proposed framework for counterfactual analysis.

The selection framework has the advantage that different wage dynamics in the cross-section can be easily modeled, which is not the case in a search and matching model with constant returns to scale. In contrast to a search and matching model with decreasing returns (see Appendix B.4), our model generates quantitative results that are much closer to the data.

As the regression-based analysis cannot tell us how much different wage cyclicalities actually matter for aggregate amplification, we use our theoretical model to perform two counterfactual exercises. First, we set the wage cyclicality of all groups to the most cyclical wage group (namely, $\kappa_1 = ... = \kappa_5 = 0.90$). Table 9 shows that this leads to a substantial drop of labor market amplification relative to the baseline model. The standard deviations of the logarithms of unemployment and the job-finding rate drop by almost two thirds. The intuition for this result is well known. When the wage of all establishments is more procyclical over the business cycle, a larger fraction of joint surpluses is captured by employees. Thus, the incentives for establishments to create additional jobs in a boom goes down and thereby the job-finding rate of workers varies less over the business cycle.

Table 9: Counterfactual Exercises

	Calibrated Baseline	All Most Flexible Group	Pure Nash Bargaining
Unemployment	0.056	0.020	0.016
Job-Finding Rate	0.037	0.013	0.011
Productivity	0.019	0.019	0.019

Note: The Table shows the standard deviation of the logarithm of simulated unemployment, vacancies and productivity.

In a second counterfactual exercise, we set the wage cyclicality parameter equal to one for all groups ($\kappa_1 = ... = \kappa_5 = 1$), i.e. we analyze how strongly the economy reacts to real business cycle shocks if wages are determined by standard Nash bargaining. Note that in this case labor market variables fluctuate by less than aggregate productivity and that the order of magnitudes of the amplification are similar as in Shimer (2005). Table 9 shows that under standard Nash bargaining the German labor market would be about three quarters less volatile over the business cycle than with its observed wage cyclicality over the business cycle.

Overall, our counterfactual exercises point to very powerful effects of different wage cyclicalities (that were calibrated to the empirical counterpart in the data) for aggregate labor market fluctuations. Although these different wage cyclicalities in the cross-section are bilaterally efficient through the lens of our model, they may be costly for the entire economy, as they lead to larger macroeconomic fluctuations.

5 Conclusion

Our paper has used the new AWFP dataset that contains administrative data for wages, job flows and worker flows for the entire universe of German establishments. The estimations have confirmed results from the existing literature that the real wage of the average establishment is indeed procyclical. However, the average real wage behavior masks that establishments have very different wage dynamics. More than 40 percent of establishments have a countercyclical wage over the business cycle.

Due to the linkage of the AWFP with the IAB Establishment Panel, we have been able to show that moderate cyclicality is associated with a higher share of establishments within collective bargaining. Furthermore, we have been able to show that differences in real wage dynamics have meaningful implications for job and worker flows. Establishments with more procyclical wages have a less procyclical (or even countercyclical) employment behavior. This is in line with our proposed theoretical framework.

Interestingly, we have not only found empirical support for the right qualitative responses in the data, but we have also found quantitative reactions that are in line with our proposed model. In a counterfactual model exercise, we have set the real wage cyclicality of all groups equal to the most procyclical wage group. This reduces aggregate labor market fluctuations by more than 60 percent and thereby provides a new data-based contribution on the role of wage rigidities for aggregate labor market dynamics.

Our paper provides support for quantitative theories where different wage dynamics affect hiring and 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

A.1 The Administrative Wage and Labor Market Flow Panel

The Administrative Wage and Labor Market Flow Panel (AWFP, see Stüber and Seth 2017a.) aggregates German administrative wage, labor market flow and stock information at the establishment level of the years 1975–2014. All data are available at an annual and quarterly frequency.[47]

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.[48] 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 (see Stüber and Seth 2017a).

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 (see Stüber and Seth 2017a). Therefore, all (marginal) part-time employees, employees in partial retirement, interns etc. are not accounted for as regular workers.

According to the AWFP, stocks and flows are calculated using the "end-of-period flow" definition (see Stüber and Seth 2017a):

- The stock of employees of an establishment in year t equals the number of regular workers on the last day of year t.
- Inflows of employees into an establishment for year t equal the number of regular 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 regular 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.

[47]For an introduction of the public release data of the AWFP, please see Stüber and Seth (2017b).
[48]The BeH also comprises marginal part-time workers employed since 1999.

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 5 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 and separation rates are calculated as sum of all hires / separations divided by the average number of full-time workers in t and t-1.

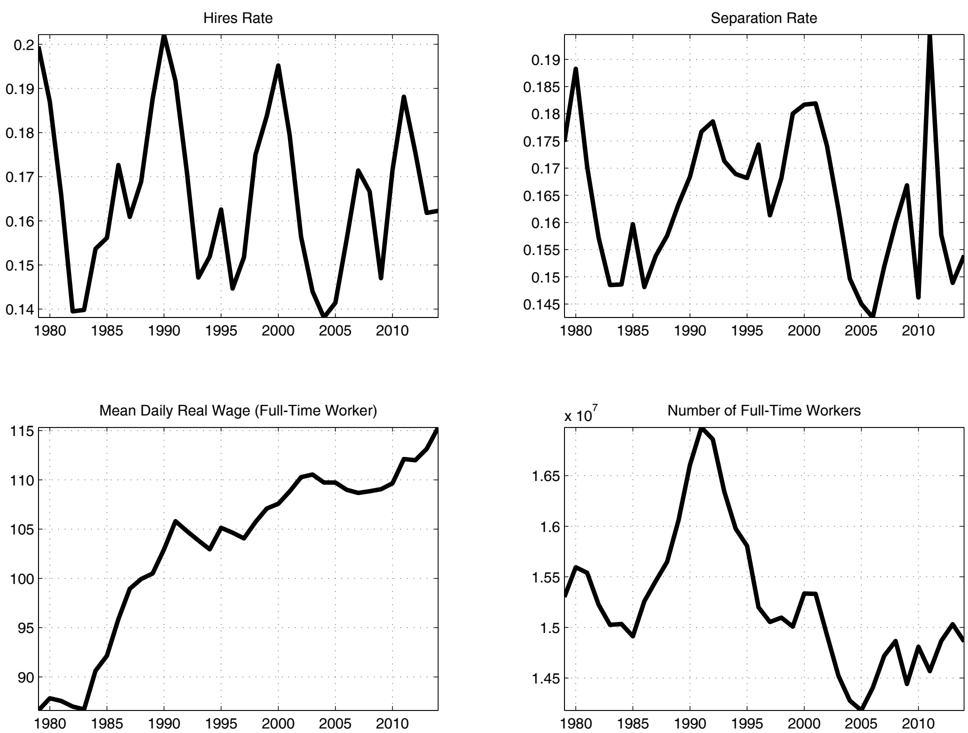

Figure 5: Aggregated time series

A.2 Average Employment and Hires Rate Cyclicality

Table 10 shows the estimated coefficient α_1 (regressions in analogy to Equation (1)), using $\Delta \ln n_{ijt}$ or Δhr_{ijt} as the dependent variable. As expected, both estimated coefficients are positive. A 1% increase of aggregate employment growth is associated with an increase of establishment-specific employment growth of 0.47 percent and an increase of the hires rate of 0.15 percentage points.

Table 10: Employment and Hires Rate Regression

Dependent Variable:	$\Delta \ln n_{ijt}$	Δhr_{ijt}
Estimated coefficient: α_1	0.465^{***}	0.147^{***}
Controls	Education shares, gender share, mean age, mean tenure, mean tenure^2, establishment fix effects, industry dummies, federal state dummies, year, year^2	
R^2 | within R^2	0.11 | 0.04	0.17 | 0.54
Observations	39,049,783	39,049,783

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

A.3 Results for 31 Industry Sectors

Table 11: Relative Measures for Industry Sectors

Estimated coefficient: w_{ijt}^r	1	2	3	4
Dependent Variable: n_{ijt}^r	-0.343^{***}	-0.230^{***}	-0.166^{***}	-0.259^{***}
Dependent Variable: hr_{ijt}^r	-0.316^{***}	-0.301^{***}	-0.156^{***}	-0.211^{***}
N	938,158	9,031	9,933	77,700
Estimated coefficient: w_{ijt}^r	5	6	7	8
Dependent Variable: n_{ijt}^r	-0.422^{***}	-0.410^{***}	-0.423^{***}	-0.517^{***}
Dependent Variable: hr_{ijt}^r	-0.478^{***}	-0.413^{***}	-0.462^{***}	-0.595^{***}
N	1,185,492	228,507	42,599	334,302
Estimated coefficient: w_{ijt}^r	9	10	11	12
Dependent Variable: n_{ijt}^r	-0.337^{***}	-0.177^{***}	-0.275^{***}	-0.383^{***}
Dependent Variable: hr_{ijt}^r	-0.420^{***}	-0.480^{***}	-0.356^{***}	-0.388^{***}
N	525,511	5,348	115,491	214,009
Estimated coefficient: w_{ijt}^r	13	14	15	16
Dependent Variable: n_{ijt}^r	-0.325^{***}	-0.397^{***}	-0.358^{***}	-0.361^{***}
Dependent Variable: hr_{ijt}^r	-0.333^{***}	-0.488^{***}	-0.458^{***}	-0.469^{***}
N	237,012	1,000,241	529,395	633,474
Estimated coefficient: w_{ijt}^r	17	18	19	20
Dependent Variable: n_{ijt}^r	-0.383^{***}	-0.499^{***}	-0.208^{***}	-0.383^{***}
Dependent Variable: hr_{ijt}^r	-0.501^{***}	-0.586^{***}	-0.439^{***}	-0.476^{***}
N	99,864	419,628	113,207	4,337,736
Estimated coefficient: w_{ijt}^r	21	22	23	24
Dependent Variable: n_{ijt}^r	-0.374^{***}	-0.282^{***}	-0.262^{***}	-0.269^{***}
Dependent Variable: hr_{ijt}^r	-0.507^{***}	-0.206^{***}	-0.280^{***}	-0.463^{***}
N	9,370,442	2,247,173	1,825,736	968,925
Estimated coefficient: w_{ijt}^r	25	26	27	28
Dependent Variable: n_{ijt}^r	-0.323^{***}	-0.545^{***}	-0.487^{***}	-0.458^{***}
Dependent Variable: hr_{ijt}^r	-0.473^{***}	-0.766^{***}	-0.680^{***}	-0.674^{***}
N	4,950,984	742,796	931,934	3,912,411
Estimated coefficient: w_{ijt}^r	29	30	31	all
Dependent Variable: n_{ijt}^r	-0.428^{***}	-0.128^{***}	-0.097^{***}	-0.369^{***}
Dependent Variable: hr_{ijt}^r	-0.572^{***}	-0.133^{***}	-0.364^{***}	-0.484^{***}
N	2,482,010	470,553	28,201	39,049,783

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.

Controls: state dummies and year dummies.

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

A.4 Characteristics of Different Wage Cyclicality Establishments

We connect the wage cyclicality measure α_{1i} (as estimated in Equation (2)) to the establishment size, defined as the number of full-time workers. Interestingly, the correlation between the establishment size and α_{1i} is equal to zero for the entire sample. When we estimate an OLS-regression with linear and quadratic establishment size terms, both estimated coefficients are not statistically significant. Thus, at first sight it appears as if there is no connection between the wage cyclicality at the establishment level and the size of the establishment.

The picture is more differentiated when we look at the wage cyclicality within certain establishment size classes. For small-, medium-, and large-sized establishments, there is no correlation between wage cyclicality and establishment size, i.e. there are many small to large establishments with procyclical or countercyclical wages over the business cycle. However, for the very largest establishments two patterns become visible. First, the largest establishments have a less dispersed wage cyclicality than smaller establishments, i.e. the pro- and countercyclicality is less extreme. Second, especially the very largest establishments tend to have relatively acyclical (or moderately procyclical) wages (see Figure 6). Although the AWFP data set does not contain any information on the bargaining regime or the existence of works councils, it is well known that the vast majority of the largest establishment is either member of a collective bargaining agreement or bargains with unions at the establishment level (e.g. Hirsch et al., 2014). In addition, a large share of these establishments has a works' council, i.e. certain decisions are co-determined by worker representatives. It appears natural that these industrial relation features prevent extreme variations of the real wage over the business cycle.

In addition to institutional features, geography may matter for wage cyclicality. Thus, we inspected the distribution of wage cyclicality measures at the West German state level. Interestingly, we could not discover any pronounced patterns based on this exercise. The median establishment in all states is relatively acyclical, i.e. α_{1i} is close to zero. This is interesting because nothing in our estimation forces the median cyclicality at the state level to be around zero. In addition, there is substantial variation around the median establishment independently of location. We find strongly procyclical and countercyclical real wages in each of the ten West German states. 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.

We also looked at the cyclicality patterns in each of the 31 industry sectors. Again, the wage cyclicality over the business cycle is very heterogeneous in all sectors. In contrast to the state level, the estimated degree of pro- and countercyclicality for the median establishment

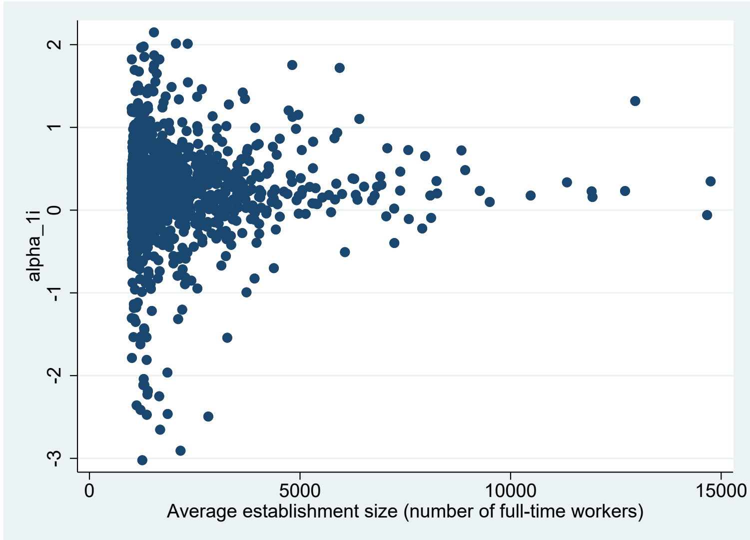

Figure 6: The picture show the α_{1i} for establishments above 1000 full-time workers. The first and 99^{th} percentile of the wage cyclicality measure it omitted for better visibility. The 99^{th} percentile for establishments above 1000 full-time workers is omitted due to confidentiality reasons.

differs somewhat more across sectors. In some sectors, the median is moderately procyclical, while it is moderately countercyclical in others. However, we could not discover any patterns that are easy to interpret (e.g. different cyclicality of manufacturing sectors versus service sectors or larger versus smaller sectors).

B Appendices for Online Publication

B.1 Comparison with Worker Level Regressions

In this Appendix, we check whether our establishment-level dataset generates similar results to the existing literature on wage cyclicalities. There are two key differences to the existing literature. First, these existing papers use worker-level data (e.g. Stüber 2017). Second, some use level-regressions instead of difference equations.[49] For comparability reasons, we estimate the following regression:

$$\ln w_{it} = \alpha_0 + \alpha_1 u_t + \alpha_2 t + \alpha_3 t^2 + \alpha_4^{'} \mathbf{C}_{it} + \mu_i + \varepsilon_{it}^{w}, \tag{35}$$

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 industry 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.

Table 12: Weighted Wage Regression

Dependent Variable:	w_{it}
Estimated coefficient: α_1	-1.16^{***}
Controls	Education shares, gender share, mean age, mean tenure, mean tenure^2, establishment fix effects, industry dummies, federal state dummies, year, year^2
R^2 | within R^2	0.94 | 0.46
Observations	39,049,783

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

How do our result compare to the existing literature on wage cyclicalities for Germany? The estimated coefficient in our regression (see Table 12) is well in line with Stüber (2017) who estimates the sensitivity of log wages to unemployment at the worker (and not the establishment) level. He estimates coefficients of -1.26 for all workers.[50]

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

[50] His estimated coefficient for newly hired workers is -1.33. This means that the incremental effect is economically small in Germany.

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

B.2 Regressions for Ongoing Jobs

The stock of ongoing jobs is more stable in terms of composition than new hires. Thus, potential composition biases are less of an issue. Therefore, we show the wage regression for ongoing jobs only (i.e. those that existed already in the previous period). Table 1 in the main part and Table 13 show that the estimated results are very similar.

Table 13: Wage Regression for Ongoing Jobs

Dependent Variable:	$\Delta \ln w_{ijt}$
Estimated coefficient : α_1	0.152^{***}
Controls	Education shares, gender share, mean age, mean tenure, mean tenure^2, establishment fix effects, industry dummies, federal state dummies, year, year^2
R^2 | within R^2	0.09 | 0.01
Observations	33,028,196

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

In addition, we estimate the connection between wage cyclicality and employment cyclicality for ongoing jobs.[51] Table 4 in the main part and Table 14 as well as Table 5 in the main part and Table 15 show very similar results.

Table 14: Effect of Wage Cyclicality on Employment Cyclicality for Ongoing Jobs

Estimated Coefficient	γ_1^n
Coefficient (t-values)	-0.307^{***}
R^2	0.02
Observations	2,856,232

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

[51] We abstain from estimating the effect between wage cyclicalities for ongoing jobs and new hires because they are not directly connected.

Table 15: Relative Measures — Employment for Ongoing Jobs

Independent Variable:	$\triangle \ln n_{ikjt}$
Estimated coefficient: α_1^n	-0.382^{***}
Controls	Education shares, gender share, mean age, mean tenure, mean tenure^2, establishment fix effects, industry dummies, federal state dummies, year dummies
R^2	0.10
Observations	33,028,196

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

B.3 Model Derivation

B.3.1 Establishment Maximization

Establishments maximize profits

$$E_0 \left\{ \sum_{t=0}^{\infty} \delta^t \left[a_t n_{it} - w_{it}^I (1-\phi) n_{i,t-1} - c_{it} s_t \eta(\tilde{\varepsilon}_{it}) \left(\frac{\bar{w}^E(\tilde{\varepsilon}_{it})}{\eta(\tilde{\varepsilon}_{it})} + \frac{H(\tilde{\varepsilon}_{it})}{\eta(\tilde{\varepsilon}_{it})} + h \right) \right] \right\}, \tag{36}$$

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

$$n_{it} = (1-\phi) n_{it-1} + c_{it} s_t \eta(\tilde{\varepsilon}_{it}). \tag{37}$$

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}:

$$n_{it} = (1-\phi) n_{it-1} + c_{it} s_t \eta(\tilde{\varepsilon}_{it}), \tag{38}$$

$$-c_{it} s_t \left(\frac{\partial \bar{w}^E(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} + \frac{\partial H(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} + \frac{\partial \eta(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} h \right) + \lambda_t c_{it} s_t \frac{\partial \eta(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} = 0, \tag{39}$$

$$a_t - \lambda_t + (1-\phi)\delta E_t \left(\lambda_{t+1} - w_{it+1}^I \right) = 0. \tag{40}$$

Isolating the Lagrange multiplier in Equation (39) yields:

$$\lambda_t = \frac{\frac{\partial \bar{w}^E(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} + \frac{\partial H(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} + \frac{\partial \eta(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} h}{\frac{\partial \eta(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}}}. \tag{41}$$

Keep in mind the three definitions:

$$\eta(\tilde{\varepsilon}_{it}) = \int_{-\infty}^{\tilde{\varepsilon}_{it}} f(\varepsilon) d\varepsilon, \tag{42}$$

$$\bar{w}^E(\tilde{\varepsilon}_{it}) = \int_{-\infty}^{\tilde{\varepsilon}_{it}} w_t^E(\varepsilon) f(\varepsilon) d\varepsilon, \tag{43}$$

$$H(\tilde{\varepsilon}_{it}) = \int_{-\infty}^{\tilde{\varepsilon}_{it}} \varepsilon f(\varepsilon) d\varepsilon. \tag{44}$$

This allows us to simplify Equation (41), using the Fundamental Theorem of Calculus:

$$\lambda_t = \frac{w^E(\tilde{\varepsilon}_{it}) f(\tilde{\varepsilon}_{it}) + \tilde{\varepsilon}_{it} f(\tilde{\varepsilon}_{it}) + f(\tilde{\varepsilon}_{it}) h}{f(\tilde{\varepsilon}_{it})} \tag{45}$$

$$= w^E(\tilde{\varepsilon}_{it}) + \tilde{\varepsilon}_{it} + h. \tag{46}$$

When we substitute this Lagrange multiplier into Equation (40), we obtain the selection condition:

$$\tilde{\varepsilon}_{it} = a_t - w^E(\tilde{\varepsilon}_{it}) - h + (1-\phi)\delta E_t \left(w^E(\tilde{\varepsilon}_{it+1}) + \tilde{\varepsilon}_{it+1} + h - w_{it+1}^I \right) \tag{47}$$

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

$$J_{it} = a_t - w_{it}^I + E_t \delta \left(1-\phi\right) J_{it+1}, \tag{48}$$

yields the selection condition, as shown in Equation (16) in the main part:

$$\tilde{\varepsilon}_{it} = a_t - w^E(\tilde{\varepsilon}_{it}) - h + E_t \delta \left(1-\phi\right) J_{it+1}. \tag{49}$$

B.3.2 Derivation of the Nash Wage

The Nash product is

$$\Lambda_t = \left(W_t - U_t\right)^{\nu} \left(J_t\right)^{1-\nu}, \tag{50}$$

with

$$W_t - U_t = w_t - b + E_t \delta \left(1 - \phi - \eta_{t+1}\right) \left(W_{t+1} - U_{t+1}\right), \tag{51}$$

and

$$J_t = a_t - w_t + E_t \delta (1-\phi) J_{t+1}. \tag{52}$$

Maximization of the Nash product with respect to the wage yields

$$\frac{\partial \Lambda_t}{\partial w_t} = \nu J_t \frac{\partial W_t}{\partial w_t} + (1-\nu)(W_t - U_t)\frac{\partial J_t}{\partial w_t} = 0, \tag{53}$$

$$\nu J_t = (1-\nu)(W_t - U_t). \tag{54}$$

After substitution:

$$\nu (a_t - w_t + E_t \delta (1-\phi) J_{t+1}) = (1-\nu)[w_t - b + E_t \delta (1 - \phi - \eta_{t+1})(W_{t+1} - U_{t+1})]. \tag{55}$$

Using Equation (54):

$$\nu (a_t - w_t + E_t \delta (1-\phi) J_{t+1}) = (1-\nu)\left[w_t - b + E_t \delta (1 - \phi - \eta_{t+1}) \frac{\nu}{(1-\nu)} J_{t+1}\right], \tag{56}$$

$$w_t = \nu (a_t + \delta \eta_{t+1} J_{t+1}) + (1-\nu) b. \tag{57}$$

B.4 Search and Matching with Decreasing Returns

In Section 2.2, we have shown that the wage dynamics across establishments is 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.[52] 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 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.

B.4.1 Model Derivation

Establishments maximize the following intertemporal profit condition

$$E_0 \sum_{t=0}^{\infty} \left(a_t n_{it}^{\alpha} - w_{it} n_{it} - \chi v_{it}\right), \tag{58}$$

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

$$n_{it} = (1-\phi)\, n_{it-1} + v_{it} q\left(\theta_t\right). \tag{59}$$

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

$$\left(\alpha a_t n_{it}^{\alpha-1} - w_{it}\right) - \lambda_{it} + \beta E_t \lambda_{it+1} \left(1-\phi\right) = 0, \tag{60}$$

$$-\chi + \lambda_{it} q\left(\theta_t\right) = 0, \tag{61}$$

where λ is the Lagrange multiplier.

[52] 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.

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

$$\frac{\chi}{q(\theta_t)} = \left(\alpha a_t n_{it}^{\alpha-1} - w_{it}\right) + \beta E_t (1-\phi) \frac{\chi}{q(\theta_{t+1})\,.} \tag{62}$$

Under decreasing returns to labor, standard Nash bargaining does not work. Therefore, we impose an ad-hoc wage formation rule:

$$w_t = \kappa_i \nu a_t + (1-\kappa_i)\,\bar{w}, \tag{63}$$

where $\bar{w} = \nu a$ is the wage norm, which corresponds to the steady state wage. 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

$$v_t = \sum_{i=1}^{E} v_{it}, \tag{64}$$

$$n_t = \sum_{i=1}^{E} n_{it}, \tag{65}$$

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

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

$$n_t = 1 - u_t. \tag{66}$$

B.4.2 Calibration

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 is normalized to 1. 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. As in the main part, we discretize the number of different wage cyclicality bins into 5 equally sized groups with $\kappa_i = [-0.71, -0.11, 0.09, 0.29, 0.90]$.

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 ($\chi = 0.54$).

B.4.3 Numerical Results

Based on the search and matching model with decreasing returns, we run the same regressions, as in Section 4.2.3. Table 16 shows the results for the following regressions:

$$\hat{\beta}_{1i}^{n} = \gamma_0 + \gamma_1^n \hat{\alpha}_{1i} + v_{it}^{\hat{\beta}^n}, \tag{67}$$

$$\hat{\beta}_{1i}^{hr} = \gamma_0 + \gamma_1^{hr} \hat{\alpha}_{1i} + v_{it}^{\hat{\beta}^{hr}}. \tag{68}$$

Table 16: Effect of Wage Cyclicality on Employment and Hires Cyclicality

Estimated Coefficient	γ_1^n	γ_1^{hr}
Coefficients	-3.156^{***}	-3.271^{***}
R^2	1.00	1.00
Observations	5	5

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

Interestingly, the estimated coefficients are an order of magnitude larger than in the theoretical framework from the main part. This is confirmed when we estimate the effects of different wage cyclicalities on hiring/employment based on the relative measures. As shown by Table 17, the estimated coefficients are about several times larger than in our main part.

$$\triangle \ln n_{it}^r = \alpha_o + \alpha_1^n \triangle \ln w_{it}^r + \mu_t + \mu_i + \varepsilon_{it}^{n^r}, \tag{69}$$

$$\triangle hr_{it}^r = \alpha_o + \alpha_1^{hr} \triangle \ln w_{it}^r + \mu_t + \mu_i + \varepsilon_{it}^{hr^r}. \tag{70}$$

Overall, in a search and matching model with decreasing returns and different wage cyclicalities, the estimated coefficients (based on simulated data) are several times larger than in our baseline model (which was based on labor selection). Thus, in this case, there is a much larger gap between the estimated coefficients from the data and from the model.

Table 17: Relative Measures

Dependent Variable:	$\triangle \ln n_{it}^{r}$	$\triangle hr_{it}^{r}$
Estimated coefficient: $\triangle \ln w_{it}^{r}$	-2.213^{***}	-1.806^{***}
Time Dummies	Yes	Yes
R^2	0.48	0.15
Observations	175	175

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

B.4.4 Some Analytics

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

$$\frac{\chi}{q(\theta)}\left(1-\beta\left(1-\phi\right)\right) = \alpha a n_i^{\alpha-1} - w_i, \tag{71}$$

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:

$$\frac{\chi}{q(\theta)}\left(1-\beta\left(1-\phi\right)\right) = 0.67 n_i^{-0.33} - w_i. \tag{72}$$

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 (72). Thus, the estimated coefficient based on relative measures (as in Table 17) can be expected to be around 3.

Note that in our calibrated version of the model above, the steady state values are $mpl = 1.17$ and $w = 0.95$, i.e. the former is about one quarter larger than the latter. As a consequence, a 1% lower wage only leads to roughly 2% more employment. If we calibrate the steady state value of mpl to be closer to w, then the estimated coefficients in Table 17 are closer to 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.