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IZA DP No. 17189

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ABSTRACT

The Illusion of Cyclicality in Entry Wages*

We show that occupation mobility creates the illusion of cyclical hiring wages. Using administrative data, we find that wages of new hires who remain in the same occupation are no more cyclical than those of existing workers, whereas wages of occupation switchers are highly cyclical. We uncover higher wage cyclicality also among workers who switch occupations within the same firm. Moreover, wage cyclicality increases, the more different current and previous occupations' required skills. Our results suggest that the widely documented cyclicality of entry wages reflects composition effects due to changes in match quality in worker's occupation, rather than wage flexibility.

JEL Classification: J31 J61 E24 E32

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

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1 Introduction

Rigidity in hiring wages is crucial for macroeconomic models to match observed fluctuations in unemployment over the business cycle (e.g. Shimer, 2005; Gertler & Trigari, 2009). However, extensive empirical work since Bils (1985) suggests that wages of new hires are highly procyclical. Some have interpreted these findings as evidence of wage flexibility, contradicting the assumed rigidity (Pissarides, 2009); while others argue that this cyclical variation reflects instead cyclicality in match quality (Gertler et al., 2020). Understanding whether cyclical variation in entry wages arises from contractual wage flexibility or composition effects is central to key questions in economics, such as the transmission of monetary policy. But this is an empirically challenging task, as workers and the jobs they perform are not necessarily comparable throughout the business cycle.

In this paper, we separate wage flexibility from cyclical changes in match quality by making a distinction between workers who switch occupations from those who do not over the business cycle. The underlying assumption is that match quality is more likely to vary for workers who change to a new occupation requiring new skills. Our approach shows that occupational sorting dynamics over the business cycle create an illusion of highly cyclical entry wages. We first find that cyclical variation in entry wages is mainly driven by new hires who switch occupations. In contrast, wages of new hires who remain in the same occupation resemble those of existing workers. We then provide novel evidence existing workers who switch occupations while remaining in the same employer experience more wage cyclicality compared to those who do not switch occupations. Thus, highly cyclical entry wages are a feature common to occupation switchers, regardless of whether they are starting a job at a new employer or not. We further show that wage cyclicality increases, the more distinct current and previous occupations are from one another in terms of the required skills, which corroborates the identification strategy. The results suggest that the standard regression in the literature confounds flexibility in entry wages with cyclical movements in match quality associated with occupation mobility.

Our analysis relies on rich linked employer-employee data from Portugal that spans the period from 1986 to 2019. This data set has a particular feature, not available in other data sets 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 with wage floors set by unions. We exploit this feature to track not only occupational mobility when workers move between employers, but also within-firm occupation changes. The latter are hard to identify in commonly used data sets because these are riddled with misclassification errors in occupation codes. As a result, the standard approach used in previous literature is to identify an occupation switch as genuine only if it coincides with another significant labour market change, such as an employer switch (e.g. Neal, 1999; Kambourov & Manovskii, 2009).[1]

To measure wage cyclicality, we use the typical specification in the literature that exploits within-individual variation in wages and the unemployment rate across years individuals are employed. The individual fixed effects take into account selection bias due to unobserved characteristics with a time-invariant effect on earnings. Additionally, we account for composition bias due to potential sorting into lower-paying occupations and lower-paying firms in bad times by controlling for occupation and firm fixed effects. We start by confirming the key findings in the literature: when compared to incumbent workers, entry wages are 0.46 percentage points lower for new hires for every percentage point increase in the unemployment rate, thus new hires' wages are more cyclical than those of stayers.

In the next step, we augment the standard specification with categorical variables that separate workers who switch occupations from those who remain in the same occupation. Following Guvenen et al. (2020), among others, who define match quality as the extent to which worker's abilities are aligned with the skills required by the occupation, workers switching occupations are the ones likely to experience a change in match quality.[2] Given this, if match quality explains—at least partially—wage movements throughout the business cycle, then we should find that occupation switchers drive most of the observed cyclicality in the wages of new hires. Hence, one is better able to isolate rigidity in entry wages by

[1] Standard data sets in the literature, such as the National Longitudinal Survey of Youth and the Current Population Survey before 1994, use "independent coding". This means that the respondent describes their occupation, and a survey official attributes an occupation code. Hence, even if the respondent provides the same description in two consecutive surveys, they may be coded as having changed occupations because the survey official fills in a different code in the next survey.

[2] Baley et al. (2022) rely on a similar definition to study the cyclical behavior of match quality. Importantly, Figueiredo (2022) shows that such a definition of match quality is negatively correlated with job tenure, lending support to the interpretation that match quality is tied to a worker's occupation.

focusing on new hires and job stayers who do not switch occupations.

When we estimate separate terms for occupation switchers and non-switchers, we find no evidence of excess wage cyclicality for new hires who do not switch occupations. Wages of new hires that switch occupations, by contrast, are highly procyclical: the difference in the wage semi-elasticity with respect to stayers that remain in the same occupation is around 0.6 percentage points and is statistically different from zero. Interestingly, because we can identify occupation mobility within firms, we show that wages of workers who remain in the same employer but change occupation are also more cyclical than job stayers who do not switch occupations. In particular, the wage semi-elasticity is higher by 0.2 percentage points. These results suggest that large variations in wages over the business cycle are associated with occupational mobility rather than employer mobility. As such, 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 required. To this end, we complement our data set with occupational-level data from O*NET and characterised occupations in terms of the requirements in four skill dimensions (math, verbal technical, and social). Following Guvenen et al. (2020)'s framework, the larger the difference between the current and previous occupations' skill requirements, the larger the change in match quality, and therefore the larger wage cyclicality, in our interpretation. Consistently, 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 workers' transitions across occupations with different skill requirements.

We probe into alternative explanations for our findings. We show that the large cyclicality in the wages of occupation switchers is not driven by differences in labour market experience, changes in collective bargaining agreements, or whether the worker is transitioning from a non-employment spell, rather than between employers. All in all, our findings suggest that the large fluctuations in new hires' wages over the cycle, widely documented in the previous literature, arise from composition effects due to the cyclical variation in match quality associated with the worker's occupation, rather than wage flexibility. This result brings important implications for the calibration of a range of macroeconomic models Specifically, it suggests 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.

Contribution This paper adds to the extensive literature that measures wage cyclicality using worker-level panel data. After the seminal paper by Bils (1985), many papers have shown that the wages of new hires are more cyclical than those workers that remain in the same job (Shin, 1994; Solon et al., 1994; Barlevy, 2001; Shin & Solon, 2007; Carneiro et al., 2012; Martins et al., 2012; Haefke et al., 2013; Stüber, 2017). Recent work suggests that large variation in new hires' wages over the business cycle capture composition effects driven by changes 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 (see also Bauer & Lochner (2020) and Figueiredo (2022) for similar findings). Grigsby et al. (2021) match job switchers with job stayers similar in a set of observables and find no difference in cyclical wage variation. Koenig et al. (2024) document the same pattern in Germany and the UK. Our paper complements these findings.

Building upon the literature that has highlighted the role of occupational mobility for earnings dynamics (Kambourov & Manovskii, 2009; Huckfeldt, 2022; Carrillo-Tudela et al., 2022), we show that the high cyclicality of entry wages is mostly driven by new hires that also switch occupation. We also uncover higher wage cyclicality among stayers who switch occupations within the same employer. Thus, we find that excess wage cyclicality is a feature of the wages of occupation switchers rather than new hires, as previously documented in the literature. Since we account for worker, firm, and occupation-invariant heterogeneity, we rule out sorting to lower-paying firms or lower-paying occupations in bad times as a driver of lower wages for occupation switchers in recessions. Instead, we view the high cyclicality of occupation switchers' wages as reflecting composition effects due to changes in match quality. An important advantage in our analysis relative to prior work is that our sample covers the universe of private sector workers in Portugal and a large period of time, 32 years.

Layout The paper is organised 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 a governmental proposal, which determines a wage floor for the majority of the labour 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 defines wage floors for each occupational category.[3] In legal terms, the agreement is only binding on the parties in the negotiations, that is, the workers who are unionised 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. For instance, in 2016, around 74% of workers in Portugal were covered by a collective agreement, but only 15%, approximately, were members of a union (Hayter & Visser, 2021).

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 more highly-educated workers, as well as those

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

working at higher-productivity firms.

3 Data and Descriptive Statistics

3.1 Sources, Sample and Main Variables

Sources Our main data source is *Quadros de Pessoal* (henceforth, QP), a longitudinal matched employer-employee data set collected and managed by the Portuguese Ministry of Employment. 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 labour in the private sector in Portugal. On average, it includes information on approximately 220,000 firms and 2.5 million employees each year. Firms and workers entering the database are assigned a unique, time-invariant identifier allowing researchers to track them over time. The data, available from 1985 onward, contains detailed information at the workers' and firms' level. The analyses in this paper are derived from data collections for each year from 1986 to 2019. Before 1993, the information refers to the month of March, and thereafter, the information refers to October.

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 employers' compliance with labour 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 occupations, 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.[4] The latter excludes apprentices from the

[4]We discard firms labeled 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

analysis who receive only 80% of the national minimum wage rate. The resulting sample comprises information on 6,837,714 workers and 460,099 firms from 1986 to 2019, yielding a total of 12,468,034 worker–firm observations and 47,903,883 worker–year observations. As our benchmark specification includes both worker and firm fixed effects, we rely on workers moving between firms for identification of both worker and firm fixed effects, even though we abstract from recovering these. This means that our regression models are effectively estimated in the set of firms connected through worker moves, i.e. the largest connected set. This covers around 99.1% of the original employee-firm pairs.

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 the total hours worked in the referenced month. This means that we primarily focus on flexibility in realised compensation, as common in the literature. Wages are winzorised 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, until 2010 QP reported workers' occupational titles in the *Classificação Nacional de Profissões* (CNP); thereafter, the occupational classification system changed to the *Classificação Portuguesa das Profissões* (CPP2010). Since the classification of occupations is not consistent across years, we converted all the occupational codes into the CPP2010 classification system before our empirical analysis.[6] We opt for the CPP2010 because it is based on the ISCO-08 classification

identify public sector firms, we proceed in two steps. First, we label as "public sector" all firms whose percentage of public/government 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 privatised firms which oftentimes maintain their public-style hierarchical structures.

[5] From 1986 to 1993, we use the March CPI, and thereafter we use the October CPI.

[6] First, we started by converting the CNP80 occupational codes, used until 1993, into the CNP94, used from 1993 to 2010. Then, we converted all CNP94 occupation codes to the CPP2010 occupational codes. In both conversions, 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

system (International Occupational Classification Codes), which is 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 level of desegregation are *Journalists and Writers*, *Doctors*, and *Nurses*.

We exploit the panel structure of the data to determine whether a worker experienced an employer and/or occupational transition. Starting 1986, the second year the dataset is available, we label a worker *stayer* if they were employed in the same firm for two consecutive years (t and $t-1$). We classify a worker as a *new hire* if they changed employers, with or without a period of non-employment in between.[7] For the latter case, we include all transitions in which the worker returned to employment within the sample, including recalls, those who returned to their previous employer after a jobless spell. Apart from employer mobility, we also track worker occupation mobility over time. As mentioned before, a key feature of our data set 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 data sets. 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 in the observed data (e.g. Neal, 1999; Kambourov & Manovskii, 2009). Therefore, the literature thus far envisions worker reallocation as occurring only between employers. Using the described previously CPP2010 3-digit occupation codes, we identify occupation switchers in t if there was a change in the occupation code relative to the previous year ($t-1$) or to the last job observed in the sample, regardless of whether they have changed employers or not.

based on the frequency of cross-occupational code changes from 1994 and 1995, and attributed the CNP94 occupational code from the cross-occupational code change that is more frequent within firms. For the remaining CNP94 codes, we created a crosswalk based on the frequency of cross-occupational code changes from 2009 and 2010 and attributed the CPP2010 occupational code from the cross-occupational codes change that is more frequent within firms.

[7] Any worker observed for the first time in the dataset in t is classified as a *new hire*.

Economic conditions In Portugal, wages are determined at least six to twelve months in advance, therefore we measure business cycle conditions using the previous year's aggregate unemployment rate among individuals aged 16 to 74, following 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, 20% have at least a college degree and 43% are female. The average worker earns 4.41 euros per hour, of which 86% comes from the base pay. About 75.5% of observations correspond to stayers and 24.5% 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. Around 28.2% of all workers in our sample are observed to switch occupations, of which a little over one-third correspond to changes in occupation within a firm. Thus, occupation transitions within firms occur at a significant rate. Occupation switchers that also transition to a new employer represent 18.5% of all observations.[8] Importantly, observable characteristics of occupation switchers and non-switchers are very similar among new hires and stayers.

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),

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

[8] 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).

where w_{ijft} is the natural logarithm of total pay per hour (in real terms) of individual i working in occupation j and firm f at time t, $cycle_t$ is a cyclical indicator such 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, i.e. workers that have been in the same firm for more than 12 months, while β_2 captures the difference in the semi-elasticity of wages between stayers and new hires. The key finding in the literature is that both β_1 and β_2 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, as shown for instance by (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 changes in match quality.

We address this issue by making a distinction between stayers and new hires who switch occupations, versus those who 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 who change occupation are more likely to capture changes in match quality. Our argument that cyclical selection bias works mainly through workers that switch occupations 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 (e.g. Guvenen et al., 2020; Baley et al., 2022; Figueiredo, 2022). Specifically, let a_i^k be worker i's ability in skill k, and r_j^k be the level required of skill k by the occupation individual has, then skill mismatch $m_{i,t}$ is defined as

$$m_{i,t} \equiv \sum_{j=1}^{K} \frac{1}{K} \left| a_i^k - r_j^k \right|, \tag{2}$$

where K 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 findings: (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). From Equation 2, only workers that change occupations may experience a change in the quality of the match, as changes in skill mismatch, i.e. match quality, are driven by changes in skill requirements r_j^k 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,

$$\begin{aligned} w_{ijft} = \beta_0 \; + \; (\; \beta_1 \; + \; \beta_2 \; NH^{NS}_{ijft} \; + \; \beta_3 \; S^{S}_{ijft} \; + \; \beta_4 \; NH^{S}_{ijft} \;) \; \times \; cycle_t \; + \\ \gamma' \; (\; NH^{NS}_{ijft} \; + \; S^{S}_{ijft} \; + \; NH^{S}_{ijft} \; + \; x_{it} \; + \; t \; + \; t^2 \;) \; + \\ \delta_i \; + \; \delta_j \; + \; \delta_f \; + \; \varepsilon_{ijft}, \end{aligned} \tag{3}$$

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 stayers (i.e. those that remain in the same firm) who 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 account for differences between booms and recessions in the composition of workers, firms, and occupations by including for occupation (δ_j), firm (δ_f), and individual (δ_i) level fixed effects, as in Equation 1. We also condition in a quadratic time trend. 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 who 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 the cyclical variation in wages. 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, $\mathbb{E}[\varepsilon_{ijft} \cdot cycle_t | x_{i,t}, t, \delta_j, \delta_f, \delta_i] = 0$. In turn, the coefficients β_3 and β_4 measure the excess wage cyclicality for stayers and new hires that *switch* occupation, respectively. 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, $\mathbb{E}[\varepsilon_{ijft} \cdot cycle_t | x_{i,t}, t, \delta_j, \delta_f, \delta_i] < 0$, implying that workers sort into better jobs during booms. 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 semi-elasticity with respect to the unemployment rate, that is, the percent 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 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 pp more when compared to stayers $\hat{beta}_2$. The excess cyclicality in the wages of new hires relative to existing workers is statistically significant at the 1% level, and its magnitude aligns with findings by C Carneiro et al. (2012). Using the same matched employer-employee data set spanning the period from 1986 to 2007, they find that the wage semi-elasticity of new hires is around 0.47 pp larger than that of stayers. Our results are also in line with Martins et al. (2012), that also use *Quadros de Pessoal*. We estimate a semi-elasticity of entry wages with respect to the unemployment rate of 1.7% ($be\hat{t}a_1 + be\hat{t}a_2$), closely matching their finding of 1.8%.

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 emphasised by Gertler et al. (2020). To cleanse our estimates from composition effects due to sorting dynamics in the labour market, we introduce dummy variables that differentiate between stayers and new hires who switch occupations and those who remain in the same occupation. As we argue in section 4, workers who switch occupations are more likely to experience a change in match quality, and thus their wages are more likely to be subject to composition bias.

Column 2 of Table 2 adds dummy variables that differentiate between new hires that switch occupations and new hires who remain in the same occupation and their interactions with the unemployment rate to the standard specification in the literature. We find that excess cyclicality in the wages of new hires disappears for those who remain in the same occupation they had in the previous employer: the estimated coefficient is small in magnitude and not statistically different from zero. Thus, for new hires who do not switch occupations, wages are no more cyclical than those of existing workers. By contrast, for new hires that switch occupations, wages are substantially more cyclical than those of stayers. In particular, the wage semi-elasticity is 0.59 pp higher and statistically significant at 1% level. Thus, our results show that the excess cyclicality in the wages of new hires, previously documented in the literature, is entirely driven by workers who start a new job in a new occupation. 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 labour 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 who switch occupations versus those who remain in the same occupation. This implies that we also clean the reference group—job stayers—from cyclical occupational selection. Two results stand out. First, as before, we find no evidence of excess wage cyclicality for new hires who do not switch occupations: the parameter estimate is again small in magnitude and statistically not 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 who switch occupation (row 3 and 5 of Column 3, respectively).

Finally, we estimate a version of Equation 1 in which we interact the unemployment rate with a dummy variable that equals one for workers switching occupation (both between and within firms) and zero otherwise. Under such specification, the coefficient of U_t measures the wage semi-elasticity of stayers and new hires that remain in the same occupation, and thus captures cyclical changes in wages cleaned from composition effects due to sorting dynamics. By contrast, the coefficient associated with the interaction term measures the difference between the wage semi-elasticity of occupation switchers and non-switchers and hence captures composition bias due to occupational sorting. The estimated coefficients, reported in Column 4, mimic the estimates of the standard regression in the literature shown in Column 1. The coefficient interacting the occupation switcher dummy with the unemployment rate is significantly negative and larger than the coefficient on U_t, implying that excess cyclicality in new hires' wages reflects wage movements due to changes in occupation, which in our interpretation reflects changes in match quality.

Overall, the results show that new hires' wages are no more cyclical than those of stayers. 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. Therefore, we take a step further and try 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. Columns 5 and 6 of Table 2 show 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.

Robustness In our data set, the information on the workers' occupations is regarded as highly reliable. Nonetheless, some coding errors 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 idiosyncratic coding mistakes. Specifically, when considering whether a worker switches occupation, we now only consider workers who have been in the 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 $t+2$). Our results remain unchanged once we condition our sample to stable switchers (Columns 1 and 2 of Table 3). In addition to this, we replicate our results using only a sample of male workers. This follows the previous literature that often restricts focus to male workers to avoid potential selection issues driven by fertility decisions. Reassuringly, Columns 2 and 3 of Table 3 show that our results are not driven by the inclusion of females in our sample.

6 Alternative Explanations

Our results show that the high cyclicality in the wages of new hires, which has been widely documented in the literature, is indeed driven by workers switching occupations, while the wage responses of new hires who remain in the same occupation mimic those of stayers. Interestingly, our findings show that excess wage cyclicality is a feature of any worker who changes occupation, regardless of whether they change employer or not. We interpret this excess cyclicality as reflecting wage changes due to an unobserved match quality component in the error term, which is negatively correlated with the unemployment rate for new hires. But, could higher wages among occupation switchers in booms be explained by reasons other than selection into better matches? In this section, we show that our results are robust to alternative explanations. Table 4 groups together the estimated parameters of these exercises.

6.1 Differences in skill requirements by occupations

In our benchmark specification, we define an occupation switcher as a worker who has been working in the current occupation, defined by the 3-digit occupation code, for less than 12 months. However, this approach ignores the fact that distinct occupation codes may share very similar skills. In such a case, a worker is less likely to be moving to a better or worse match as their ability to perform two similar occupations is the same. Understanding whether the estimated high cyclicality of occupational switchers' wages is driven by workers who are simply switching between two similar occupations versus workers switching across two different occupations in terms of the required skills is important for the interpretation of our results. Indeed, if the large wage variation is driven by transitions across similar occupations, it is unlikely that excess wage cyclicality of occupational switchers reflects composition effects due to procyclical upgrading of job match quality. We address this issue by estimating a version of the baseline regression where we interact the cycle variable with a measure of dissimilarity between the previous and the current occupation:

$$w_{ijft} = \beta_0 \ + \ (\ \beta_1 \ + \ \beta_2 \ \varphi(\boldsymbol{q}_j, \boldsymbol{q}_{j'}) \ ) \times cycle_t \ + \\ \gamma' \ (\varphi(\boldsymbol{q}_j, \boldsymbol{q}_{j'}) \ + \ controls) + \delta_i \ + \ \delta_j \ + \ \delta_f \ + \ \varepsilon_{ijft}, \quad (4)$$

where $\varphi(\boldsymbol{q}_j, \boldsymbol{q}_{j'})$ is a dissimilarity measure between the occupation pair j and j', and $\boldsymbol{q}_j$ and $\boldsymbol{q}_{j'}$ denote the $K \times 1$ vector of skills for occupation j and j', respectively. Given Equation 4, β_1 measures the wage semi-elasticity of stayers and new hires who remain in an 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_2 measures the differential in wage cyclicality along the occupation dissimilarity distribution for both stayers and new hires. In our interpretation, the larger is $\varphi(\boldsymbol{q}_j, \boldsymbol{q}_{j'})$, the more likely it is that wage variation over the business cycle reflects composition bias due to cyclical changes in match quality.

We measure how distinct two occupations are 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),

$$\phi(\boldsymbol{q}_j, \boldsymbol{q}_{j'}) = \cos^{-1}\left(\frac{\boldsymbol{q}_j \cdot \boldsymbol{q}_{j'}}{\lVert \boldsymbol{q}_j \rVert \, \lVert \boldsymbol{q}_{j'} \rVert}\right) \in [0, \pi/2], \tag{5}$$

and the Euclidean distance,

$$d(\boldsymbol{q}_j, \boldsymbol{q}_{j'}) = \Big[\sum_{k=1}^{K} (q_{j,k} - q_{j',k})^2\Big]^{1/2}, \tag{6}$$

with $\boldsymbol{q}_j$ and $\boldsymbol{q}_{j'}$ denoting the $K \times 1$ vector of skills for occupation j and j'. Under both measures, lower values reflect greater similarity between two 3-digit occupation codes in terms of the required skills. They are, however, different. The angular distance captures differences in the skill mix between two occupations, while the Euclidean distance will reflect both differences in the skill mix, as well as differences in the level at which skills are required. Figure 2 illustrates our empirical approach for the case where $K = 2$. In the left panel, moving from q_j to $q_{j'}$ implies a change in the skill mix as skills are used in different proportions ($\phi(\boldsymbol{q}_j, \boldsymbol{q}_{j'}) > 0$) and also a change in the skill level. By contrast, in the example depicted in the right panel, a worker moving from q_j to $q_{j'}$ experiences no change in the skill mix as both skills are used in the same proportion, hence $\phi(\boldsymbol{q}_j, \boldsymbol{q}_{j'}) = 0$, but there is change in the skill level, therefore $d(\boldsymbol{q}_j, \boldsymbol{q}_{j'}) > 0$.

To compute $\phi(\boldsymbol{q}_j, \boldsymbol{q}_{j'})$ and $d(\boldsymbol{q}_j, \boldsymbol{q}_{j'})$, we complement our data set 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, which we use to create a O*NET analogue of each ASVAB test category.[9] Then, we collapsed these scores into three skill dimensions, verbal, technical, 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 to a single dimension using Principal Components. All scores are normalised in terms of percentile ranks.[10] Table 5 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 and Euclidean distance between pairs of occupations using Equations 5 and 6, respectively. Table 6 provides an example of occupation similarity between the 3-digit occupation "Doctors" and a selection of 3-digit occupational titles through the angular distance measure. By definition, both the angular and Euclidean distance from "Doctors" to "Doctors" are zero. In this example, the skill mix required by "Nurses" is fairly similar to "Doctors". In contrast, the skill mix

[9]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.

[10]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.

required by the 3-digit occupation "Waiters and Bartenders" is substantially different when compared to that of "Doctors".

Columns 1 and 2 of Table 4 report OLS estimates of Equation 4 using the angular distance and the Euclidean distance, respectively. We find that, regardless of the distance measure used, wage cyclicality increases the more distinct the current and previous occupations are from one another. For instance, for workers at the top of the angular distance distribution, wages decrease by 2% when the unemployment rate increases by 1 percentage point, which is twice the wage semi-elasticity of workers who do not switch occupations or who switch between occupations with the same skill mix. This evidence shows that excess cyclicality of wages is not about changes in the place where the workers do their job (firm identity) but changes in the type of job they do. This result lends further support to the interpretation that high cyclicality in wages captures wage movements due to changes in match quality experienced by workers who switch occupations.

6.2 Labour Market Experience

Another potential explanation of the excess cyclicality of occupation switchers' wages is that workers changing occupations during economic expansions have accumulated more skills in the labour market, implying higher wages relative to those that do not switch occupations. While our baseline specification controls for the education level of the worker, we further address this issue by adding labour market experience as a control, approximated using the total amount of years we observe the worker in our data set. Column 3 of Table 4 shows that our results remain unchanged. We only obtain a negative and statistically significant coefficient on the interaction term for new hires and stayers who switch occupations. Thus, excess cyclicality in the wages of occupation switchers is not driven by composition bias due to differences in labour market experience of workers transitioning across occupations in booms relative to recessions.

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. Therefore, a natural question to ask is to what extent our results are driven by sorting into occupations with lower negotiated wage floors in times when unemployment is higher. To address this issue, 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 allows us to also control for time dynamics in occupational returns driven, for instance, by changes in occupation-specific labour demand.

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 a 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.[11]

Column 4 of Table 4 shows that our results are robust to controlling for the agreed wage floor between unions and firms. Specifically, we find no excess cyclicality in the wages of new hires that remain in the same occupation, while the wages of stayers and new hires that switch occupations remain more cyclical than those that remain in the same occupation. We find, nevertheless, that collective agreements account for a small portion of the excess wage cyclicality of occupation switchers. For new hires that switch occupation, the difference in the wage semi-elasticity relative to job stayers that do not switch occupations decreases in 0.27 percentage points, from -0.57% to -0.30%. Wage cyclicality of occupation switchers within-firm exhibits a similar pattern, decreasing from -0.20 to -0.10. Thus, not accounting for wage floors induces a small procyclical bias in wages, suggesting that during recessions

[11] Cardoso & Portugal (2005) infer the bargained wage from the mode of the base wage in an 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 found that our results are robust to this approach.

workers are more likely to downgrade in the ladder and sort into professional categories with lower wage floors. We attribute the remaining excess cyclicality in occupational switchers to variations in match quality.

6.4 Movements in the Firm Hierarchy

In our interpretation, the large movements in the wages of workers who switch occupations relative to those who remain in the same occupation reflect changes in unobserved match quality. Alternatively, higher wage changes during booms could capture the re-assignment of workers (e.g., promotions) within the firm hierarchy as a response of employers to labour shortages. We exploit information in QP about the worker's position in the firm hierarchy to address this issue. This is possible because every year, each worker has to be assigned to a category following a standardised (and compulsory) classification defined by Portuguese law. The layers in the defined hierarchy are based on the task performed and each layer can be considered as a level in a hierarchy defined in terms of increasing responsibility and task complexity. Table 7 contains the layers of the hierarchy. Using this information, we define a dummy variable that equals one if the worker moved up one layer in the hierarchy and another that equals one if the worker moved down one layer, otherwise they we set them to zero. We add these as controls to Equation 3 and find that our results remain unchanged (column 5 of Table 4). This implies that larger wages in booms among workers switching occupations, within or across firms, do not capture changes in wages due to promotions.

6.5 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 who 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 another for 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 who do not switch occupations is explained by workers coming out from non-employment.

Column 6 of Table 4 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 the excess wage cyclicality of occupation switchers who transition from non-employment is substantially smaller than that of occupation switchers who change employers (-0.32% vs. -0.85%). This evidence is in 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. Importantly, among workers that remain in the same occupation, both the wages of job switchers and new hires from non-employment mimic the wages of stayers. Thus, our results are not driven by newly hired workers from the pool of non-employed.[12]

Column 7 of Table 4 adds the negotiated wage floor as a control to the specification in Column 6. As before, we find no evidence of excess wage cyclicality for workers who remain in the same occupation. In contrast, the coefficients associated with the interaction between the occupation switcher dummies and the unemployment rate are negative and statistically significant for all worker types—stayers, job switchers, and new hires from unemployment. We find, however, that sorting into professional categories with lower wage floor explains a larger fraction of the excess wage cyclicality of job switchers that also switch occupation: around 50% of the excess wage cyclicality is driven by starting working in a new occupation in a profession with a lower wage floor; the residual excess cyclicality (0.409%) we attribute to changes in the quality of the match.

[12] Gertler et al. (2020) and Bauer & Lochner (2020) estimate similar regressions using data for the US and Germany, respectively, and find that wages of job switchers that do not switch occupation are more cyclical than those of stayers. These results could be explained by sorting into high-paying firms or high-paying occupations when unemployment is low, which they do not account for. To the extent that differences in firms and occupations over the cycle are larger among job switchers, our findings are consistent.

7 Conclusion

This paper revisits the issue of wage cyclicality using longitudinal matched employer-employee data from Portugal that allows us to measure—with little error—wages and occupational mobility, both between and within employers. We exploit this feature to distinguish between new hires and stayers who change occupations versus those who remain in the same occupation. In doing so, we find that the high cyclicality in the wages of new hires, previously documented in the literature, is mostly driven by workers switching occupations. Indeed, we uncover excess wage cyclicality for workers who remain in the same employer but switch occupations. Thus, large fluctuations in wages are associated with occupation mobility rather than employer mobility. We further show that wage cyclicality is higher the more distinct the current and previous occupations are in terms of the skills required. Our results suggest that excess wage cyclicality of new hires captures composition effects due to occupation sorting dynamics in the labour market which result in changes in match quality.

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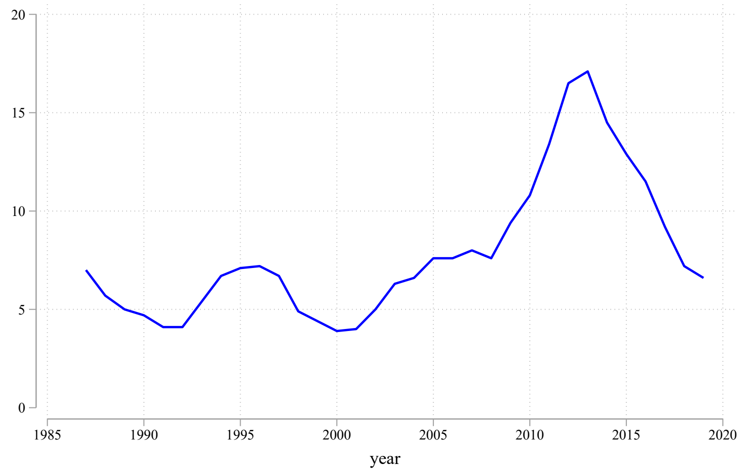
Tables and Figures

Figure 1: Unemployment Rate (%)



Notes: The graph plots the unemployment rate among individuals aged 16 to 74 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)	32.48	33.88	36.96	38.81	37.16
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)	3.35	3.50	4.57	4.76	4.41
Mean base pay per hour (in 1985 euros)	2.91	3.03	3.95	4.07	3.78
% of all matches	18.3	6.2	9.8	65.7	100
PANEL B. LARGEST CONNECTED SET					
Mean age (years)	32.47	33.88	36.95	38.81	37.16
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)	3.35	3.51	4.57	4.77	4.41
Mean base pay per hour (in 1985 euros)	2.91	3.03	3.96	4.07	3.78
% of all matches	18.5	6.2	9.7	65.6	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 labour 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

	Total Pay				Base Pay	
	(1)	(2)	(3)	(4)	(5)	(6)
U_t	-1.163***	-1.144***	-1.142***	-1.135***	-1.139***	-1.122***
	(0.0224)	(0.0224)	(0.0229)	(0.023)	(0.0199)	(0.0203)
U_t × New Hire	-0.448***				-0.434***	
	(0.0169)				(0.0165)	
U_t × (New Hire, Occ. Switcher)		-0.590***	-0.567***			-0.552***
		(0.0178)	(0.0185)			(0.0181)
U_t × (New Hire, Occ. Non-Switcher)		0.00945	0.0361			0.0620*
		(0.0273)	(0.0273)			(0.0252)
U_t × (Stayer, Occ. Switcher)			-0.201***			-0.155***
			(0.0297)			(0.0289)
U_t × Occ. Switcher				-0.578***		
				(0.0181)		
Observations	38,693,092	38,693,092	38,693,092	38,693,092	38,693,092	38,693,092
Adjusted R^2	0.860	0.860	0.861	0.860	0.860	0.861

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 columns 5 and 6. 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. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Table 3: Robustness Checks

	Measurement Error		Males	
	(1)	(2)	(3)	(4)
U_t	-1.228***	-1.209***	-1.301***	-1.277***
	(0.0227)	(0.0231)	(0.0268)	(0.0271)
U_t × New Hire	-0.457***		-0.497***	
	(0.0182)		(0.0205)	
U_t × (New Hire, Occ. Switcher)		-0.611***		-0.649***
		(0.0205)		(0.0226)
U_t × (New Hire, Occ. Non-Switcher)		0.0691*		-0.0236
		(0.0275)		(0.0236)
U_t × (Stayer, Occ. Switcher)		-0.182***		-0.165***
		(0.0302)		(0.0277)
Observations	37,675,587	37,675,587	22,317,569	22,317,569
Adjusted R^2	0.865	0.865	0.858	0.858

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) is defined as total total pay, which includes base wage, benefits and overtime pay, divided by total hours worked. Column 1 and 2 consider only occupation switchers that had a stable occupation prior to switching and remain in the new occupation for two years after switching. Column 3 and 4 restricts the sample to male workers. 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. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Table 4: Alternative Explanations

	Occ. Similarity		Experience	Wage Floors	Hierarchy	EE vs. UE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
U_t	-1.005***	-0.996***	-1.213***	-0.606***	-1.134***	-1.125***	-0.595***
	(0.0223)	(0.0222)	(0.0228)	(0.0184)	(0.0230)	(0.0230)	(0.0185)
U_t × Distance	-0.689***	-0.00649***					
	(0.0325)	(0.000456)					
U_t × (New Hire, Occ. Switcher)			-0.474***	-0.296***	-0.577***		
			(0.0186)	(0.0190)	(0.027)		
U_t × (New Hire, Occ. Non-Switcher)			0.120***	0.0648**	0.026		
			(0.0276)	(0.0233)	(0.027)		
U_t × (Stayer, Occ. Switcher)			-0.223***	-0.102***	-0.160***	-0.194***	-0.0977***
			(0.0299)	(0.0223)	(0.0297)	(0.0223)	(0.0223)
U_t × (UE, Occ. Switcher)						-0.315***	-0.240***
						(0.0168)	(0.0152)
U_t × (UE, Occ. Non-Switcher)						0.109***	0.0703**
						(0.0250)	(0.0217)
U_t × (EE, Occ. Switcher)						-0.847***	-0.409***
						(0.0251)	(0.0265)
U_t × (EE, Occ. Non-Switcher)						-0.0503	0.0395
						(0.0406)	(0.0335)
Observations	33,287,943	33,287,943	38,693,092	38,547,789	38,693,092	38,693,092	38,547,789
Adjusted R^2	0.838	0.838	0.862	0.865	0.860	0.861	0.861

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. In column 1, the distance between two occupations is measured using the angular distance and in column 2 using the Euclidean distance. Column 3 controls for the worker labour market experience. Column 4 controls for the wage floor negotiated by the collective agreement for the worker's professional category and column 5 adds categorical variables that equal one in the worker moved up or moved down the firm hierarchy, and zero otherwise. Column 6 distinguishes between job-to-job transitions (EE) and newly hired workers from non-employment (UE) and column 7 replicates column 6 controlling for the negotiated wage floor. 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. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Table 5: 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 6: Occupation Similarity: An Example

Occupation (3-digit)	**Distance**		**Requirements**			
	$\phi(\boldsymbol{q}_{doctor}, \boldsymbol{q}_j)$	$d(\boldsymbol{q}_{doctor}, \boldsymbol{q}_j)$	Math	Verbal	Technical	Social
Waiters and Bartenders	0.83	147.3	10	9	6	57
Child Care Workers	0.72	130.6	18	22	9	80
Fishers & Hunters	0.73	148.7	12	12	44	4
Tour Guides	0.57	116.3	25	31	18	78
Legal Professionals	0.37	79.8	50	70	24	84
Electrical Equipment Installers	0.32	60.4	81	77	97	31
Mathematicians & Statisticians	0.25	46.3	98	85	94	40
Hotel & Restaurant Managers	0.17	40.0	78	77	65	100
Nurses	0.03	7.7	93	95	89	93
Doctors	0	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. Column 2 reports the angular distance (Equation 5), and column 3 the eucleadian distance (Equation 5). Column 3 to 6 report the skill requirements vector for each 3-digit occupation.

Table 7: Classification of Workers According to Hierarchical Levels

Hierarchical Level
1. Top executives (top management)
2. Intermediary executives (middle management)
3. Supervisors, team leaders
4. Higher-skilled professionals
5. Skilled professionals
6. Semi-skilled professionals
7. Non-skilled professionals
8. Apprentices, interns, trainees

Notes: Hierarchical levels defined according to Decreto Lei 121/78 of July 2nd (Caliendo et al., 2020).

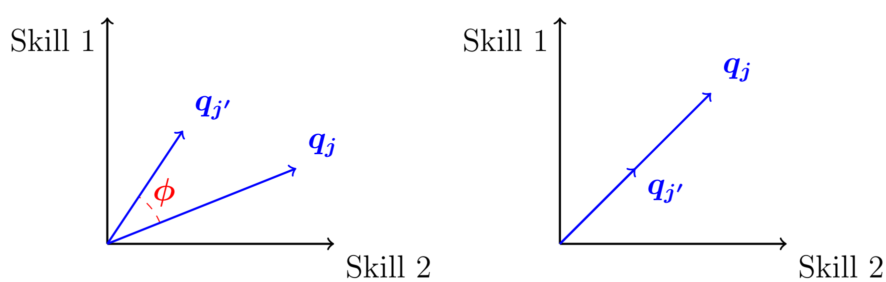


Figure 2: Illustration of distance between two occupations j and $j^{'}$ for $K = 2$