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DISCUSSION PAPER SERIES

IZA DP No. 16911

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Rodrigo Barrela
Nova School of Business and Economics

Eduardo Costa
CEGIST - Centre for Management Studies at Instituto Superior Técnico

Pedro Portugal
Banco de Portugal and IZA

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

On the Asymmetrical Sensitivity of the Distribution of Real Wages to Business Cycle Fluctuations*

We provide evidence showing, for the first time, that the sensitivity of real wages to the business cycle is much stronger for higher-wage workers than for lower-wage workers. Using matched employer-employee data for Portugal covering the period 1986-2021, we show that a one percentage point increase in the unemployment rate is associated with a decrease in real hourly wages of workers in the 90th percentile of the conditional wage distribution of around 1.3%, contrasted with 0.8% for those in the 10th percentile. This gap is even larger for newly hired workers – the estimates for the 90th percentile workers are double of those in the bottom decile. This pattern also holds for bargained wages and the wage cushion. These results can be explained by composition effects and heterogeneous sensitivities of firms and collective bargaining agreements (CBAs) to the cycle. First, the considerable gap in new hires' cyclicality arises mostly from match quality fluctuations over the business cycle and is sharply attenuated after we account for job match composition. Second, by estimating cyclicality coefficients for each firm/CBA, we find that firms and CBAs tend to provide a lower degree of insurance against aggregate cyclical fluctuations to higher paid individuals. These findings provide strong empirical evidence on the role of business cycles as amplifiers of inequality trends.

JEL Classification: E24, E32, J64

Keywords: wage cyclicality, quantile regressions, match quality, collective bargaining agreements

Corresponding author:
Pedro Portugal
Banco de Portugal
Av. Almirante Reis 71
1150-012 Lisboa
Portugal
E-mail: pportugal@bportugal.pt

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1 Introduction

The question of wage cyclicality is a long-contested issue (Abraham and Haltiwanger, 1995). While earlier evidence based on aggregate data showed conflicting results regarding the impact of the business cycle on wages (Bodkin, 1969; Sumner and Silver, 1989), studies that use individual-level longitudinal data generally conclude that real wages are procyclical, falling in recessions and rising during expansions (Bils, 1985; Solon et al., 1994; Carneiro et al., 2012). These studies also show that the sensitivity of wages to the cycle is stronger for job movers, a claim that helped to reconcile the canonical search and matching model with the evidence on aggregate unemployment volatility (Pissarides, 2009). The canonical interpretation of this relationship, however, has recently been questioned by Gertler et al. (2020).

These findings are instrumental to inform the discussions on business cycle and unemployment fluctuations theory. However, a key methodological limitation in these empirical approaches is the sole consideration of the impact of the cycle on average wages, which is insufficient if one wants to understand asymmetric dynamics of wages and employment. The present paper revisits the topic of real wage cyclicality by characterizing the impact of the business cycle along the conditional real wage distribution. Using matched employer-employee data for Portugal, we provide what we believe is compelling microeconometric evidence showing, for the first time, that the sensitivity of real wages to the business cycle is much stronger for high-wage workers than for low-wage workers. This evidence supports models with worker and firm heterogeneity (Robin, 2011; Lise and Robin, 2017), or asymmetric search and matching frameworks (Ravenna and Walsh, 2012; Mueller, 2017; Dolado et al., 2021). Furthermore, very few studies have tackled the question of how wage-setting institutions influence wage cyclicality. This paper bridges this gap by studying how minimum and collectively bargained wages react to the business cycle and how this translates into the cyclicality of observed wages.

First, we consider how wage cyclicality differs across the conditional real hourly wage distribution. We use a rich matched employer-employee administrative dataset from Portugal covering the universe of private sector wage earners during the period 1986-2021 to estimate wage cyclicality parameters for the 10^{th}, 50^{th}, and 90^{th} percentiles of the distribution. For this purpose we employ conventional conditional quantile regressions (Koenker and Bassett Jr., 1978) and method of moments quantile regressions (Machado and Silva, 2019), the latter of which allows the inclusion of high-dimensional fixed effects to control for composition effects stemming from worker, firm, and match unobserved time-invariant heterogeneity. According to our estimates, a one percentage point fall in the unemployment rate leads to a 0.8 percent real wage increase for workers in the 10th percentile of the (conditional) wage distribution whereas it generates a 1.3 percent real wage increase for workers in the 90th percentile. If we consider newly hired workers, the semi-elasticities are -1% for workers in the 10th percentile and -2% for workers in the 90th percentile. An important implication of this asymmetrical reaction is that economic expansions tend to exacerbate wage inequality whereas economic contractions tend to attenuate it.

To investigate the sources of real wage cyclicality we explore two new routes. First, we look into the cyclicality of minimum wages and bargained wages. As in other Southern European countries, the wage-setting process in Portugal is multi-staged, characterized by the prevalence of a national minimum wage decreed by the government and collectively bargained agreements at the sector level that usually define wage floors on top of the minimum wage. Thus, by building on the decomposition of total wages of Cardoso and Portugal (2005) and Card and Cardoso (2022), we explore how the minimum wage and bargained wages evolve with the cycle and how their sensitivity reflects the observed dynamics of total hourly wages. We provide empirical evidence supporting the notion that both real minimum wages and real bargained wages are procyclical. Observed real hourly wages, nevertheless, still exhibit considerable asymmetrical responses to changes in the unemployment rates after controlling for the influence of minimum wages and bargained wages in the formation of wages.

Second, we account for composition bias by including worker and firm fixed effects in the wage regression models. It has been shown that low wage workers bear the brunt of recessions by suffering greater drops in employment than higher wage workers (Bils et al., 2012) and failing to account for this generates a countercyclical bias in estimated cyclicality parameters. The inclusion of multiple high-dimensional fixed effects, which is only possible with the method of moments quantile regression estimator, is crucial in this setting. We confirm that the employment losses of low wage workers during economic recessions tend to downwardly bias the cyclicality of real wages. Be that as it may, the asymmetrical reaction on the part of high and low wage workers remains after the inclusion of minimum wages, bargained wages, and the worker and firm fixed effects in the wage equation.

Another novel feature of our empirical approach is that we compute a direct measure of the job match quality. This measure is constructed using a high-dimensional regression model in which the job match fixed effect is decomposed into three components: the worker fixed effect, the firm fixed effect, and the job match quality fixed effect. Critically, we calculate the job match quality fixed effect assuming it to be orthogonal to the worker and firm fixed effects. A noteworthy result of this decomposition is that once we account for job match quality, there is no longer a distinct wage reaction for job stayers and new hires, a result that vindicates the claim of Gertler et al. (2020) and explains the striking gap in the cyclicality coefficients between workers in the top and bottom deciles.

Finally, we address the possibility of heterogeneous wage responses to aggregate economic fluctuations. First, after restricting the sample to larger and more perennial firms, we estimate firm-specific semi-elasticities and verify, with some surprise, that close to one-quarter of the firms exhibit a countercyclical behavior. The remaining firms display procyclical responses to changes in the unemployment rate, driving the (negative) sign of aggregate semi-elasticity. Second, we consider the likelihood that real wages in distinct collective wage agreements, which largely identify different industries, may respond differently to business cycle fluctuations. Here, we uncover, again, widespread heterogeneity in the responses to the business cycle. Furthermore, we show that conditional on worker and firm unobserved heterogeneity, firms and CBAs tend to react more procyclically regarding the wages of workers in the top decile of the wage distribution vis-à-vis those on the bottom decile. This implies a lower degree of insurance against aggregate fluctuations for higher-paid workers.

In a context in which labor demand for higher wage workers increases during expansions, complementarities between labor skills and capital, as in Lindquist (2004) and Dolado et al. (2021), may underlie the dynamics implied by our results, to the extent that higher wages reflect better labor skills. This could be further exacerbated if higher wage workers face fewer frictions in the labor market (lower separation rates, better match efficiency), as postulated by Dolado and co-authors. Our results can also be rationalized by a sequential auctions search and matching model in which match productivity is a function of worker ability and aggregate productivity, as in Robin (2011). In this case, a positive aggregate shock increases the value of matches with high-ability workers, which also leads to wage increases from poaching and promotions. This creates a stronger impact of the shock on the wages of those on the top of the wage distribution versus remaining workers.

Related Literature Our work contributes to several strands of research. First, we contribute to the literature on the estimation of measures of real wage cyclicality using worker-level longitudinal data. There is a large amount of microeconometric evidence supporting the notion that real wages are procyclical, especially those of new hires (Bils, 1985; Shin, 1994; Solon et al., 1994; Carneiro et al., 2012; Martins et al., 2012; Stüber, 2017). As argued in Pissarides (2009), these results confirm the idea that canonical models of search and matching (Mortensen and Pissarides, 1994; Pissarides, 2000) can be reconciled with aggregate unemployment volatility. The argument in Pissarides (2009) is that job creation is influenced specifically by wages of new matches, and models that explain unemployment volatility should thus preserve the fluctuations of these workers' wages. Recent evidence suggests that the estimated higher cyclicality of new hires stems from composition effects due to cyclical job movements (Gertler et al., 2020; Bauer and Lochner, 2020; Grigsby et al., 2021; Black and Figueiredo, 2022). The idea follows from the arguments in Gertler and Trigari (2009), according to which during a recession workers may move to lower-paying jobs that do not match well with their skills, creating artificial estimates of cyclicality in the wages of new hires. We contribute to this discussion by first presenting new estimates for real wage cyclicality that not only consider the impact on the average but also leverage the full distribution of hourly wages to infer the different impacts of the cycle on workers with distinct levels of labor earnings. We also find new evidence corroborating the hypothesis that new hires' wages are no more cyclical than stayers' due to match-quality effects, as we are able to disentangle the impact of worker, firm, and match-quality time-invariant unobserved heterogeneity on the cycle estimates.

Our focus on the non-linear effects of the cycle also connects to a closely related strand of research that investigates the heterogeneity of wage cyclicality across workers and firms. Early papers examining U.S. wage cyclicality using longitudinal data present scarce evidence on wage cyclicality heterogeneity across workers' characteristics (Bils, 1985; Keane and Prasad, 1993; Solon et al., 1994). However, Ziliak et al. (1999) analyze the reaction of wages to local and aggregate fluctuations, and when interacting these with workers' characteristics, find significant cyclicality heterogeneity across skill (education), among others. More recently, Martins (2007) finds that younger workers and job switchers are particularly affected during downturns. We also complement our analysis with firm-side heterogeneity, investigating how firms react differently to the cycle. Merkl and Stüber (2017) are among the first to look at establishment-level dynamics by estimating individual coefficients for each establishment. They find that although most establishments behave procyclically, about 40 percent present countercyclical estimates. We present a different estimation method based on the interaction of the cycle variable with firm or collective bargaining agreement effects, finding that close to 26 percent of firms and 21 percent of bargaining agreements show countercyclical wage coefficients. Furthermore, we uncover a sorting mechanism in which higher wage workers tend to work for firms/agreements with more procyclical behavior.

Furthermore, our evidence is also connected to the recent wave of papers investigating the correlation between aggregate shocks and inequality. In an influential paper, Guvenen et al. (2014) unveil the behavior of labor income throughout the business cycle by analyzing the distribution of income risk. They find that workers in the 10^{th} percentile of the earnings distribution suffer more from recessions than those in the 90^{th}, a result reciprocal to ours. Borrowing from a DSGE with capital-skill complementarity, Dolado et al. (2021) show how an expansionary monetary policy shock leads to an increase in the skill wage premium due to an amplification effect on skilled labor demand, a result that the authors also confirm empirically. Other models such as those of Kaplan et al. (2018), Bayer et al.

(2020), and Gornemann et al. (2021) use recently popularized Heterogeneous Agents New Keynesian models to study the impact of monetary policy and other shocks on wealth and income inequality. By providing empirical evidence on the procyclicality of inequality, we are contributing to further motivate the use of these types of models.

Lastly, we contribute to the literature on the impact of institutions on wage dynamics. Very few papers have looked into the role of institutions on wage cyclicality, with most of them focusing on estimating different reactions to the cycle depending on the type of institutional relations prevalent (Devereux and Hart, 2006; Holden and Wulfsberg, 2008; Knoppik and Beissinger, 2009; Gartner et al., 2013). We present a novel approach based on the wage decomposition in Cardoso and Portugal (2005) and Card and Cardoso (2022), which leverages the multi-staged wage-setting process in Portugal. This allows us to partition the impact of the cycle into the contributions from the national minimum wage, the bargained wage, and the wage cushion, shedding light on the weight of the wage setting institutions determining wages and wage cyclicality.

Layout The paper unfolds as follows. The next section describes wage-setting mechanisms in Portugal. Section 3 introduces the data and provides details on the sample and its characteristics, and Section 4 discusses the empirical methodology. Section 5 presents the main results. Section 6 concludes.

2 Wage-setting in Portugal

In the private sector, wages in Portugal are determined in three main stages. First, a national minimum wage is set by the government. As of 2023, close to one-quarter of wage earners in the country earn this amount (760€, about 52% of the national average).

Second, collective bargaining agreements (CBAs) are negotiated between employers and trade unions. These agreements are formally recognized and considered valid sources of labor law. Conventional bargaining results from direct negotiations between employers' and workers' representatives. These can be set at the industry, group of firms, or individual firm level, remaining in place until a new agreement is settled (although most have a nominal duration of one year, as per Card and Cardoso, 2022).

CBAs determine work conditions and practices, in particular wage floors for each professional category, overtime pay, and the normal duration of work. Table 1 illustrates an example of the reigning agreement for the hotels, restaurants and accommodation sector. According to the Labor Law, CBAs should cover only unionized workers. However, due to extension mechanisms - either voluntary or government-led - the agreements are extended to the respective entire workforce regardless of union membership. As a consequence, Portugal has levels of CBA coverage close to 85% of the workforce (Reis and de Almeida Vilares, 2022), despite union density being low - close to 10 percent. A large number of agreements combined with a high degree of granularity in the wage tables imply that, in a given year, there are more than 30,000 job titles and 5,000 wage floors settled (Martins, 2021; Card and Cardoso, 2022). Note that CBAs are set under the national legal minimum wage system. Thus, the bargained wage floors apply only if they are set above the national minimum wage, which can be updated on a yearly basis.

Lastly, firms decide whether to pay the bargained wage floors or to pay some sort of cushion on top. Regardless of the bargained wage floor, firms are free to pay higher wages. Cardoso and Portugal (2005) define this difference between the actual wage and the bargained wage floor as the "wage cushion". Section 3.2 provides further details.

3 Data

3.1 The Quadros de Pessoal Data Set

We use Relatório Único/Quadros de Pessoal (QP, Lists of Personnel), a unique matched employer-employee administrative dataset sourced from the Ministry of Employment and Social Security. This is a mandatory survey filled in by every establishment having at least a single wage-earner, containing information on Portuguese workers and firms. The survey is responded to in October of each year (March prior to 1993). Currently, this dataset contains annual information on more than 700,000 firms and about seven million workers. The years considered are 1986-2021, with gaps for 1990 and 2001.

Since this is a compulsory annual survey, this dataset gathers information from virtually all private firms in the manufacturing and services sectors, which reduces the severity of typical problems with survey panel data sets such as panel attrition. The completeness and reliability of this dataset are guaranteed by the requirement that the data are publicly available at the place of work. This ensures that measurement error, missing values, and miss-classification errors are minimized for the reported variables. It does not, however, include civil servants, self-employed, or any information about the unemployed. Its coverage of the agricultural sector is also lacking due to the high prevalence of self-employed and informal work.

Each firm entering the database is assigned a unique identifying number, allowing researchers to track the same firm over time, as well as to identify firms that enter or exit the market in a given year. The dataset contains information about the firm's industry, sales, employment, location, ownership, and legal basis.

Each worker is also identified with a unique number which allows the researcher to follow her throughout the database. Data on workers includes monthly wages (including base, overtime, and supplements), hours worked (regular and overtime), demographics (age, gender, education, nationality), occupation, and starting date with the firm. This also allows us to identify the worker-firm pair. Furthermore, it includes information on whether the worker is covered by a CBA, and, if so, the job title as defined by the CBA. This job title is narrower than the reported occupation, reflecting not only the type of work but also experience, task complexity, skill level, and firm hierarchy. QP does not include wage floors.

A set of restrictions was implemented to conduct the analysis. First, the final sample was restricted to full-time workers aged 18-64 who earn at least 80% of the national minimum wage. In the Portuguese labor market, apprenticeships may collect 80 percent of the minimum wage. Second, only workers in the services and manufacturing sectors were included, implying the exclusion of those working in agriculture, fisheries, energy, and extraction sectors. Third, we exclude workers not covered by a CBA. On top of this, to reduce measurement error in our definition of wage floors, we consider only job titles held by at least 10 workers.

Overall, the final sample includes 52,342,436 worker-firm observations, corresponding to 7,225,931 workers and 765,618 firms.

3.2 Bargained Wage Floors and Wage Cushions

We are interested in evaluating the cyclicality of different measures of wages. As mentioned above, wage components in QP are precise and detailed, with information on base pay, overtime, and supplements. Our main measure of wages is the log of real total hourly wages, which can be constructed by dividing total monthly wages (the sum of all wage components) by monthly hours worked, adjusted for the Portuguese CPI. On top of this measure, we also decompose total wages into the components derived from the wage-setting process, namely the bargained wage floors and wage cushions.

Bargained wage floors are calculated as the modal base wage in a given job title $\times$ year. The assumption is that a large number of workers in each job title earns the minimum contracted wage. As shown in Cardoso and Portugal (2005), this measure works remarkably well in capturing actual wage floors. When comparing the mode in each worker category within a CBA with the actual floor as posted in official sources for a selected number of industries, the authors find a correlation between 77% to 99%. In fact, the authors claim that "for a very high proportion of the working population, the contractual wage set by collective bargaining is exactly equal to the mode of the distribution of the base wage".

Considering the availability of data on actual wages and the estimated bargained wage floors, one can define wage cushions as follows:

$$\text{cushion}_{ifjt} = log(\text{actual}_{ifjt}) - log(\text{bargained})_{ifjt} \tag{1}$$

where i, f, j, t define, respectively, individual, firm, job title, and year.

Our measures of wage floors and cushions are not free from measurement error. If, for a specific category, a large number of firms with generous remuneration policies pay wages above negotiated floors, then the mode will overestimate actual floors. We believe, nonetheless, that this issue is not a notable problem in our results. First, if the measurement error is derived from firm, job title, or CBA-specific time-invariant conditions, then the introduction of fixed effects should address the problem. Second, the wage floor distribution (and its dynamics) follow closely the results of Card and Cardoso (2022) (CC). In their paper, the authors retrieve wage floors from official sources for more than 21,000 categories, thus removing any issues in measurement. When contrasting Figures 2 and 3 from CC with our Figures 1 and 2, we find no significant disparities.

Figures 3 and 4 show the wage cushion distribution obtained from Quadros de Pessoal when defining the bargained wage as the modal monthly wage in a given year × job title cell. It can be seen that most firms pay a positive cushion on top of the collectively negotiated base wage, due simply to either a premium on the base wage or to wage supplements, such as meal subsidies. On average, firms pay a 12% or 37% premium over the base wage, depending on whether we include wage supplements or not.

Figure 1 shows the evolution of bargained wages (relative to the minimum wage) and wage cushions from 1986 until 2021. Relative floors remained fairly stable until 2006, after which they sharply declined, going from close to 40% to 20%. As is well documented, the financial crisis was an especially turbulent period for the Portuguese economy, with the government having to request a bailout plan from the so-called *Troika* - the European Central Bank, the European Commission, and the International Monetary Fund. During this period the country suffered from an unprecedented rate of job destruction and generalized wage freezes (Carneiro et al., 2014), with the unemployment rate reaching as high as 17.7% in 2012 (Figure 5). As a consequence of this turbulence, collectively bargained wages were also frozen, leading to a period of adjustment with falling real wages (Figure 6). At the same time, the period from 2006 onward encompassed a rapid growth in the national minimum wage, with a small *interregnum* on 2011-2014. This rapid rise in the mandatory minimum wage combined with the generalized slowdown in bargained wages led to the documented fall in relative wage floors after 2006.

3.3 Summary Statistics

Table 2 shows summary statistics for wages, employment, demographics, education, and firm size. In our sample, 42% are females, 10% have a college degree, and 16% are new hires. The average worker is 38 years old, earning a monthly real wage of 259 Euros (1986 prices). The average wage cushions are of 37% (including supplements and overtime pay) or 14% (excluding supplements and overtime pay).

4 Methodology

We begin by considering a conventional regression model in which real wages respond to lagged unemployment rates. In line with previous work, we admit that the wages of newly hired workers may respond differently to the business cycle. Our benchmark wage regression model can be written as:

$$w_{(i,t)} = \alpha_1 UR_{(t-1)} + \alpha_2 t + \alpha_3 t^2 + (\gamma_0 + \gamma_1 UR_{(t-1)} + \gamma_2 t + \gamma_3 t^2) \times \mathbb{1}\{H = 1\} + \boldsymbol{x}_{(i,t)}\beta + \epsilon_{(i,t)} \tag{2}$$

where $w_{(i,t)}$ denotes the (log) real hourly wage of worker i at year t. $UR_{(t-1)}$ is the unemployment rate in the previous year and the presence of t and t^2 enable a quadratic time trend. The operator $\mathbb{1}\{H = 1\}$ serves to identify a newly-hired worker. $\boldsymbol{x}_{(i,t)}$ represents a vector of other explanatory variables (a quadratic term on age and tenure, schooling, and a gender dummy); and $\epsilon_{(i,t)}$ is an error term, assumed to be orthogonal to the explanatory variables.

We will also consider the role of worker and firm heterogeneity to address the possibility that compositional changes may occur over the business cycle.

$$w_{(i,t)} = \alpha_1 UR_{(t-1)} + \alpha_2 t + \alpha_3 t^2 + (\gamma_0 + \gamma_1 UR_{(t-1)} + \gamma_2 t + \gamma_3 t^2) \times \mathbb{1}\{H = 1\} + \boldsymbol{x}_{(i,t)}\beta + \theta_i + \psi_{f(i,t)} + \epsilon_{(i,t)}, \tag{3}$$

where θ_i denotes the worker fixed effect and $\psi_{f(i,t)}$ the firm fixed effect.

Furthermore, we take advantage of conditional quantile regression methods to explore the impact of the business cycle, as measured by fluctuations in the unemployment rate, over the entire wage distribution. We start by extending the linear regression framework to the conditional quantile setup:

$$Q_w(\tau | UR_{(t-1)}, H, \boldsymbol{x_{it}}) = \alpha_1(\tau) UR_{(t-1)} + \alpha_2(\tau) t + \alpha_3(\tau) t^2 + (\gamma_0(\tau) + \gamma_1(\tau) UR_{(t-1)} + \gamma_2(\tau) t + \gamma_3(\tau) t^2) \times \mathbb{1}\{H = 1\} + \boldsymbol{x_{it}}'\beta(\tau), \tag{4}$$

where $Q_w(\tau|)$ denotes the conditional quantile of w corresponding to percentile τ. It is clear that the regression coefficients vary with τ. In particular, we are allowing for distinct cyclical responsiveness when we distinguish between high wage and low wage workers.

To address the role of worker and firm heterogeneity in a fashion comparable to the one defined for the linear regression framework, that is, an AKM-type model, it will prove useful to consider the location-scale representation of the quantile regression:

$$Q_w(\tau|\boldsymbol{z_{it}}) = \phi^l + \boldsymbol{z_{it}}'\boldsymbol{\beta^l} + \sigma(\phi^s + \boldsymbol{z_{it}}'\boldsymbol{\beta^s})q(\tau), \tag{5}$$

where, for simplicity, $\boldsymbol{z_{it}}$ is a vector representing all the covariates and σ identifies the scale function. $q(\tau)$ is simply $F^{-1}(\tau)$. ϕ^l and $\boldsymbol{\beta^l}$, and ϕ^s and $\boldsymbol{\beta^s}$, correspond to the intercept and regression coefficients in the location and scale functions, respectively.

To incorporate worker and firm fixed effects we apply the method of moments quantile regression estimator (MM-QR), recently proposed by Machado and Silva (2019), which can accommodate multiple high-dimensional fixed effects that can affect the whole distribution instead of just a location shift (Addison et al., 2023). Accordingly, we will use this estimator to analyze the impact of the unemployment fluctuations on different locations of the wage distribution. A critical advantage of this approach is that it is based on the OLS solutions to two high-dimensional fixed effects regression equations, one corresponding to the location function and the other to the scale function.

The quantile regression model expanded to include worker and firm fixed effects, considering that $\sigma(.)$ is the identity function, can be written as:

$$Q_w(\tau|\boldsymbol{z_{it}}) = \phi^l_i + \psi^l_f + \boldsymbol{z'_{it}}\boldsymbol{\beta^l} + (\phi^s_i + \psi^s_f + \boldsymbol{z'_{it}}\boldsymbol{\beta^s})q(\tau), \tag{6}$$

where ϕ^l_i (ϕ^s_i) and ψ^l_f (ψ^s_f) are the worker and firm fixed effects in the location (scale) function, respectively.

Estimation of this model can be achieved in four simple steps.

(1) Obtain the parameters of the location function minimizing the sum of the squares of the residuals from the model:

$$w = \phi^l_i + \psi^l_f + \boldsymbol{z'_{it}}\boldsymbol{\beta^l} + \epsilon^l, \tag{7}$$

using, for example, the algorithm of Guimarães and Portugal (2010). This procedure corresponds exactly to the OLS solution which was estimated before;

(2) Compute the estimation residuals from this model, $\hat{R}_{it}$, and calculate $|\hat{R}_{it}|$;

(3) Obtain the parameters of the scale function minimizing the sum of the squares of the

residuals from the model:

$$|\hat{R}_{it}| = \phi_i^s + \psi_f^s + \boldsymbol{z'_{it}}\boldsymbol{\beta^s} + \epsilon^s; \text{ and,} \tag{8}$$

(4) Obtain $q(\tau)$ as the τ-th sample quantile from a standardized residual $\hat{R}_{it}/(\widehat{|R_{it}|})$.

5 Results

5.1 Quantile Regression

Table 3 shows the coefficients of cyclicality for stayers and new hires for the mean, the 10^{th}, the 50^{th}, and the 90^{th} percentiles. Column 1 exhibits the results from a standard OLS regression results à la Bils (1985), and it shows that a 1 percentage point increase in the unemployment rate is associated with a 1.19 percent decrease in the real hourly wages for stayers. These are lower than the estimates in Carneiro et al. (2012) and Martins et al. (2012) using QP, who find that a 1 percentage point increase in the unemployment rate decreases wages of stayers on average by 1.6 and 1.8, respectively. Using more recent data, Black and Figueiredo (2022) find a coefficient of -1.16, which is in line with our estimate. Our results also show a statistically significant increment of new hires' wages cyclicality of -0.42 percent, in line with the aforementioned studies.

The results for the mean conceal the fact that the cyclicality of wages is quite asymmetrical along the hourly wage distribution. Columns 2 to 7 show the impact of the cycle on wages for different percentiles, based on conditional quantile regressions (QR, Koenker and Bassett Jr., 1978) or method of moments quantile regressions (MM-QR) by Machado and Silva (2019). Both estimators provide similar estimates across the distribution, with a slight difference in the 10^{th} percentile. We find that as we move along the distribution of hourly wages, wages become more procyclical, which means that workers in the right tail of the distribution react more strongly to the cycle than those on the left. The QR estimates for stayers go from -0.82 for the 10^{th} percentile, to -1.19 in the 50^{th} and -1.32 in the 90^{th}, implying a P90-P10 difference in cyclicality responses of close to 0.5 log points. This is a remarkable novel result that has important implications for the dynamics of inequality over the business cycle, as it tells us that economic expansions tend to exacerbate inequality, whereas recessions attenuate it. It is interesting to note that this difference between percentiles is still present in new hires' coefficients, demonstrating that the results are not driven by worker mobility. In fact, the results for new hires illustrate that excess cyclicality is present in estimations for the mean is also captured across percentiles.

It is important to underline that the results in Table 3 can be driven by institutional factors. For instance, the cyclicality of low wage workers may be specifically driven by an anchoring to minimum wage changes. On the opposite end of the distribution, a higher sensitivity to the cycle may be induced by either strong reactions of the bargained wage or adjustments in the wage cushion. To understand the relative importance of these factors, we partition our analysis into three steps. First, we estimate the degree of cyclicality of the real minimum wage. Then, we perform a similar exercise for the bargained wage, taking into account that collectively bargained wages are also impacted by minimum wage changes, as discussed in section 3.2. Lastly, we re-analyze the cyclicality of hourly wages considering the potential impact of the minimum and bargained wages.

Table 4 shows the results of an OLS regression of the log minimum real wage on the cycle variable, as well as a quadratic time trend. Results suggest that a 1 percentage point increase in the unemployment rate is associated with a 0.43 percent decrease in the real minimum wage. Therefore, even though the nominal minimum wage is determined by the government, there is evidence that the real minimum wage is cyclical. One should note, however, that such cyclicality is less intense than the one estimated for the observed wage. Since the nominal minimum wage experiences downward rigidity, results suggest that in recession periods, policymakers increase the minimum wage below the inflation rate, thus decreasing its real value. Similarly, expansion periods may be followed by real gains in the minimum wage.

As discussed above in 3.2, since collectively bargained wages are affected by the minimum wage, it is likely that their cyclicality is affected as well. Table 5 presents the estimated cyclicality of the collectively bargained wages, controlling for the impact of the minimum wage. First, the results confirm that the collectively bargained wages are significantly influenced by the minimum wage. On average, a 1 percent increase in the minimum wage is associated with a 0.60 percent increase in the collectively bargained wage. Interestingly, the impact of the minimum wage decreases along the distribution. This suggests that higher collectively bargained wages are more detached from the evolution of minimum wages, which is compatible with the hypothesis that the lower end of the distribution is likely to be compressed by minimum wage changes. Furthermore, the semi-elasticities with respect to the unemployment rate show that collectively bargained wages are also cyclical, with lower bargained wages being more sensitive to the cycle, akin to observed real wages. The MM-QR estimates for stayers range from -0.50 for the 10^{th} percentile to -0.96 in the 90^{th}.

Such asymmetry in the cyclicality along the distribution of collectively bargained wages directly impacts that of overall observed real wages. Table 6 revisits the previous results with the real hourly wages as the dependent variable, now with the extended model, i.e. controlling for the minimum and collectively bargained wages. According to this table, and similarly to the previous results, the minimum wage affects mostly low-wage workers. Still, collectively bargained wages are more important to the determination of observed wages than the minimum wage, with a passthrough of bargained wages around 0.68 percent, in line with the estimates of Card and Cardoso (2022). This passthrough is higher for workers in the left tail of the wage distribution, which could be a reflection of lower wage cushions for these workers.

Nevertheless, the extended model still shows that observed real wages exhibit significant asymmetrical responses to changes in the unemployment rate after controlling for the influence of the minimum wage and bargained wages. For stayers, the semi-elasticity for workers in the 10^{th} percentile is -0.19, 0.21 log points lower (in absolute value) than for those in the 50^{th} percentile and 0.46 lower than those in the 90^{th}. This shows that collectively bargained wages play a role in determining how cyclical real wages are, but the different sensitivities to the cycle are still present. Furthermore, the fact that wages of the P50 are less sensitive to the cycle than those of the P90 reveals that the documented asymmetries are not caused solely by the cyclicality of the minimum wage. Should this be the case, then semi-elasticites should be similar across the P50 and P90. Thus, bargained floors and minimum wages do not seem the explain why wages for the lower part of the wage distribution are much less cyclical than the wages of those on top. This point can be better visualized in figure 8, where we plot the P90-P10 cyclicality coefficients gap for the base model (i.e. without including minimum and bargained wages) and the extended model (i.e. including these two controls). The figure clearly shows that the P90-P10 gap for stayers in the QR base model is of -0.49 points versus -0.46 in the extended model; for hires, this gap is -0.93 in the base model versus -0.78 points in the extended model. These reflect the small impact of minimum and bargained wages in explaining wage cyclicality asymmetries.

As a complementary exercise, we also look at the cyclicality of the wage cushion. We have argued that bargained wages contribute to a significant portion of a worker's wage, being also key in determining the response of wages to the cycle but not its asymmetries. Nonetheless, it is also important to understand the role of the wage cushion in absorbing or amplifying the business cycle. Many firms may use the wage cushion to effectively accommodate recessions by reducing the premium to the wage floor. Conversely, firms may provide bonuses to their workers during expansions that go beyond the collectively negotiated terms. These effects may also be heterogeneous depending on where a worker stands on the distribution of labor earnings. For instance, should higher wage workers be better compensated during expansions, then the cushion would serve as an amplifier of wage inequality. Table 7 shows that, on average, the wage cushion is procyclical, with a decrease of 0.12 percent for the wage cushion of job stayers when the unemployment rate increases by 1 percentage point, while the cushion of hires decreases by 0.32 percent. This is a much smaller effect than the one for the bargained wage, albeit expected as we noted how bargained wages have a high impact on cyclicality of real wages. Nevertheless, it is interesting to note that, for stayers, the semi-elasticity of workers in the 10$^{\text{th}}$ percentile of the wage cushion distribution is not statistically significant. Similarly to before, this coefficient increases (in absolute value) as we move along the distribution. This points to a potential role of the wage cushion in explaining the asymmetrical responses of real wages to business cycle fluctuations.

5.1.1 Heterogeneity by Gender and Education Level

To further characterize our results, we estimate the cyclicality semi-elasticity for different groups of workers. First, we distinguish by gender. Table 8 shows the results of the base model (i.e. without controlling for the minimum or bargained wages) regression estimated for real hourly wages, with the sample split between male and female. Male workers' wages exhibit larger procyclicality than females', as seen by the OLS coefficients. A 1 percentage point increase in the unemployment rate lowers the real wages of male workers by 1.25 percent and of female workers by 1.05 percent. When we turn to the semi-elasticities across the wage distribution, an interesting pattern emerges. Both low wage males and females exhibit less cyclicality than their higher wage counterparts, although the P90-P10 and P90-P50 differences are greater for females than males. Focusing on stayers, female workers in the 10$^{\text{th}}$ percentile of the distribution see their real wages drop by, on average, 0.72 percent when the unemployment rate increases by 1 point, which contrasts with a semi-elasticity of -1.34% for the 90$^{\text{th}}$ percentile. For males, these coefficients are of -0.94% and -1.25%, respectively. The similarity in cyclicality sensitivities for workers in the 90$^{\text{th}}$ percentile across genders indicates that the heterogeneity between men and women is driven mostly by those on the left tail of the wage distribution. While the investigation of the reasons behind this heterogeneity is beyond the scope of this paper, some possibilities can be conjectured. Male and female workers may exhibit unequal reactions to the cycle due to different occupations and industries (Blau and Kahn, 2017), different cyclicalities of hours (Gomme et al., 2004), job sorting, and/or bargaining power (Card et al., 2016).

Table 9 splits the sample into high- and low-educated workers. We consider a high-education worker to have more than a high school diploma, i.e. at least 13 years of schooling. The differences are large. High-educated stayers have a very strong sensitivity with a semi-elasticity of -1.78, almost 0.6 log points larger than for the low-educated, and the gap grows wider if we consider new hires. Across the distribution of log wages, while the low-educated group shows a monotonic increase in procyclicality akin to our previous results, the high-educated group's stayers show no presence of asymmetries, with workers in the 10$^{\text{th}}$, 50$^{\text{th}}$, and 90th percentile all presenting similar coefficients (even slightly lower in the 50th and 90th percentiles than in the 10th). We can rationalize these results in the context of a model with capital-skill complementarity, as in Dolado et al. (2021), where the wage cyclicality of the high-skilled is higher due to a higher volatility of the labor demand for these workers. To the extent that our group of high-educated workers is not very heterogeneous in skill (which could be true due to their similar levels of schooling), then there would be no reason for some to see their wages react more to the cycle than others, except for new hires. This would not be true in the more heterogeneous group of low-educated workers, in which high-school completion may be a factor affecting their matching with firms.

5.2 Accounting for Worker and Firm Unobserved Heterogeneity

The results in the previous section show a significant degree of wage cyclicality for both stayers and new hires, in line with earlier evidence. However, they do not take into account composition differences that may explain some of the cyclical dynamics of wages. To adequately control for these composition effects, we follow Carneiro et al. (2012) and introduce worker and firm fixed effects that capture time-invariant unobserved characteristics that can potentially contaminate our results. The introduction of worker fixed effects controls for issues that may arise, for instance, when the composition of employment shifts towards higher-wage individuals during recessions (Bils et al., 2012). In such a case, the coefficient in equation 2 is estimated with a countercyclical bias (i.e. the coefficient is biased towards zero). We may also find similar results in a context in which low-paying firms exit the market during recessions, hence the need for a firm fixed effect. Furthermore, the problem of job upgrading/downgrading may also be addressed using this method, provided that it is not driven by changes in job title premia or match quality differences.

Table 10 presents evidence for the cyclicality of real wages after accounting for worker and firm fixed effects. Column 1 shows the results of a regression in the style of Abowd et al. (1999), while columns 2-4 show the MM-QR results. We also perform the same exercise for bargained wages in Table A2, in the appendix. As discussed in the literature, low-wage workers are usually the most affected by recessionary periods, which shifts the distribution of employment to higher wage workers and induces a countercyclical bias in models without fixed effects. This is visible in figure 9, where we visually display the coefficients from Tables 6 and 10. The semi-elasticity of the lagged unemployment rate in the former model is -0.48 versus -0.71 in the latter. Interestingly, this bias is also present throughout the distribution of log wages, but only for stayers. The incremental semi-elasticities of new hires move towards zero (with the exception of the P10), showing that either workers switch to higher-paying firms during expansions or that those who are hired during these periods are, in general, high-wage workers. These findings point us towards the hypothesis that new hires' wages are potentially no more procyclical than stayers', as what we observe in reduced form estimations are results biased by compositional changes in the work force. As for the asymmetric sensitivities to the cycle, the inclusion of fixed effects seems to have no impact on the gap between the coefficients of 10^{th} and 90^{th} percentiles stayers, although it does change that of job movers. While the P90-P10 differential for stayers remains fairly similar in both specifications, it is attenuated for new hires. Without fixed effects, the new hires' P90-P10 and P90-P50 differentials are -0.82 and -0.51, respectively. Controlling for time-invariant unobserved heterogeneity decreases the magnitude to -0.33 and -0.15, respectively, more than half of the previous. We investigate potential job upgrading and downgrading effects further in the next section.

5.3 The Impact of Match Quality on the Wages of New Hires

Since the study of Gertler and Trigari (2009), researchers have sought to understand the degree to which match quality cyclicality affects classic reduced form estimations of wage cyclicality. The question of whether new hires are simply moving to better matches during expansions and poorer ones during recessions is critical to understanding the role of these workers in explaining overall unemployment fluctuations in a model à la Pissarides (2009). To answer this question, we turn to the following specification:

$$\begin{aligned} w_{(i,t)} = {} & \alpha_1 UR_{(t-1)} + \alpha_2 t + \alpha_3 t^2 + (\gamma_0 + \gamma_1 UR_{(t-1)} + \gamma_2 t + \gamma_3 t^2) \times \mathbb{1}\{H=1\} \\ & + \boldsymbol{x}_{(i,t)}\beta + \eta_0 bargained_{(i,t)} + \eta_1 mw_t + \psi_{w\times f} + \epsilon_{(i,t)} \end{aligned} \tag{9}$$

Equation 9 introduces a novel methodology to account for match quality through a job match fixed effect, $\psi_{w\times f}$, which is estimated from each worker-firm pair. This fixed effect is a function of worker quality, firm quality, and a third component that reflects match quality purged of worker and firm fixed effects. Therefore, by controlling for it, we are implicitly taking into account match quality composition differences across workers, which may not occur if we simply condition for worker and firm effects. Should match quality be the driver of the incremental cyclicality of new hires, then the inclusion of this fixed effect should capture this, and the sensitivity to the unemployment rate of job movers should be no stronger than that of stayers.

Columns 1-4 in Table 11 show the results of estimating equation 9 for the mean and the different percentiles using OLS and the MM-QR estimator, respectively. The results for the mean (column 1) show that when we consider a match fixed effect in our model the incremental cyclicality of new hires disappears, a result that vindicates Gertler et al. (2020). This is true also for the median, but not for the bottom and top deciles. The semi-elasticity for hires in the 10^{th} percentile is -0.63% while for those in the 90^{th} is -0.80%. Interestingly, we find in this specification that hires in the 90^{th} percentile have wages that are less procyclical than stayers, a new insight that was not present in the previous regressions, albeit the result is not statistically significant at the 5% level. This shows that the considerable gap in cyclicality coefficients between new hires in the top and bottom deciles is strongly attenuated after accounting for job match composition. We can deduce that match quality composition provokes a large procyclical bias in wage cyclicality coefficients for workers in the right tail of the wage distribution, which indicates that moving to higher wage job matches during expansions and the opposite during recessions has a strong effect on the cyclicality coefficient of these workers. This highlights the importance of our approach, as looking at the results for the mean conceals different dynamics over the distribution. A researcher looking purely at the mean would miss this asymmetric importance of match composition.

Gertler et al. (2020) claim that a composition-free estimate of new hires' cyclicality can be obtained by separating those who transition from job to job and from those who come from non-employment. The assumption is that procyclical job match quality upgrading exists mostly among job movers, as these are the workers who are moving to improve match conditions. To investigate this, we rework equation 11:

$$\begin{aligned} w_{(i,t)} = {} & \alpha_1 UR_{(t-1)} + \alpha_2 t + \alpha_3 t^2 + (\zeta_0 + \zeta_1 UR_{(t-1)} + \zeta_2 t + \zeta_3 t^2) \times \mathbb{1}\{EE = 1\} \\ & + (\delta_0 + \delta_1 UR_{(t-1)} + \delta_2 t + \delta_3 t^2) \times \mathbb{1}\{NEE = 1\} + \boldsymbol{x}_{(i,t)}\beta + \eta_0 bargained_{(i,t)} \\ & + \eta_1 mw_t + \psi_{w \times f} + \epsilon_{(i,t)} \end{aligned} \tag{10}$$

The results are in columns 5-8 of Table 11. We find no evidence of excess cyclicality for job movers (EE) *vis-à-vis* those who come from non-employment (NEE). Once we account for match fixed effects, both coefficients are no longer statistically significant for the mean and median, so we discard the notion that NEE workers are a better variable to estimate composition-free wage cyclicality parameters.

5.3.1 Decomposing the Impact of Job Match Fixed Effects on Cyclicality

The job match fixed effect highlighted in equation 10 does not merely reflect match quality. It is a combination of the effect of worker and firm heterogeneity with the quality of the match. Therefore, it is useful to decompose it into its different constituents to isolate the impact of quality and understand how important it is in explaining the cyclicality of wages.

To do this, we resort to the methodology proposed by Gelbach (2016), which appeals to the omitted variable bias formula to derive an *exact* detailed decomposition that calculates the contribution of each added covariate to the model. Methodological details are presented in Appendix B. Assuming that the job match fixed effect is a linear function of worker, firm, and match quality fixed effects, and that the latter is orthogonal to worker and firm effects, we show that we can decompose the difference between the unemployment rate coefficients in the model without fixed effects versus the model with them as:

$$\widehat{\gamma_{\text{base}}} - \widehat{\gamma_{\text{full}}} = \widehat{\boldsymbol{\delta}_{\text{W}}} + \widehat{\boldsymbol{\delta}_{\text{F}}} + \widehat{\boldsymbol{\delta}_{\text{MQ}}}, \tag{11}$$

where $\widehat{\gamma_{\text{base}}}$ and $\widehat{\gamma_{\text{full}}}$ are the cyclicality coefficients in the model without and with fixed effects, respectively; $\widehat{\boldsymbol{\delta}_{\text{W}}}$ represents the contribution of the worker component; $\widehat{\boldsymbol{\delta}_{\text{F}}}$ represents the contribution of the firm component; and $\widehat{\boldsymbol{\delta}_{\text{MQ}}}$ represents the contribution of the match quality effect. In short, $\widehat{\boldsymbol{\delta}_{\text{MQ}}}$ indicates how changes in match quality over the cycle impact the cyclicality coefficients of job movers.

Table 12 presents the results of this decomposition exercise, which is performed solely for the mean (OLS) estimates in the previous specification.[1] The three columns show the cyclicality coefficients for job stayers, job-to-job movers (*EE*), and those who join a firm out of non-employment (*NEE*). First, we consider the estimates for the base model, i.e. without fixed effects. We see that the semi-elasticity of the cycle is negative and statistically significant for both types of movers, in line with our results from Table 3. When compared with table 3, the attenuated coefficients stem from the inclusion of the minimum and bargained wages in this specification. The second row presents the estimates from Table 11, from which we can see that the inclusion of the match fixed effect renders the coefficients statistically non-significant for both types of new hires. The last three rows decompose the difference between the coefficients in the base model (without fixed effects) and the full model (with fixed effects) into the impact of worker and firm heterogeneity, as well as match quality. The coefficients' sum of the last three rows should be exactly equal to the difference between rows 1 and 2.

Starting with job stayers, the inclusion of match fixed effects reduces the cyclicality coefficient by 0.18 log points. Of these, we see that the largest impact stems from the firm fixed effects, contributing with 0.1 log points to the gap between the base and full models. We can interpret this as evidence that, after controlling for time trends, workers' characteristics and match quality, firm-specific heterogeneity increases the procyclicality of

[1]We abstain from performing this exercise for the MM-QR estimates as the decomposition is not exact in such cases.

real wages by almost 56%. As previously discussed, a possible explanation for this fact is that the composition of firms switches to higher-paying firms during recessions due to the exit of low-wage firms. Next, the component of pay that is associated with workers' time-invariant characteristics contributes with 0.096 log points, about half of the gap. This means that workers' wages would be close to 54% more procyclical if employment were not to shift towards higher-wage workers during recessions. Lastly, match quality seems to have statistically significant, yet small effect on the cyclicality of wages for job stayers.

Moving to job-to-job movers (EE), the base-full-model gap is -0.2 log points. With a coefficient of -0.24, we confirm that the biggest contributor to this gap is match quality. In movers were randomly assigned along the match quality distribution, their wages should be no more cyclical than those of stayers. In other words, the incremental procyclicality for movers found in the base model is driven mostly by the shifting composition of match quality during recessions and expansions. Thus, during a recession, on average, workers move to poorer matches (and *vice-versa* in expansions), all else constant. Firm-specific time-invariant characteristics also contribute negatively to the omitted variable bias (that is, base-full-model gap) with -0.09 log points, while worker heterogeneity contributes positively with 0.13 log points. One possible interpretation of these coefficients is that while those who switch jobs during recessions are usually high-wage individuals, they tend to move to lower-paying firms.

As for workers coming from non-employment (NEE), the conclusions are very similar to the job movers'. Match quality has the largest impact on the gap between the base and full models, explaining -0.2 of -0.32 log points. Firm effects contribute with -0.07 log points and worker effects with -0.05, both statistically insignificant at the 5% level. This further serves to reject the claim that the reaction of wages of NEE workers represents a composition-free measure of cyclicality since both NEE and EE estimates are greatly affected by a match quality composition bias.

5.4 Firm and CBA-Specific Asymmetries

To understand why workers with different levels of earnings have unequal wage sensitivities to the business cycle it is key to investigate the behavior of the firms and collective bargaining agreements that set their wage. First, we describe the distribution of cyclicality coefficients across firms and CBAs. Then, we bridge this with worker-side asymmetries to understand how firm-specific (or CBA-specific) sensitivities might translate to workers' real wages.

We start by estimating one cyclicality coefficient for each firm/CBA. To reduce incidental parameter bias, we consider only firms/CBAs with at least 1000 employees and that are present in the sample for 10 years or more. The specification is:

$$
\begin{aligned}
w_{(i,t)} = {} & \alpha_1 UR_{(t-1)} + \alpha_2 t + \alpha_3 t^2 + (\gamma_0 + \gamma_1 UR_{(t-1)} + \gamma_2 t + \gamma_3 t^2) \times \mathbb{1}\{H = 1\} + \boldsymbol{x}_{(i,t)}\beta \\
& + \phi_i + UR_{t-1} \times \psi_{k,UR} + \epsilon_{(i,t)}
\end{aligned} \tag{12}
$$

where $k = f, j$ depending on whether we consider firm or CBA fixed effects. The coefficient of interest is $\psi_{k,UR}$, representing the individual reaction to the business cycle. This effectively estimates an individual slope for each firm/CBA considered.

Figure 10 presents the results. As expected, most firms and CBAs obtain procyclical coefficients, even though roughly 25% of firms and 18% of CBAs show countercyclical responses to the unemployment rate. Table 13 shows some statistics on these distributions. We see that workers in the average firm have their real wages drop by 0.7% when faced with an increase in the unemployment rate by 1 percentage point. The cyclicality coefficient for workers in the average CBA is very similar at -0.68%.

We are also interested in understanding how the estimated heterogeneity differs along the hourly wage distribution. This can be done by taking our method of moments quantile regressions with high-dimensional fixed effects, except that this time we consider worker and firm fixed effects plus the firm- or CBA-level cyclicality effects introduced in equation 12. This framework allows for the estimation of different firm- or CBA-specific cyclicality parameters depending on where a worker stands on the conditional real wage distribution. As such, plotting the distribution of these estimates for workers in the 10^{th} versus the 90^{th} percentile of the real wage distribution provides insight into how firms and CBAs react differently to the cycle.

Figure 11 shows histograms with the estimated coefficients for firm- and CBA-specific slopes for workers in the 10^{th} and 90^{th} percentiles of the hourly wage distribution, after controlling for worker and firm unobserved heterogeneity. It is seen that firms and CBAs tend to have a stronger reaction, i.e. a more negative cyclicality coefficient, for workers on the right tail of the hourly wage distribution than those on the left. In fact, there seems to be a significant portion of low-wage workers whose firms present acyclical or even counteryclical reactions. This suggests that firms and CBAs provide a lower degree of insurance to business cycle fluctuations to higher paid individuals, which can be a source of the asymmetrical reactions initially described in table 3. In fact, these results also tie with the findings in table 7, where we show that the wage cushion is more procyclical for workers at the top of its distribution. Firms may adjust the wage cushion in reaction to business cycle fluctuations, which can act as an insurance mechanism for lower wage workers. This is then reflected in less procyclical firm/CBA-level estimates for these individuals. Other factors such as the bargaining power of workers in a given CBA, different outside option values (Reis and de Almeida Vilares, 2022), labor supply and demand mismatch in a given market (Dolado et al., 2021), among others, may also be a cause for asymmetric firm and CBA reactions. These explanations remain to be investigated in further research.

5.5 Why is Wage Cyclicality Non-Linear Across the Conditional Wage Distribution?

Throughout the paper, we have identified the presence of asymmetries in the semi-elasticities of wages with respect to the unemployment rate along the conditional real wage distribution. The common trend across most of our specifications is that there seems to be a monotonic increase in the procyclicality of wages along the distribution, i.e. those in the 90^{th} percentile tend to have a stronger response to the cycle than those in the 50^{th} and in the 10^{th}. Sections 5.1 and 5.2 questioned whether these results are driven by wage-setting institutions or composition effects. Interestingly, the asymmetrical reactions of high- and low-wage workers remain after the inclusion of minimum and collectively bargained wages, as well as after controlling for worker, firm, and match-quality fixed effects.

In section 5.4 we unveiled a certain mechanism in which firms and CBAs behave more procyclically for workers in the top of the wage distribution. While our discussion does not quantify the extent to which this mechanism is driving the observed asymmetries, it provides evidence that can be backed up by a model with amplifying demand effects originating from capital-skill complementarities, as in Lindquist (2004) and Dolado et al. (2021). In the latter paper, the authors derive a DSGE with search and matching frictions in which high-skilled workers are complements to capital whereas low-skilled are substitutes. On top of this, the high-skilled face fewer frictions in the labor market, such as lower separation rates and better match efficiencies. Under these assumptions, whenever the economy is faced with an expansionary shock, firms increase their relative demand for skilled labor, which is then amplified by the fact that higher-skilled employment improves the marginal product of capital, thus encouraging a further demand increase for skilled work, pushing the relative wage of skilled workers up. These dynamics are also affected by asymmetric search and matching frictions, as firms prefer to hire workers with fewer frictions. This model creates a strongly procyclical skill premium that can be reconciled with our results to the extent that higher wage workers are more skilled. In this case, our results merely reflect a dynamic demand effect coming from the desire to hire more high-skilled workers during expansions. It may also help to explain why we observe such a sorting mechanism in Figure 11. Table 9 is also in line with this reasoning, as higher-educated workers present stronger procyclicality than lower-wage workers.

The relationship with the model in Dolado et al. (2021) hinges on the assumption that our results reflect changes in the relative demand for skilled work. Happily, this need not be the only explanation for different reactions to the cycle. Robin (2011) extends the Postel-Vinay and Robin (2002) sequential auction model to allow for aggregate productivity shocks. In the model, workers are *ex-ante* heterogeneous and have different ability levels. This creates heterogeneous match efficiencies, which will determine the output of firms that are *ex-ante* homogeneous. Furthermore, the sequential auction framework allows for workers to search on-the-job and receive outside offers that their own firms may counter. This poaching and offer-matching game creates wage dispersion and can generate interesting dynamics in the wage distribution. When faced with a positive aggregate productivity shock, the complementarity between ability and aggregate productivity increases the value of a match, and subsequently the value of poaching wages. When calibrated and estimated using US data, Robin's model shows cyclicality patterns akin to ours, as the wages of those in the lowest percentiles of the wage distribution are less volatile than those in the top (see Table 4 in Robin, 2011). The author claims that these dynamics stem from both the match productivity complementarity and the fact that the lower part of the distribution comprises starting wages, contrasting with the top part, which comprises promotion wages. Once again, this explanation relies on the assumption that workers at the top of the distribution receive a wage proportional to their match value.

The aforementioned models provide some structure to think about the labor market mechanisms behind our results. The underlying conclusion between both is that there has to be some degree of complementarity between worker ability and aggregate productivity that enhances the effect of the cycle for higher wage workers. To the extent that workers are paid a fraction of the match value, our results seem to give support to these theoretical models.

6 Conclusion

This paper presents, for the first time, empirical evidence of asymmetrical wage cyclicality across the distribution of real wages. First, we observe that the wages of workers in the top percentiles are more procyclical than those workers in the bottom. This is true both for job stayers and new hires. Second, we find that including fixed effects is important to obtain composition-free estimates of wage cyclicality, although they do not seem to explain the differences in cyclicality across the distribution for stayers. We also uncover evidence that supports the belief that new hires' wages are no more cyclical than stayers once we account for match quality composition. Third, we relate our results to the institutional setting in Portugal. Both the minimum wage and the negotiated wage floors have a prominent role in determining wage cyclicality. However, these do not seem to lead the distributional cyclicality dynamics of the total hourly wages. A stronger candidate would be the wage cushion, which also reacts more procyclically for workers in the 90^{th} percentile of its distribution. Lastly, we tie our results with heterogeneity in firms' reactions to the cycle by estimating cyclicality coefficients for each firm/collective agreement. We find a non-negligible number of firms whose wages react countercyclically, especially for workers in the bottom decile. There is evidence of a mechanism whereby firms and CBAs have a stronger reaction to the cycle for workers at the top of the conditional wages distribution, which helps rationalize our results.

Our novel results harness the benefits of using a rich dataset to explore the full distribution of wages. We show how important it is to move beyond the linear model of Bils (1985), as different workers and firms show different reactions to the cycle. As such, we provide empirical evidence on the role of the business cycle as amplifier of inequality trends.

We elicit some possible theoretical explanations for the asymmetries found in the data. Models that incorporate complementarities in production between worker ability and productivity seem to fit well with our findings. Nonetheless, an interesting avenue for future research would be the modeling of the non-linear relationship between the cycle and the wage distribution, providing theoretical rigor that could support our empirical evidence.

References

Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High Wage Workers and High Wage Firms. *Econometrica*, 67(2):251–333.

Abraham, K. G. and Haltiwanger, J. C. (1995). Real Wages and the Business Cycle. *Journal of Economic Literature*, 33(3):1215–1264.

Addison, J. T., Portugal, P., and de Almeida Vilares, H. (2023). Union Membership Density and Wages: The Role of Worker, Firm, and Job-title Heterogeneity. *Journal of Econometrics*, 233(2):612–632.

Bauer, A. and Lochner, B. (2020). History Dependence in Wages and Cyclical Selection: Evidence From Germany. *Labour Economics*, 67:101932.

Bayer, C., Born, B., and Luetticke, R. (2020). Shocks, Frictions, and Inequality in US Business Cycles.

Bils, M., Chang, Y., and Kim, S.-B. (2012). Comparative Advantage and Unemployment. *Journal of Monetary Economics*, 59(2):150–165.

Bils, M. J. (1985). Real Wages Over the Business Cycle: Evidence From Panel Data. *Journal of Political Economy*, 93(4):666–689.

Black, I. and Figueiredo, A. (2022). The False Illusion of Wage Cyclicality. *Available at SSRN 4208152*.

Blau, F. D. and Kahn, L. M. (2017). The Gender Wage Gap: Extent, Trends, and Explanations. *Journal of Economic Literature*, 55(3):789–865.

Bodkin, R. G. (1969). Real Wages and Cyclical Variations in Employment: a Re-examination of the Evidence. *The Canadian Journal of Economics/Revue canadienne d'Economique*, 2(3):353–374.

Card, D. and Cardoso, A. R. (2022). Wage Flexibility Under Sectoral Bargaining. *Journal of the European Economic Association*, 20(5):2013–2061.

Card, D., Cardoso, A. R., and Kline, P. (2016). Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women. *The Quarterly Journal of Economics*, 131(2):633–686.

Cardoso, A. R. and Portugal, P. (2005). Contractual Wages and the Wage Cushion Under Different Bargaining Settings. *Journal of Labor Economics*, 23(4):875–902.

Carneiro, A., Guimarães, P., and Portugal, P. (2012). Real Wages and the Business Cycle: Accounting for Worker, Firm, and Job Title Heterogeneity. *American Economic Journal: Macroeconomics*, 4(2):133–152.

Carneiro, A., Portugal, P., and Varej
o, J. (2014). Catastrophic Job Destruction During the Portuguese Economic Crisis. *Journal of Macroeconomics*, 39:444–457.

Devereux, P. J. and Hart, R. A. (2006). Real Wage Cyclicality of Job Stayers, Within-company Job Movers, and Between-company Job Movers. *ILR Review*, 60(1):105–119.

Dolado, J. J., Motyovszki, G., and Pappa, E. (2021). Monetary Policy and Inequality Under Labor Market Frictions and Capital-skill Complementarity. *American Economic Journal: Macroeconomics*, 13(2):292–332.

Gartner, H., Schank, T., and Schnabel, C. (2013). Wage Cyclicality Under Different Regimes of Industrial Relations. *Industrial Relations*, 52(2):516–540.

Gelbach, J. B. (2016). When Do Covariates Matter? And Which Ones, and How Much? *Journal of Labor Economics*, 34(2):509–543.

Gertler, M., Huckfeldt, C., and Trigari, A. (2020). Unemployment Fluctuations, Match Quality, and the Wage Cyclicality of New Hires. *The Review of Economic Studies*, 87(4):1876–1914.

Gertler, M. and Trigari, A. (2009). Unemployment Fluctuations with Staggered Nash Wage Bargaining. *Journal of Political Economy*, 117(1):38–86.

Gomme, P., Rogerson, R., Rupert, P., and Wright, R. (2004). The Business Cycle and the Life Cycle. *NBER Macroeconomics Annual*, 19:415–461.

Gornemann, N., Kuester, K., and Nakajima, M. (2021). Doves for the Rich, Hawks for the Poor? Distributional Consequences of Monetary Policy. Technical report, Federal Reserve Bank of Minneapolis.

Grigsby, J., Hurst, E., and Yildirmaz, A. (2021). Aggregate Nominal Wage Adjustments: New Evidence From Administrative Payroll Data. *American Economic Review*, 111(2):428–71.

Guimarães, P. and Portugal, P. (2010). A Simple Feasible Procedure to Fit Models with High-dimensional Fixed Effects. *The Stata Journal*, 10(4):628–649.

Guvenen, F., Ozkan, S., and Song, J. (2014). The Nature of Countercyclical Income Risk. *Journal of Political Economy*, 122(3):621–660.

Holden, S. and Wulfsberg, F. (2008). Downward Nominal Wage Rigidity in the OECD. *The BE Journal of Macroeconomics*, 8(1).

Kaplan, G., Moll, B., and Violante, G. L. (2018). Monetary Policy According to HANK. *American Economic Review*, 108(3):697–743.

Keane, M. P. and Prasad, E. S. (1993). The Relation Between Skill Levels and the Cyclical Variability of Employment, Hours, and Wages. *IMF Working Papers*, 1993(044).

Knoppik, C. and Beissinger, T. (2009). Downward Nominal Wage Rigidity in Europe: An Analysis of European Micro Data From the ECHP 1994–2001. *Empirical Economics*, 36:321–338.

Koenker, R. and Bassett Jr., G. (1978). Regression Quantiles. *Econometrica*, pages 33–50.

Lindquist, M. J. (2004). Capital–skill Complementarity and Inequality Over the Business Cycle. *Review of Economic Dynamics*, 7(3):519–540.

Lise, J. and Robin, J.-M. (2017). The Macrodynamics of Sorting Between Workers and Firms. *American Economic Review*, 107(4):1104–1135.

Machado, J. A. and Silva, J. S. (2019). Quantiles via Moments. *Journal of Econometrics*, 213(1):145–173.

Martins, P. S. (2007). Heterogeneity in Real Wage Cyclicality. *Scottish Journal of Political Economy*, 54(5):684–698.

Martins, P. S. (2021). 30,000 Minimum Wages: The Economic Effects of Collective Bargaining Extensions. *British Journal of Industrial Relations*, 59(2):335–369.

Martins, P. S., Solon, G., and Thomas, J. P. (2012). Measuring What Employers Do About Entry Wages Over the Business Cycle: a New Approach. *American Economic Journal: Macroeconomics*, 4(4):36–55.

Merkl, C. and Stüber, H. (2017). Wage Cyclicalities and Labor Market Dynamics at the Establishment Level: Theory and Evidence. *IZA Discussion Paper*.

Mortensen, D. T. and Pissarides, C. A. (1994). Job Creation and Job Destruction in the Theory of Unemployment. *The Review of Economic Studies*, 61(3):397–415.

Mueller, A. I. (2017). Separations, Sorting, and Cyclical Unemployment. *American Economic Review*, 107(7):2081–2107.

Pissarides, C. A. (2000). *Equilibrium Unemployment Theory*. MIT press.

Pissarides, C. A. (2009). The Unemployment Volatility Puzzle: Is Wage Stickiness the Answer? *Econometrica*, 77(5):1339–1369.

Postel-Vinay, F. and Robin, J.-M. (2002). Equilibrium Wage Dispersion with Worker and Employer Heterogeneity. *Econometrica*, 70(6):2295–2350.

Raposo, P., Portugal, P., and Carneiro, A. (2021). The Sources of the Wage Losses of Displaced Workers: the Role of the Reallocation of Workers Into Firms, Matches, and Job Titles. *Journal of Human Resources*, 56(3):786–820.

Ravenna, F. and Walsh, C. E. (2012). Screening and Labor Market Flows in a Model with Heterogeneous Workers. *Journal of Money, Credit and Banking*, 44:31–71.

Reis, H. and de Almeida Vilares, H. (2022). Who's Got the Power? Wage Determination and Its Resilience in the Great Recession. Technical report, Centre for Economic Performance, LSE.

Robin, J.-M. (2011). On the Dynamics of Unemployment and Wage Distributions. *Econometrica*, 79(5):1327–1355.

Shin, D. (1994). Cyclicality of Real Wages Among Young Men. *Economics Letters*, 46(2):137–142.

Solon, G., Barsky, R., and Parker, J. A. (1994). Measuring the Cyclicality of Real Wages: How Important Is Composition Bias? *The Quarterly Journal of Economics*, 109(1):1–25.

Stüber, H. (2017). The Real Wage Cyclicality of Newly Hired and Incumbent Workers in Germany. *The Economic Journal*, 127(600):522–546.

Sumner, S. and Silver, S. (1989). Real Wages, Employment, and the Phillips Curve. *Journal of Political Economy*, 97(3):706–720.

Woodcock, S. D. (2023). The Determinants of Displaced Workers' Wages: Sorting, Matching, Selection, and the Hartz Reforms. *Journal of Econometrics*, 233(2):568–595.

Ziliak, J. P., Wilson, B. A., and Stone, J. A. (1999). Spatial Dynamics and Heterogeneity in the Cyclicality of Real Wages. *Review of Economics and Statistics*, 81(2):227–236.

7 Figures

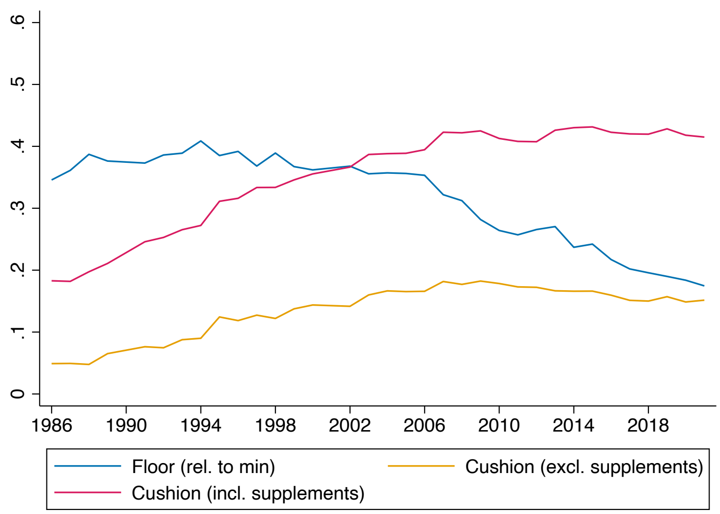


Figure 1: Evolution of Bargained Wages and Wage Cushions

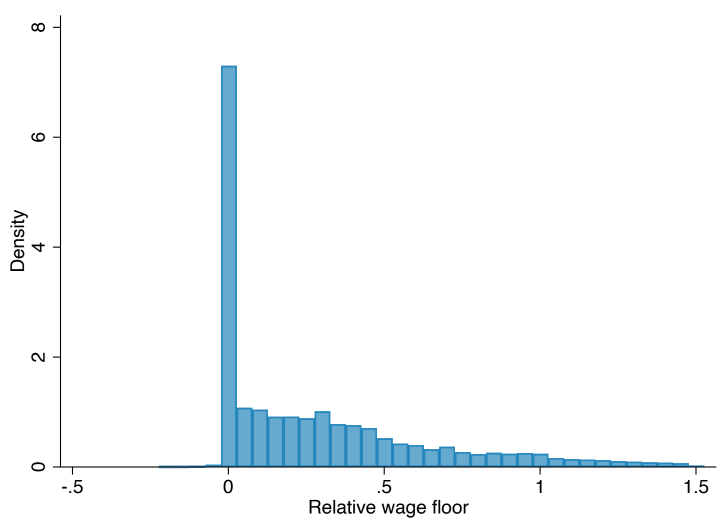


Figure 2: Wage Floors (Rel. to Minimum) Distribution

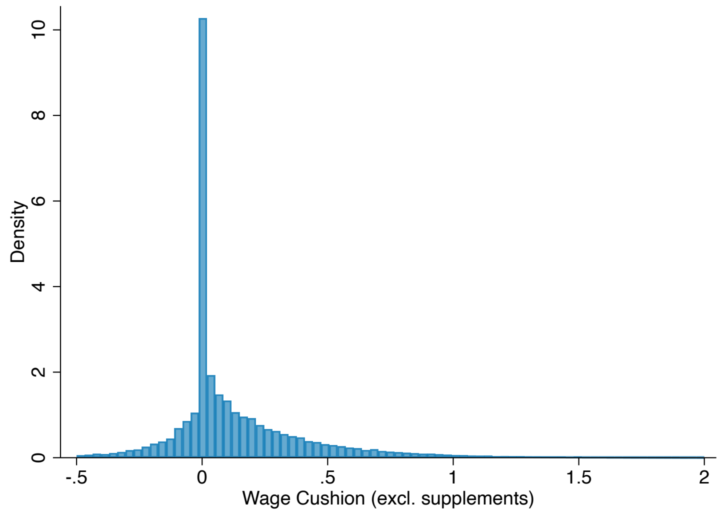


Figure 3: Wage Cushion (Excluding Supplements) Distribution

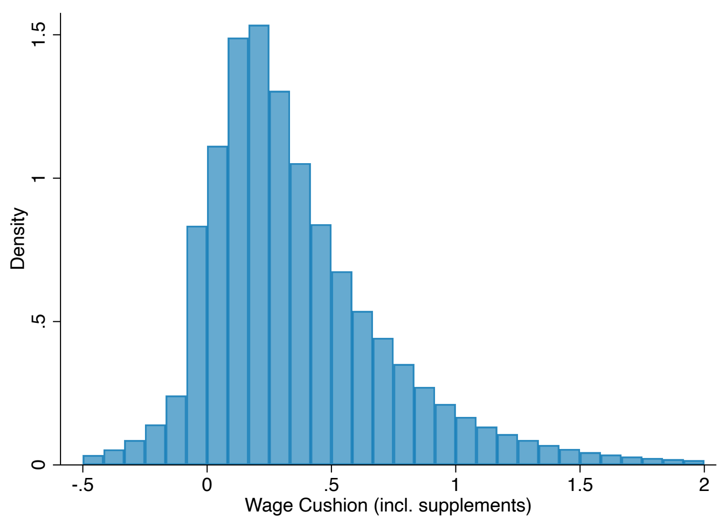


Figure 4: Wage Cushion (Including Supplements) Distribution

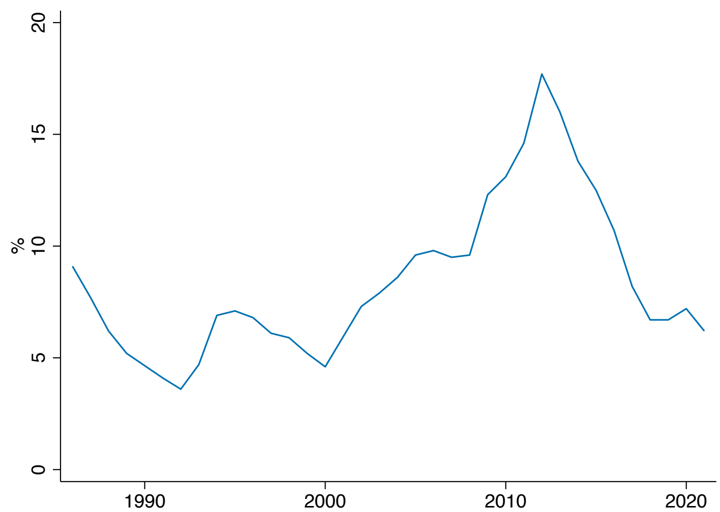


Figure 5: Unemployment Rate

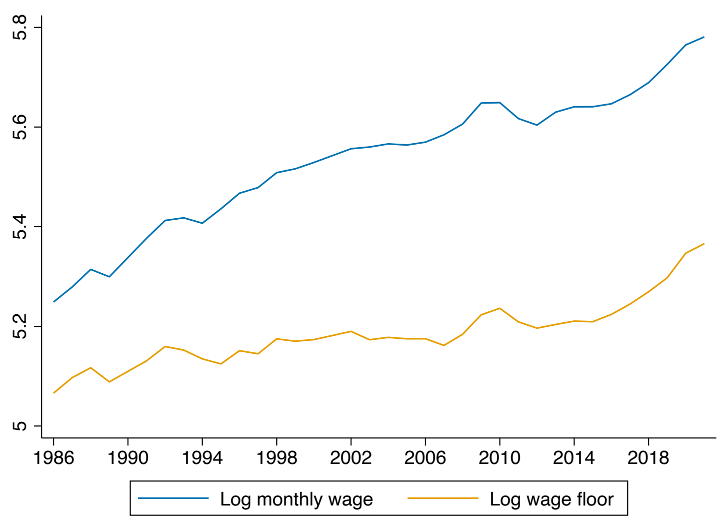


Figure 6: Evolution of Real Hourly Log Total Wages and Real Hourly Log Bargained Wages

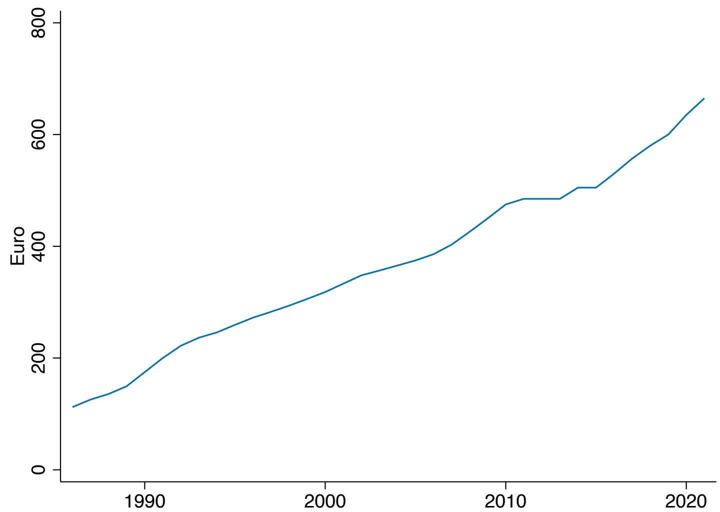


Figure 7: National Minimum Wage

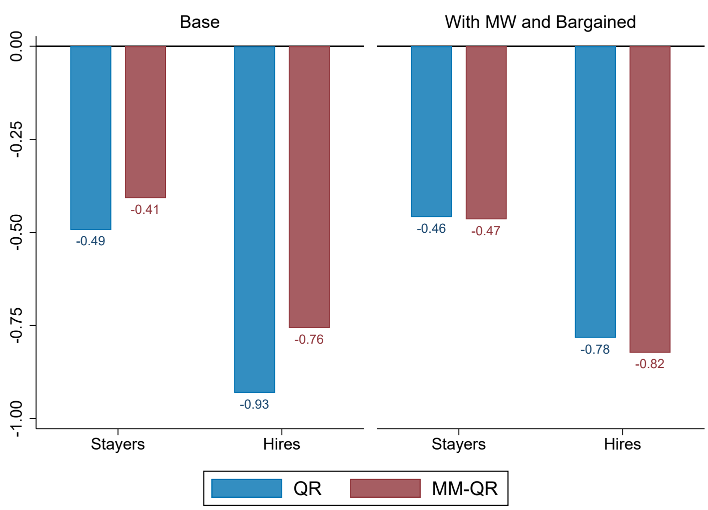


Figure 8: Comparison of P90-P10 gap in cyclicality coefficients between base and extended models

Note: Each column presents the difference between the cyclicality coefficients for the P90 and the P10 in the QR (blue) and MM-QR (red) models, without minimum and bargained wages as controls (base, on the left) and with these controls (on the right). As an example, to understand the impact of adding minimum and bargained wages as controls on the P90-P10 coefficient gap, the comparison to be made for stayers should be between -0.49 (left) and -0.46 (right), or -0.41 (left) and -0.47 (right).

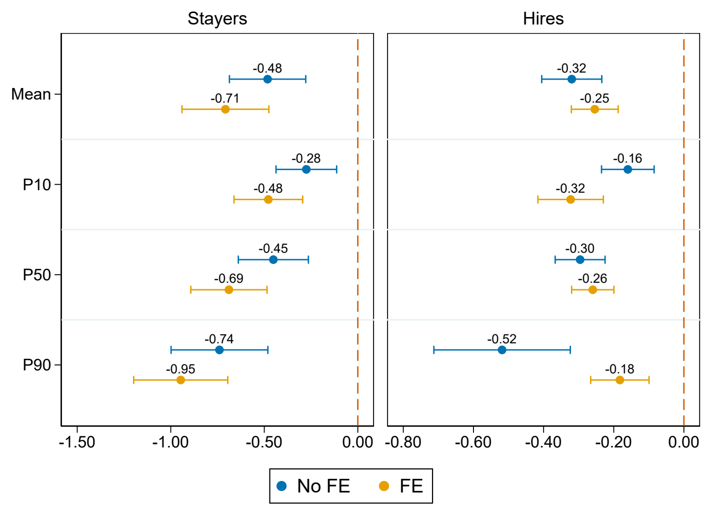
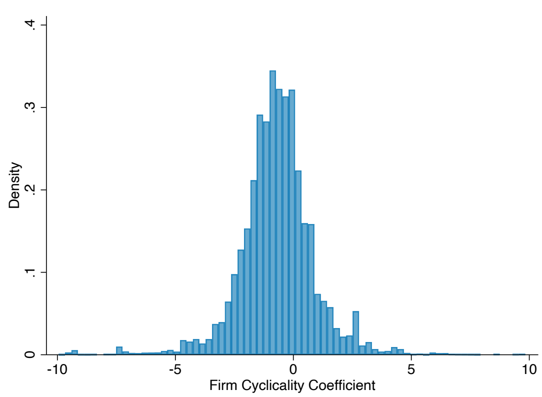
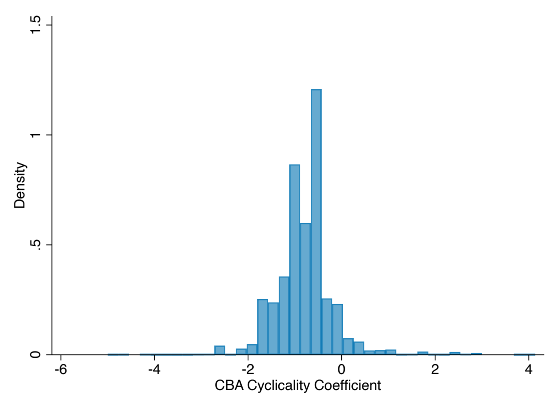


Figure 9: Comparison of cyclicality coefficients between MM-QR model with and without fixed effects

Note: Each horizontal bar presents the MM-QR cyclicality coefficients from tables 6 (blue) and 10 (yellow) alongside 95% confidence intervals.

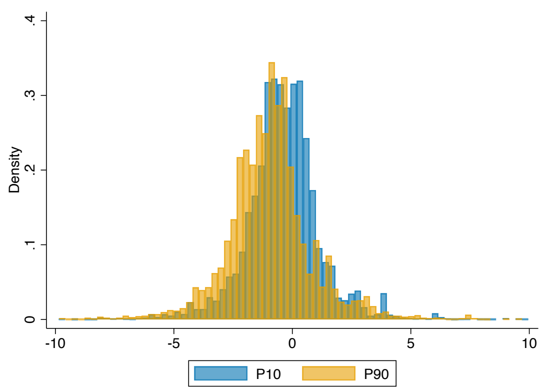


(a) Firm

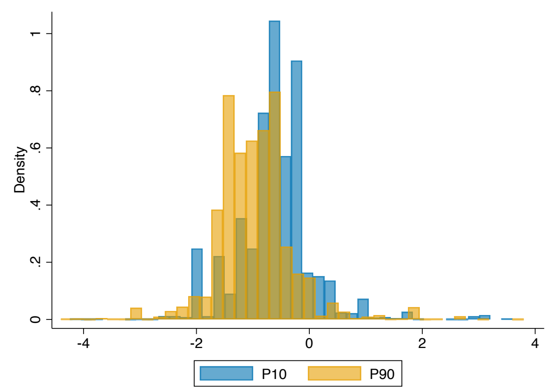


(b) Collective Bargaining Agreement

Figure 10: Distribution of Firm and CBA Cyclicality Coefficients



(a) Firm



(b) Collective Bargaining Agreement

Figure 11: Distribution of Firm and CBA Cyclicality Coefficients by Decile of Hourly Wages Distribution

8 Tables

Table 1: Example of Collective Bargaining Agreement Wage Table

Professional category	Bargained Wage
Hotel Manager	2,422.00€
Commercial Manager	1,373.00€
Financial Manager	1,373.00€
Accountant	1,211.00€
Golf Instructor	1,211.00€
Chief Cook	1,050.00€
Treasury Officer	1,050.00€
Head of Reception	974.00€
Receptionist	934.00€
Chief Driver	859.00€
Gardener	847.00€
Intern	830.00€
Apprentice	813.00€

Note: Snippet of the 2024 sector agreement between *AHRESP* – the national employer association for the hotels, restaurants and accommodation sector – and *SITESE* – the services sector workers' union. National minimum wage as of 2024 is 820€. Source: Boletim do Trabalho e Emprego, 2023.

Table 2: Summary Statistics

	Mean	SD	Min	Max	P10	P50	P90
Wages							
Log Monthly Real Wage	5.56	0.56	4.49	12.74	4.97	5.44	6.34
Log Bargained Wage	5.19	0.39	4.49	9.34	4.82	5.09	5.76
Wage Cushion (excl. supplements)	0.14	0.35	-4.29	7.12	-0.09	0.02	0.53
Wage Cushion (incl. supplements)	0.37	0.41	-4.15	7.71	-0.00	0.28	0.87
Demographics							
Age	38.36	11.01	18.00	64.00	24.00	38.00	54.00
Share of Females	0.42	0.49	0.00	1.00	0.00	0.00	1.00
Education							
Less than High-School	0.69	0.46	0.00	1.00	0.00	1.00	1.00
High-School	0.19	0.39	0.00	1.00	0.00	0.00	1.00
College Degree	0.10	0.30	0.00	1.00	0.00	0.00	1.00
Employment							
Percent of New Hires	0.16	0.37	0.00	1.00	0.00	0.00	1.00
Months With Firm	103.49	105.89	0.00	600.00	6.00	65.00	264.00

Table 3: Cyclicality of Real Wages (Total Hourly Wages)

	Mean	P10		P50		P90	
	OLS	QR	MM-QR	QR	MM-QR	QR	MM-QR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{UR}_{(t-1)}$	-1.186***	-0.822***	-0.997***	-1.188***	-1.165***	-1.315***	-1.405***
	(0.141)	(0.121)	(0.127)	(0.133)	(0.137)	(0.150)	(0.167)
$\text{UR}_{(t-1)} \cdot \mathbb{1}\{H = 1\}$	-0.419***	-0.214***	-0.257***	-0.344***	-0.401***	-0.652***	-0.606***
	(0.059)	(0.047)	(0.060)	(0.051)	(0.056)	(0.099)	(0.103)
Worker/Firm FE	No						
Observations	52,342,436						

Note: The dependent variable is the logarithm of real hourly total wages. All regressions include a quadratic time trend and its interaction with a new hire dummy, a quadratic term on age and tenure, schooling, and a gender dummy. QR refers to conditional quantile regression. MM-QR refers to the method of moments quantile regression as in Machado and Silva (2019). Year-clustered standard errors are in parentheses. All coefficients and standard errors are multiplied by 100.
*** Denotes statistical significance at the 0.01 level.

Table 4: Cyclicality of the Minimum Wage

	(1)	(2)
$UR_{(t-1)}$	-0.429***	-0.437***
	(0.106)	(0.107)
Observations	52,342,436	34

Note: OLS regression with the log of real minimum wage as dependent variable and the lagged unemployment rate and a quadratic time trend as independent variables. Year-clustered standard errors are in parentheses. The coefficient on the unemployment rate and standard errors are multiplied by 100. The first column uses the full panel, whereas column 2 considers only the time-series of the minimum wage.
*** Denotes statistical significance at the 0.01 level.

Table 5: Cyclicality of Real Wages (Bargained Wages – Extended Model)

	Mean	P10		P50		P90	
	OLS	QR	MM-QR	QR	MM-QR	QR	MM-QR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log Minimum Wage	0.602***	1	0.721***	0.670***	0.620***	0.548***	0.436***
	(0.080)	(–)	(0.071)	(0.093)	(0.076)	(0.101)	(0.121)
$UR_{(t-1)}$	-0.690***	–	-0.499***	-0.689***	-0.661***	-0.795***	-0.956***
	(0.095)	(–)	(0.079)	(0.090)	(0.090)	(0.110)	(0.139)
$UR_{(t-1)} \cdot \mathbb{1}\{H = 1\}$	-0.143***	–	-0.022	-0.091***	-0.124***	-0.298***	-0.312***
	(0.036)	(–)	(0.057)	(0.028)	(0.033)	(0.061)	(0.103)
Worker/Firm FE	No						
Observations	52,342,436						

Note: The dependent variable is the logarithm of real bargained wages. Bargained wages are defined as the modal value in a given job title × year cell. All regressions include a quadratic time trend and its interaction with a new hire dummy, a quadratic term on age and tenure, schooling, and a gender dummy. QR refers to conditional quantile regression. MM-QR refers to the method of moments quantile regression as in Machado and Silva (2019). Year-clustered standard errors are in parentheses. $UR_{(t-1)}$ and $UR_{(t-1)} \cdot \mathbb{1}\{H = 1\}$ coefficients and standard errors are multiplied by 100. For the model without the minimum wage as independent variable, refer to table A1.

*** Denotes statistical significance at the 0.01 level.

Table 6: Cyclicality of Real Wages (Hourly Wages – Extended Model)

	Mean	P10		P50		P90	
	OLS (1)	QR (2)	MM-QR (3)	QR (4)	MM-QR (5)	QR (6)	MM-QR (7)
Log Minimum Wage	0.136	0.245**	0.183**	0.051	0.143	0.094	0.078
	(0.092)	(0.080)	(0.081)	(0.088)	(0.088)	(0.127)	(0.123)
Log Bargained Wage	0.680***	0.703***	0.751***	0.823***	0.691***	0.616***	0.593***
	(0.011)	(0.008)	(0.006)	(0.012)	(0.010)	(0.016)	(0.020)
$\text{UR}_{(t-1)}$	-0.482***	-0.193***	-0.275***	-0.407***	-0.451***	-0.652***	-0.740***
	(0.100)	(0.081)	(0.083)	(0.093)	(0.096)	(0.127)	(0.132)
$\text{UR}_{(t-1)} \cdot \mathbb{1}\{H = 1\}$	-0.320***	-0.224***	-0.160***	-0.178***	-0.296***	-0.548***	-0.518***
	(0.042)	(0.030)	(0.038)	(0.028)	(0.036)	(0.091)	(0.099)
Worker/Firm FE	No						
Observations	52,342,436						

Note: The dependent variable is the logarithm of real hourly total wages. Bargained wages are defined as the modal value in a given job title × year cell. All regressions include a quadratic time trend and its interaction with a new hire dummy, a quadratic term on age and tenure, schooling, and a gender dummy. QR refers to conditional quantile regression. MM-QR refers to the method of moments quantile regression as in Machado and Silva (2019). Year-clustered standard errors are in parentheses. $\text{UR}_{(t-1)}$ and $\text{UR}_{(t-1)} \cdot \mathbb{1}\{H = 1\}$ coefficients and standard errors are multiplied by 100.

* Denotes statistical significance at the 0.10 level; *** denotes statistical significance at the 0.01 level.

Table 7: Cyclicality of the Wage Cushion

	Mean	P10		P50		P90	
	OLS	QR	MM-QR	QR	MM-QR	QR	MM-QR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{UR}_{(t-1)}$	-0.119**	-0.020	0.038	-0.120***	-0.086**	-0.356***	-0.331***
	(0.046)	(0.034)	(0.031)	(0.040)	(0.041)	(0.084)	(0.083)
$\text{UR}_{(t-1)} \cdot \mathbb{1}\{H=1\}$	-0.206***	-0.109***	-0.077**	-0.076***	-0.179***	-0.396***	-0.379***
	(0.038)	(0.030)	(0.036)	(0.029)	(0.029)	(0.101)	(0.108)
Observations	52,342,436						

Note: The dependent variable is the wage cushion, defined as the difference between log monthly wages and log bargained wages. All regressions include a quadratic time trend and its interaction with a new hire dummy, a quadratic term on age and tenure, schooling, and a gender dummy. QR refers to conditional quantile regression. MM-QR refers to the method of moments quantile regression as in Machado and Silva (2019). Year-clustered standard errors are in parentheses. All coefficients and standard errors are multiplied by 100.
** Denotes statistical significance at the 0.05 level; *** denotes statistical significance at the 0.01 level.

Table 8: Cyclicality of Real Wages By Gender

	Mean	P10		P50		P90	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	QR	MM-QR	QR	MM-QR	QR	MM-QR
Female							
$\text{UR}_{(t-1)}$	-1.054***	-0.715***	-0.796***	-0.985***	-1.021***	-1.344***	-1.372***
	(0.130)	(0.119)	(0.119)	(0.125)	(0.125)	(0.154)	(0.160)
$\text{UR}_{(t-1)} \cdot \mathbb{1}\{H=1\}$	-0.506***	-0.222***	-0.332***	-0.438***	-0.483***	-0.687***	-0.720***
	(0.055)	(0.045)	(0.049)	(0.049)	(0.053)	(0.065)	(0.074)
Observations	22,155,471						
Male							
$\text{UR}_{(t-1)}$	-1.254***	-0.943***	-1.150***	-1.344***	-1.243***	-1.254***	-1.370***
	(0.149)	(0.134)	(0.140)	(0.150)	(0.146)	(0.155)	(0.170)
$\text{UR}_{(t-1)} \cdot \mathbb{1}\{H=1\}$	-0.377***	-0.165***	-0.211***	-0.313***	-0.361***	-0.640***	-0.563***
	(0.072)	(0.055)	(0.075)	(0.053)	(0.067)	(0.165)	(0.150)
Observations	30,186,965						

Note: The dependent variable is the logarithm of real hourly total wages. All regressions include a quadratic time trend and its interaction with a new hire dummy, a quadratic term on age and tenure, and schooling. Year-clustered standard errors are in parentheses. All coefficients and standard errors are multiplied by 100.
*** Denotes statistical significance at the 0.01 level.

Table 9: Cyclicality of Real Wages By Education Level

	Mean	P10		P50		P90	
	(1) OLS	(2) QR	(3) MM-QR	(4) QR	(5) MM-QR	(6) QR	(7) MM-QR
Low education							
$\text{UR}_{(t-1)}$	-1.179***	-0.794***	-0.948***	-1.177***	-1.147***	-1.345***	-1.455***
	(0.135)	(0.123)	(0.123)	(0.130)	(0.131)	(0.150)	(0.164)
$\text{UR}_{(t-1)} \cdot \mathbb{1}\{H=1\}$	-0.226***	-0.140***	-0.111**	-0.165***	-0.210***	-0.464***	-0.363***
	(0.053)	(0.046)	(0.055)	(0.044)	(0.049)	(0.097)	(0.101)
Observations	46,233,588						
High education							
$\text{UR}_{(t-1)}$	-1.777***	-1.954***	-1.825***	-1.740***	-1.778***	-1.743***	-1.728***
	(0.261)	(0.254)	(0.246)	(0.262)	(0.257)	(0.254)	(0.273)
$\text{UR}_{(t-1)} \cdot \mathbb{1}\{H=1\}$	-0.537***	0.314**	-0.101	-0.641***	-0.527***	-0.886***	-0.980***
	(0.128)	(0.151)	(0.139)	(0.115)	(0.126)	(0.121)	(0.143)
Observations	6,108,848						

Note: The dependent variable is the logarithm of real hourly total wages. All regressions include a quadratic time trend and its interaction with a new hire dummy, a quadratic term on age and tenure, and gender. High-education refers to workers with more than a high-school diploma. Low-education workers are those with at most a high-school diploma. Year-clustered standard errors are in parentheses. All coefficients and standard errors are multiplied by 100.
*** Denotes statistical significance at the 0.01 level.

Table 10: Cyclicality of Real Wages (Hourly Wages – FE Model)

	(1) Mean	(2) P10	(3) P50	(4) P90
Log Minimum Wage	0.383***	0.340***	0.380***	0.428***
	(0.094)	(0.069)	(0.085)	(0.111)
Log Bargained Wage	0.149***	0.174***	0.151***	0.124***
	(0.009)	(0.009)	(0.009)	(0.009)
$\mathrm{UR}_{(t-1)}$	-0.708***	-0.478***	-0.689***	-0.947***
	(0.114)	(0.094)	(0.104)	(0.128)
$\mathrm{UR}_{(t-1)} \cdot \mathbb{1}\{H=1\}$	-0.254***	-0.323***	-0.260***	-0.182***
	(0.033)	(0.048)	(0.031)	(0.042)
Worker FE	Yes			
Firm FE	Yes			
Observations	52,342,436			

Note: The dependent variable is the logarithm of real hourly total wages. Bargained wages are defined as the modal value in a given job title × year cell. All regressions include a quadratic time trend and its interaction with a new hire dummy, a quadratic term on age and tenure, schooling, and a gender dummy. MM-QR refers to the method of moments quantile regression as in Machado and Silva (2019). Year-clustered standard errors are in parentheses. $\mathrm{UR}_{(t-1)}$ and $\mathrm{UR}_{(t-1)} \cdot \mathbb{1}\{H=1\}$ coefficients and standard errors are multiplied by 100.
*** Denotes statistical significance at the 0.01 level.

Table 11: Cyclicality of Real Wages (Hourly Wages – Match Fixed Effect)

	Mean	P10	P50	P90	Mean	P10	P50	P90
	OLS (1)	MM-QR (2)	MM-QR (3)	MM-QR (4)	OLS (5)	MM-QR (6)	MM-QR (7)	MM-QR (8)
Log Minimum Wage	0.393***	0.344***	0.389***	0.442***	0.397***	0.341***	0.392***	0.453***
	(0.096)	(0.069)	(0.085)	(0.108)	(0.095)	(0.065)	(0.083)	(0.110)
Log Bargained Wage	0.092***	0.106***	0.094***	0.079***	0.089***	0.102***	0.091***	0.077***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)
$\text{UR}_{(t-1)}$	-0.688***	-0.467***	-0.670***	-0.910***	-0.732***	-0.518***	-0.714***	-0.948***
	(0.120)	(0.098)	(0.106)	(0.131)	(0.132)	(0.098)	(0.115)	(0.149)
$\text{UR}_{(t-1)} \cdot \mathbb{1}\{H = 1\}$	-0.027	-0.165***	-0.038	0.112*				
	(0.058)	(0.053)	(0.051)	(0.067)				
$\text{UR}_{(t-1)} \cdot \mathbb{1}\{EE = 1\}$					-0.050	-0.172***	-0.061	0.072
					(0.051)	(0.045)	(0.044)	(0.071)
$\text{UR}_{(t-1)} \cdot \mathbb{1}\{NEE = 1\}$					-0.002	-0.136**	-0.013	0.133*
					(0.073)	(0.066)	(0.064)	(0.079)
Worker FE	No	No	No	No	No	No	No	No
Firm FE	No	No	No	No	No	No	No	No
Match FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,522,072	46,522,072	46,522,072	46,522,072	43,059,202	43,059,202	43,059,202	43,059,202

Note: The dependent variable is the logarithm of real hourly total wages. Bargained wages are defined as the modal value in a given job title × year cell. All regressions include a quadratic time trend and its interaction with a new hire dummy, a quadratic term on age and tenure, schooling, and a gender dummy. MM-QR refers to the method of moments quantile regression as in Machado and Silva (2019). Year-clustered standard errors are in parentheses. EE workers are defined as new hires who were employed at $t-1$ and switch firms at t. NEE workers are new hires who were not in the sample at $t-1$. $\text{UR}_{(t-1)}$, $\text{UR}_{(t-1)} \cdot \mathbb{1}\{H = 1\}$, $\text{UR}_{(t-1)} \cdot \mathbb{1}\{EE = 1\}$, and $\text{UR}_{(t-1)} \cdot \mathbb{1}\{NEE = 1\}$ coefficients and standard errors are multiplied by 100.
* Denotes statistical significance at the 0.10 level; ** denotes statistical significance at the 0.05 level; *** denotes statistical significance at the 0.01 level.

Table 12: Gelbach Decomposition of Hourly Wage Cyclicality

	Stayers	EE	NEE
$\text{UR}_{(t-1)\mathbf{base}}$	-0.555***	-0.229***	-0.338***
	(0.110)	(0.060)	(0.044)
$\text{UR}_{(t-1)\mathbf{full}}$	-0.732***	-0.033	-0.017
	(0.144)	(0.072)	(0.068)
Worker FE	0.096***	0.128***	-0.049
	(0.025)	(0.028)	(0.035)
Firm FE	0.103***	-0.086***	-0.071*
	(0.021)	(0.033)	(0.040)
Match Quality	-0.022**	-0.238***	-0.200***
	(0.009)	(0.060)	(0.046)

Note: The Worker FE, Firm FE, and Match Quality rows represent the impact on the cyclicality coefficient of adding each component to the base model. Base and full models include dummies for EE and NEE workers, quadratic time trend and its interaction with EE and NEE dummies, a quadratic term on age and tenure, schooling, and a gender dummy. EE workers are defined as new hires who were employed at $t-1$ and switch firms at t. NEE workers are new hires who were not in the sample at $t-1$. Year-clustered standard errors are in parentheses. All coefficients and standard errors are multiplied by 100.
*** Denotes statistical significance at the 0.01 level.

Table 13: Distribution Statistics of Firm and CBA-specific Cyclicality Coefficients

	Mean	P10	P50	P90
Firm	-0.70	-2.39	-0.69	1.01
Collective Bargaining Agreement	-0.68	-1.75	-0.67	-0.28

Note: The table shows moments of the distribution of cyclicality coefficients estimated according to equation 12. The first row reports the coefficients obtained by interacting firm fixed effects with the cycle variable; the second row indicates the analog for the interaction of CBA fixed effects with the cycle. All coefficients multiplied by 100.

Appendix

A Tables

Table A1: Cyclicality of Real Wages (Bargained Wages – Base Model)

	Mean	P10		P50		P90	
	OLS	QR	MM-QR	QR	MM-QR	QR	MM-QR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{UR}_{(t-1)}$	-0.948***	-0.527***	-0.805***	-0.975***	-0.927***	-1.039***	-1.146***
	(0.116)	(0.172)	(0.120)	(0.118)	(0.115)	(0.120)	(0.129)
$\text{UR}_{(t-1)} \cdot \mathbb{1}\{H=1\}$	-0.145***	-0.063	-0.027	-0.084**	-0.127***	-0.289***	-0.309***
	(0.039)	(0.075)	(0.058)	(0.038)	(0.036)	(0.063)	(0.104)
Worker/Firm FE	No						
Observations	52,342,436						

Note: The dependent variable is the logarithm of real bargained wages. Bargained wages are defined as the modal value in a given job title × year cell. All regressions include a quadratic time trend and its interaction with a new hire dummy, a quadratic term on age and tenure, schooling, and a gender dummy. MM-QR refers to the method of moments quantile regression as in Machado and Silva (2019). Year-clustered standard errors are in parentheses. $\text{UR}_{(t-1)}$ and $\text{UR}_{(t-1)} \cdot \mathbb{1}\{H=1\}$ coefficients and standard errors are multiplied by 100.
*** Denotes statistical significance at the 0.01 level.

Table A2: Cyclicality of Real Wages (Bargained Wages – FE Model)

	(1) Mean	(2) P10	(3) P50	(4) P90
Log Minimum Wage	0.564***	0.644***	0.570***	0.474***
	(0.073)	(0.048)	(0.066)	(0.102)
$\text{UR}_{(t-1)}$	-0.538***	-0.312***	-0.521***	-0.794***
	(0.080)	(0.054)	(0.072)	(0.110)
$\text{UR}_{(t-1)} \cdot \mathbb{1}\{H=1\}$	-0.030	-0.029	-0.030	-0.031
	(0.026)	(0.032)	(0.023)	(0.038)
Worker FE	Yes			
Firm FE	Yes			
Observations	52,342,436			

Note: The dependent variable is the logarithm of real bargained wages. Bargained wages are defined as the modal value in a given job title × year cell. All regressions include a quadratic time trend and its interaction with a new hire dummy, a quadratic term on age and tenure, schooling, and a gender dummy. MM-QR refers to the method of moments quantile regression as in Machado and Silva (2019). Year-clustered standard errors are in parentheses. $\text{UR}_{(t-1)}$ and $\text{UR}_{(t-1)} \cdot \mathbb{1}\{H=1\}$ coefficients and standard errors are multiplied by 100.
*** Denotes statistical significance at the 0.01 level.

Table A3: Cyclicality of Real Wages (Base Wages)

	Mean	P10		P50		P90	
	OLS (1)	QR (2)	MM-QR (3)	QR (4)	MM-QR (5)	QR (6)	MM-QR (7)
$\text{UR}_{(t-1)}$	-1.089***	-0.756***	-0.970***	-1.102***	-1.076***	-1.130***	-1.235***
	(0.129)	(0.122)	(0.127)	(0.125)	(0.127)	(0.136)	(0.137)
$\text{UR}_{(t-1)} \cdot \mathbb{1}\{H=1\}$	-0.427***	-0.165***	-0.219***	-0.324***	-0.405***	-0.694***	-0.680***
	(0.064)	(0.040)	(0.043)	(0.045)	(0.060)	(0.090)	(0.106)
Observations	52,342,436						

Note: The dependent variable is the logarithm of real hourly base wages, i.e. without any supplements or bonuses. All regressions include a quadratic time trend and its interaction with a new hire dummy, a quadratic term on age and tenure, schooling, and a gender dummy. Year-clustered standard errors are in parentheses. All coefficients and standard errors are multiplied by 100.
*** Denotes statistical significance at the 0.01 level.

B Gelbach Decomposition

To obtain a better insight from our decomposition exercise in section 5.3.1 it is useful to present the benchmark wage regression equation in a matrix formulation, singling out the regression coefficients of particular interest:

$$\boldsymbol{Y} = \mathbf{Z}\boldsymbol{\beta_0} + \mathbf{U}\boldsymbol{\gamma_0} + \boldsymbol{\epsilon_0}, \tag{13}$$

where $\mathbf{Y}$ stands for the vector of wages; $\mathbf{Z}$ denotes the matrix of control variables; $\boldsymbol{\beta_0}$ is a vector of regression coefficients; $\mathbf{U}$ is a matrix that represents the two unemployment rate variables ($UR_{(t-1)}$ and $UR_{(t-1)} \times \mathbb{1}\{H = 1\}$), $\boldsymbol{\gamma_0}$ represents the corresponding coefficients (α_1 and γ_1); and $\boldsymbol{\epsilon_0}$ gives the error term.

Making use of the Frisch-Waugh-Lovell theorem, we can express the OLS estimate of $\boldsymbol{\gamma_0}$ by running a regression of $\boldsymbol{Y}$ on $\mathbf{U}$ after partialling out the effect of $\mathbf{Z}$ on both variables. That is,

$$\widehat{\boldsymbol{\gamma_0}} = (\mathbf{U}'\mathbf{P_Z}\mathbf{U})^{-1}\mathbf{U}'\mathbf{P_Z}\mathbf{Y}, \tag{14}$$

where, $\mathbf{P_Z}$ is the familiar residual-maker matrix, $\mathbf{P_Z} = (\mathbf{I} - \mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{\mathbf{-1}}\mathbf{Z}')$.

More compactly, we can write:

$$\widehat{\boldsymbol{\gamma_0}} = \mathbf{A_Z}\mathbf{Y}, \tag{15}$$

where it is useful to retain the meaning of the matrix $\mathbf{A_Z} = (\mathbf{U}'\mathbf{P_Z}\mathbf{U})^{-1}\mathbf{U}'\mathbf{P_Z}$ which, for any given dependent variable, always gives the regression coefficient estimates of $\mathbf{U}$ from an OLS regression that also includes $\mathbf{Z}$.

Consider now our model of job match fixed effects. In this case, the job match fixed effect will compound the worker fixed effect, the firm fixed effect, and the match quality fixed effect. In matrix form, we can write

$$\boldsymbol{Y} = \mathbf{Z}\widehat{\boldsymbol{\beta_2}} + \mathbf{U}\widehat{\boldsymbol{\gamma_2}} + \mathbf{M}\widehat{\boldsymbol{\rho_2}} + \widehat{\boldsymbol{\epsilon_2}}, \tag{16}$$

where $\boldsymbol{M}$ corresponds to the matrix that identifies the job matches and $\widehat{\boldsymbol{\rho_2}}$ denotes the estimates of the job match fixed effects.

To further disentangle the impact of worker self-selection, sorting among firms with different wage policies, and the allocation into job matches with distinct match quality, some strong assumptions will be necessary. A workable assumption, and in this framework a natural one, is to treat the match quality fixed effect as orthogonal to the worker and firm fixed effects. This approach has been used by Raposo et al. (2021) and Woodcock (2023) to study the wage losses of displaced workers.

To grasp the impact of worker, firm, and match quality heterogeneity we define an equation for the match fixed effect including worker-identifying dummies ($\mathbf{W}$) and firm-identifying dummies ($\mathbf{F}$):

$$\mathbf{M}\widehat{\rho_2} = \mathbf{Z}\widehat{\boldsymbol{\eta}_2} + \mathbf{U}\widehat{\boldsymbol{\delta}_2} + \mathbf{W}\widehat{\phi_2} + \mathbf{F}\widehat{\psi_2} + \widehat{\boldsymbol{\upsilon}_2}, \tag{17}$$

where $\widehat{\phi_2}$ denotes the worker fixed effects, $\widehat{\psi_2}$ embodies the firm fixed effects, $\widehat{\boldsymbol{\delta}_2}$ identifies the impact of match quality, and $\widehat{\boldsymbol{\upsilon}_2}$ represents the residual term.

Multiplying both terms of equation (17) by $\mathbf{A_X}$ we can finally split the match component into three parts (Gelbach, 2016):[2]

$$\widehat{\gamma_0} - \widehat{\gamma_2} = \widehat{\boldsymbol{\delta}_\phi} + \widehat{\boldsymbol{\delta}_\psi} + \widehat{\boldsymbol{\delta}_2}, \tag{18}$$

where $\widehat{\boldsymbol{\delta}_\phi}$ represents the worker component and $\widehat{\boldsymbol{\delta}_\psi}$ represents the firm component.

[2]Note that, by construction, $\mathbf{A_Z}\mathbf{Z}\widehat{\boldsymbol{\eta}_2} = \mathbf{0}$, $\mathbf{A_Z}\mathbf{U}\widehat{\boldsymbol{\delta}_2} = \widehat{\boldsymbol{\delta}_2}$, and $\boldsymbol{A_Z}\widehat{\boldsymbol{\upsilon}_2} = \mathbf{0}$.