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' average 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 that is able to replicate these facts. When we set the wage cyclicalities of all establishments to the one of the most procyclical establishments, labor market volatilities drop by more than 50 percent.

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 Fisher 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.

To our knowledge, there is not a single paper that documents the heterogeneity of real wages over the business cycle across establishments and its implications on labor market flows. Given the renewed interest in the implications of wage flexibility (e.g. Galí and Monacelli 2016), 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 Seth and Stüber 2017). The dataset comprises the entire universe of German establishment for the years 1975–2014 and thereby contains longitudinal data for each establishment. The *AWFP* contains, inter alia, detailed wage 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 contribution to the literature is fourfold. First, our paper documents a substantial heterogeneity of real wage cyclicalities. 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 than 40 percent of establishments behave in a countercyclical manner, some of them very strongly.

Figure 1 shows the average real wage growth for establishments with the most procyclical and the most countercyclical wages.[2] 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 major real wage increase. Our paper shows that the

[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] We define establishments with the most procyclical (countercyclical) wage as those above (below) the 80^{th} (20^{th}) percentile of our wage cyclicality measure α_i. See Sections 2 and 5.3 for details.

average wage cyclicality over the business cycle masks the fact that establishments have very different wage dynamics. Some of them are more in line with traditional Keynesian theories, while others behave more in line with frameworks such as the real business cycles theory.

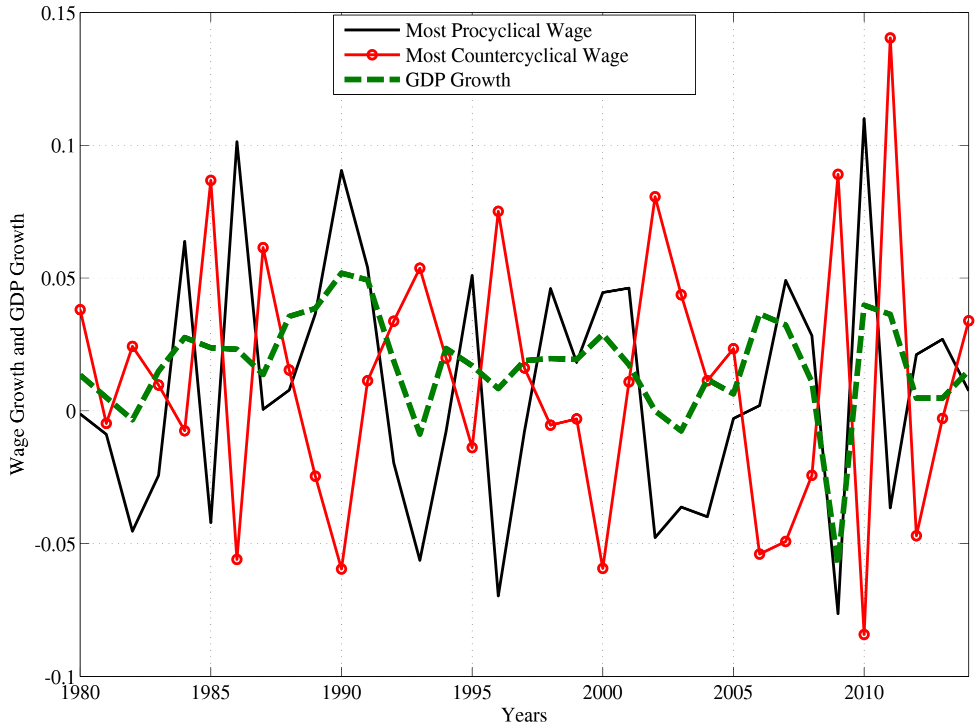

Figure 1: The figure shows the real GDP growth, the average real wage growth for the establishments with the most procyclical wages, and the establishments with the most countercyclical wages. Real Wages are defined as wages/salaries per full-time workers (including all bonuses).

Second, our paper documents the effects of different real wage cyclicalities on job and worker flows. We find that more procyclical wage establishments have less procyclical job creation and employment dynamics.[3] 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 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.

[3]See previous footnote for details.

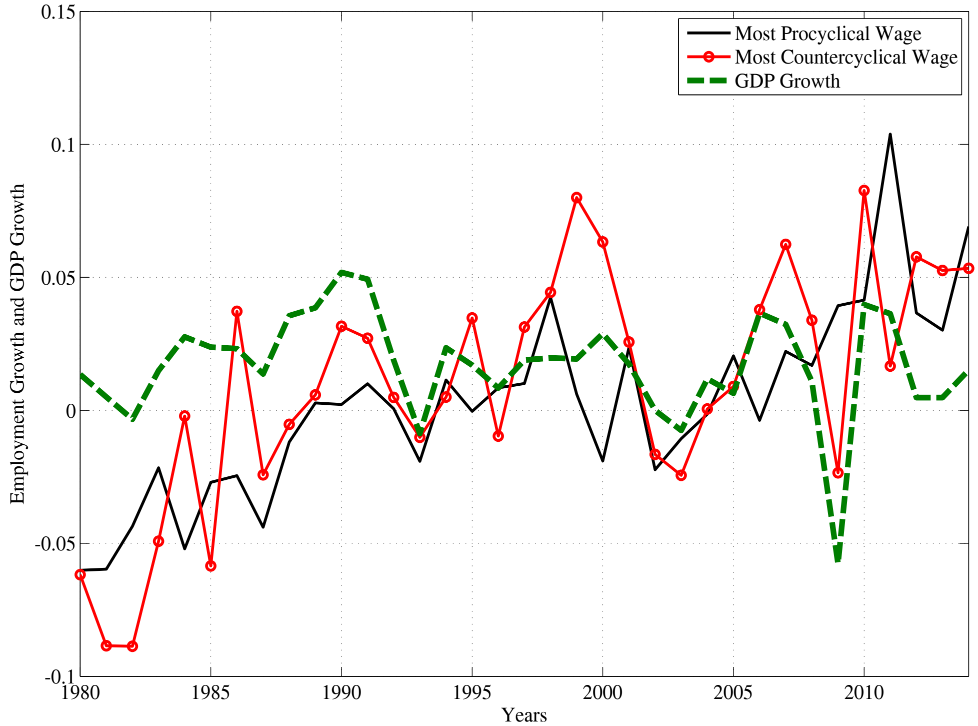

Figure 2: The figure shows the real GDP growth, the average employment growth (job flows) for the establishments with the most procyclical wages, and the establishments with the most countercyclical wages.

In order to set the stage and to understand the effects of different wage cyclicalities on labor market flow dynamics, 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, this model environment allows all establishments — despite having different wage cyclicalities — to hire in every time period. In addition, different wage cyclicalities are bilaterally efficient, as wages in our simulations are in between workers' and establishments' reservations wages. Thus, our model does not run afoul of the Barro Critique (1977).[4] The model allows us to make qualitative and quantitative predictions on the expected effects of different wage cyclicalities on job and worker flows. In addition, we

[4]According to the Barro 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.

can use our model to analyze the suitability of different ways of measuring wage cyclicality at the establishment level.

Third, 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. When wages become less procyclical over the business cycle in search and matching models, the present value of a match moves by more over the cycle and job creation as well as (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 over the business cycle (e.g. Carneiro et al. 2012, Martins et al. 2012, Haefke et al. 2013, Gertler et al. 2016, Stüber 2017). However — to the best of our knowledge — 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 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. If worker-establishment pairs find a commitment mechanism such that they 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 (or credit constrained) workers, without any effect on hiring. However, our 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.

Fourth, the quantitative similarities between simulation and empirical results allow us to perform counterfactual exercises. When we set the wage cyclicality of all establishments to the one of the most cyclical establishments, the standard deviations of the job-finding rate and unemployment drop by more than 50 percent. 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 countercyclical wages over the business cycle.

Germany offers a 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. Although wage formation may change over time (as can be seen by the decline of collective bargaining), it does not change at a very frequent basis (e.g. we do not observe a lot of establishments switching back and forth to different regimes). Establishments inherit a wage formation mechanisms from the past, which affects their wage cyclicality over the business cycle. Thus, we treat the wage cyclicality over the business cycle as exogenous in our theoretical model.

There is a small literature on the effects of different labor market institutions on wage cyclicalities over the business cycle. 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. Gartner et al. (2013) analyze the impact of collective bargaining and work councils on real wage changes in Germany. They find limited effects of labor market institutions on wage rigidity. The *AWFP* is not suitable for contributing to this stream of the literature because it does not contain any information on unionization, membership in a collective bargaining agreement or the existence of a works council.[5] By contrast, we are the first to analyze the implications of wage cyclicality on hiring and employment over the business cycle.

There is also 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). The two available 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.[6]

[5]Analyzes of this sort are usually performed with the IAB Establishment Panel, which is only available from 1993 onwards and covers only between 4,265 and 16,000 establishments per year.

[6]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).

Our paper looks at the effects of wage cyclicality through the lens of a model with random search and labor market flows. 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 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 2007).

The rest of the paper proceeds as follows. Section 2 provides a description of the *AWFP* dataset, shows how wages evolve at the establishment level and provides information on the procyclicality and countercyclicality of different establishments over the business cycle. Section 3 derives a model of heterogeneous wage cyclicalities across establishments, which is able to match key facts from the data. In Section 4, we calibrate our model, show quantitative results, and discuss implications. Section 5 applies the model-based measures to the *AWFP* dataset and interprets our results. Section 6 performs counterfactual model exercises and Section 7 concludes.

2 Heterogeneous Wage Cyclicalities: Evidence

This section proceeds in two steps. First, we provide a brief description of the employed *AWFP* data. Second, we estimate how strongly wages at the establishment level comove with aggregate employment and we show that there is substantial cross-sectional heterogeneity in terms of the cyclicality of wages.

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, 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, where the type of analysis that we perform in this paper is not feasible. Before aggregating the data to the establishment level, several adjustments and imputations were conducted at the micro data. For more detailed information on the *AWFP* see Appendix A.1 or Seth and Stüber (2017).

One disadvantage of the *AWFP* is that we do not have information on the exact number of hours worked. To have a homogenous reference group, we therefore restrict ourselves to full-time workers.[7] Wages are defined as the average wages/salary subject to social security (including bonus pay) of all employed full-time workers in a particular establishment. Wages above the contribution assessment ceiling are imputed following Card et al. (2015). For details see Appendix 8.2 of Schmucker et al. (2016). 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 $t-1$.[8]

We use the *AWFP* at the annual frequency and restrict the data to West German establishments (excluding Berlin) and the years 1979–2014.[9] 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. For coherency, we focus on wages and flows for full-time workers.[10]

2.2 Wage Cyclicalities: Time Dimension and Cross-Section

Figure 3 shows the average real wage growth (for full-time workers) in Germany from 1979-2014 for the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile of the wage growth distribution at the establishment level in each time period.[11] Figure 3 illustrates that there is substantial heterogeneity in the real wage growth across establishments. In this section, we are interested whether this heterogeneity can be explained by different comovements with the aggregate business cycle indicator. Do all establishments behave in a procyclical fashion, as for example

[7] It is important to note that the extensive margin is a lot more important than the intensive margin in Germany. The importance of the extensive margin over long time horizons was for example shown by Reicher (2012).

[8] 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 each year t the growth rate of real wage ($\Delta \ln w_{it}$), the growth rate of full-time workers ($\Delta \ln n_{it}$), and the change in the hires rate (Δhr_{it}) and drop establishment-year observations below the 1^{st} and above the 99^{th} percentile of the three measures.

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

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

[11] Establishments may change the percentile in each time period.

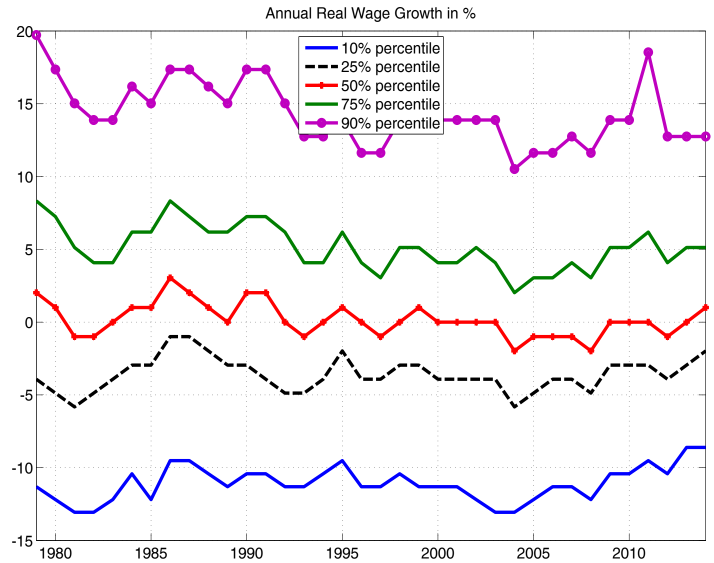

Figure 3: Real wage growth of different percentiles.

in real business cycle models? Is there a substantial fraction of countercyclical real wage establishments, as suggested by models with nominal wage rigidities in the spirit of Keynes (1936)? To answer these questions, we estimate the average wage cyclicality over the business cycle in the next step and provide a measure for its heterogeneity.

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 (as depicted in Figure 3) 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

$$\Delta \ln w_{it} = \alpha_0 + \alpha_1 \Delta \ln N_t^j + \alpha_2 t + \alpha_3 t^2 + \alpha_4 C_{it} + \mu_i + \varepsilon_{it}, \tag{1}$$

where $\Delta \ln w_{it}$ is the growth rate of real wage of establishment i in year t and $\Delta \ln N_t^j$ is the growth rate of full-time workers in the respective industry sector j. μ_i is a establishment-fixed effect, and 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 within the establishment. We also include federal state and industry sector dummies. In addition, we include a linear and quadratic time trend.

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: Wage Regression

Dependent Variable:	$\Delta \ln w_{it}$
Estimated coefficient : $\Delta \ln N_t^j$	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	0.12
Observations	39,663,986

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

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.

As a next step, we quantify the heterogeneous reaction of different establishments to the business cycle. We aim at estimating an equation of the following form:

$$\Delta \ln w_{it} = \alpha_0 + (\alpha_1 + \alpha_{1i}) \Delta \ln N_t^j + \alpha_2 t + \alpha_3 t^2 + \alpha_4 C_{it} + \mu_i + v_{it}^w, \tag{2}$$

where α_{1i} shows how strongly the wage growth of establishment i reacts to changes of the business cycle indicator. The sum of the coefficients $\alpha_1 + \alpha_{1i}$ tells us how procyclical or countercyclical a certain establishment is.

Equation (2) generates more than three million coefficients α_{1i}, which corresponds to the number of establishments in our analysis. In order to be able to estimate these coefficients, we perform a two-step procedure. In a first step, we estimate equation (1). In a second step, we use the estimated residual wage term $\hat{\varepsilon}_{it}$. We regress the residual wages ($\hat{\varepsilon}_{it}$) for each establishment, i, for each time period, t, on aggregate employment growth in the respective sector ($\Delta \ln N_t^j$). Note that we have a time-varying residual wage for each establishment and we are interested how much this residual wage comoves with the sector-specific full-time employment growth:

$$\hat{\varepsilon}_{it} = \alpha_{0i} + \alpha_{1i} \Delta \ln N_t^j + v_{it}^w. \tag{3}$$

Table 2 shows the percentiles for all estimated $\hat{\alpha}_{1i}$. In contrast to Figure 3, where establishments may have a different percentile position every year, each establishment has an estimated $\hat{\alpha}_{1i}$ that is fixed for the entire life span. Intuitively, $\hat{\alpha}_{1i}$ describes how much establishment i deviates from the average procyclicality in the economy.

Table 2 confirms that wage growth is very heterogeneous across establishments. It is unsurprising that establishments below (above) the median have a negative (positive) sign for $\hat{\alpha}_{1i}$. However, 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: Wage Regression

Descriptive statistics	$\hat{\alpha}_{1i}$	$\hat{\alpha}_1 + \hat{\alpha}_{1i}$
30^{th} percentile	-0.68	-0.56
40^{th} percentile	-0.28	-0.15
Median	0.01	0.13
60^{th} percentile	0.30	0.42
70^{th} percentile	0.71	0.84
Observations	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 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. In other words, the wage dynamics for the majority of establishments resembles the one in a real business cycle model, where real wages increase when aggregate employment increases. By contrast, many establishments have real wage dynamics that resembles a traditional Keynesian model with countercyclical real wages. Our paper is the first to document this fact.

Despite this heterogeneity in real wage growth across establishment over the business cycle, almost all establishments above a certain size hire at any point in time. For establishments with more than 50 employees, more than 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. In the next section, we propose a model that can replicate these two facts.

3 Heterogeneous Wage Cyclicalities: Theory

We need a model that allows for heterogeneous wage cyclicalities over the business cycle and the possibility that establishments hire at any point in time.[12] An obvious choice would be a segmented labor market framework, as in Barnichon and Figura (2015). However, we find substantial heterogeneity in wage cyclicalities independently of the disaggregation level (national or 31 industry sectors). Thus, market segmentation is not the key driver for different wage cyclicalities and we need to model different wage cyclicalities within a labor market segment.

In our model, we therefore 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.[13]

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

[12] 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.

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

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 5, 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.3, 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.

3.1 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.[14] 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 establishment will receive a equal fraction of searching workers in the economy, where the number of overall contacts in the economy is equal to the number of searching workers in the period. This corresponds to a degenerate contact function.[15]

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

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

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

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

where a_t is productivity, which is subject to aggregate productivity shocks, w_t^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.

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

[15]In Appendix B.3, we show an alternative model, where establishments act along the vacancy margin instead of the selection margin. In this model, workers are also randomly assigned to establishments.

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 (4) shows how much the establishment has to pay for the average new hires, namely the average wage for an entrant, $\bar{w}^E(\tilde{\varepsilon}_{it})/\eta(\tilde{\varepsilon}_{it})$, the average training costs, $H(\tilde{\varepsilon}_{it})/\eta(\tilde{\varepsilon}_{it})$, both conditional on being hired. In addition, there is a fixed 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:

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

Solving the maximization problem (see Appendix B.2) yields the evolution of the establishment-specific employment stock and the optimal selection condition:

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

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

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

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

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.

3.2 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.[16] As argued in Section 1, establishments inherit their wage formation from the past. Therefore, we take different

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

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. We assume that the steady state wage is equal to the Nash bargaining solution. The real wage over the business cycle may deviate from this Nash solution.

We assume that the idiosyncratic training costs and hiring costs are sunk at the time of bargaining and production.[17] Thus, all worker establishment-pairs have the same flow value, namely J_{it} from equation (6), and thereby have the same wage $w_t = w_t^I = w^E(\tilde{\varepsilon}_{it})$. The establishments' fallback option in case of disagreement is 0.

Workers' flow value in case of a match is

$$W_t = w_t + E_t\delta\left(1-\phi\right)W_{t+1} + E_t\delta\phi U_{t+1}. \tag{10}$$

Workers' fallback option is the value of unemployment:

$$U_t = b + E_t\delta\left(1-c_{t+1}\eta_{t+1}\right)U_{t+1} + E_t\delta\eta_{t+1}W_{t+1}, \tag{11}$$

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

Thus, the standard Nash product is

$$\Lambda_t = \left(W_t - U_t\right)^{\nu}\left(J_t\right)^{1-\nu}. \tag{12}$$

Maximization with respect to wages yields the following result:[18]

$$w_t = \nu\left(a_t + E_t\delta c_{t+1}\eta_{t+1}J_{t+1}\right) + \left(1-\nu\right)b, \tag{13}$$

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

$$w_{it} = \kappa_i w_t + \left(1-\kappa_i\right)w^{norm}, \tag{14}$$

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 ($w^{norm} = w = \nu\left(a + \delta c\eta J\right) + \left(1-\nu\right)b$). 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 $\kappa_i \neq 1$,

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

[18] See Appendix B.2.2 for the derivation.

the establishment converges to the Nash bargaining solution with a certain delay.

3.3 Aggregation

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

$$\eta_t = \frac{\sum_{i=1}^{E} \eta_{it}}{E}, \tag{15}$$

where E is the number of establishments.

The aggregate employment rate is

$$n_t = (1 - \phi)\, n_{t-1} + s_t c_t \eta_t, \tag{16}$$

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

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

$$u_t = s_t \left(1 - c_t \eta_t\right), \tag{17}$$

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.

$$n_t = 1 - u_t. \tag{18}$$

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.[20] 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

$$c_{it} = \frac{1}{E}, \tag{19}$$

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

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

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.

4 Simulation-Based Effects

4.1 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* dataset, the exogenous quarterly separations 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 1. The first-order autocorrelation coefficient is set to 0.8.[21] 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 $z = 1$.[22] 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

[21] 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).

[22] 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.

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 quantiles and calculate the average real wage growth per full-time worker at the establishment level for each of these groups. Table 7 in Section 5.3 shows the estimated comovement of the real wage growth with aggregate employment.

We match these numbers, by setting $\kappa_i = [0.730, 0.285, 0.090, -0.145, -0.678]$. 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 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 $\kappa_1 = 0.73$) has the most procyclical wage, while establishment 5 (with $\kappa_5 = -0.68$) has the most countercyclical wage over the business cycle.[23] Due to a series of positive aggregate productivity shocks, we see an increase of aggregate employment (see upper left panel).[24] The different wage dynamics for all establishment types is depicted in the lower left panel. Due to our calibration, wages go up for types 1,2,3 in a boom, while they drop for type 4 & 5 establishments (see lower left panel). Under our calibration, all establishments have an incentive to hire a larger share of their applicants because the present value of a match increases. This means that the selection

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

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

rate (not depicted in the Figure 4) in equation (9) goes up for each establishment type in an economic upturn.[25] 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 some episodes, the hires rate drops for establishments of type 1 (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 type 1 (see lower right panel). The decline of the hires rates and employment stock for procyclical wage establishments in booms is due to a general 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 1 increase their selection rate by the least, their hires rate and employment stock may actually decline in a boom.

This is an important observation for constructing measures for the effect of wage cyclicalities on establishment-specific employment. 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 6). 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.

4.3 Model Based Regression Results

As shown in the previous subsection, when we measure the effects of different establishment-specific wage cyclicalities on the establishment-specific employment cyclicality, our chosen measures have to take the direction of the movement into account. This is the case for the two measures we propose below. We use our model to establish a quantitative benchmark for the effect of wage cyclicalities on hiring/employment dynamics.

[25] Although the wage of two groups is countercyclical, the present value in equation (6) has a strong positive correlation with aggregate productivity for all five establishment types.

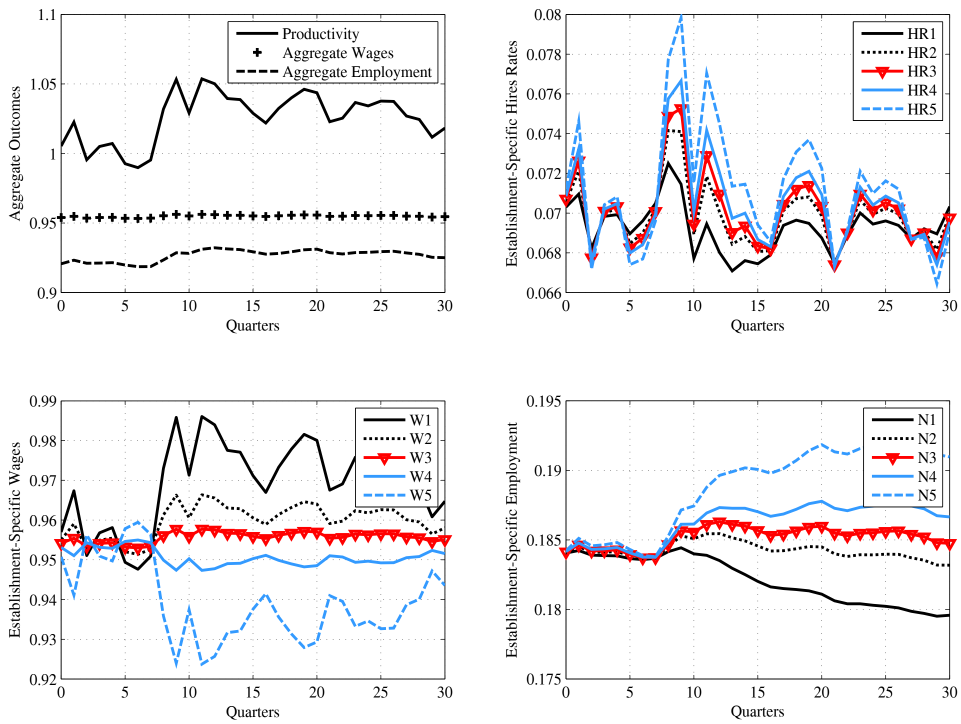

Figure 4: The upper left panel shows aggregate variables. The lower left panel shows the real wage movement of the five different groups. The upper right panel shows the hires rate and the lower right panel the employment stock.

4.3.1 Comovement with the Aggregate State

We calibrated κ_i in order to obtain the same procyclicality of real wages as in the data ($\Delta \ln w_{it} = \alpha_{0i} + \alpha_{1i}\Delta \ln N_t + v_{it}^{w}$).[26] In analogy with the wage regression, we estimate the cyclicality of hires and employment for each establishment type ($i = 1, ..., 5$):[27]

$$\Delta \ln n_{it} = \beta_0^n + \beta_{1i}^n \Delta \ln N_t + v_{it}^n, \tag{20}$$

$$\Delta hr_{it} = \beta_0^{hr} + \beta_{1i}^{hr} \Delta \ln N_t + v_{it}^{hr}. \tag{21}$$

These two regressions tell us how strongly the establishment-specific employment and 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. To determine the quantitative magnitude and to provide a benchmark for the empirical exercise, we estimate the following two regressions:[28]

$$\hat{\beta}_{1i}^n = \gamma_0 + \gamma_1^n \hat{\alpha}_{1i} + v_{it}^{\hat{\beta}^n}, \tag{22}$$

$$\hat{\beta}_{1i}^{hr} = \gamma_0 + \gamma_1^{hr} \hat{\alpha}_{1i} + v_{it}^{\hat{\beta}^{hr}}. \tag{23}$$

There is a negative comovement between $\hat{\beta}_{1i}^n$ and $\hat{\alpha}_{1i}$ as well as between $\hat{\beta}_{1i}^{hr}$ and $\hat{\alpha}_{1i}$ (see Table 3). In other words, 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. These results will be an important benchmark for the estimations based on the *AWFP* dataset in Section 5.

4.3.2 Relative Measures

While the regression-based comovement measure works perfectly well in the simulated data, it has the clear disadvantage that it assigns a fixed value for the wage cyclicality and employ-

[26]In contrast to the empirical wage regression (2), 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).

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

[28]Note that this estimation strategy is equivalent to estimating $\left(\hat{\beta}_1^n + \hat{\beta}_{1i}^n\right) = \gamma_0 + \gamma_1^n \left(\hat{\alpha}_1 + \hat{\alpha}_{1i}\right) + v_i^{\beta^n}$, because the fixed terms $\hat{\beta}_1^n$ and $\hat{\alpha}_1$ are absorbed by the intercept γ_0.

Table 3: Effect of Wage Cyclicality on Employment and Hires Cyclicality

Estimated Coefficient	γ_1^n	γ_1^{hr}
Coefficients	-0.370^{***}	-0.490^{***}
R^2	1.00	1.00
Observations	5	5

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

ment/hiring cyclicality to each establishment for the entire observation period. This is well in line with the assumptions in the model where wage cyclicality groups are fixed. However, in the data, wage cyclicalities may change over time, especially because we look at a time span of more than three decades.

In order to check the robustness of results, we define a relative measure that shows how much the wage growth and employment growth (hires rate) deviate from the average in a certain sector of the economy. As visible in Figure 4, establishments' wages and their hires rate or employment, respectively, move in different directions. Thus, we define $\triangle \ln w_{it}^r$ as a relative wage measure

$$\triangle \ln w_{it}^r = \triangle \ln w_{it} - \frac{\sum_{i=1}^{E} \triangle \ln w_{it}}{E}, \tag{24}$$

where E is the number of establishments. The second term on the right hand side of this equation shows the average wage growth in the economy. Thus, $\triangle \ln w_{it}^r$ is the relative wage growth of establishment i compared to all other establishments. 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 define:

$$\triangle \ln n_{it}^r = \triangle \ln n_{it} - \frac{\sum_{i=1}^{E} \triangle \ln n_{it}}{E}, \tag{25}$$

$$\triangle hr_{it}^r = \triangle hr_{it} - \frac{\sum_{i=1}^{E} \triangle hr_{it}}{E}, \tag{26}$$

which all denote establishment-specific employment growth ($\triangle \ln n_{it}^r$) and hires rate change ($\triangle hr_{it}^r$) relative to the mean in the economy.

To test how well these measures work within our model, we estimate the following regression equation based on simulated data:

$$x_{it}^r = \alpha_o + \alpha_1 \triangle \ln w_{it}^r + \varepsilon_{it}, \tag{27}$$

where x_{it}^r may either be $\triangle \ln n_{it}^r$ or $\triangle hr_{it}^r$. In the empirical section, this specification will be enhanced by establishment fixed-effects, time variant observables and time dummies.

Table 4: Relative Measures

Dependent Variable:	$\triangle \ln n_{it}^r$	$\triangle hr_{it}^r$
Estimated coefficient: $\triangle \ln w_{it}^r$	-0.383^{***}	-0.473^{***}
Time Dummies	No	No
R^2	0.51	0.94
Observations	180	180

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

Table 4 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 work well in our simulated data and are quantitatively similar to the comovement based measures. Therefore, we use them for our empirical analysis in the next section.

When we estimate the effects of the degree of procyclicality of wages on the volatility of employment instead, we obtain no statistically significant results (due to the U-shape of results). A volatility-based measure also does not work in the data.

5 Empirical Effects

This section uses the *AWFP* dataset. It analyzes how different wage cyclicalities at the establishment level affect the flow and stock cyclicalities, based on the theoretical measures from Section 4.

5.1 Comovement with the Aggregate State

In Section 2, we have estimated a wage cyclicality measure α_{1i} for each establishment according to the following regression:

$$\Delta \ln w_{it} = \alpha_0 + (\alpha_1 + \alpha_{1i}) \Delta \ln N_t^j + \alpha_2 t + \alpha_3 t^2 + \alpha_4 C_{it} + \mu_i + v_{it}^w. \tag{28}$$

In contrast to the theoretical section, we control for time-invariant heterogeneity, using establishment fixed effects. We further add various control variables (age, tenure, tenure squared, qualification shares, gender, industry sectors, and state dummies). In analogy, we use the same two-step procedure to estimate employment and hires rate cyclicality measures for each establishment (see Appendix A.2 for results):

$$\Delta \ln n_{it} = \beta_0^n + (\beta_1^n + \beta_{1i}^n)\, \Delta \ln N_t^j + \alpha_2 t + \alpha_3 t^2 + \beta_3 C_{it} + \mu_i + v_{it}^n, \tag{29}$$

$$\Delta hr_{it} = \beta_0^{hr} + \left(\beta_1^{hr} + \beta_{1i}^{hr}\right) \Delta \ln N_t^j + \alpha_2 t + \alpha_3 t^2 + \beta_3 C_{it} + \mu_i + v_{it}^{hr}. \tag{30}$$

To obtain an estimate for the quantitative effects of different wage cyclicalities, 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 4):

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

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

Table 5 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. Interestingly, the estimation based on the *AWFP* data delivers the predicted sign for the coefficients. In addition, the order of magnitude is similar to the results from the model. The estimated γ_1^n is somewhat smaller than in the simulated model. By contrast, the estimated γ_1^{hr} is somewhat larger than in the model. 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. This could be the driving source for the slight quantitative difference between model and data.

It is worthwhile discussing whether our empirical results could be driven by establishment-specific revenue cycles. Imagine two establishments with the same wage cyclicality. Imagine that establishment A's revenues and thereby wages go up in a boom, while establishment B's revenues and thereby wages go down in a boom. The way we measure wage cyclicality, we would identify establishment A as procyclical (due to the positive comovement of the wage with the business cycle) and establishment B as countercyclical. Note, however, that in such

Table 5: Effect of Wage Cyclicality on Employment and Hires Rate Cyclicality

Estimated Coefficient	γ_1^n	γ_1^{hr}
Coefficient (t-values)	-0.255^{***}	-0.655^{***}
R^2	0.02	0.01
Observations	3,388,708	3,388,708

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

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 cycles cannot be the key driver of our results.

Overall, our results are well in line with our proposed economic theory. The empirical analysis shows 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 chosen 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, our measures have the disadvantage that they are somewhat inflexible. In our regressions, we assign the same cyclicality measure to an establishment for its entire life span (up to 36 years). Thus, we check for the robustness in the next section using the more flexible relative measures.

5.2 Relative Measures

Against the background of the discussion in the previous paragraph, we use relative measures for wages, employment and the hires rate. The three measures are defined equivalently to Section 4. We repeat them for convenience:

$$\triangle \ln w_{it}^r = \triangle \ln w_{it} - \frac{\sum_{i=1}^{E} \triangle \ln w_{it}}{E}, \tag{33}$$

$$\triangle \ln n_{it}^r = \triangle \ln n_{it} - \frac{\sum_{i=1}^{E} \triangle \ln n_{it}}{E}, \tag{34}$$

$$\triangle hr_{it}^r = \triangle hr_{it} - \frac{\sum_{i=1}^{E} \triangle hr_{it}}{E}, \tag{35}$$

which all describe the relative position of establishment-specific employment growth rate and the hires rate relative to the mean of the sector in the economy.

These specifications are more flexible than the previous approach. If an establishment has an above average wage growth in one period of a boom, but switches to a below average wage growth in the next period of the boom, the relative measures take this into account.

The theoretical model predicts that establishments with a below mean growth rate of wages should have an above mean growth rate of hires and employment. The same holds true for the hires rate. To test these outcomes, we estimate the following regression equation:

$$x_{it}^r = \alpha_o + \alpha_1 \bigtriangleup \ln w_{it}^r + \alpha_2 C_{it} + \sum T + \mu_i + \varepsilon_{it}^{x^r}, \tag{36}$$

where x_{it}^r may either be $\bigtriangleup \ln n_{it}^r$ or $\bigtriangleup hr_{it}^r$. $\sum T$ are time fixed effects and μ_i are establishment fixed effects.

In contrast to the theoretical simulation where establishments are homogenous in all other dimensions except for wage cyclicalities, differences in the data may also be driven by other factors such as skill composition or sectoral effects. Thus, we add a vector of control variables C_{it} (same controls as in Sections 2 and 5.1).

Table 6: Relative Measures — Employment and Hires Rate

Independent Variable:	$\bigtriangleup \ln n_{it}^r$	$\bigtriangleup hr_{it}^r$
Estimated coefficient: $\bigtriangleup \ln w_{it}^r$	-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	0.15	0.26
Observations	39,663,986	39,663,986

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

Table 6 shows that our estimation results are in line with our expectations. Again, the estimations with the *AWFP* do not only deliver the expected signs. In addition, the estimated parameters are remarkably close to the theoretical simulation exercise.

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.

5.3 Illustration and Composition Effects

We complement our regression-based analysis with an illustration for five different quantiles. We classify establishments into five groups according to their estimated coefficient $\hat{\alpha}_{1i}$.[29] Figure 1 in Section 1 shows the time series behavior of the growth rate of the real wage per worker at the establishment level for the most procyclical and the most countercyclical wage quantiles.[30] It is clearly visible that these two groups have an inverse cyclical pattern. Figure 2 in Section 1 shows the average employment growth for these two groups and thereby the flip side of the coin.

Table 7 shows the comovement of the average real wage growth with real GDP growth and employment growth for each of these quantiles. We run the following regression: $\Delta \ln w_{qt} = \alpha_{0q} + \alpha_{1q} \Delta \ln N_t + v_{qt}$, where $\Delta \ln w_{qt}$ corresponds to the growth rate of the average real wage of establishments within the respective quantile q. Table 8 shows the comovement of employment with real GDP for each of these quantiles. As predicted by our theoretical model, the more procyclical the wage, the less procyclical is employment.

Table 7: Comovement of Average Real Wage Growth with Aggregate GDP Growth and Employment Growth in Different Quantiles

Comovement with quantiles ...	1	2	3	4	5
GDP Growth	1.51	0.64	0.16	-0.28	-1.12
Employment Growth ($\Delta \ln N_t$)	1.97	0.77	0.24	-0.39	-1.84

Table 8: Comovement of the Average Establishments' Full-Time Employment with Aggregate GDP Growth and Employment Growth in Different Quantiles

Comovement with quantiles ...	1	2	3	4	5
GDP	0.11	0.44	0.49	0.75	0.86
Employment Growth ($\Delta \ln N_t$)	-0.22	0.31	0.40	0.71	0.83

Note that Figure 1 and Table 7 show the growth rate of the average full-time worker's wage at the establishment level. Could the cyclicality pattern be driven by a composition effect that generates reverse causality in our regressions? Assume that an establishment employs high-skilled workers (with higher wages) and low-skilled workers (with lower wages). Assume

[29] Note that we repeat the estimation of equations (2), (29), and (30) with aggregate employment growth $\Delta \ln N_t$ instead of sectoral employment growth $\Delta \ln N_t^j$. Repeating the exercise on the aggregate level allows us to illustrate the comovement with aggregate variables such as GDP.

[30] For better visibility, we abstain from showing all five groups.

further that the establishment fires the low-skilled workers in a recession. This would lead to a decline of employment and an increase of the wages per full-time worker due to a pure composition effect.[31]

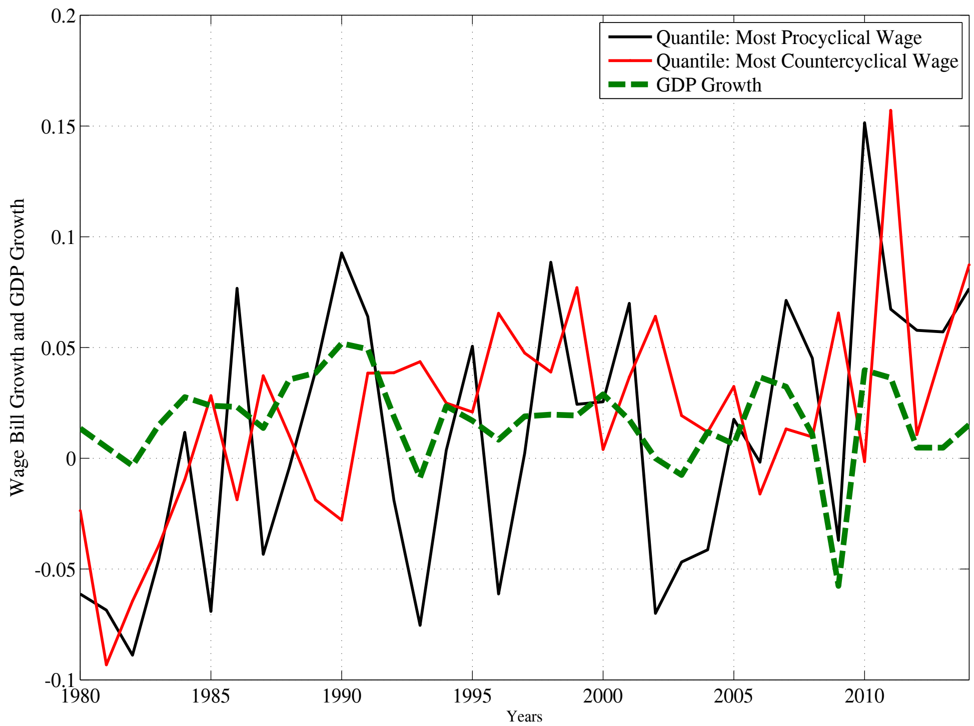

Figure 5: Growth rate of the entire wage bill $(w \cdot n)$ at the establishment level for the most procyclical and the most countercyclical group.

In order to check whether this effect could be the key driving force, Figure 5 shows the growth rate of the wage bill at the establishment level ($w_t n_t$ instead of w_t) for the two groups. Interestingly, the growth rate of the overall 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 average wage per worker. In addition, when we consider all five quantiles, switching from the average wage to the entire wage bill

[31] Assume that low-skilled workers earn w and high-skilled 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-skilled workers in recessions. In this case, the average wage would increase from $1.5 \cdot w$ to $2 \cdot w$ during the recession.

does not change the relative ranking of the cyclicality for these five groups. This shows that the composition effect cannot be the key driver of our results.[32]

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 (in Section 1) and 5, our empirical analysis was based on residual wages. We have controlled for time-invariant heterogeneity and various observables (skill, gender, age, etc.) in the first step. Furthermore, we have used the sector-specific employment growth rate as indicator for the aggregate state of the economy. It can be expected that workforces within establishment are more similar in terms of observable and unobservable characteristics, the more we disaggregate in terms of the sectors. This prevents that our results are driven by heterogeneity across sectors.

Table 9 shows the estimated $\hat{\alpha}_1 + \hat{\alpha}_{1i}$ at different percentiles for equation (29) at two different aggregation levels (national and 31 industry sectors). Although the countercyclicality drops somewhat with the degree of disaggregation, with 31 sectors the 30^{th} percentile has a substantial degree of countercyclicality.

Table 9: Cyclicality at Different Disaggregation Levels

$\hat{\alpha}_1 + \hat{\alpha}_{1i}$	National level	31 Sectors
Cyclicality at 30^{th} percentile	-0.75	-0.56
Cyclicality at 40^{th} percentile	-0.21	-0.15
Cyclicality at 50^{th} percentile	0.20	0.13
Cyclicality at 60^{th} percentile	0.60	0.42
Cyclicality at 70^{th} percentile	1.14	0.84
Observations	3,388,708	3,388,708

Overall, we ensured that composition is not the key driver of our results. There is a substantial heterogeneity of wage formation over the business cycle in Germany, even after controlling for a broad set of observables and independently of the disaggregation. This heterogeneity in wage dynamics generates very heterogeneous labor market dynamics across establishments.

6 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

[32]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 by procyclical.

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.3), our model generates quantitative results that are much closer to the data.

Remember that we have calibrated the wage cyclicality in the model to the numbers from the data. Under our calibration, the model delivers a connection between wage dynamics and hiring/employment dynamics that is quantitatively very close to the data. This puts us in a position to use our model for counterfactual analyzes.

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, $\kappa_1 = ... = \kappa_5 = 0.73$). Table 10 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 more than 50%. 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 10: Counterfactual Exercises

	Calibrated Baseline	All Most Flexible Group	Pure Nash Bargaining
Std. Dev. log(u)	0.059	0.028	0.016
Std. Dev. log(eta)	0.039	0.019	0.011
Std. Dev. log(a)	0.020	0.020	0.020

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 6 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 points to very powerful effects of different wage cyclicalities 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.

Our results are both important from a quantitative model perspective and from an economic policy perspective. From a quantitative model perspective, we are the first to show empirically that different real wage dynamics actually matters for labor market dynamics at the establishment level. From an economic policy perspective, it is important to better understand the driving forces for the strong differences of wage cyclicalities within German industry sectors. Unfortunately, the *AWFP* dataset only contains administrative data (flows, wages, establishment, and average person characteristics), but no information on bargaining regimes or unionization. While there are many papers that analyze the steady state implications of different institutions, there are just a few papers on their effects on wage cyclicalities. Against the background of our results, further research in this direction based on complementary survey datasets can be expected to be very promising.

7 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 and thereby behave in line with traditional Keynesian models.

Our dataset does not allow us to determine the driving force for these differences (e.g. different bargaining regimes or different price setting behavior). However, we have been able to show that differences in 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 to the one of the most procyclical wage group. This reduces aggregate labor market fluctuations by more than 50 percent.

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 Seth and Stüber 2017.) 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 annually and quarterly frequency.[33]

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.[34] 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 adjustments and imputations were conducted at the micro data (see Seth and Stüber 2017).

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 Seth and Stüber 2017). 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 Seth and Stüber 2017):

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

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

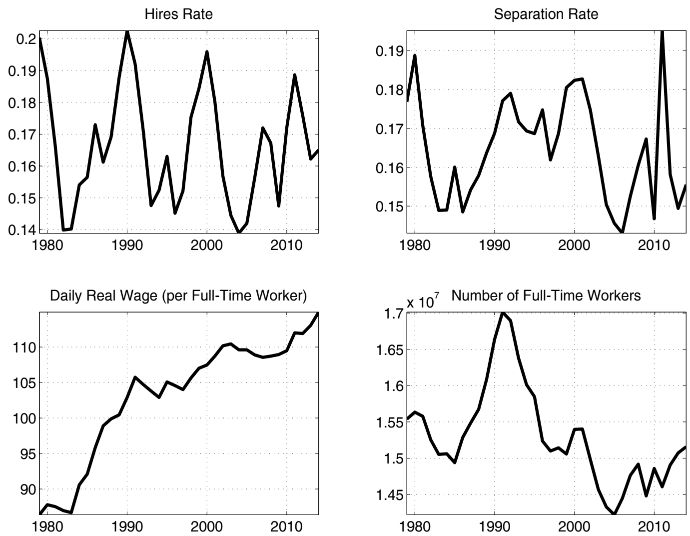

Figure 6: Aggregated time series

We use the *AWFP* at the annually 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 6 shows the time series for the aggregated hires rate, separation rate, daily real wage per full-time worker (in 2010 prices), and the number of full-time workers. Hires and separations rate are calculated as sum of all hires / separations divided by the average number of full-time workers in t and t-1.

A.2 First Stage Regressions

Table 11 shows the estimated coefficients $\hat{\beta}_1^n$ and $\hat{\beta}_1^{hr}$. As expected, both estimated coefficients are positive. A 1% increase of aggregate employment is associated with an increase of establishment-specific employment of 0.47 percent[35] and an increase of the hires rate of 0.15 percentage points.

[35] Note that the estimated coefficient $\hat{\beta}_1^n$ does not necessarily have to be one due to the panel structure of the estimation, where all establishments obtain the same weight independently of the establishment characteristics such as size.

Table 11: Employment and Hires Rate Regression

Dependent Variable:	$\Delta \ln n_{it}$	Δhr_{it}
Estimated coefficient for $\Delta \ln N_t^j$	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	0.13	0.26
Observations	39,663,986	39,663,986

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

A.3 Results for 31 Industry Sectors

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.

Table 12: Relative Measures for Industry Sectors

Estimated coefficient: w_{it}^r	1	2	3	4
Dependent Variable: n_{it}^r	-0.343^{***}	-0.230^{***}	-0.166^{***}	-0.259^{***}
Dependent Variable: hr_{it}^r	-0.316^{***}	-0.301^{***}	-0.156^{***}	-0.211^{***}
N	952,406	9,287	10,056	78,024
Estimated coefficient: w_{it}^r	5	6	7	8
Dependent Variable: n_{it}^r	-0.422^{***}	-0.410^{***}	-0.423^{***}	-0.517^{***}
Dependent Variable: hr_{it}^r	-0.478^{***}	-0.413^{***}	-0.462^{***}	-0.595^{***}
N	1,193,155	231,423	42,938	336,055
Estimated coefficient: w_{it}^r	9	10	11	12
Dependent Variable: n_{it}^r	-0.337^{***}	-0.177^{***}	-0.275^{***}	-0.383^{***}
Dependent Variable: hr_{it}^r	-0.420^{***}	-0.480^{***}	-0.356^{***}	-0.388^{***}
N	530,550	5,393	116,346	215,761
Estimated coefficient: w_{it}^r	13	14	15	16
Dependent Variable: n_{it}^r	-0.325^{***}	-0.397^{***}	-0.358^{***}	-0.361^{***}
Dependent Variable: hr_{it}^r	-0.333^{***}	-0.488^{***}	-0.458^{***}	-0.469^{***}
N	238,868	1,011,584	593,620	638,830
Estimated coefficient: w_{it}^r	17	18	19	20
Dependent Variable: n_{it}^r	-0.383^{***}	-0.499^{***}	-0.208^{***}	-0.383^{***}
Dependent Variable: hr_{it}^r	-0.501^{***}	-0.586^{***}	-0.439^{***}	-0.476^{***}
N	100,904	423,704	114,328	4,400,489
Estimated coefficient: w_{it}^r	21	22	23	24
Dependent Variable: n_{it}^r	-0.374^{***}	-0.282^{***}	-0.262^{***}	-0.269^{***}
Dependent Variable: hr_{it}^r	-0.507^{***}	-0.206^{***}	-0.280^{***}	-0.463^{***}
N	9,520,423	2,329,402	1,863,912	982,115
Estimated coefficient: w_{it}^r	25	26	27	28
Dependent Variable: n_{it}^r	-0.323^{***}	-0.545^{***}	-0.487^{***}	-0.458^{***}
Dependent Variable: hr_{it}^r	-0.473^{***}	-0.766^{***}	-0.680^{***}	-0.674^{***}
N	5,057,100	744,389	939,821	3,938,500
Estimated coefficient: w_{it}^r	29	30	31	all
Dependent Variable: n_{it}^r	-0.428^{***}	-0.128^{***}	-0.097^{***}	-0.369^{***}
Dependent Variable: hr_{it}^r	-0.571^{***}	-0.133^{***}	-0.364^{***}	-0.484^{***}
N	2,519,834	495,931	28,838	39,663,986

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 7). 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.[36]

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

[36] It is possible to link the AWFP to the IAB Establishment Panel, which is a survey among up to 16,000 establishments that contains institutional details. By doing so, we lose the vast majority of our more than 3 million establishments. However, preliminary results show that the (remaining) establishments with the strongest pro- and countercyclicality over the business cycle are more likely not being part of a collective bargaining agreement and not having a works' council. This is in line with our result that the largest establishments show less heterogeneous wage cyclicalities and our hypothesis that this is due to collective bargaining and works' councils.

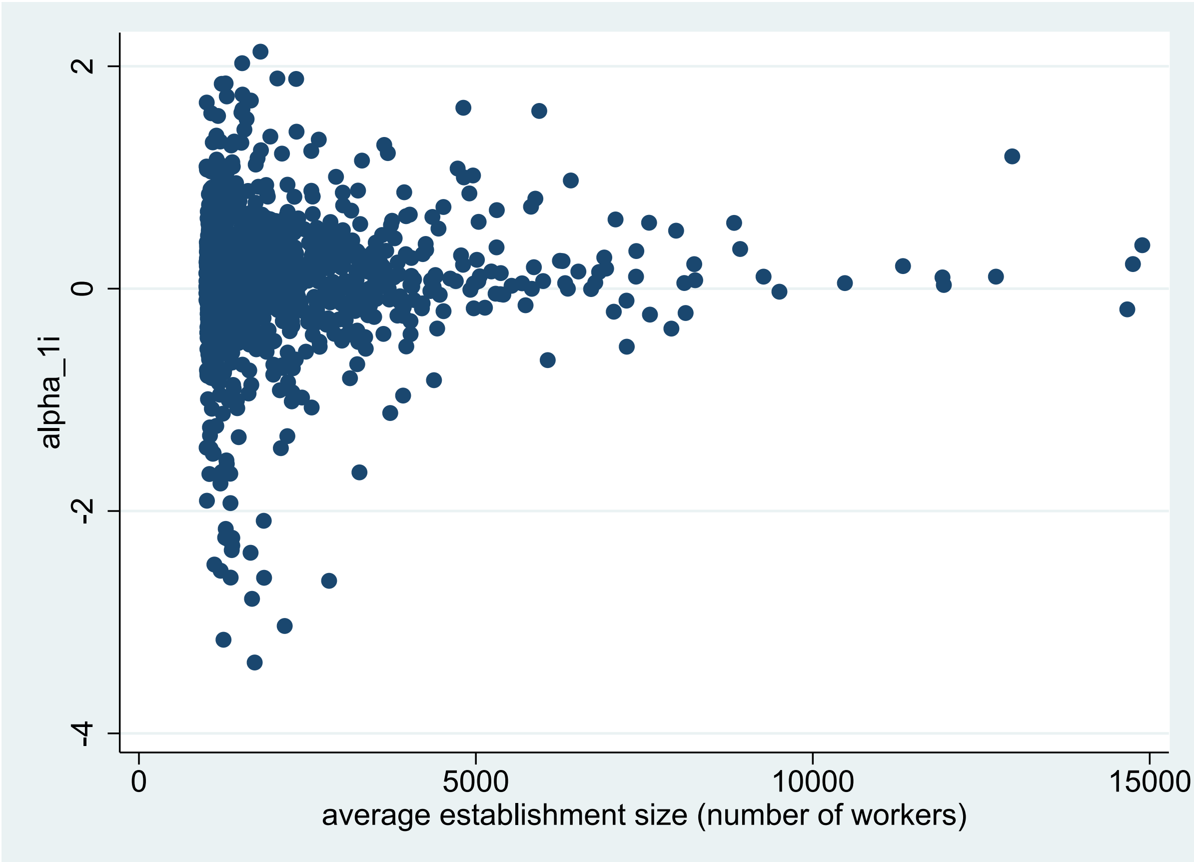

Figure 7: The picture show the α_{1i} for establishments above 1000 full-time workers. The first and 99^{th} percentile of the wage cyclicality measure it omitted for better visibility. The 99^{th} percentile for establishments above 1000 full-time workers is omitted due to confidentiality reasons.

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 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.[37] For comparability reasons, we estimate the following regression:

$$\ln w_{it} = \alpha_0 + \alpha_1 u_t + \alpha_2 t + \alpha_3 t^2 + \alpha_4 C_{it} + \mu_i + \varepsilon_{it}^w, \tag{37}$$

where w_{it} is the real average daily wage of all matches 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 13: Weighted Wage Regression

Dependent Variable:	w_{it}
Estimated coefficient: u_t	-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	0.94
Observations	39,663,986

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 13) 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.[38]

[37] 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.

[38] His estimated coefficient for newly hired workers is -1.33. This means that the incremental effect is

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 Model Derivation

B.2.1 Establishment Maximization

Establishments maximize profits

$$E_0 \left\{ \sum_{t=0}^{\infty} \delta^t \left[a_t n_{it} - w_t^I (1-\phi) n_{i,t-1} - c_{it} s_t \eta(\tilde{\varepsilon}_{it}) \left(\frac{\bar{w}^E(\tilde{\varepsilon}_{it})}{\eta(\tilde{\varepsilon}_{it})} + \frac{H(\tilde{\varepsilon}_{it})}{\eta(\tilde{\varepsilon}_{it})} + h \right) \right] \right\}, \tag{38}$$

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

$$n_{it} = (1-\phi) n_{it-1} + c_{it} s_t \eta(\tilde{\varepsilon}_{it}). \tag{39}$$

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}:

$$n_{it} = (1-\phi) n_{it-1} + c_{it} s_t \eta(\tilde{\varepsilon}_{it}), \tag{40}$$

$$-c_{it} s_t \left(\frac{\partial \bar{w}^E(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} + \frac{\partial H(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} + \frac{\partial \eta(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} h \right) + \lambda_t c_{it} s_t \frac{\partial \eta(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} = 0, \tag{41}$$

$$a_t - \lambda_t + (1-\phi) \delta E_t \left(\lambda_{t+1} - w_{t+1}^I \right) = 0. \tag{42}$$

Isolating the Lagrange multiplier in equation (41) yields:

$$\lambda_t = \frac{\frac{\partial \bar{w}^E(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} + \frac{\partial H(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} + \frac{\partial \eta(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}} h}{\frac{\partial \eta(\tilde{\varepsilon}_{it})}{\partial \tilde{\varepsilon}_{it}}}. \tag{43}$$

Keep in mind the three definitions:

economically small in Germany.

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

$$\bar{w}^E(\tilde{\varepsilon}_{it}) = \int_{-\infty}^{\tilde{\varepsilon}_{it}} w_t^E(\varepsilon) f(\varepsilon) d\varepsilon, \tag{45}$$

$$H(\tilde{\varepsilon}_{it}) = \int_{-\infty}^{\tilde{\varepsilon}_{it}} \varepsilon f(\varepsilon) d\varepsilon. \tag{46}$$

This allows us to simplify equation (43), using the Fundamental Theorem of Calculus:

$$\begin{aligned} \lambda_t &= \frac{w^E(\tilde{\varepsilon}_{it}) f(\tilde{\varepsilon}_{it}) + \tilde{\varepsilon}_{it} f(\tilde{\varepsilon}_{it}) + f(\tilde{\varepsilon}_{it}) h}{f(\tilde{\varepsilon}_{it})} && (47) \\ &= w^E(\tilde{\varepsilon}_{it}) + \tilde{\varepsilon}_{it} + h. && (48) \end{aligned}$$

When we substitute this Lagrange multiplier into equation (42), we obtain the selection condition:

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

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

$$J_{it} = a_t - w_{it}^I + E_t \delta \left(1-\phi\right) J_{it+1}, \tag{50}$$

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

$$\tilde{\varepsilon}_{it} = a_t - w^E(\tilde{\varepsilon}_{it}) - h + E_t \delta \left(1-\phi\right) J_{it+1}. \tag{51}$$

B.2.2 Derivation of the Nash Wage

The Nash product is

$$\Lambda_t = \left(W_t - U_t\right)^{\nu} \left(J_t\right)^{1-\nu}, \tag{52}$$

with

$$W_t - U_t = w_t - b + E_t \delta \left(1 - \phi - \eta_{t+1}\right) \left(W_{t+1} - U_{t+1}\right), \tag{53}$$

and

$$J_t = a_t - w_t + E_t \delta (1-\phi) J_{t+1}. \tag{54}$$

Maximization of the Nash product with respect to the wage yields

$$\frac{\partial \Lambda_t}{\partial w_t} = \nu J_t \frac{\partial W_t}{\partial w_t} + (1-\nu)(W_t - U_t) \frac{\partial J_t}{\partial w_t} = 0, \tag{55}$$

$$\nu J_t = (1-\nu)(W_t - U_t). \tag{56}$$

After substitution:

$$\nu (a_t - w_t + E_t \delta (1-\phi) J_{t+1}) = (1-\nu)[w_t - b + E_t \delta (1-\phi-\eta_{t+1})(W_{t+1} - U_{t+1})]. \tag{57}$$

Using equation (56):

$$\nu (a_t - w_t + E_t \delta (1-\phi) J_{t+1}) = (1-\nu)\left[w_t - b + E_t \delta (1-\phi-\eta_{t+1}) \frac{\nu}{(1-\nu)} J_{t+1}\right], \tag{58}$$

$$w_t = \nu (a_t + \delta \eta_{t+1} J_{t+1}) + (1-\nu) b. \tag{59}$$

B.3 Search and Matching with Decreasing Returns

In Section 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.[39] 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.3.1 Model Derivation

Establishments maximize the following intertemporal profit condition

$$E_0 \sum_{t=0}^{\infty} \left(a_t n_{it}^{\alpha} - w_{it} n_{it} - \chi v_{it}\right), \tag{60}$$

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:

$$n_{it} = (1-\phi)\, n_{it-1} + v_{it} q\left(\theta_t\right). \tag{61}$$

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

$$\left(\alpha a_t n_{it}^{\alpha-1} - w_{it}\right) - \lambda_{it} + \beta E_t \lambda_{it+1} (1-\phi) = 0, \tag{62}$$

$$-\chi + \lambda_{it} q\left(\theta_t\right) = 0, \tag{63}$$

where λ is the Lagrange multiplier.

[39] The standard search and matching's job-creation condition is $\frac{\kappa}{q(\theta_t)} = a_t - w_t + E_t \delta (1-\phi) \frac{\kappa}{q(\theta_{t+1})}$. 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:

$$\frac{\chi}{q(\theta_t)} = \left(\alpha a_t n_{it}^{\alpha-1} - w_{it}\right) + \beta E_t (1-\phi) \frac{\chi}{q(\theta_{t+1})}. \tag{64}$$

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

$$w_t = \kappa_i \nu a_t + (1-\kappa_i)\bar{w}, \tag{65}$$

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

$$v_t = \sum_{i=1}^{E} v_{it}, \tag{66}$$

$$n_t = \sum_{i=1}^{E} n_{it}, \tag{67}$$

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.

$$n_t = 1 - u_t. \tag{68}$$

B.3.2 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 $\kappa_i = [0.730, 0.285, 0.090, -0.145, -0.678]$.

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.3.3 Numerical Results

Based on the search and matching model with decreasing returns, we run the same regressions, as in Section 4.3. Table 14 shows the results for the covariance-based measures, namely:

$$\gamma_i^x = \alpha_0^x + \alpha_1^x \beta_i + \varepsilon_i^{\gamma^x}. \tag{69}$$

Table 14: Effect of Wage Cyclicality on Employment and Hires Cyclicality

Estimated Coefficient	γ_1^n	γ_1^{hr}
Coefficients	-3.210^{***}	-3.355^{***}
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 15, the estimated coefficients are about several times larger than in our main part.

$$x_{it}^r = \alpha_o + \alpha_1 w_{it}^r + \varepsilon_{it}^{x^r}, \tag{70}$$

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.

B.3.4 Some Analytics

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

Table 15: Relative Measures

Dependent Variable:	$\triangle \ln n_{it}^r$	$\triangle hr_{it}^r$
Estimated coefficient: $\triangle \ln w_{it}^r$	-2.233^{***}	-1.839^{***}
Time Dummies	No	No
R^2	0.48	0.15
Observations	180	180

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

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

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 15) 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 15 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.