Canadian Labour Economics Forum

Working Paper Series

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CLEF WP #80

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November 28, 2024

Abstract

We consider how firms' organization of production relates to workers' wages. Using matched employer-employee data from Portugal, we document that firms differ starkly in their occupational employment concentration, even within detailed industries, with some firms employing workers across a broad range of occupations and others being much more specialized. These differences are robustly predictive of wages: a worker employed in a specialized, i.e. 'fissured' firm, earns less than that same worker employed in a less specialized firm. This wage penalty for working in a fissured firm is observed across occupations of all skill levels. Firm specialization helps account for the role of firms in inequality, as specialization is strongly negatively related to estimated AKM firm fixed effects. Around two-thirds of the wage penalty from fissuring is explained by differences in firm productivity. Fissured firms also engage in lower rates of rent-sharing conditional on productivity, accounting for around one-quarter of the difference in wage premia between high- and low-specialization firms. Finally, we show that being employed in a specialized firm is also associated with worse longer-term career outcomes for workers.

Keywords: Occupational Segregation; Between-Firm Wage Inequality; Firm Productivity; Rent-Sharing

JEL Codes: J24, J31

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1 Introduction

The modern economy has been characterized as one in which production is organized across fissured workplaces (Weil, 2014): firms have become increasingly focused on their core business, relying on other specialized firms for the provision of ancillary services and intermediate inputs. This implies increasing specialization at the firm level in terms of the occupational and skill composition of their employees. Despite the prominence of these trends in the academic and public policy debates (e.g. see Bernhardt et al. 2016; OECD 2021b), there is limited empirical evidence on the implications of firm specialization for worker outcomes. As argued by Bernhardt et al. (2016), understanding these patterns is critical for policymakers and other stakeholders in light of the changing nature of work.

In this paper, we investigate the link between firms' occupational specialization and workers' wages, and explore key mechanisms underlying this link. Using matched employer-employee data from Portugal for the period 2010–2019, and leveraging various measures of occupational specialization, we show that firms exhibit significant heterogeneity in their occupational employment concentration, even within detailed industries. Our results reveal a robust and significant negative relationship between a firm's occupational specialization and its workers' wages: workers in more specialized (i.e. 'fissured') firms earn lower wages compared to their counterparts in more occupationally diverse firms.

We rule out that this pattern is explained by firm size effects. Moreover, we show that these wage differences cannot be (solely) attributed to worker sorting across firms: a pay penalty for working in more fissured firms remains even when comparing the same individual across firms. Our within-worker estimates imply that a one standard deviation increase in firm specialization predicts a wage decrease of around 0.5%, which is quantitatively similar to the within-worker impact of a 50% increase in firm size. Interestingly, firm specialization is associated with wage reductions that are widespread across the occupation and industry spectrum, including in highly skilled jobs. We also find that wages in specialized firms are lower for workers in both large and small occupations within the firm, i.e. there appears to be a firm-wide penalty of specialization, not one limited to only peripheral or core functions.

The finding that specialized firms tend to pay lower wages to all of their workers motivates us to focus on the link between specialization and a measure of the firm wage premium, namely its estimated AKM firm fixed effect (Abowd et al., 1999). Consistent with our findings from the individual-level data, we show robust evidence of a negative firm-level correlation between specialization and AKM wage premia. We then leverage a decomposition analysis along the lines of Beauregard et al. (2024) to analyze whether the lower wage premia in specialized firms can be explained by (a) lower levels of productivity, or (b) lower levels of rent sharing, conditional on productivity. Comparing firms in the top versus bottom deciles of the occupational specialization distribution, the lower productivity of specialized firms (conditional on firm industry and size) accounts for around 60–70% of the gap in firm pay premia. Firm differences in rent sharing are also quantitatively important, accounting for an additional 20–30% of the gap.

Finally, we show that exposure to employment in a specialized firm predicts worse longer-term earnings outcomes for workers. Specifically, workers initially employed in more specialized firms experience significantly slower earnings growth over the subsequent five years of their careers. This is mostly driven by persistently reduced hours worked. Workers in more specialized firms are substantially more likely to switch firms over the next five years; however, the lack of faster earnings growth for these workers suggests that their mobility patterns are primarily due to less stable employment relationships, rather than career-building.

Our findings contribute to four strands of literature. First, we contribute to a literature that highlights the importance of between-firm pay differences in accounting for overall worker-level inequality (e.g Abowd et al., 1999; Barth et al., 2016; Card et al., 2018; Song et al., 2019; Bonhomme et al., 2023). While this literature has documented the quantitative importance of these differences, there is less evidence on what drives these pay gaps. We investigate heterogeneity in occupational specialization as a specific factor contributing to the dispersion in wage-setting practices between firms. We find that more occupationally specialized firms pay lower premia, both because they exhibit lower productivity levels, and because they engage in lower rates of rent-sharing. This literature also highlights the importance of worker sorting for wage inequality. Our results indicate that sorting that leads to higher levels of occupational homophily within firms would not only affect wage *inequality* (by increasing the covariance of worker and firm fixed effects), but would also affect wage *levels* through lower firm pay premia.

Our focus on occupational specialization relates to work studying firms' occupational hierarchies (Caliendo et al., 2015, 2020). These papers show that higher value-added firms tend to have more occupational layers, and that more managerial layers are added in response to positive productivity or demand shocks— a result that is consistent with our finding that more occupationally diverse firms exhibit higher levels of labor productivity and wages.[1] We contribute to this body of work by studying the consequences of exposure to firm specialization for individual workers.

A third related strand of the literature considers worker outsourcing. Domestic outsourcing would naturally lead to changes in firm specialization according to the measures that we consider here, as discussed, for example, by OECD (2021a) and Bergeaud et al. (2024). The literature on domestic outsourcing has tended to focus on a specific set of occupations or industries such as logistics, cleaning, security, and food catering (Dube & Kaplan, 2010; Goldschmidt & Schmieder, 2017; Dorn et al., 2018; Katz & Krueger, 2019; Scheer et al., 2022; Drenik et al., 2023; Daruich et al., 2024).[2] These papers find that workers experience wage losses when transitioning from direct employment with a firm to an employment relationship with a service contractor, payrolling firm, or temporary work agency. Rather than focusing on the wage changes experienced by outsourced workers (who would, by definition, be switching to a firm in a different industry), we compare wages across firms in the same detailed industry, and document differences in worker wages according to the level of occupational specialization of the firm (after accounting for worker characteristics). By going beyond the (low-skill) occupations that are traditionally viewed as 'outsourceable' or the sectors that are normally considered 'outsourcing sectors', we provide a broader analysis of firm fissuring – which may be driven by many factors that go beyond outsourcing – and show that the negative wage impacts of fissuring are pervasive across occupations. Our results suggest that even the high-skilled workers retained by fissured firms could be negatively impacted by the ensuing lack of occupational diversity within their firm. An additional novel aspect of our paper is our analysis of the extent to which the lower wages observed in fissured firms are driven by differences in productivity and differences in rent sharing. Although the literature has hypothesized that wages for workers in fissured firms might be lower because they have less bargaining power (e.g. OECD, 2021b), our results provide direct evidence on the quantitative importance of this channel.

The papers most closely related to ours are Handwerker & Spletzer (2016) and Handwerker (2023), who also focus on the link between firms' occupational specialization and the

[1] Cortes & Salvatori (2019) and Harrigan et al. (2021) document strong occupational specialization in British and French firms, respectively, and highlight the importance of changes in workplace specialization in accounting for the evolution of aggregate occupational employment shares. Arntz et al. (2024) link changes in firm composition to firm-level technology adoption.

[2] Bilal & Lhuillier (2022) consider the aggregate implications of domestic outsourcing in terms of wages and productivity; and Estefan et al. (2024) show that a domestic outsourcing ban in manufacturing sectors in Mexico increased wages without reducing employment, and increased firm exit.

wages that they pay. A major advantage of our analysis is our ability to control fully flexibly for worker composition by including individual worker fixed effects (in Handwerker & Spletzer (2016) and Handwerker (2023) this is precluded due to data restrictions). This allows us to determine the extent to which worker sorting (along fixed unobservable dimensions) accounts for the lower wages observed at more specialized firms. We also extend their analysis in substantive ways by exploring the role of productivity differences and differences in rent sharing in accounting for the lower wages in specialized firms, and by longitudinally studying the relationship between exposure to firm specialization and workers' subsequent career outcomes.

2 Data

2.1 *Quadros de Pessoal*

We use administrative matched employer-employee data from Portugal's *Quadros de Pessoal*, provided by the Ministry of Labor, Solidarity and Social Security, and the National Institute of Statistics. Data originate from compulsory annual surveys covering the universe of private-sector employees and firms with at least one employee. Firms report a comprehensive set of individual-level information for each person employed at the firm during a particular reference week in October. We consider the period from 2010 to 2019, during which no changes in occupational or industry classifications occurred, and during which all methodological attributes of the data remained constant.

We restrict the analysis to individuals aged 17 to 68. We drop individuals with missing occupation (around 9% of the data), as well as a small number of observations with missing data for education and/or for the individual identifier. We also exclude individuals in agricultural occupations, and firms in the agricultural, defense, public administration or extraterritorial organization sectors. We winsorize worker-year observations above the 99th and below the 1st percentile of the monthly earnings distribution. Following Card et al. (2016), we compute hourly wages by dividing monthly earnings (base payment and benefits paid every month) by the number of regular monthly hours worked. We deflate nominal values to 2012 euros using the Consumer Price Index.

To have meaningful variation in occupational specialization across firms, we restrict the sample to firms with at least ten employees: these firms employ around 77% of the workers in our sample. Our final sample comprises 19,168,215 worker-year observations, and 375,905 firm-year observations. Firms operate across 453 4-digit industries, and workers are employed in 116 different 3-digit occupations. Appendix Table A1 presents descriptives.

2.2 Occupational Specialization Measures

We employ two different firm-level measures of occupational specialization (OS). The first is the Herfindahl-Hirschman Index (HHI), as in Handwerker & Spletzer (2016), defined for each firm j in each year t as:

$$\text{OS}_{jt} = \sum_{o} \left(\frac{E_{jot}}{E_{jt}} \right)^2 ,$$

where E is employment and o indexes occupations, so $\frac{E_{jot}}{E_{jt}}$ is each occupation's employment share within firm j in year t. A higher HHI indicates a higher degree of occupational concentration of employment within the firm. We use persons employed in our baseline analysis, and do robustness checks using hours-weighted measures of employment.

As an alternative and easily interpretable measure of occupational specialization, we use the employment share of the largest occupation within the firm:

$$\text{OS}_{jt} = \max_{o} \left\{ \frac{E_{jot}}{E_{jt}} \right\} .$$

We consider two levels of occupational aggregation when constructing these measures: our baseline uses 1-digit occupation codes (8 categories), and for robustness checks we use 3-digit occupation codes (116 categories).

2.3 Heterogeneity in Occupational Specialization

Table 1 provides information on the distribution of occupational specialization across firm-year observations. Panel A assigns equal weight to all firm-year observations, while panel B weights firm-year observations according to their total employment, thus presenting statistics that are representative at the worker- rather than the firm-level.

Column 1 considers the HHI using 1-digit occupations. This measure can range from 0.125 (if a firm has equal shares of all 8 occupations) to 1 (if a firm only employs workers in one occupation). The average firm has an HHI of 0.51. There is a lot of variation across firm-year cells. As the bottom rows indicate, the overall standard deviation across firms is 0.22. This is not driven by temporal variation: the standard deviation remains 0.22 across firms *within* years. Moreover, only a small part of this variation is due to differences across industries: the standard deviation across firms within industries, and across firms within industry-year cells, is 0.19 — only slightly lower than the overall standard deviation. This is a first key finding: Portuguese firms exhibit significant heterogeneity in their workforce's occupational composition, indicating that they organize production differently even when producing similar goods or services (i.e. when operating within the same 4-digit industry).

The remaining columns confirm that this finding also holds when measuring specialization based on more detailed (3-digit) occupational categories, or using the employment share of the firm's largest occupation rather than the HHI. In all cases, there is significant heterogeneity in specialization patterns across firms, primarily observed *within* industry-year cells.[3]

The employment-weighted statistics in Table 1, panel B, indicate that we also observe substantial heterogeneity in exposure to specialization at the worker level, and this is largely observed across workers in different firms within industry-year cells.[4]

3 Occupational Specialization and Worker Earnings

3.1 Main Results

To investigate the link between a firm's occupational specialization and the earnings of its workers, we estimate the following regression model:

$$y_{ijt} = \beta \mathrm{OS}_{jt} + \gamma Z_{ijt} + \delta_t + \zeta_{s(j)} + \eta_{o(it)} + \theta_i + \varepsilon_{ijt}, \qquad (1)$$

where y_{ijt} is an outcome for worker i employed in firm j in year t. OS_{jt} is a measure of occupational specialization of firm j in year t, as described in Section 2.2. Z_{ijt} is a vector of worker characteristics, namely gender, nationality, and a set of fully interacted age by

[3] Appendix Table A2 confirms that the observed variation in specialization is largely within industry-year cells by reporting the R^2 from regressions of each measure of specialization on different combinations of fixed effects. Irrespective of the measure of specialization, at least 93% of the variation is within 1-digit industry-by-year cells, and around 75% of the variation is within 4-digit industry-by-year cells.

[4] Appendix Figure A1 documents how exposure to specialization varies across different worker groups. Workers who are younger, female, foreign born, and have lower levels of education tend to work in more occupationally-specialized firms. Exposure also varies according to workers' occupations. In the analysis below we control for demographic characteristics and include occupation fixed effects, hence identifying the link between firm specialization and worker wages exploiting variation in exposure to specialization *conditional* on demographics and *within* occupations.

education fixed effects.[5] The remaining control variables are various fixed effects, which we add sequentially when presenting our results: δ_t is a year fixed effect, $\zeta_{s(j)}$ is a fixed effect for the 4-digit industry s that firm j operates in, $\eta_{o(it)}$ is a fixed effect for the occupation o that individual i works in at time t, and θ_i is a worker fixed effect. ε_{ijt} is an error term that satisfies standard properties. Our coefficient of interest is β, capturing the relationship between firms' occupational specialization and their workers' outcomes. When including worker fixed effects, β is identified only from within-worker comparisons across firms with different occupational specializations. We cluster standard errors by firm $\times$ year.

Table 2 shows our baseline results, using the HHI based on 1-digit occupational employment shares within the firm as our measure of specialization (OS_{jt}). We consider three different worker outcomes y_{ijt}: log monthly earnings (panel A), log total monthly hours worked (panel B), and log hourly wages (panel C). Column 1 reports a specification that only includes worker characteristics and year fixed effects as controls. The estimated coefficient on HHI is negative and highly statistically significant in all three panels. Workers in a firm with a one standard deviation higher firm specialization (a HHI difference of 0.22; see Table 1) have 7.2% lower monthly earnings (-0.326×0.22 log points). These lower earnings arise from both lower monthly hours worked and lower hourly wages, as shown in panels B and C; in particular, 3.1% lower monthly hours worked (-0.141×0.22), and 4.0% lower hourly wages (-0.183×0.22).

One might worry that our index of specialization proxies for other firm characteristics, particularly firm size, which positively correlates with wages (Lester 1967; Brown & Medoff 1989; Abowd et al. 1999; Even & Macpherson 2012; Bloom et al. 2019). In column 2 we therefore control for log firm employment. Interestingly, the estimated coefficient on the HHI variable is virtually unaffected across all three panels.

In column 3, we replace year fixed effects with a full set of year by 4-digit industry fixed effects. In this specification, the coefficient on HHI is identified solely from variation across firms within detailed industries in a given year. The magnitude of the HHI coefficient is reduced (in absolute value), indicating that specialized firms tend to be concentrated in lower-wage industries. However, even within detailed industries, individuals working in more specialized firms tend to earn significantly lower monthly and hourly wages and work fewer hours, conditional on their observable characteristics and the size of the firm.

Columns 4 and 5 of Table 2 add controls for the worker's 1- and 3-digit occupation,

[5] We consider three educational categories: less than high school, high school, and college.

respectively. The magnitude of the HHI coefficient is reduced, indicating that workers in high-paying occupations are less likely to work in specialized firms (see Appendix Figure A1). However, even within detailed occupations, and accounting for observable characteristics as well as firm size and industry-year effects, workers employed in more specialized firms earn lower wages and work fewer hours.

Finally, in column 6 we add worker fixed effects. This is our most exacting specification, controlling for any permanent worker characteristics (including unobserved ones), and relying solely on variation in wages and firm specialization within individuals over time. Even here we find that the same worker employed in a more specialized firm earns lower monthly and hourly wages, and works fewer hours. The estimate in panel C implies that hourly wages are 0.51% (-0.023×0.22) lower for a one standard deviation increase in firm specialization. While seemingly small, it is worth noting that this is more than half the magnitude of the (oppositely-signed) within-worker effect of moving to a firm that is *twice* as large (as the coefficient on log firm size is around 0.01 in this same specification). Moreover, this is compounded by a decrease in hours worked, leading to a further decline in monthly earnings (around 1.74% for a one standard deviation increase in firm specialization).

These findings are robust to various alternative measures of firm specialization, as shown in the appendix. This includes using the HHI index based on 3-digit (rather than 1-digit) occupational employment shares within the firm (Table A3), using hours-weighted employment shares of each 1-digit occupation rather than headcounts (Table A4), and using the employment share of the largest occupation within the firm as the measure of specialization (Table A5).

3.2 Heterogeneity Across Job Types

Next, we explore whether the wage penalty observed for workers in more specialized firms is concentrated among those who are employed in low-paid jobs—the types of jobs that have been the primary focus of the domestic outsourcing literature—or is observed more broadly. To do this, we expand our regression analysis in equation (1) by adding interaction terms between the firm's HHI and the worker's 1-digit occupation or the firm's 1-digit industry. We thus obtain occupation- or industry-specific penalties (or benefits) of specialization. For brevity, we focus on the specification with all controls (including worker fixed effects), and with log hourly wages as the dependent variable.

The occupation-specific coefficients obtained from this analysis are plotted in panel A of

Figure 1, where occupations are ranked by their mean log hourly wage.[6] Interestingly, we find that firm specialization is associated with worker wage penalties that are widespread across the occupational spectrum, including in highly paid jobs such as technicians and managers. Appendix Figure A2 shows that the same holds for one-digit industries: wage penalties for workers in more specialized firms are not only observed within lower-paid industries such as manufacturing and construction, but also higher-paid ones such as information and communication, and financial and insurance activities.

As an additional dimension of heterogeneity, we explore whether the wage penalties observed within more specialized firms are mostly borne by workers in the largest occupation in the firm, or are more widespread. This informs on whether wage penalties from specialization only affect workers who are potentially outsourced—and therefore end up working in a firm that specializes in their occupation.[7] We augment our regression specification from equation (1) as follows:

$$\begin{aligned} y_{ijt} = \beta_1 \ \mathrm{OS}_{jt} + \beta_2 \ \mathrm{LargestOcc}_{ijt} + \beta_3 \ \mathrm{OS}_{jt} \times \mathrm{LargestOcc}_{ijt} \\ + \gamma Z_{ijt} + \delta_t + \zeta_{s(j)} + \eta_{o(it)} + \theta_i + \varepsilon_{ijt}, \end{aligned} \tag{2}$$

where $\mathrm{LargestOcc}_{ijt}$ is an indicator variable equal to one if individual i works in the largest one-digit occupation at firm j in year t. To match this, we use the firm's share of the largest occupation to measure firm specialization (OS_{jt}). Our parameters of interest are β_1 and β_3. A negative value for β_3 would indicate that workers in the largest occupation in more specialized firms (i.e. those who work in the occupation that the firm specializes in) earn particularly low wages. Conversely, if β_1 is negative but β_3 is not, it would mean that the depressed wages in more specialized firms are not confined to workers in the main occupation but are more broadly distributed across all workers in the firm.

Estimates and confidence intervals for $\beta_1 + \beta_3$ (capturing the wage penalty of firm specialization for workers in the largest occupation in the firm) and for β_1 (capturing the wage penalty for workers in all other occupations) are presented in panel B of Figure 1 (with

[6]Appendix Table A6 provides the estimates underlying panel A of Figure 1.

[7]This may also be informative about the role of pay transparency as a driver of lower wages in fissured firms. Cullen & Pakzad-Hurson (2023) show that pay transparency— modeled as the probability of observing peer wages— reduces average wages. More specialized firms may exhibit more pay transparency for individuals in the largest occupation(s) in the firm, given that they have a larger pool of peers to compare themselves to. Workers in smaller occupations within specialized firms would not be subject to higher pay transparency. Thus, if the wage penalty that we have identified were confined to workers in the largest occupation within the firm, this would be consistent with wage transparency as a contributing force.

detailed estimates reported in Appendix Table A8). The figure shows that the wage penalty for working in a specialized firm is not limited to workers in the largest occupation within the firm. Without controlling for worker fixed effects, wage penalties are actually larger for workers outside of the firm's largest occupation; when worker fixed effects are included, estimates are statistically indistinguishable between the firm's largest occupation and all other occupations.

4 Mechanisms: Firm Productivity and Rent-Sharing

The finding that specialized firms tend to pay lower wages to *all* of their workers, even conditional on worker fixed effects, motivates us to focus on the link between specialization and a general measure of firm wage premia such as AKM firm fixed effects (Abowd et al., 1999). Therefore, we estimate an AKM-type regression of the following form:

$$y_{ijt} = \gamma Z_{ijt} + \delta_t + \eta_{o(it)} + \theta_i + \psi_j + \varepsilon_{ijt}, \tag{3}$$

where Z_{ijt}, δ_t, $\eta_{o(it)}$, and θ_i are as defined above. y_{ijt} is the log hourly wage of worker i, and ψ_j is the firm fixed effect, which captures the wage premium paid by the firm conditional on its workers' observed and time-invariant unobserved characteristics.[8]

In panel A of Figure 2, we group firms into (employment-weighted) deciles of occupational specialization. The circles (corresponding to the left y-axis) confirm that there is a clear negative correlation between a firm's occupational specialization and its estimated firm fixed effect $\widehat{\psi}_j$, consistent with the results from our individual-level regressions above. The figure also highlights a clear negative correlation between a firm's occupational specialization and its labor productivity, measured as average log sales per worker (as indicated by the triangles corresponding to the right y-axis). This suggests that the lower wage premia paid by specialized firms are at least partly due to differences in productivity.[9] However, it may also be the case that, conditional on firm productivity, workers are able to extract a lower share of the rents in more specialized firms. The outsourcing literature (e.g., Weil 2014, Dube

[8]We are able to estimate firm fixed effects for a total of 70,752 firms (out of 71,836 unique firms in our dataset; see Appendix Table A1). In our analysis below, we exclude 757 of these firms because they have missing sales information or report zero total sales.

[9]The link between occupational diversity and productivity shown in the figure is consistent with the literature documenting that higher value-added firms tend to have more occupational layers (Caliendo et al., 2015, 2020).

et al. 2022, Guo et al. 2024) considers that this may be the case because outsourcing circumvents within-firm fairness norms and avoids collective bargaining agreements, reducing worker bargaining power.[10]

To disentangle the relative importance of differences in firm productivity and differences in rent sharing, we implement a decomposition analysis along the lines of Beauregard et al. (2024). Specifically, we express the AKM firm wage premium as:

$$\widehat{\psi}_j = \phi_1 + \phi_2 \mathrm{OS}_j + \pi_1 V_j + \pi_2 V_j \mathrm{OS}_j + \chi_j, \tag{4}$$

where OS_j, as before, is the firm's occupational specialization, and V_j represents log sales per worker for firm j (standardized to have an employment-weighted mean of zero and standard deviation of one). V_j serves as a measure of firm-level productivity.[11]

Given equation (4), the partial derivative of $\widehat{\psi}_j$ with respect to OS_j is $\phi_2 + \pi_2 V_j$. Since V_j is standardized to have mean zero, we can interpret ϕ_2 as the partial effect of specialization on firm wage premia (holding productivity constant), for firms with average productivity levels. Meanwhile, the partial derivative of $\widehat{\psi}_j$ with respect to V_j, which we can interpret as a measure of pass-through from productivity to wage premia, is given by $\pi_1 + \pi_2 \mathrm{OS}_j$. Thus, π_1 reflects a base level of pass-through for all firms, regardless of their specialization level. A nonzero π_2 coefficient would indicate that the degree of rent-sharing, i.e. how productivity variation translates into wage premia, depends on firms' specialization levels.

We estimate equation (4) using our baseline specialization measure (the HHI index based on 1-digit occupations), adding controls for firm size as well as industry fixed effects, and employment-weighting each firm, and obtain $\widehat{\phi}_2 = -0.032$, $\widehat{\pi}_1 = 0.060$, and $\widehat{\pi}_2 = -0.013$, all with p-values below 0.001. The negative ϕ_2 estimate implies that there are differences in firm wage premia between more and less specialized firms, even after controlling for their productivity levels. Meanwhile, the negative π_2 estimate implies a lower rate of pass-through from productivity to firm wage premia for more specialized firms.[12]

To quantify the relative importance of differences in productivity and differences in rent-

[10]For evidence on the prevalence of within-firm pay equity norms see, e.g., Giupponi & Machin (2024). Firm differences in rent-sharing have been linked to factors such as individual bargaining power (Cho & Krueger, 2022), firm union density (Barth et al., 2020), and managerial practices (Acemoglu et al., 2022).

[11]We omit time subscripts in equation (4) because AKM estimation yields a time-invariant estimate of ψ_j for each firm. OS_j and V_j represent averages across years where we observe firm j.

[12]These results are robust to allowing productivity to enter equation (4) non-linearly, by controlling for indicator variables for each productivity quintile.

sharing, we decompose the gap between firms in the top versus bottom decile of the occupational specialization distribution (i.e. the gap between the rightmost and the leftmost circles in panel A of Figure 2). Based on equation (4), and using $p10$ to denote averages for the most occupationally diverse firms, and $p90$ to denote averages for the most specialized firms, we can express this gap as

$$\begin{aligned}\widehat{\psi}^{p10} - \widehat{\psi}^{p90} = & \underbrace{(\pi_1 + \pi_2 \mathrm{OS}^{p90})(V^{p10} - V^{p90})}_{\text{productivity component}} \\ & + \underbrace{\left(\phi_2 + \pi_2 V^{p10}\right)\left(\mathrm{OS}^{p10} - \mathrm{OS}^{p90}\right)}_{\text{rent-sharing component}} \\ & + \underbrace{\left(\chi^{p10} - \chi^{p90}\right)}_{\text{diff in residuals}}.\end{aligned} \tag{5}$$

The first term captures the differences that can be attributed to the gap in productivity levels between highly specialized and highly diverse firms, $V^{p10} - V^{p90}$. The decomposition in equation (5) uses a pass-through factor from productivity to firm wage premia of $\pi_1 + \pi_2 \mathrm{OS}^{p90}$, i.e. the pass-through of highly specialized firms. Since $\widehat{\pi}_2$ is negative and OS^{p90} is high, this assumes a relatively low pass-through and can therefore be thought of as a lower bound on the importance of productivity differences in accounting for the difference in firm wage premia.

The second term is the rent sharing component, reflecting differences in firm wage premia *conditional on firm productivity*. Specifically, this term captures differences in firm wage premia between more and less specialized firms ($\mathrm{OS}^{p10} - \mathrm{OS}^{p90}$), holding productivity constant at the level of occupationally diverse firms (V^{p10}). Since V^{p10} is high, this can be thought of as an upper bound on the importance of rent-sharing in accounting for the difference in firm wage premia.

The final term in equation (5) reflects differences in residuals between more and less specialized firms. In our empirical implementation, we also control for firm size and industry fixed effects when estimating equation (4), thereby introducing an additional term in the decomposition which reflects differences across the two groups in their predicted wage premia based on these observables.

Alternatively, the decomposition can be written as

$$\begin{aligned}\widehat{\psi}^{p10} - \widehat{\psi}^{p90} = {} & (\pi_1 + \pi_2 \mathrm{OS}^{p10})(V^{p10} - V^{p90}) \\ & + \left(\phi_2 + \pi_2 V^{p90}\right)\left(\mathrm{OS}^{p10} - \mathrm{OS}^{p90}\right) \\ & + \left(\chi^{p10} - \chi^{p90}\right).\end{aligned} \tag{6}$$

Equation (6) has the same components as equation (5), but uses a different counterfactual pass-through rate in the productivity component (based on OS^{p10} instead of OS^{p90}), and a different counterfactual productivity level in the rent-sharing component (V^{p90} instead of V^{p10}). This now yields an upper bound on the relative importance of productivity differences, and a lower bound on the relative importance of rent sharing differences.

Panel B of Figure 2 presents results for both these decompositions. The term corresponding to the difference in residuals ($\chi^{p10} - \chi^{p90}$) accounts for around 1% of the overall gap, and is omitted from the figure. We find that differences in productivity and differences in rent sharing are both quantitatively relevant in accounting for the gap in firm wage premia between specialized and non-specialized firms. While differences in size and industry affiliation account for only around 8% of the gap in firm wage premia, differences in productivity account for the majority (59–71%) of the gap.

Differences in firm wage premia conditional on productivity (i.e. rent sharing) are also empirically relevant. They account for the remaining 20–32% of the gap in firm wage premia. This means that firms' organizational structures, in terms of the occupational composition of the workers that they hire, are an important proximate source of between-firm wage inequality, even after accounting for differences in productivity.

5 Subsequent Career Outcomes

Our results have shown that workers employed in specialized firms face a contemporaneous wage penalty. We now investigate whether being employed in a specialized firm also harms workers' longer-term careers.

We do this by estimating the following model for time intervals of increasing length T, in the spirit of local projections (Jordà, 2005):

$$\Delta y_{ij[t+T]} = \beta \mathrm{OS}_{j,[t-1]} + \delta_t + \eta_{o(i,[t-1])} + \zeta_{s(j,[t-1])} + \gamma Z_{i,[t-1]} + \varepsilon_{ijt}, \tag{7}$$

where

$$\Delta y_{ij[t+T]} \equiv \left(y_{ij[t+T]} - y_{ij[t]}\right) - \left(y_{ij[t-1]} - y_{ij[t-2]}\right)$$

The dependent variable is outcome growth between years t and T, where $T \in \{1, ..., 5\}$, relative to outcome growth over the pre-period (i.e., between years $t-2$ and $t-1$). This follows empirical specifications used to study the impact of trade and technology exposure (Autor et al., 2014; Kogan et al., 2023). As outcomes, we consider log monthly earnings, log hourly wages, and log monthly hours worked (as before), as well as indicators for switching to non-employment, switching firms, or switching three-digit occupations.

The β coefficient in each regression captures how initial exposure to firm specialization ($\mathrm{OS}_{j,[t-1]}$) impacts worker outcomes over time windows of expanding length T. We add fixed effects for year t (δ_t), for the worker's occupation in $t-1$ ($\eta_{o(i,[t-1])}$), and for the firm's industry in $t-1$ ($\zeta_{s(j,[t-1])}$). We also control for worker observables in $t-1$ ($Z_{i,[t-1]}$), namely gender, nationality, age by education fixed effects, and log earnings.[13] Standard errors are clustered at the firm level.

Results are shown in Figure 3. Panel A shows estimates for monthly earnings, hourly wages, and monthly hours worked. This highlights that the earnings losses faced by workers who work in a specialized firm persist over the subsequent five years of their careers. Monthly earnings are around 3.2 to 4.2% lower: this is mostly driven by reduced hours worked, but in the first year, losses also accrue from a 0.8% wage penalty, similar to the one identified from cross-sectional models highlighted in Table 2.

Panel B of Figure 3 considers firm and occupational mobility as well as switching to non-employment as outcomes. Here, we find that workers exposed to more specialized firms are substantially more likely to switch firms over the next five years: this difference increases over the career and amounts to 7.1 percentage points over the full five-year interval. Despite higher firm mobility, workers do not increase their wage growth, indicating this mobility reflects less stable employment relationships rather than career-building. Consistent with this interpretation, more specialization-exposed workers do not have higher rates of occupational mobility – if anything, by the fifth year following exposure, occupational mobility is reduced by 2.5 percentage points (an estimate which is marginally statistically significant). Moreover, workers face a higher chance of becoming non-employed following exposure to specialization

[13] The control for workers' log earnings in $t-1$ is included to avoid capturing patterns of mean reversion. Our results are robust to additionally interacting these initial earnings by a full set of age by education fixed effects.

(ranging between 1.6 and 2.1 percentage points), especially in the first two years, though an effect persists even five years after exposure.[14]

6 Conclusion

Firms play an important role in inequality: paraphrasing Barth et al. (2016), where you work matters. We show it also matters who you work with: wages are lower in firms employing workers in a smaller variety of occupations ('fissured firms').

Using matched employer-employee data from Portugal, we document that, within detailed industries, firms differ starkly in their occupational employment concentration, with some firms employing workers across a broad range of occupations and others being much more specialized. While recent work has related firms' occupational organization of production to outsourcing, we highlight that the implications are broader. First, the wage penalty for being employed in a fissured firm is not limited to lower-paid service jobs typically considered subject to outsourcing, but pervasive across occupational categories. Second, the wage penalty does not solely reflect worker-firm sorting or worker segregation across firms, since it persists even when controlling for worker fixed effects. Third, the negative consequences of working in a fissured firm are persistent over workers' careers.

Firm specialization helps account for the role of firms in inequality: specialization is strongly negatively related to AKM firm fixed effects. This is in large part because specialized firms are less productive, and to a lesser extent also because they share rents with their workers at a lower rate.

The findings in this paper suggest further study into firms' organization of production and its role for worker wages and careers. Future research may seek to understand the factors that explain why occupationally diverse firms tend to be more productive than similarly-sized occupationally homogeneous peers within the same detailed industry. With access to task data at the worker-firm level, it would be interesting to analyze whether workers in the same occupation in fissured firms perform different job tasks than ones in more occupationally diverse counterparts. For example, individuals in fissured firms might perform tasks of lower complexity—e.g. through less diverse task bundles—which are more easily replaceable, thus commanding lower wages.

[14] All results shown in Figure 3 are robust to using a limited set of years where we can use a more balanced panel of workers over time.

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Table 1: Distribution of occupational specialization across firm-year observations

A. Not Employment-Weighted

	(1) HHI 1-dig	(2) HHI 3-dig	(3) Share 1-dig	(4) Share 3-dig
Mean	0.51	0.42	0.63	0.55
p10	0.26	0.16	0.37	0.27
p25	0.34	0.23	0.47	0.36
p50	0.46	0.36	0.62	0.51
p75	0.66	0.56	0.80	0.73
p90	0.85	0.82	0.92	0.90
Sd. overall	0.22	0.24	0.20	0.23
Sd. within year	0.22	0.24	0.20	0.23
Sd. within industry	0.19	0.21	0.18	0.20
Sd. year × industry	0.19	0.21	0.18	0.19

B. Employment-Weighted

	(1) HHI 1-dig	(2) HHI 3-dig	(3) Share 1-dig	(4) Share 3-dig
Mean	0.49	0.39	0.62	0.53
p10	0.25	0.13	0.36	0.24
p25	0.32	0.20	0.45	0.33
p50	0.43	0.31	0.59	0.48
p75	0.65	0.56	0.80	0.73
p90	0.86	0.81	0.92	0.90
Sd. overall	0.22	0.25	0.21	0.24
Sd. within year	0.22	0.25	0.21	0.24
Sd. within industry	0.17	0.19	0.16	0.18
Sd. year × industry	0.17	0.18	0.16	0.18

The table presents distributional statistics for the measures of firm specialization described in Section 2.2. The analysis is based on 375,905 firm-year observations from *Quadros de Pessoal* data for 2010–2019.

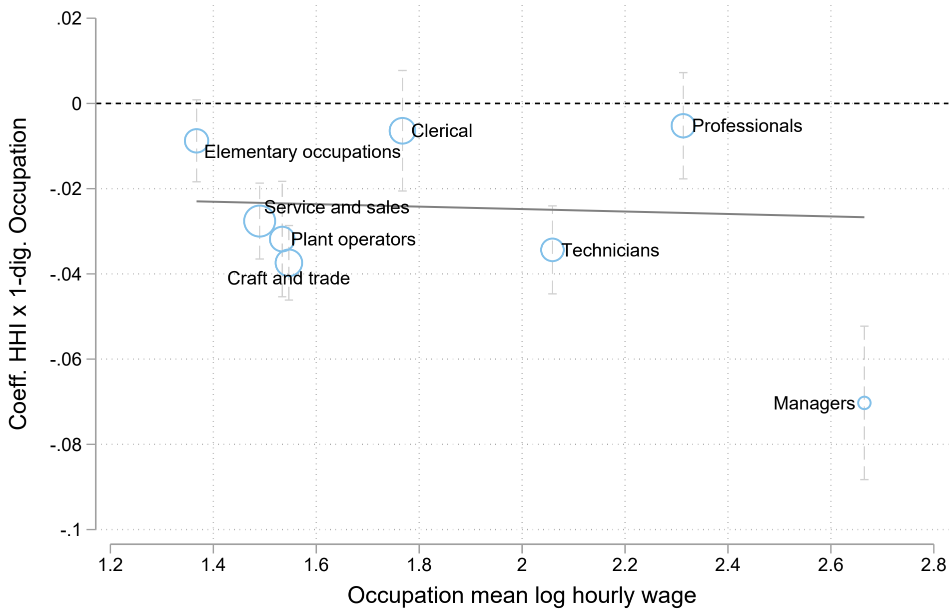
Table 2: Wage regressions using HHI based on 1-digit occupations as the measure of specialization

	(1)	(2)	(3)	(4)	(5)	(6)
A. Dependent Variable: Log monthly earnings						
HHI 1-dig.	-0.326***	-0.330***	-0.203***	-0.156***	-0.144***	-0.079***
	(0.013)	(0.013)	(0.006)	(0.006)	(0.006)	(0.004)
Log firm employment		0.015***	0.021***	0.023***	0.023***	-0.003***
		(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.36	0.36	0.47	0.52	0.54	0.83
B. Dependent Variable: Log total monthly hours						
HHI 1-dig.	-0.141***	-0.137***	-0.092***	-0.090***	-0.079***	-0.054***
	(0.007)	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)
Log firm employment		-0.019***	-0.010***	-0.010***	-0.009***	-0.012***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.04	0.05	0.11	0.12	0.13	0.49
C. Dependent Variable: Log hourly wage						
HHI 1-dig.	-0.183***	-0.191***	-0.110***	-0.068***	-0.066***	-0.023***
	(0.008)	(0.010)	(0.005)	(0.005)	(0.005)	(0.003)
Log firm employment		0.034***	0.030***	0.032***	0.032***	0.009***
		(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.46	0.48	0.59	0.66	0.68	0.94
Year FE	X	X				
Demographic controls	X	X	X	X	X	X
4-dig ind. × year FE			X	X	X	X
1-dig occupation FE				X		
3-dig occupation FE					X	X
Worker FE						X
N	19,168,215	19,168,215	19,168,215	19,168,215	19,168,215	18,462,154

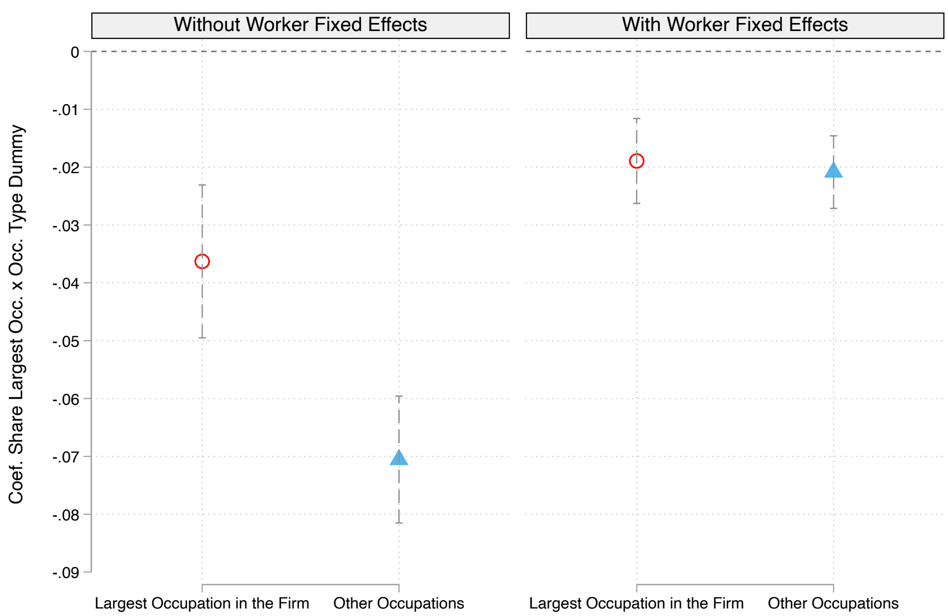
The table shows the results from the estimation of the wage regression in equation (1), using the HHI based on 1-digit occupations as the measure of firm specialization. The analysis is based on *Quadros de Pessoal* data for 2010–2019. Standard errors clustered by firm × year are reported in parentheses.
$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1: Occupational heterogeneity in hourly wage effects of firm specialization

A. By one-digit occupation



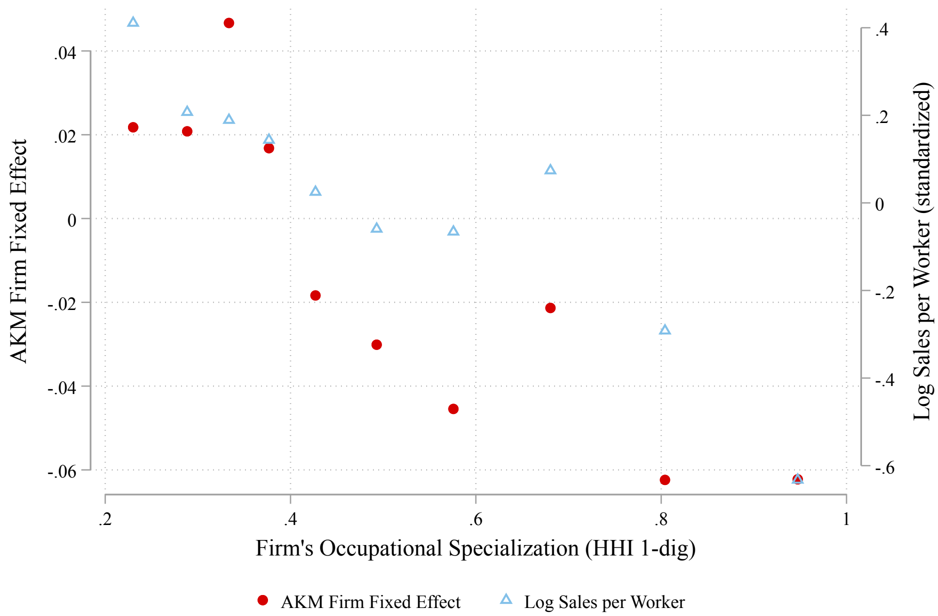
B. By within-firm occupation size



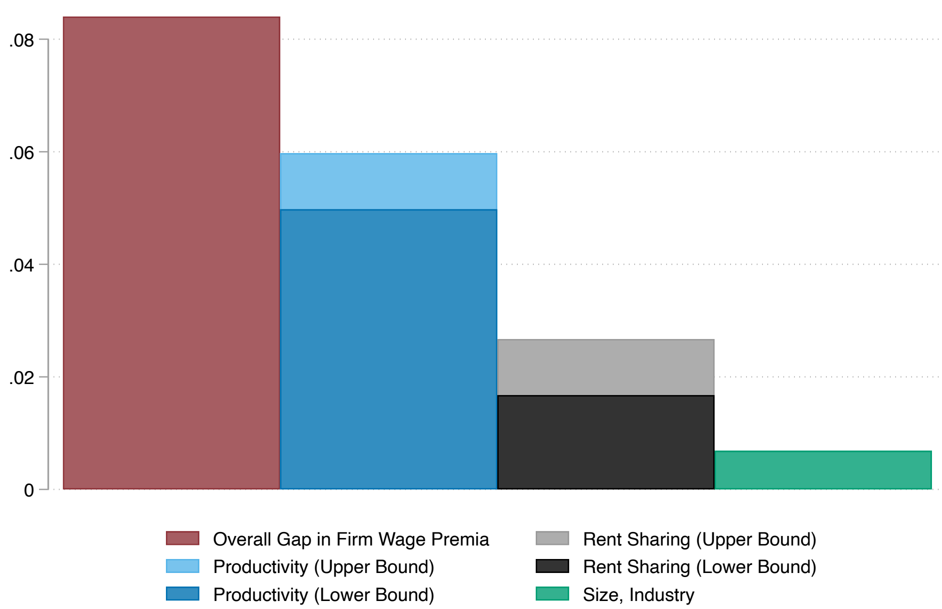
Regressions in both panels use log hourly wages as the dependent variable. Panel A plots the marginal effect of firm specialization for workers in each 1-digit occupation (as well as the associated 95% confidence interval). The underlying regression coefficients are presented in column 3 of Table A6. Occupations are ranked by their mean hourly wage. The sizes of the circles reflect hours worked shares, which are used as weights for the fitted line. Panel B plots the marginal effect of specialization for workers in the firm's largest occupation, and for workers in all other occupations within the firm. The underlying regressions are presented in Table A8. The analysis is based on *Quadros de Pessoal* data for 2010–2019.

Figure 2: Occupational specialization and AKM firm wage premia

A. Relationship between occupational specialization, AKM firm premia, and productivity



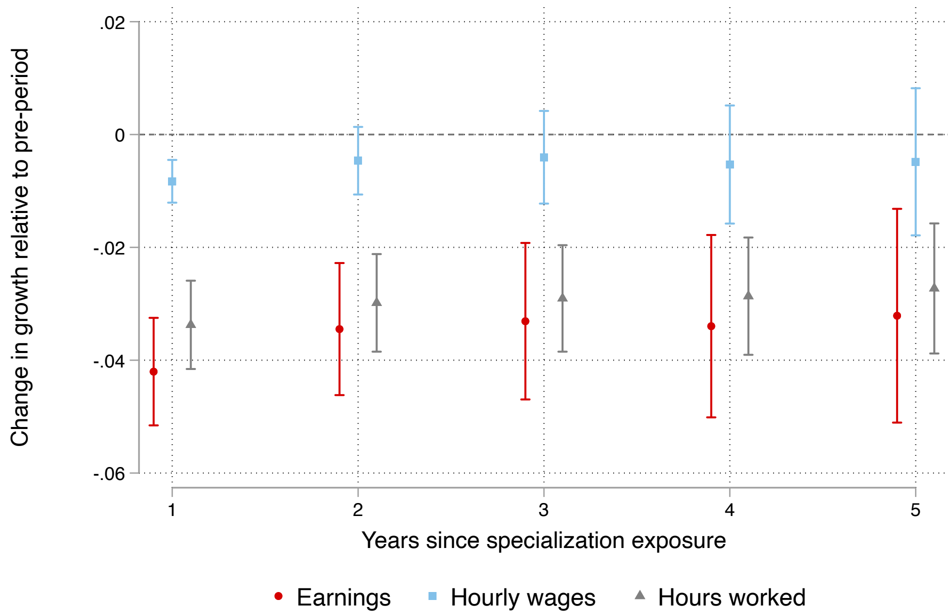
B. Decomposition of difference in AKM firm wage premia between occupationally diverse and occupationally specialized firms



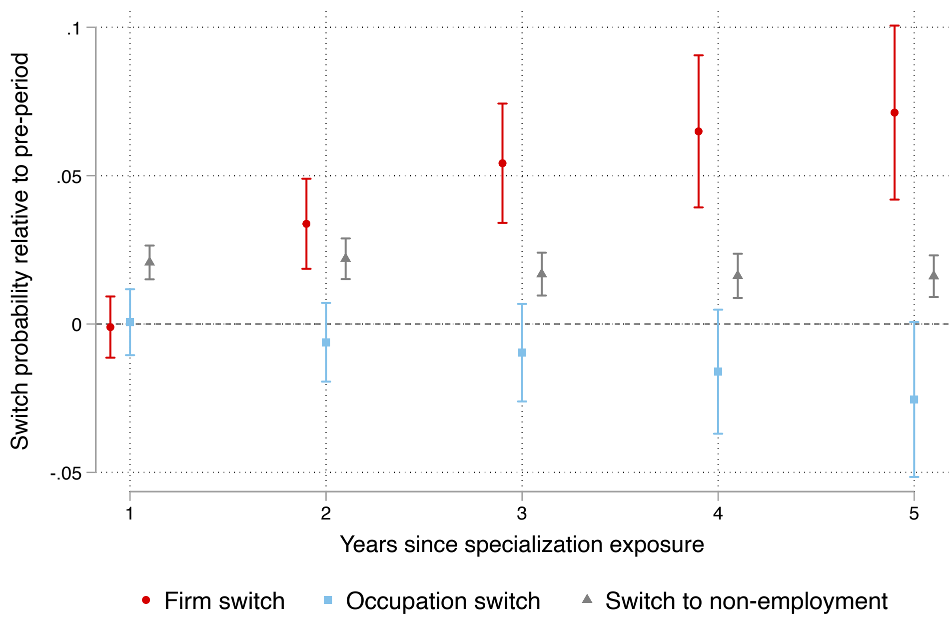
Panel A plots the relationship between firm-level occupational specialization and estimated AKM firm wage premia (left axis), and firm labor productivity, measured as log sales per worker (right axis). AKM firm premia are obtained from the estimation of equation (3). The firm-level data is aggregated into (employment-weighted) deciles of specialization, and averages within each decile are shown. Panel B decomposes the difference in estimated AKM firm wage premia between firms in the bottom and top decile of the occupational specialization distribution. Details of the decomposition components are presented in equations (5) and (6). The difference in residuals that appears in equations (5) and (6) accounts for less than 1% of the overall gap and is omitted from the figure. The analysis is based on *Quadros de Pessoal* data for 2010–2019.

Figure 3: Occupational specialization and worker career outcomes

A. Impacts on wage growth



B. Impacts on firm and occupation switching



The figure shows estimates of the β coefficient from equation (7) for different dependent variables and for time intervals of increasing length T. The analysis is based on *Quadros de Pessoal* data for 2010–2019, and uses the HHI based on 1-digit occupations as the measure of firm specialization. Standard errors are clustered at the firm level. For all three outcomes in panel A, and for panel B's firm and occupation switch, the number of observations are as follows: $N_{T=1} = 8,333,443$, $N_{T=2} = 6,664,088$, $N_{T=3} = 5,243,392$, $N_{T=4} = 3,990,198$, $N_{T=5} = 2,861,944$. For panel B's switch to non-employment, $N_{T=1} = 11,534,064$, $N_{T=2} = 9,461,345$, $N_{T=3} = 7,651,450$, $N_{T=4} = 6,036,474$, $N_{T=5} = 4,580,905$. Results are robust to using a limited set of years where we can use a more balanced panel of workers over time.

Appendix

Table A1: Summary statistics

A. Worker-level variables

	Mean	Sd
Real hourly wage (euros)	6.88	7.89
Age (years)	39.64	11.01
Education:		
- No Highschool	0.52	0.50
- Highschool	0.28	0.45
- College	0.20	0.40
Female	0.48	0.50
Native	0.96	0.20
Full time workers	0.94	0.24
Tenure at firm (years)	8.13	9.08
Occupation:		
- Managers	0.03	0.18
- Professionals	0.12	0.32
- Technicians	0.11	0.31
- Clerical	0.14	0.35
- Service and sales	0.21	0.41
- Craft and trade	0.15	0.35
- Plant operators	0.12	0.33
- Elementary occupations	0.13	0.33
Observations	19,168,215	
Unique individuals	3,337,571	

B. Firm-level variables

	Mean	Sd
Firm size	51	267
Firm sales (euros)	7,737,025	87,598,574
Observations	375,905	
Unique Firms	71,836	

The table presents summary statistics for our sample from the *Quadros de Pessoal* data for 2010–2019, which only includes firms with at least 10 employees.

Table A2: Variation in specialization explained by different sets of fixed effects

Specialization Measure	*Fixed Effects:* 1-dig. ind	4-dig. ind	1-dig. × year	4-dig.× year
HHI 1-dig	0.05	0.24	0.05	0.25
HHI 3-dig	0.06	0.26	0.06	0.26
Main occ share 1-dig	0.05	0.24	0.05	0.24
Main occ share 3-dig	0.05	0.26	0.07	0.26

The table presents the R^2 obtained when regressing the measure of occupational specialization indicated in the first column on the corresponding set of industry, or industry-year fixed effects. The analysis is based on 375,905 firm-year observations from the *Quadros de Pessoal* data for 2010–2019.

Table A3: Wage regressions using HHI based on 3-digit occupations as the measure of specialization

	(1)	(2)	(3)	(4)	(5)	(6)
A. Dependent Variable: Log monthly earnings						
HHI 3-dig.	-0.300***	-0.301***	-0.204***	-0.153***	-0.142***	-0.077***
	(0.012)	(0.012)	(0.006)	(0.006)	(0.006)	(0.004)
Log firm employment		0.014***	0.020***	0.022***	0.023***	-0.003***
		(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.36	0.36	0.47	0.52	0.54	0.83
B. Dependent Variable: Log total monthly hours						
HHI 3-dig.	-0.116***	-0.114***	-0.088***	-0.085***	-0.075***	-0.051***
	(0.007)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)
Log firm employment		-0.020***	-0.010***	-0.010***	-0.009***	-0.012***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.04	0.05	0.11	0.12	0.13	0.49
C. Dependent Variable: Log hourly wage						
HHI 3-dig.	-0.182***	-0.185***	-0.115***	-0.068***	-0.066***	-0.025***
	(0.008)	(0.009)	(0.005)	(0.005)	(0.005)	(0.003)
Log firm employment		0.033***	0.030***	0.032***	0.032***	0.009***
		(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.46	0.48	0.59	0.67	0.68	0.94
Year FE	X	X				
Demographic controls	X	X	X	X	X	X
4-dig ind. × year FE			X	X	X	X
1-dig occupation FE				X		
3-dig occupation FE					X	X
Worker FE						X
N	19,168,215	19,168,215	19,168,215	19,168,215	19,168,215	18,462,154

The table shows the results from the estimation of the wage regression in equation (1), using the HHI based on 3-digit occupations as the measure of firm specialization. The analysis is based on *Quadros de Pessoal* data for 2010–2019. Standard errors clustered by firm × year are reported in parentheses.
$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A4: Using hours-weighted employment measures to construct firm-level occupational specialization

	(1)	(2)	(3)	(4)	(5)	(6)
A. Dependent Variable: Log monthly earnings						
Hr. weighted HHI 1-dig.	-0.300***	-0.301***	-0.174***	-0.128***	-0.117***	-0.050***
	(0.012)	(0.013)	(0.006)	(0.006)	(0.006)	(0.004)
Log firm employment		0.014***	0.021***	0.023***	0.023***	-0.003**
		(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.36	0.36	0.47	0.52	0.54	0.83
B. Dependent Variable: Log total monthly hours						
Hr. weighted HHI 1-dig.	-0.110***	-0.109***	-0.060***	-0.058***	-0.049***	-0.022***
	(0.007)	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)
Log firm employment		-0.020***	-0.009***	-0.009***	-0.009***	-0.012***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.04	0.05	0.11	0.12	0.13	0.49
C. Dependent Variable: Log hourly wage						
Hr. weighted HHI 1-dig.	-0.189***	-0.190***	-0.114***	-0.071***	-0.068***	-0.026***
	(0.009)	(0.010)	(0.005)	(0.005)	(0.005)	(0.003)
Log firm employment		0.033***	0.030***	0.032***	0.032***	0.009***
		(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.46	0.48	0.59	0.66	0.68	0.94
Year FE	X	X				
Demographic controls	X	X	X	X	X	X
4-dig ind. × year FE			X	X	X	X
1-dig occupation FE				X		
3-dig occupation FE					X	X
Worker FE						X
N	19,168,215	19,168,215	19,168,215	19,168,215	19,168,215	18,462,154

The table shows the results from the estimation of the wage regression in equation (1), using an alternative version of the HHI based on 1-digit occupations as the measure of firm specialization. Specifically, to construct the employment shares of each 1-digit occupation within the firm (which are used to compute the firm's HHI), hours-weighted measures of employment are used. The analysis is based on *Quadros de Pessoal* data for 2010–2019. Standard errors clustered by firm × year are reported in parentheses.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A5: Wage regressions using the employment share of the largest occupation within the firm as the measure of specialization

	1 digit occupation		3 digit occupation	
	(1)	(2)	(3)	(4)
A. Dependent Variable: Log monthly earnings				
Share largest occupation	-0.142***	-0.074***	-0.135***	-0.071***
	(0.006)	(0.005)	(0.006)	(0.004)
Log firm employment	0.024***	-0.003**	0.024***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.54	0.83	0.54	0.83
B. Dependent Variable: Log total monthly hours				
Share largest occupation	-0.075***	-0.052***	-0.071***	-0.050***
	(0.003)	(0.003)	(0.003)	(0.003)
Log firm employment	-0.009***	-0.012***	-0.009***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.13	0.49	0.13	0.49
C. Dependent Variable: Log hourly wage				
Share largest occupation	-0.068***	-0.021***	-0.063***	-0.020***
	(0.005)	(0.003)	(0.005)	(0.003)
Log firm employment	0.032***	0.009***	0.032***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.68	0.94	0.68	0.94
Demographic controls	X	X	X	X
4-dig ind. × year FE	X	X	X	X
3-dig occupation FE	X	X	X	X
Worker FE		X		X
N	19,168,215	18,462,154	19,168,215	18,462,154

The table shows estimates of the wage regression in equation (1), using the employment share of the largest 1-digit (3-digit) occupation within the firm as the measure of firm specialization. The analysis is based on *Quadros de Pessoal* data for 2010–2019. Standard errors clustered by firm × year are reported in parentheses.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A6: Heterogeneous wage impacts of specialization across occupations

	Dependent variable: Log hourly wage		
	(1)	(2)	(3)
Managers × HHI 1-dig.	-0.139***	-0.185***	-0.070***
	(0.017)	(0.014)	(0.009)
Professionals × HHI 1-dig.	-0.005	-0.004	-0.005
	(0.014)	(0.014)	(0.006)
Technicians × HHI 1-dig.	-0.099***	-0.100***	-0.034***
	(0.011)	(0.011)	(0.005)
Clerical × HHI 1-dig.	-0.068***	-0.067***	-0.006
	(0.011)	(0.010)	(0.007)
Service and sales × HHI 1-dig.	-0.056***	-0.119***	-0.028***
	(0.008)	(0.008)	(0.005)
Craft and trade × HHI 1-dig.	-0.104***	-0.057***	-0.037***
	(0.005)	(0.005)	(0.004)
Plant operators × HHI 1-dig.	-0.092***	-0.054***	-0.032***
	(0.015)	(0.013)	(0.007)
Elementary occupations × HHI 1-dig.	-0.011	-0.011	-0.009+
	(0.010)	(0.009)	(0.005)
Log firm employment	0.032***	0.032***	0.009***
	(0.001)	(0.001)	(0.001)
Demographic Controls	X	X	X
4-dig ind. × year FE	X	X	X
1-dig occupation FE	X		
3-dig occupation FE		X	X
Worker FE			X
N	19,168,215	19,168,215	18,462,154
R^2	0.67	0.68	0.94

The table shows estimates of a wage regression which augments the specification in equation (1) by adding interactions between the firm specialization measure and indicator variables for the worker's 1-digit occupation. Firm specialization is measured as the HHI based on 1-digit occupations. The dependent variable is the log real hourly wage for worker i employed in firm j in year t. The analysis is based on *Quadros de Pessoal* data for 2010–2019. Standard errors clustered by firm × year are reported in parentheses. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A7: Heterogeneous wage impacts of specialization across industries

	Dependent variable: Log hourly wage		
	(1)	(2)	(3)
Accommodation and food service act. × HHI 1-dig.	0.005	-0.033*	-0.001
	(0.016)	(0.015)	(0.007)
Administrative and support service activities × HHI 1-dig.	0.117***	0.148***	0.071***
	(0.022)	(0.021)	(0.011)
Arts, entertainment and recreation × HHI 1-dig.	0.058+	0.001	-0.079***
	(0.033)	(0.033)	(0.020)
Construction × HHI 1-dig.	-0.177***	-0.157***	-0.103***
	(0.012)	(0.011)	(0.008)
Education × HHI 1-dig.	0.147***	0.024	0.065***
	(0.024)	(0.025)	(0.016)
Electricity, gas, steam and air cond. supply × HHI 1-dig.	-0.379***	-0.306***	0.030
	(0.083)	(0.079)	(0.055)
Financial and insurance act. × HHI 1-dig.	0.083*	0.003	-0.051**
	(0.032)	(0.033)	(0.017)
Human health and social work act. × HHI 1-dig.	-0.092***	-0.125***	-0.057***
	(0.010)	(0.009)	(0.006)
Information and communication × HHI 1-dig.	-0.063*	-0.046	-0.037**
	(0.029)	(0.029)	(0.012)
Manufacturing × HHI 1-dig.	-0.100***	-0.078***	-0.037***
	(0.005)	(0.005)	(0.003)
Mining and quarrying × HHI 1-dig.	0.045	0.022	0.008
	(0.034)	(0.033)	(0.021)
Other service activities × HHI 1-dig.	-0.115***	-0.123***	0.002
	(0.031)	(0.029)	(0.008)
Professional, scientific and technical act. × HHI 1-dig.	-0.103***	-0.069***	-0.044***
	(0.019)	(0.019)	(0.010)
Real estate act. × HHI 1-dig.	-0.452***	-0.461***	-0.127***
	(0.039)	(0.038)	(0.025)
Transportation and storage × HHI 1-dig.	-0.274***	-0.268***	-0.094***
	(0.042)	(0.037)	(0.018)
Water supply; sewerage, waste managment × HHI 1-dig.	-0.146***	-0.057	-0.042*
	(0.036)	(0.037)	(0.019)
Wholesale and retail trade × HHI 1-dig.	-0.025*	-0.060***	-0.021***
	(0.011)	(0.010)	(0.005)
Log firm employment	0.032***	0.032***	0.010***
	(0.001)	(0.001)	(0.001)
Demographic Controls	X	X	X
4-dig ind. × year FE	X	X	X
1-dig occupation FE	X		
3-dig occupation FE		X	X
Worker FE			X
N	19,168,215	19,168,215	18,462,154
R^2	0.67	0.68	0.94

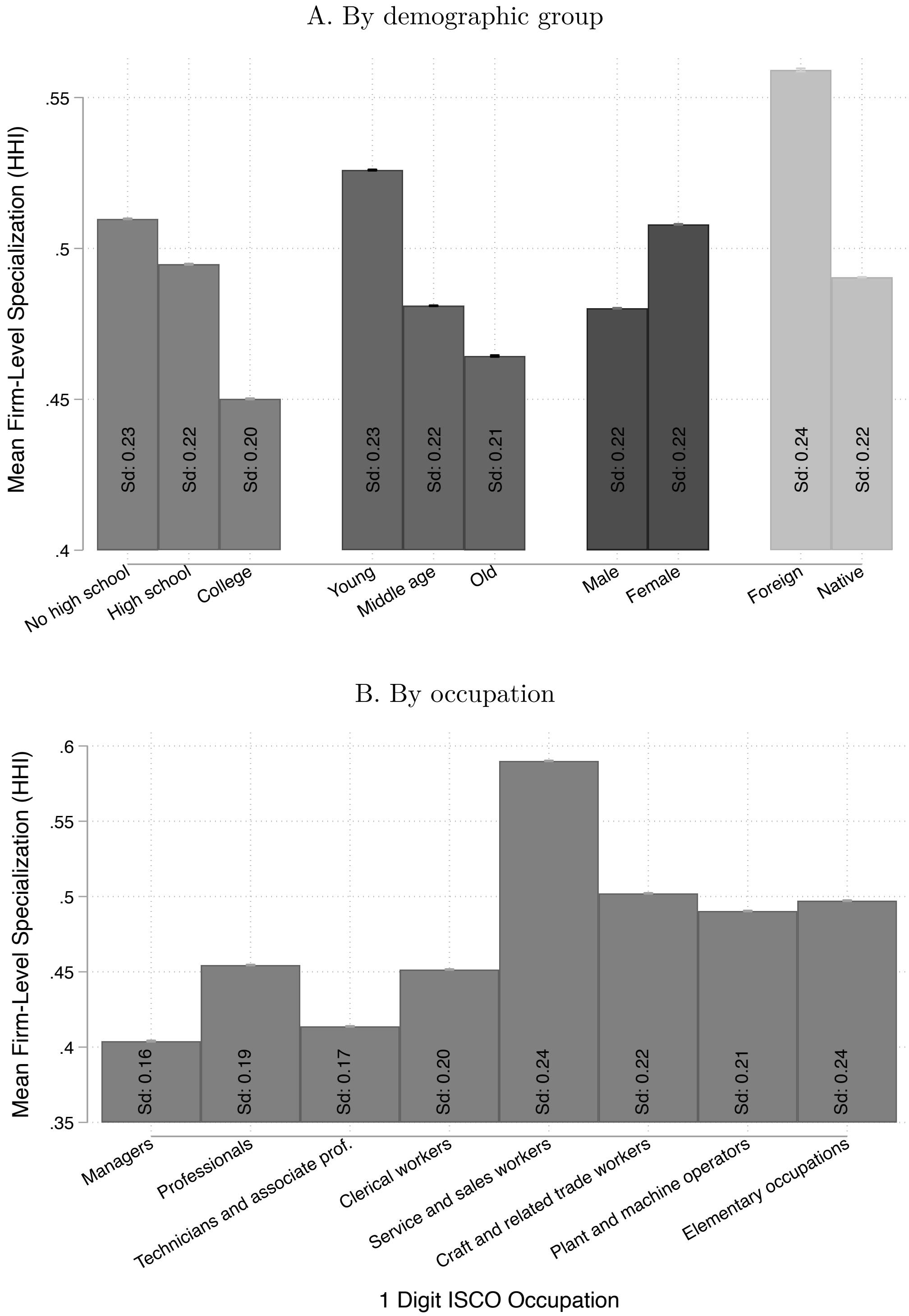
The table shows estimates of a wage regression which augments the specification in equation (1) by adding interactions between the firm specialization measure and indicator variables for the firm's 1-digit industry. Firm specialization is measured as the HHI based on 1-digit occupations. The dependent variable is the log real hourly wage for worker i employed in firm j in year t. The analysis is based on *Quadros de Pessoal* data for 2010–2019. Standard errors clustered by firm × year are reported in parentheses. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A8: Wage impacts of specialization for workers in firms' largest vs. smaller occupations

	Dependent variable: Log hourly wage			
	1 digit occupation		3 digit occupation	
	(1)	(2)	(3)	(4)
Share largest occupation	-0.071***	-0.021***	-0.065***	-0.020***
	(0.006)	(0.003)	(0.005)	(0.003)
Largest occ. dummy=1	-0.026***	-0.003	-0.023***	-0.003
	(0.005)	(0.002)	(0.004)	(0.002)
Share largest × Largest occ.=1	0.034***	0.002	0.033***	0.001
	(0.008)	(0.004)	(0.007)	(0.003)
Log firm employment	0.032***	0.009***	0.032***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Demographic Controls	X	X	X	X
4-dig ind. × year FE	X	X	X	X
3-dig occupation FE	X	X	X	X
Worker FE		X		X
N	19,168,215	18,462,154	19,168,215	18,462,154
R^2	0.68	0.94	0.68	0.94

The table shows estimates of the wage regression in equation (2), using the employment share of the largest occupation within the firm (either at the 1-digit or at the 3-digit level) as the measure of firm specialization. Largest occ.=1 is an indicator variable for individuals who are employed in the largest occupation within the firm (either at the 1-digit or at the 3-digit level). The dependent variable is the log real hourly wage for worker i employed in firm j in year t. The analysis is based on *Quadros de Pessoal* data for 2010–2019. Standard errors clustered by firm × year are reported in parentheses.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A1: Mean exposure to specialization by demographic group and occupation



The figure depicts the mean exposure to specialization (measured as the average specialization level of the firms that individuals work for, using the HHI based on 1-digit occupations for each firm), and the standard deviation of this exposure measure, for workers from different demographic groups or in different 1-digit occupations. The analysis is based on 19,168,215 worker-year observations from the *Quadros de Pessoal* data for 2010–2019.

Figure A2: Industry heterogeneity in hourly wage effects of firm specialization

The figure plots the marginal effect of firm specialization on log hourly wages for workers in each 1-digit industry (as well as the associated 95% confidence interval). The underlying regression coefficients are presented in column 3 of Table A7. Industries are ranked by their mean hourly wage. The sizes of the circles reflect hours worked shares, which are used as weights for the fitted line. The analysis is based on *Quadros de Pessoal* data for 2010–2019.