The False Illusion of Wage Cyclicality

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Abstract

We show that cyclical variation in entry wages is driven by occupation mobility. To this end, we use Portuguese administrative data from 1986-2019 that accurately identifies occupation transitions between and within firms. We find that wages of new hires that remain in the same occupation are no more cyclical than those of stayers. By contrast, wages of workers switching occupation across and within firms are highly cyclical. Furthermore, we show that cyclicality increases, the more distinct the previous and current occupations are in terms of the required skills. Our results suggest that the standard framework in the literature conflates wage flexibility of new hires with cyclical changes in match quality associated with the worker's occupation.

Keywords: wage cyclicality, occupational mobility, reallocation, match quality

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1 Introduction

Starting with Bils (1985), a large empirical literature using individual-level data has shown that wages of new hires are substantially more cyclical than those of incumbent workers. This result has been widely interpreted as evidence of wage flexibility for new hires (Pissarides, 2009). However, the large variation observed in new hires' wages might arise from cyclical movements in match quality, as emphasized by Gertler et al. (2020). In this paper, we employ a new strategy to measure the degree of true wage flexibility in the economy.

To separate wage flexibility from cyclical changes in match quality, we differentiate between workers that switch occupation versus those that do not switch occupation. Importantly, we make this distinction for both new hires and stayers, as workers' occupation codes in our data are highly reliable. In doing so, we show that cyclical variation in wages is mainly driven by workers switching occupation, both when transitioning to a new firm and when moving to a new occupation within the same employer, rather than employer mobility as previously documented in the literature. Moreover, we find that wage cyclicality increases, the more distinct current and previous occupations are from one another in terms of the required skills. These results suggest that the standard regression in the literature confounds flexibility in entry wages with cyclical movements in match quality associated with occupation mobility, creating an illusion of highly cyclical wages for new hires.

We base our empirical analysis on rich linked employer-employee data from Portugal that spans the period from 1986 and 2019. This dataset has a particular feature, not available in other datasets used in prior work. The information on the worker's current occupation is regarded as highly reliable because it is monitored to check firms' compliance to wage floors set by unions. We thus exploit this feature to track occupational mobility when workers move between employers, but also within-firm occupation changes. The latter are hard to identify in commonly used datasets because these are riddled with misclassification error in occupation codes, therefore the standard approach is to identify an occupation switch as genuine only if it coincides with some other significant labor market change, such as an employer switch (e.g. Neal, 1999; Kambourov & Manovskii, 2009).[1]

[1]Standard datasets in the literature, such as the National Longitudinal Survey of Youth and the Current Population Survey before 1994, use "independent coding", a practice that is believed to overstate occu-

To measure wage cyclicality, we start from the typical specification in the literature that relies on within-individual variation in wages and the unemployment rate across years individuals are employed (Carneiro et al., 2012; Gertler et al., 2020; Figueiredo, 2022). While the individual fixed effect accounts for selection based on unobserved characteristics with a time-invariant effect on earnings, we account for composition bias due to potential sorting into lower paying occupation and lower paying firms in bad times by controlling for occupation and firm fixed effects. We begin by confirming the key result in the literature that new hires' wages are more cyclical than those of job stayers. Specifically, we find that, when compared to incumbent workers, entry wages are 0.45% lower for new hires for every percentage point increase in the unemployment rate. Next, we address the question of whether the excess cyclicality in new hires' wages hides variation in wages due to workers moving to better jobs during expansions. We do this by augmenting the standard specification with categorical variables that separate workers that switch occupation from those that remain in the same occupation. To the extent that the quality of a match is tied to the worker's occupation, specifically in how well his/her abilities align with the skills required by the occupation—an interpretation that follows recent work by Guvenen et al. (2020), Baley et al. (2022) and Figueiredo (2022)—we are better able to isolate rigidity in entry wages by focusing on new hires and job stayers that do not switch occupation.

When we estimate separate terms for occupation switchers and non-switchers, we find no evidence of excess wage cyclicality for new hires that do not switch occupation. Wages of new hires that switch occupation, by contrast, are highly procyclical: the difference in the wage semi-elasticity with respect to stayers that remain in the same occupation is around 0.57 percentage points and is statistically different from zero. Interestingly, because we can identify occupation mobility within firms, we show that wages of workers that remain in the same employer but change occupation are also more cyclical than job stayers that do not switch occupation. In particular, the wage semi-elasticity is higher in 0.2 percentage points. These results suggest that large variations in wages over the business cycle are associated

pational mobility. When using "independent coding", the respondent describes his/her occupation, and a survey official attributes a code using census occupation codes. This means that even if the respondent provides the same description two surveys in a row, he/she may be coded as having changed occupations because the survey official fills in a different code in the next survey.

with occupational mobility rather than employer mobility. From this we conclude that by pooling occupation switchers and non-switchers, the standard regression in the literature conflates possible wage flexibility of new hires with changes in match quality for occupation switchers.

To corroborate our interpretation, we measure how different the current and previous occupations are in terms of the skills they required as in Baley et al. (2022). To this end, we complement our dataset with occupational level data from O*NET and characterized occupations in terms of the requirements in four skill dimensions (math, verbal technical and social). We argue that the more different the skill requirements are between the current and previous occupations, the larger is the variation in match quality. Therefore, wages of workers remaining in the same occupation or transitioning across very similar occupations provide a composition-free estimate of wage flexibility, while the same is not true for workers transitioning across different occupations. In particular, the larger is difference between the current and the previous occupation the larger is the composition effect captured by changes in wages over the cycle. We find that wage cyclicality increases as the current and previous occupations become more distinct from one another in terms of the skill required, implying that the cyclical variation in wages of occupational switchers is driven by transitions across different occupations in terms of the skills required. These findings suggest that previously measured wage flexibility indeed reflects procyclical match improvements for workers changing occupations.

Overall, our results show that the high cyclicality of new hires' wages widely documented in the previous literature arises from composition effects due to the cyclical variation in match quality associated with the worker's occupation, rather than wage flexibility. This implies that wage adjustments of stayers, in particular those that do not change occupation, provide a sufficient statistic for gauging the degree of wage rigidity in the economy.

Related Literature These results contribute to the extensive literature that measures wage cyclicality using worker-level panel data. Following the seminal work by Bils (1985), the typical empirical model regresses wages on the unemployment rate and its interaction with an indicator variable that equals one if the worker is a new hire and zero, accounting for worker unobserved heterogeneity through a first-differences estimator or worker fixed effects. Reported point estimates suggest that new hires' wages are more cyclical than those of job stayers (Shin, 1994; Solon et al., 1994; Barlevy, 2001; Shin & Solon, 2007; Haefke et al., 2013). Carneiro et al. (2012) and Stüber (2017) show that this finding remains unchanged once one accounts for composition effects due to sorting into low-paying occupations and/or low-paying firms during recessions.

Recent evidence, however, suggests that the high cyclicality of new hires' wages reflects instead composition effects driven by variation in match quality. First, Gertler et al. (2020) study wages of new hires from non-employment, which they regard to be less affected by composition bias than the wages of job switchers, and find that for these workers wages are as cyclical as those of job stayers. Bauer & Lochner (2020) and Figueiredo (2022) document a similar pattern using German employer-employee data and the National Longitudinal Survey of Youth, respectively. More recently, Grigsby et al. (2021) use a matching estimator that matches job switchers to similar incumbent workers and find that new hires wages are weakly procyclical. Our work adds to these findings by showing that the large variation in wages over the business cycle is associated with occupational mobility, rather than job mobility, as previously documented in the literature, suggesting that indeed cyclical wage changes are associated with movements in match quality. The novelty in our approach is that we can accurately identify occupational mobility between firms but also within the same employer. In doing so, we show that wages are highly cyclical for both new hires and incumbent workers that reallocate across different occupations.

Layout The paper is organized as follows. The next section describes the wage setting system in Portugal. Section 3 introduces the data and provides details on the sample and its characteristics, and Section 4 discusses our estimation strategy. Section 5 presents the empirical results, and Section 6 several robustness checks. Section 7 concludes.

2 Wage Setting in Portugal

Wages of private sector workers in Portugal are conditioned by the definition of two lower bounds. One is the national minimum wage, updated annually by the parliament under government proposal, and that determines a wage floor for the majority of the labor force. In 2019, 21% of full-time workers in the private sector earned the national minimum wage, which represented around 67% of the average total pay.

The second restriction is defined by collective bargaining between employers' and unions, mostly at the industry level, which define wage floors for each occupational category.[2] In legal terms, the agreement is only binding on the parties in the negotiations, that is, the workers who are unionized and the firms within employer associations. However, the Portuguese Ministry of Employment often extends the collective agreement to all firms and workers in the sector. Hence, collective bargaining coverage extends well beyond the membership of trade unions and employer associations.

Even though there is a wage floor agreed upon for each occupational category, firms can offer wages that are higher than the minimum agreed for the workers' occupational category. As firms set the actual wage, not the collective agreement, there is a high degree of wage flexibility, which allows firms to adjust to firm-specific conditions as well as macroeconomic shocks. This is different from union contracts in the U.S., which specify wages for different jobs, and all workers in the same job receive the same pay. In this regard, Card & Cardoso (2022) show that in Portugal workers receive, on average, a 20% premium over the prevailing wage floor, with larger premiums for older and better-educated workers as well as those working at higher-productivity firms.

3 Data

3.1 Dataset and Variables

Our main data source is *Quadros de Pessoal* (henceforth, QP), a longitudinal matched employer-employee dataset collected and managed by the Portuguese Ministry of Employ-

[2]Note that the bargaining sets wage levels and not wage changes.

ment. The data are available from 1985 onward and contain detailed information at the workers' and firms' level. Before 1993, the information refers to the month of March, and thereafter, the information refers to October. QP is a compulsory annual employment survey to any firm employing at least one wage earner at the end of the reference month, therefore it virtually covers all firms employing paid labor in the private sector in Portugal. On average, it has information on approximately 220,000 firms and 2.5 million employees in any given year. Firms and workers entering the database are assigned a unique, time-invariant identifier that allows the researcher to track them over time.

An important feature of QP is that particular care is placed on the reliability of the information, as it is used by the Ministry of Employment to check employer's compliance with labor law. Moreover, by law, the survey's information is made available to every worker in a public space of the establishment. Together with the administrative nature of the data, this implies a high degree of coverage and reliability, reducing measurement error in reported wages and misclassification in worker's occupation, two key variables in our empirical exercise.

Sample We restrict our attention to female and male workers between the ages of 17 and 61 years old who are single job-holders. Furthermore, we only include those who worked at least 120 hours in the private non-farm sector and earned more than 80 percent of the prevailing minimum wage in the reference month.[3] The latter excludes apprentices from the analysis who receive only 80% of the national minimum wage rate. The resulting sample comprises information on 7,163,878 workers and 470,461 firms from 1986 to 2019, yielding a total of 13,076,525 worker–firm observations and 49,345,103 worker–year observations. Following previous work (Card et al., 2013; Cardoso et al., 2016), we further restrict our analysis to observations in the largest set of connected of firms and workers that are linked by worker mobility across firms in order to separately identify worker and employer pay

[3] We discard firms who are labelled as "public sector" at any point in time since hierarchical structures in the public sector are very different from the private sector, with little cross-sector or within-firm mobility. To identify public firms, we proceed in two steps. First, we label as "public sector" firms those whose percentage of public capital exceeds 50%. Second, we identify as "public sector" firms those that have at least fifty of the same employees as a firm formerly identified as a "public sector" firm and that no longer appears in the data. This amounts to identifying privatized firms which oftentimes maintain their public-style hierarchical structures.

components. This covers 98.8% of the employee-firm pairs. Our final sample includes 99.1% of observations. Table 1 shows that the sample subject to the criteria described earlier and the restricted subsample in the largest connected set look similar.[4]

Wages and Employment For each wage earner in a firm, QP has information on the hiring date, total hours worked (contractual and overtime) and earnings in the reference month. In particular, QP reports the base wage (gross pay for normal hours of work), regular and non-regular benefits and overtime pay. Using this information, we construct total pay per hour as the sum of the base wage, benefits and overtime divided by total hours worked in the referenced month, that includes normal hours of work and overtime. This means that we primarily focus on flexibility in realized compensation, as common in the literature. Wages are winzorized at the top 1% of observations and expressed in 1985 Euros using the Consumer Price Index (CPI) from Statistics Portugal.[5]

QP also has detailed information on the worker's occupation. More specifically, QP reports workers' occupational titles in the Classificação Nacional de Profissões—CNP80 until 1995 and CNP94 from 1995 until 2010—; thereafter, the occupational classification system changed to the Classificação Portuguesa das Profissões (CPP2010). Since the classifications of occupations are not consistent across years, before our empirical analysis, we converted all the occupational codes into the CPP2010 classification system in order to make the categorization time-consistent.[6] We opt for the CPP2010 because it is based on the ISCO-08 classification system (International Occupational Classification Codes), which is fairly similar to the Standard Occupational Classification used by the U.S. Census. In our analysis, an "occupation" is defined by the CPP2010 3-digit codes. Examples of occupations at this

[4] Abowd et al. (1999, 2002) prove that, within each connected set, the employee and firm effects are identified only in relation to each other. Therefore, we normalize the firm effect by omitting the dummy of a random firm, as standard in the literature

[5] From 1986 to 1993, we use the March CPI, whereas from 1994 to 2019, the CPI corresponds to October.

[6] We converted the CNP80 occupational codes into CNP94. Afterwards, we converted all CNP94 occupational codes to the CPP2010 occupational codes in two steps. In both convertions, we proceeded in two steps. First, we used the official crosswalk provided by Statistics Portugal. For CNP80/CNP94 codes that have a unique correspondence to an occupational code in the CNP94/CPP2010, we used the official crosswalk. For the remaining CNP80 codes, we created a crosswalk based on the frequency of cross-occupational codes changes from 1994 and 1995 and attribute the CNP94 occupational code from the cross-occupational codes change that is more frequent within firms. For the remaining CNP94 codes, we created a crosswalk based on the frequency of cross-occupational codes changes from 2009 and 2010 and attribute the CPP2010 occupational code from the cross-occupational codes change that is more frequent within firms.

level of desegregation are *Journalists and Writers*, *Doctors*, and *Nurses*.

Exploiting the panel structure of the data, we identify *stayers* as workers employed in the same firm for two consecutive years, i.e. workers with tenure in the current employer greater than or equal to 12 months, and *new hires* as workers with firm tenure less than 12 months. Therefore, the latter include job-to-job transitions, workers coming from non-employment and recalls, individuals that return to their previous employer, as long as firm tenure is less than 12 months. Apart from worker mobility across firms, we also track worker occupation mobility over time. As mentioned before, a key feature of our dataset is that information on the worker's current occupation is regarded as highly reliable because it is monitored to check firms' compliance to wage floors set by unions. This allows us to pinpoint not only transitions across occupations when workers change employers, but also occupation transitions within the same employer. The latter are hard to identify in commonly used datasets. This is because due to misclassification error in occupation codes, the standard approach is to consider an occupation switch as genuine only if it coincides with an employer switch (e.g. Neal, 1999; Kambourov & Manovskii, 2009). Therefore, the literature thus far envisions worker reallocation as occurring only between employers. Using the CPP2010 3-digit occupation codes, we define an occupational switcher as a worker that changed occupation between two consecutive surveys, regardless of whether the worker changed employers or not.

Economic conditions In Portugal, wages are determined at least six to twelve months in advance, therefore we measure business cycle conditions using the aggregate unemployment rate among individuals older than 16 years old in the previous year, as in Carneiro et al. (2012). From 1986 to 2019, the unemployment rate was approximately 7.8%, on average, varying from 3.9% to 17.1%, as shown in Figure 1.

3.2 Summary Statistics

Table 1 presents summary statistics on the relevant sample from 1986-2019. Workers are, on average 37 years old, 19% have at least a college degree and 43% are female. The average worker earns 4.51 euros per hour, of which 86% comes from the base pay, on average.

About 75.5% of observations correspond to stayers and 24.6% refer to new hires. There are considerable differences between stayers and new hires, both in the earnings and demographics dimensions. Compared to stayers, new hires are younger and earn less per hour, but are equally educated. Using CPP2010 3-digit codes to track occupational mobility, we find that around 28.1% of all workers in the sample are observed to switch occupation, of which approximately one third correspond to changes in occupation within a firm. Thus, occupation transitions within firms are significant. Occupation switchers that also transition to a new employer represent 18.3% of all observations. The level of occupational mobility across employers we find in Portugal is similar to the estimates of mobility in the U.S. that account for the coding error (e.g. Guvenen et al., 2020).[7]

4 Empirical Methodology

To study how wages move along the cycle, we estimate the wage semi-elasticity with respect to the aggregate unemployment rate, as standard in the literature (Pissarides, 2009). To this end, we start from the baseline specification in Carneiro et al. (2012),

$$\begin{aligned} w_{ijft} = \beta_0 \; + \; (\; \beta_1 \; + \; \beta_2 \; NH_{ijft} \;) \times U_t \; + \\ \gamma' \; (\; NH_{ijft} \; + \; controls \;) \; + \; \delta_i \; + \; \delta_j \; + \; \delta_f \; + \; \varepsilon_{ijft} \end{aligned} \quad (1)$$

where w_{ijft} is the log real hourly earnings of individual i in occupation j working in firm f at time t, U_t is the aggregate unemployment rate and NH_{ijft} is a new hire dummy that equals if the worker is a new hire, i.e. has been in the same firm for less than 12 months, and zero otherwise. δ_i, δ_j and δ_f correspond, respectively, to worker, occupation and firm fixed effects. Lastly, ε_{ijft} is the error term, which includes all unobserved determinants of wages for worker i in occupation j working in firm f at time t.

The coefficients of interest are β_1 and β_2. β_1 measures the wage semi-elasticity of stayers, while β_2 captures the difference in the semi-elasticity of wages between stayers and new

[7] Regarding occupational transitions within a firm, Papageorgiou (2018) uses the 1996 Panel of the Survey of Income and Program Participation, which uses dependent interviewing and thus has little occupational coding error, and finds that, in the U.S., 8% of workers switch occupations within their firm, similar to what we find in Portugal.

hires. The key finding in the literature is that both β_1 and β_1 are significantly negative, suggesting greater cyclical sensitivity in the wages of new hires. This result has been widely interpreted as evidence of contractual wage flexibility (Pissarides, 2009). However, even though specification 1 accounts for sorting into higher-paying firms/occupations during good times by controlling for firm and occupation time invariant heterogeneity, it does not account for cyclical composition effects due to workers moving to better jobs in expansions. This is particular important in light of recent work showing that recessions have a sullying effect among new hires, decreasing average job quality for these group of workers (Baley et al., 2022). Thus, excess cyclicality in new hires' wages ($\beta_2 < 0$) may not reflect true wage flexibility, but instead wage variation due to cyclical movements in match quality.

We address this issue by making a distinction between stayers and new hires who switch occupation versus those that remain in the same occupation in two consecutive surveys. To the extent that match quality is tied to the worker's current occupation, we are better able to isolate wage flexibility from composition effects due to variations in match quality by focusing on new hires and stayers who remain in the same occupation. In contrast, wages of those that change occupation are more likely to capture changes in match quality.

Our argument that cyclical selection bias works mainly through workers that switch occupation follows recent work that measures match quality through the lens of a skill mismatch index defined by the misalignment between worker's abilities and occupation skill requirements (Guvenen et al., 2020; Baley et al., 2022; Figueiredo, 2022). Specifically, let a_i^j be worker i's ability in skill j, and $r_{c_{it}}^j$ be the level required of skill j by the occupation individual i has in his/her job at time t, c_{it}, then skill mismatch $m_{i,t}$ is defined as

$$m_{i,t} \equiv \sum_{j=1}^{J} \frac{1}{J} \left| a_i^j - r_{c_{it}}^j \right|, \tag{2}$$

where J is the number of relevant skills. The interpretation of skill mismatch $m_{i,t}$ as a measure (of the lack) of match quality hinges on two empirical regularities: (i) Guvenen et al. (2020) show that skill mismatch reduces wages; and (ii) Figueiredo (2022) finds that skill mismatch is negatively associated with job duration, a measure used in the literature as a proxy for match quality (Bowlus, 1995). Given Equation 2, only workers that change occupations may experience a change in the quality of the match, as skill mismatch varies driven by differences in skill requirements $r^j_{c_{it}}$ across occupations. Given this, we augment Equation 1 with categorical variables that distinguish between stayers and new hires who switch occupation versus those that do not change occupation and estimate the following wage level equation,

$$w_{ijft} = \beta_0 \ + \ (\ \beta_1 \ + \ \beta_2 \ NH^{NS}_{ijft} \ + \ \beta_3 \ S^S_{ijft} \ + \ \beta_4 \ NH^S_{ijft} \ ) \ \times \ U_t \ + \\ \gamma' \ (\ NH^{NS}_{ijft} \ + \ S^S_{ijft} \ + \ NH^S_{ijft} \ + \ x_{it} \ + \ t \ + \ t^2 \ ) \ + \\ \delta_i \ + \ \delta_j \ + \ \delta_f \ + \ \varepsilon_{ijft}, \quad (3)$$

where NH^{NS}_{ijft} equals one for new hires that remain in the same occupation and zero otherwise, NH^S_{ijft} equals one for new hires that switch occupation and zero otherwise, and S^S_{ijft} equals one for job stayers that switch occupation and zero otherwise. The term $x_{i,t}$ is a set of time-varying controls at the individual level including age, its square and a set of dummies for education levels, which aim to capture that new hires and stayers, that switch or do not switch occupation, may also be different in other dimensions. We also condition in a quadratic time-trend. This controls for human capital dynamics over time. Moreover, as in Equation 1, we include occupation (δ_j), firm (δ_f) and individual (δ_i) level fixed effects. This means that we account for differences between booms and recessions in the composition of workers, firms and occupations. In our setting, the occupation dummy corresponds to 3-digit occupation codes, as described in the previous section. The term ε_{ijft} should be interpreted as the unobserved heterogeneity that is left, after conditioning on the set of mentioned controls. Standard errors are clustered at the firm level to allow for serial correlation in the error term within a firm.

In Equation 3, β_1 captures the wage semi-elasticity of stayers that *do not switch* occupation, and β_2 measures the differential in wage cyclicality between new hires and stayers that *do not switch* occupation. Following the above definition of match quality (Equation 2), workers that remain in the same occupation do not experience a variation in match quality. Therefore, we interpret these parameters as being a composition-free measure of wage flexibility. The identifying assumption is that, conditional on the included covariates, changes in unemployment are uncorrelated with unobserved determinants of wages for workers that do not switch occupation, $\mathbb{E}[\varepsilon_{ijft} \cdot U_t | x_{i,t}, t, \delta_j, \delta_f, \delta_i] = 0$. In turn, the coefficients β_3 and β_4 measure the excess wage cyclicality for stayers and new hires that *switch* occupation. For these workers, changes in unemployment are likely to be correlated with the error term ε_{ijft} due to unobserved changes in match quality that correlate with U_t. Specifically, $\mathbb{E}[\varepsilon_{ijft} \cdot U_t | x_{i,t}, t, \delta_j, \delta_f, \delta_i] < 0$, implying that new hires sort into better jobs during booms, consistent with recent evidence by Baley et al. (2022). As such, we regard β_3 and β_4 as capturing changes in wages driven by procyclical selection into better matches.

5 Results

In this section, we present the main results. Table 2 reports OLS estimates of the specifications described in Section 4. Coefficients on the unemployment rate are multiplied by 100 and thus correspond to the % wage change following a 1 percentage point (pp) increase in the unemployment rate.

Revisiting the Literature We start by confirming the key findings in the literature. Column 1 of Table 2 presents the estimated coefficients for the commonly estimated specification, Equation 1. This columns shows that the coefficient interacting the new hires dummy with unemployment is negative, suggesting that new hires' wages are more cyclical than those of stayers. In particular, for every percentage point increase in the unemployment rate, entry wages decrease by 0.45% more when compared to stayers. This excess cyclicality in the wags of new hires is statistically significant at the 1% level, and its magnitude is consistent with Carneiro et al. (2012). Using the same same matched employer-employee dataset, they find that the wage semi-elasticity of new hires is around 0.47pp larger than that of incumbent workers.

Cyclicality and Occupation Mobility As hinted in section 4, the high cyclicality of new hires' wages does not imply that entry wages are more flexible than those of stayers. Indeed, even though Column 1 in Table 2 controls for differences in the composition of workers, firms and occupations over the business cycle, it does not fully account for the fact that the quality of the matches is not necessarily comparable in expansions versus recessions, as emphasized by Gertler et al. (2020).

To cleanse our estimates from composition effects due to sorting dynamics in the labor market, we introduce dummy variables that differentiate between workers that switch occupation and those that remain in the same occupation. As we argue in section 4, workers that do not switch occupation do not experience a change in match quality, thus the wages of those switching occupation are more likely to be subject to composition-bias. Column 2 of Table 2 adds an interaction terms between the new hire dummy and a dummy that equals one for occupational switchers to Equation 1 . In doing so, we find that the excess cyclicality in the wages of new hires is explained by those workers that start a new job in a new occupation. As Column 2 shows, the new hire excess wage cyclicality disappears for workers that start a job in a new employer but in the same occupation they had in the previous employer. The coefficient estimate is small in magnitude and not statistically different from zero. Thus, for new hires that remain in the same occupation wages are no more cyclical than those of existing workers. Interestingly, while the new hire excess wage cyclicality disappears for those that do not switch occupation, we find that for new hires that do switch occupation wages are more cyclical than those of existing workers. In particular, the difference in the wage semi-elasticity between stayers and new hires that switch occupation is 0.59pp and statistically significant at 1% level. We regard the excess wage cyclicality of occupation switchers as evidence of procyclical match quality for new hires. This interpretation is consistent with recent evidence by Baley et al. (2022) and Haltiwanger et al. (2021) showing that recessions have a sullying effect in the labor market, decreasing the match quality of new hires.

Next, Column 3 of Table 2 presents OLS estimates of Equation 3, in which we also distinguish between stayers that switch occupation versus those that remain in the same occupation. In doing so, we also clean the reference group, that is job stayers, from cyclical occupational selection. Two results stand out. First, as before, we find no evidence of excess wage cyclicality for new hires that do not switch occupation: the parameter estimate is again small in magnitude and statistically different from zero. Second, we find that, regardless of whether workers are stayers or new hires, if they experienced an occupation change their wages exhibit larger cyclical movements than the wages of occupation non-switchers: from the OLS estimation, we obtain a negative and statistically significant coefficient on the interaction term for new hires and stayers that switch occupation (row 5 and 7 of Column 3, respectively) . Overall, the results show that new hires' wages are no more cyclical than those of stayers, contrarily to the findings in the literature. Instead, there is a large difference in wage cyclicality between occupation switchers versus non-switchers. From this, we conclude that the high cyclicality of new hires is driven by composition effects due to cyclical variation in match quality, as argued by Gertler et al. (2020), rather than arising from contractual wage flexibility.

Base Wage vs. Overtime Pay The dependent variable in our baseline regression is total pay per hour. This includes the base wage, regular and non-regular benefits as well as overtime pay. One particular feature of QP is that it records separately each component of the worker's compensation—base wage, regular and non-regular benefits and overtime pay—, as well as, normal and overtime hours worked in the reference month. Thus, we take a step further in trying to understand whether accounting for benefits and overtime pay changes the cyclicality of total pay per hour. To this end, we estimate the semi-elasticity of the hourly base wage with respect to the aggregate unemployment rate. Base earnings per hour is defined as the monthly base wage, the gross pay for normal hours of work in a month, divided by the normal hours of work. Column 4 of Table 2 shows that the cyclicality of hourly compensation is relatively unchanged when excluding regular and non-regular benefits and overtime pay. Thus, the cyclicality of base wages drives hourly wage cyclicality for stayers and new hires. These results stem from the fact that, for the average worker, overtime and benefits compensation are quantitatively small. Our findings are consistent with Grigsby et al. (2021) who show, for a sample of workers that remain in the same firm over two consecutive years, that base wages almost entirely determine wage movements along the business cycle.

6 Robustness Checks

In this section, we present some robustness tests about our key finding that large variations in wages over the cycle are driven by workers switching occupation. First, we show that wage cyclicality is higher the more distinct current and previous occupations are from one another in terms of the required skills. Second, we show that our results remain unchanged when considering a more conservative definition of occupation switchers that addresses any remaining concerns about misclassification errors in occupation codes. Third, we re-estimate our baseline regression separating new hires between job switchers and newly hired workers from non-employment. Table 3 groups together the estimated parameters of the three robustness exercises.

6.1 A Task-Based Approach to Occupational Mobility

Our findings rely on a definition of occupation switcher as a worker that has a different 3-digit occupation code in two consecutive years. However, such approach ignores the fact that distinct occupation codes may share very similar skills. In such a case, by changing across two 3-digit occupations that require similar skills, a worker is less likely to be moving to a better or worst match as his/her ability to perform two similar occupations is the same. In this context, understanding whether the estimated high cyclicality of occupational switchers' wages is driven by workers that are switching between two similar occupations or workers switching across two different occupations in terms of the required skills is important for the interpretation of our results. In particular, if the large wage variation is driven by transitions across similar occupations, then, rather than composition effects due to procyclical upgrading of job match quality, excess cyclicality of occupational switchers is more likely to reflect true wage flexibility.

We address this issue by measuring the similarity between two occupations in terms of the required skills through the lens of the angular distance between pairs of occupations j and j', as in Baley et al. (2022):

$$\varphi(\boldsymbol{q}_j, \boldsymbol{q}_{j'}) = \cos^{-1}\left(\frac{\boldsymbol{q}_j \cdot \boldsymbol{q}_{j'}}{\left\|\boldsymbol{q}_j\right\| \left\|\boldsymbol{q}_{j'}\right\|}\right) \in [0, \pi/2] \tag{4}$$

where $\boldsymbol{q}_j$ and $\boldsymbol{q}_{j'}$ denote the $K \times 1$ vector of skills for occupation j and j', respectively. $\varphi(\boldsymbol{q}_j, \boldsymbol{q}_{j'})$ ranges between 0 and $\pi/2$, with lower values reflecting higher similarity between two 3-digit occupation codes in terms of the required skills. With a measure of occupation similarity at hand, we estimate the following regression,

$$\begin{aligned} w_{ijft} = \beta_0 \;+\; (\; \beta_1 \;+\; \beta_2 \; NH_{ijft} \;+\; \; \beta_3 \; \varphi(\boldsymbol{q}_j, \boldsymbol{q}_{j'}) \;+\; \beta_4 \; NH_{ijft} \cdot \varphi(\boldsymbol{q}_j, \boldsymbol{q}_{j'}) \;) \times cycle_t \;+ \\ \gamma' \; (NH_{ijft} \;+\; \varphi(\boldsymbol{q}_j, \boldsymbol{q}_{j'}) \;+\; controls) + \delta_i \;+\; \delta_j \;+\; \delta_f \;+\; \varepsilon_{ijft}. \quad (5) \end{aligned}$$

Given Equation 5, β_1 and the linear combination of the parameters β_1 and β_2 $(\beta_1 + \beta_2)$ measure, respectively, the wage semi-elasticity of incumbent workers and new hires that remain in a occupation with a similar skill-mix relative to the occupation in the previous year, i.e. those workers for which $\varphi(\boldsymbol{q}_j, \boldsymbol{q}_{j'}) = 0$. In turn, β_3 and β_4 measure the differential in wage cyclicality along the angular distance distribution for existing workers and new hires, respectively. In our interpretation, the larger is $\varphi(\boldsymbol{q}_j, \boldsymbol{q}_{j'})$, the more likely it is that wage variation when unemployment decreases reflects composition bias due to selection into better matches during good times.

To compute $\varphi(\boldsymbol{q}_j, \boldsymbol{q}_{j'})$, we complement our dataset with occupation level data from O*NET, which describes occupations using a list of 277 descriptors in terms of the required knowledge and skills. Using the cross-walk in Hardy et al. (2018), we start by merging ISCO08 codes to the O*NET SOC10 occupation codes and average all the scores across occupations to the 3-digit ISCO08 occupational code level, which is consistent with the definition of occupations used in our baseline results. Next, we follow the procedure of Guvenen et al. (2020) to reduce O*NET descriptors to a smaller set of $K = 4$ dimensions: math, verbal, technical and social. This procedure has two steps. First, we focus on a subset of 26 descriptors with a relatedness score to ASVAB test categories, that we use to create a O*NET analogue of each ASVAB test category.[8] Then, we collapsed these scores into two skill dimensions, verbal and math, using Principal Components. Finally, to obtain a measure of social requirements, we use another six descriptors linked to social skills, which are reduced

[8] The ASVAB is a general test that measures knowledge and skills in 10 different components. We focus on a subset of six components (arithmetic reasoning, mathematics knowledge, paragraph comprehension, word knowledge) which are linked to math, verbal and technical skills.

to a single dimension using also Principal Components. All scores are normalized in terms of percentile ranks.[9] Table 4 reports the mean percentile rank score of each major occupation category in the ISCO08 occupation system and shows that the computed skill requirement scores characterize occupations reasonably well. Having each 3-digit occupation code described by a vector of skill requirements, we then measure the angular distance between pairs of occupations using Equation 4. Table 5 presents an example of occupation similarity between the 3-digit occupation "Doctors" and a selection of 3-digit occupational titles through the angular distance measure. Column 1 reports the angular distance, Columns 2 to 4 report the skill requirements scores. By definition, the angular distance from "Doctors" to "Doctors" is zero. In this example, the skill-mix required by "Nurses" is fairly similar to "Doctors". In contrast, the skill-mix required by the 3-digit occupation "Waiters and Bartenders" is substantially different when compared to "Doctors".

Column 1 of Table 3 reports OLS estimates of Equation 5. Note that Row 4 presents differential in the wage semi-elasticity for new hires for different levels of the angular distance $\varphi(\boldsymbol{q}_j, \boldsymbol{q}_{j'})$, $(\hat{\beta}_3 + \hat{\beta}_4)$. We find that both for stayers and new hires wage cyclicality increases the more distinct the current and previous occupations are from one another. This result corroborates our interpretation that high cyclicality in wages captures wage movements due to changes in match quality experienced by workers that switch occupation.

6.2 Measurement Error in Occupational Coding

In our dataset, the information on the workers' occupation is regarded to be highly reliable. Nonetheless, some coding error might be present. Following Groes et al. (2014), we address this issue by focusing on a set of workers whose occupation is stable over several years and thus less likely to be subject to temporary coding mistakes. Specifically, when considering whether a worker switches occupation, we now only consider workers who have been in the

[9] The set of 26 O*NET descriptors that are related to ASVAB categories includes: oral comprehension, written comprehension, deductive reasoning, inductive reasoning, information ordering, mathematical reasoning, number facility, reading comprehension, mathematics skill, science, technology design, equipment selection installation, operation and control, equipment maintenance, troubleshooting, repairing, computers and electronics, engineering and technology, building and construction, mechanical, mathematics knowledge, physics, chemistry, biology, English language. For the social dimension, we follow Guvenen et al. (2020) and use the following O*NET descriptors: social perceptiveness, coordination persuasion, negotiation instructing, service orientation) into a single dimension.

same occupation for at least two years prior to switching at time t ($t-1$ and t) and then stay in the new occupation for at least two years after switching at time t ($t+1$ and $t+2$). Estimates of the semi-elasticity of wages are reported in Column 2 of Table 3 and show that our results remain unchanged once we condition our sample to stable switchers.

6.3 Occupation Wage Floors

As mentioned in section 2, in Portugal, collective bargaining agreements set a lower bound on the base wage for each occupational category. The categories that form the basis of collective agreement are more detailed than the 3-digit occupation codes used to identify occupation mobility between and within firms. Thus, potentially, a worker can remain in the same 3-digit occupation but change across occupational categories subject to different wage floors. To assess whether this phenomena has an impact on our results, we re-estimate Equation 3 adding the negotiated minimum for the worker's professional category as a control. This departs from Carneiro et al. (2012), who include a set of dummies that identify the collective agreement occupational category, thus accounting for any unobserved time-invariant effect on earnings at the collective bargaining level. Instead, controlling for the prevailing wage floor in a year as we do, allows us to also control for time dynamics in occupational returns driven, for instance, by changes in occupation-specific labor demand. This seems particular important given the changes in occupational employment that occurred during the sample period in analysis.

Unfortunately, QP does not report the actual wage floor, but it reports the occupational category of the worker and the respective collective agreement. Since the wages set by collective agreement are binding, we exploit this information and approximate wage floors using the minimum base wage observed in our sample for each professional category within each collective agreement.[10]

Column 3 of Table 3 shows that our results are robust to controlling for the agreed wage

[10] Cardoso & Portugal (2005) infer the bargained wage from the mode of the base wage in a occupational category within each collective agreement. We opt for the minimum because our analysis relies on a sample of full time-workers, i.e. individuals working more than 120 hours in the reference month. Therefore, we regard this approach as providing us with a good approximation of the wage floor. Nonetheless, we also computed the mode base wage of each occupational category and find that our results are robust to this approach.

floor between unions and firms. We find, nevertheless, that collective agreements account for a small portion of wage cyclicality. For new hires that switch occupation, the difference in the wage semi-elasticity relative to job stayers that do not switch occupations decreases in 0.26 percentage points, from -0.57% to -0.31%. Wage cyclicality of occupation switchers within-firm exhibits a similar pattern. Thus, not accounting for wage floors induces a small procyclical bias in wages, suggesting that during recessions workers are more likely to sort into professional categories with low wage floors. We attribute the remaining excess cyclicality in occupational switchers to variations in match quality.

6.4 Job Switchers vs. New Hires from Non-employment

Gertler et al. (2020) find that the cyclical variation in new hires' wages is driven by workers that switch jobs, while wages of workers coming from non-employment are no more cyclical than those of job stayers. Building on this work, we add a separate interaction term for job-to-job transitions and new hires from non-employment to specification 3. To do so, we define a job switcher as a worker observed in two consecutive years in QP with firm tenure lower than 12 months in the second year, and a new hire from non-employment as a worker that is not observed in QP files in a given year and has tenure less than 12 months in the subsequent period. Our goal is to understand the extent to which the small wage response of new hires that do not switch occupation is explained by workers coming out from non-employment.

Column 4 of Table 3 presents the results. The estimated coefficients show that, among both new hires from non-employment and job-to-job transitions, wages of occupation switchers are more cyclical than wages of occupation non-switchers. It is interesting to note that excess wage cyclicality of occupation switchers that transition from non-employment is substantially smaller than that of occupation switchers that change employers (-0.32% vs. -0.85%). This is line with the idea put forward by Gertler et al. (2020) that new hires from non-employment are less affected by composition bias than job-to-job transitions. Additionally, when compared to existing workers that remain in the same occupation, neither the wages of job switchers nor those of new hires from non-employment show excess wage cyclicality. This evidence suggests that our results are not driven by newly hired workers from the pool of non-employed.[11]

7 Conclusion

This paper revisits the issue of wage cyclicality using a longitudinal matched employer-employee data from Portugal that allow us to measure—without error—wages and occupational mobility between and within employers. We exploit this feature to distinguish between new hires and incumbent workers that change occupation in two consecutive surveys versus workers that remain in the same occupation. In doing so, we find that the high cyclicality in new hires wages previously documented in the literature is driven by workers switching occupations. Importantly, we also find that cyclicality is higher the more distinct the current and previous occupations are in terms of the skills required. Thus, our results suggest that it captures composition effects due to sorting dynamics in the labor market rather than wage flexibility. This interpretation relies on recent work that defines match quality as tied to a worker's occupation and how his/her abilities aligned with the skills required.

[11]In a robustness check, Gertler et al. (2020) also distinguish between job changers and new hires from unemployment that switch occupation versus those that do not switch occupation (Table 3 in their paper). They find that for new hires non-employment that remain in the same occupation wages are no more cyclical than stayers, while the wages of job switchers that do not switch occupation exhibit larger cyclicality relative to stayers. This result looks at odds with our findings. However, our approach differs in two ways. First, we account for potential sorting into lower-paying firms during recessions. To the extent that this is more likely to happen among job switchers, then this reconciles our findings. Second, we also clean the reference group, that is job stayers, from cyclical occupational selection.

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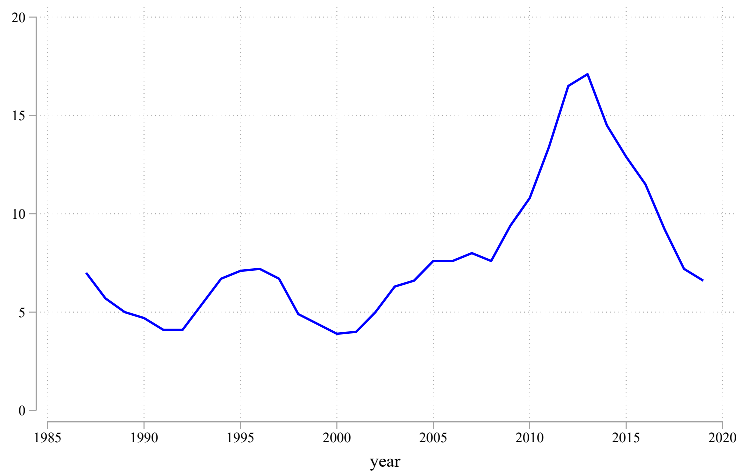
Tables and Figures

Figure 1: Unemployment Rate (%)



Notes: The graph plots the unemployment rate among individuals older than 16 years old from 1987 to 2019. Source: Statistics Portugal.

Table 1: Summary Statistics

	New Hires		**Stayers**		**Total**
	Occ. Switcher	Occ. Non-Switcher	Occ. Switcher	Occ. Non-Switcher	
PANEL A. FULL SAMPLE					
Mean age (years)	32.49	33.98	36.97	38.84	37.19
Share female	0.41	0.38	0.43	0.44	0.43
Share college degree	0.23	0.19	0.21	0.18	0.20
Mean total pay per hour (in 1985 euros)	3.43	3.61	4.73	4.88	4.52
Mean base pay per hour (in 1985 euros)	2.99	3.13	4.11	4.18	3.89
% of all matches	18.3	6.3	9.8	65.7	100
PANEL B. LARGEST CONNECTED SET					
Mean age (years)	32.48	33.98	36.96	38.83	37.19
Share female	0.41	0.40	0.44	0.44	0.43
Share college degree	0.23	0.19	0.21	0.18	0.20
Mean total pay per hour (in 1985 euros)	3.43	3.61	4.74	4.88	4.52
Mean base pay per hour (in 1985 euros)	2.99	3.13	4.12	4.18	3.89
% of all matches	18.3	6.3	9.8	65.7	100

Notes: The table reports summary statistics for the relevant sample from 1986–2019 separately for the overall population and for the four types of labor market status: stayers and new hires that remain in the same occupation and existing workers and new hires that switch occupation. In Panel A, the sample consists of worker-job matches in *Quadros de Pessoal* subject to the selection criteria described in the main text, which has 49,345,103 worker–year observations. In Panel B, the sample consists of worker-job matches in the relevant sample that are captured by the largest connected set, which has 48,900,997 worker–year observations.

Table 2: Wage Cyclicality

Base Pay	Total Pay			
	(1)	(2)	(3)	(4)
U_t	-1.163***	-1.142***		-1.120***
	(0.0228)	(0.0232)		(0.0202)
New hire × U_t	-0.447***			
	(0.0170)			
(New hire, Occ. Non-Switcher) × U_t		0.0395		0.0684**
		(0.0272)		(0.0254)
(New hire, Occ. Switcher) × U_t		-0.567***		-0.554***
		(0.0188)		(0.0184)
(Stayer, Occ. Switcher) × U_t		-0.201***		-0.160***
		(0.0289)		(0.0286)
Observations	39,800,355	39,800,355		39,800,355
Adjusted R^2	0.859	0.859		0.859

Notes: The table reports coefficients from an OLS regression with robust standard errors clustered at the firm level reported in parentheses. Coefficients and standard errors on U_t are multiplied by 100. The dependent variable is the real hourly wage (log) in columns 1 to 4, defined as total total pay, which includes base wage, benefits and overtime pay, divided by total hours worked, and the real base wage per hour (log) in column 4. All columns control for a quadratic polynomial in age, education dummies, a quadratic time trend, and fixed effects at the individual, firm and occupation (3-digit) level. Sample consists of worker-job matches in the largest connected set subject to the selection criteria described in the main text.

Table 3: Wage Cyclicality: Robustness Checks

	Occ. Similarity	Meas. Error	Wage Floors	EE vs. UE
	(1)	(2)	(3)	(4)
U_t	-1.005***	-1.116***	-0.891***	-1.125***
	(0.0228)	(0.0233)	(0.0214)	(0.0233)
New hire $\times$ U_t	-0.0925***			
	(0.0216)			
Stayer $\times$ $\varphi(\boldsymbol{q}_j, \boldsymbol{q}_{j'})$ $\times$ U_t	-0.888***			
	(0.0596)			
New Hire $\times$ $\varphi(\boldsymbol{q}_j, \boldsymbol{q}_{j'})$ $\times$ U_t	-0.361***			
	(0.0717)			
(New hire, Occ. Switcher) $\times$ U_t		-0.646***	-0.309***	
		(0.0210)	(0.0193)	
(New hire, Occ. Non-Switcher) $\times$ U_t		0.0516	0.0809***	
		(0.0274)	(0.0240)	
(Stayer, Occ. Switcher) $\times$ U_t		-0.172***	-0.0917***	-0.195***
		(0.0303)	(0.0226)	(0.0289)
(UE, Occ. Switcher) $\times$ U_t				-0.315***
				(0.0166)
(UE, Occ. Non-Switcher) $\times$ U_t				0.112***
				(0.0252)
(EE, Occ. Switcher) $\times$ U_t				-0.848***
				(0.0254)
(EE, Occ. Non-Switcher) $\times$ U_t				-0.0436
				(0.0402)
Observations	34,274,155	36,686,037	39,800,355	39,800,355
Adjusted R^2	0.859	0.862	0.889	0.859

Notes: The table reports coefficients from an OLS regression with robust standard errors clustered at the firm level reported in parentheses. Coefficients and standard errors on U_t are multiplied by 100. The dependent variable is the real hourly wage (log), defined as total pay, which includes base wage, benefits and overtime pay, divided by total hours worked. Column 2 considers only occupation switchers that had a stable occupation prior to switching and remain in the new occupation for two years after switching. Column 3 controls for the wage floor negotiated by the collective agreement for the worker's professional category. Column 4 distinguishes between job-to-job transitions (EE) and newly hired workers from non-employment (UE). All columns control for a quadratic polynomial in age , education dummies, a quadratic time trend, and fixed effects at the individual, firm and occupation (3-digit) level. Sample consists of worker-job matches in the largest connected set subject to the selection criteria described in the main text.

Table 4: Skill Requirements for Major Occupation Groups

Occupation (1-digit)	**Requirements**			
	Math	Verbal	Technical	Social
Managers	79.6	79.5	67.4	92
Professionals	76.1	79.8	64.7	71.0
Technicians and Associate Professionals	63.8	65.2	59.6	58.2
Clerical Support Workers	31	34.9	13.6	40.6
Services and Sales Workers	20.6	21.8	15.7	63.6
Skilled Agric., Forestry and Fishery Workers	37.3	32.6	54.9	24.2
Craft and Related Trade Workers	46.4	41.0	61.8	21.1
Plant and Machine Operators and Assemblers	34.5	31.9	61.8	22.2
Elementary Occupations	12.32	10.7	22.6	24.4

Notes: The table reports the mean percentile rank scores along the four skill dimensions considered in the empirical analysis for the main occupation categories of the ISCO-08 occupation classification system.

Table 5: Angular Distance: An Example

Occupation (3-digit)	**Distance**	**Requirements**			
	$\varphi(\boldsymbol{q}_{doctor}, \boldsymbol{q}_j)$	Math	Verbal	Technical	Social
Waiters and Bartenders	0.83	10	9	6	57
Child Care Workers	0.72	18	22	9	80
Fishers & Hunters	0.73	12	12	44	4
Tour Guides	0.57	25	31	18	78
Legal Professionals	0.37	50	70	24	84
Electrical Equipment Installers	0.32	81	77	97	31
Mathematicians & Statisticians	0.25	98	85	94	40
Hotel & Restaurant Managers	0.17	78	77	65	100
Nurses	0.03	93	95	89	93
Doctors	0	93	96	86	86

Notes: The table presents an example of occupation similarity between the 3-digit occupation “Doctors” and a selection of 3-digit occupational titles through the angular measure described in Equation 4.