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Jaime Arellano-Bover,
Fernando Saltiel

WARWICK
THE UNIVERSITY OF WARWICK

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Jaime Arellano-Bover† and Fernando Saltiel‡

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Abstract

We present evidence consistent with large disparities across firms in the on-the-job learning their young employees experience, using administrative datasets from Brazil and Italy. We categorize firms into discrete "classes"—which our conceptual framework interprets as skill-learning classes—using a clustering methodology that groups together firms with similar distributions of unexplained wage growth. Mincerian returns to experience vary widely across experiences acquired in different firm classes. Moreover, past experiences at firms with better on-the-job learning lead to subsequent jobs featuring greater non-routine task content. Three empirical tests leveraging firm stayers and movers, hiring wages, and displaced workers point towards a portable and general human capital interpretation. Heterogeneous employment experiences explain an important share of wage variance by age 35, thus contributing to shape wage inequality. Lastly, we show that firms' observable attributes only mildly predict on-the-job learning opportunities.

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†Tor Vergata University of Rome, Einaudi Institute for Economics and Finance (EIEF), and IZA. Email: **j.arellano.bover@gmail.com**

‡McGill University and IZA. Email: **fernando.saltiel@mcgill.ca**

1 Introduction

Workplaces vary greatly across many dimensions that impact workers' day-to-day experiences on the job, including the use of new technologies, management practices, training schemes, and coworkers' quality, among others. These differences suggest the existence of heterogeneous learning opportunities across firms, which may be particularly relevant for young workers, given the importance of on-the-job human capital accumulation in driving early career outcomes (Rubinstein and Weiss, 2006). While the firm as a driver of variation in learning opportunities has long received theoretical attention (e.g. Rosen, 1972; Gibbons and Waldman, 2006), accompanying empirical evidence on this front is still limited.

In this paper, we find evidence consistent with large disparities across firms in the on-the-job learning their employees experience. We present a two-step empirical approach, which first classifies firms into discrete types—using the information contained in firms' distributions of wage growth—and then estimates returns to heterogeneous experiences acquired across these different firm classes. We rely on matched employer-employee records from Brazil and Italy, consisting of population data on the state of Rio de Janeiro for 1994–2010, and population data on the Veneto region for 1984–2001. Our analysis largely focuses on cohorts observed from labor-market entry through their mid-thirties. As such, we can measure workers' entire employment histories across firms and estimate heterogeneous returns to different types of experiences during the part of the lifecycle where wage growth is steepest. Our parallel analysis in two very different economies is valuable: the broadly consistent findings we uncover in both countries speak to the generality of firm heterogeneity in on-the-job learning as a labor market phenomenon.

We start by introducing a conceptual framework in which workers accumulate general and portable human capital at work through learning-by-doing. Firms differ in the amount of learning their workers experience and in their pay premia. We assume a discrete number of firm classes in the on-the-job learning dimension, where employees draw from a class-specific distribution of human capital growth in each period. Wages are determined by a worker's human capital and their employer's pay premium, which is common to all workers in a firm. This framework leads to two results. First, a wage equation featuring returns to experience that can vary depending on the firm class where such experience was acquired—a generalization of the classical Mincerian experience term which implicitly assumes homogeneous experience. Second, the possibility of categorizing firms into learning classes using firms' distributions of stayers' wage growth.

Following the conceptual framework, our empirical approach consists of assigning firms to classes in a first step, and estimating heterogeneous returns to experiences acquired across firm classes in a second step. We carry out these two steps following a split sample approach: we use half of the workers in our data to categorize firms into classes, and the other half to estimate returns to heterogeneous experiences. We implement the categorization of firms into classes using firms' distributions of stayers' unexplained wage growth as inputs in a k-means clustering algorithm (Bonhomme et al., 2019). The number of firm classes is set ex-ante, and we classify firms into ten classes.[1] Assuming a discrete number of firm classes allows us to estimate richer models relative to a framework in which each firm has its own idiosyncratic type.

We estimate heterogeneous returns to experiences acquired in different firm classes for workers aged 18–35. In particular, we estimate log wage regressions that include firm and person fixed effects, and allow for each of the ten different types of experience to have a different return. We find sizable disparities in the returns to experiences acquired in different firm classes. Relative to an homogeneous experience benchmark (of 3% in Rio and 2.1% in Veneto), returns to experience acquired in the "top learning" firm-classes are between two and three times as large, both in Rio (8.8%) and Veneto (4.5%). Returns to experiences acquired in firm classes offering the lowest learning opportunities are instead close to zero. Moreover, we show that heterogeneous experiences explain a meaningful share of wage inequality through a wage variance decomposition (Card et al., 2013): variance components involving heterogeneous experiences explain 9–11% of wage variance for workers in their mid-thirties.[2] Lastly, going beyond wages, we examine how heterogeneous experiences shape workers' subsequent job task contents (Acemoglu and Autor, 2011). We show that experience acquired in top learning firm-classes is associated with subsequent increases in workers' non-routine analytic and interpersonal task contents.

We then propose three empirical tests that assess the plausibility of a general human capital interpretation behind our findings. These tests aim to address the possibility that the heterogeneity in returns estimated in the full sample might be explained by other channels of wage growth, including firm-specific human capital, outside offers and bargaining dynamics, firm productivity shocks, or seniority-based pay schemes. The three tests leverage settings where existing theories indicate that such alternative channels should not impact wages, whereas portable human capital could do so instead. The first test estimates separate returns for job stayers and job switchers, following Topel (1991). The second test estimates heterogeneous returns using hiring wages, blending our generalized Mincer wage equation with the dual wage ladder model of Di Addario et al. (2023). Lastly, the third test narrows in on the subset of hiring wages that follow an involuntary job displacement event (Dustmann and Meghir, 2005). The results of all three tests point toward strong portability of past experience returns and, thus, to general human capital being the main driver of heterogeneity in returns to different experience types.

To allay concerns related to a worker-driven interpretation of our results (e.g., sorting on unobserved ability to learn not captured by worker fixed effects) or an occupation-driven interpretation, we assess whether returns to heterogeneous experiences vary by workers' unobserved skills, education, and occupation. Workers with higher unobserved skills (measured by their person fixed effect) have higher returns to experiences in *all* firm classes compared to their lower-skilled counterparts, yet we find no meaningful differences in the

[1]We select ten firm classes, as this choice aligns with related literature (Bonhomme et al., 2019) while allowing us to account for an important share of between-firm wage growth variance.

[2]The traditional approach assuming all experiences to be homogeneous substantially underestimates the share of the variance accounted for by experience returns. As such, we uncover a novel channel through which firm heterogeneity shapes wage inequality.

relative returns across classes. We find a similar pattern across education levels. Results by the occupation held at the time such experience was acquired indicate that white-collar experience is more valuable than blue-collar experience, but the within-occupation cross-firm class patterns remain comparable.[3] In sum, there are level differences in the returns to experiences for different types of workers, but patterns of relative returns across firm-classes are quite similar, thus reinforcing a firm-driven interpretation.

We then aim to improve our understanding of which firms offer strong learning opportunities. First, we document the relationship between learning opportunities and wage levels. Contrary to what equalizing differentials would predict (Rosen, 1972), we find no evidence of a negative relationship between firms' pay premia and their learning opportunities. If anything, the correlation between these two dimensions of firm heterogeneity is slightly positive. We then consider the informational value of firm observable characteristics more broadly. That is, without observing firms' wage growth distributions, how well could a worker or an econometrician predict the quality of learning opportunities? This is a policy-relevant assessment since being able to recognize better-learning firms would be valuable for young job seekers and policymakers alike.

We train a random forest classification algorithm (Athey and Imbens, 2019) to determine how well firm observables jointly predict firm classes. The goal of the algorithm is to assign each (out of sample) firm to one of the ten possible classes.[4] The algorithm correctly classifies 22–23% of firms. We also estimate unconditional tabulations of workforce/firm characteristics, and a multinomial logit model that renders *ceteris paribus* associations of firm characteristics and firm class. The results from these exercises are broadly consistent with the limited predictive power of the random forest algorithm: some mild associations emerge, but we do not find evidence of indisputably strong predictors of on-the-job learning opportunities across firms.

This paper contributes to the literature on post-schooling human capital accumulation (e.g. Neal, 1995; Acemoglu and Pischke, 1999; Dustmann and Meghir, 2005; Kambourov and Manovskii, 2009; Gathmann and Schönberg, 2010; Adda and Dustmann, 2023) by presenting evidence consistent with large disparities in human capital accumulation where firms are relevant units of heterogeneity. In this context, other work has explored how learning on-the-job varies depending on workplace characteristics such as exporter status (Macis and Schivardi, 2016; Ma et al., 2021), employer pay premia and entrepreneurship (Gendron-Carrier, 2021), the quality of coworkers (Nix, 2020; Jarosch et al., 2021), firm size (Arellano-Bover, 2020) or city size (De La Roca and Puga, 2017). We add to this work by freely allowing firms—regardless of their observed attributes—to embody different learning opportunities. The importance of our approach is reinforced by our finding that, in the two distinct economies we study, firm observables only mildly predict on-the-job learning.[5] Furthermore, our wage equation allowing for heterogeneous types of experiences

[3] In the Brazilian data we also estimate returns that are specific to each of the nine one-digit occupation codes.

[4] The firm observables we feed the random forest include mean annual earnings, firm pay premium, firm size, sector, geographic location, and workforce characteristics.

[5] By carrying out our empirical strategy in Rio de Janeiro and in Veneto, we also contribute to previous work

represents a generalization of the traditional Mincerian approach that has long been used to estimate the returns to experience and seniority (e.g., Mincer, 1974; Altonji and Shakotko, 1987; Topel, 1991; Altonji and Williams, 2005; Dustmann and Meghir, 2005).

We also contribute to a literature that studies how firm-driven wage differentials shape the wage structure (e.g., Abowd et al., 1999; Card et al., 2013, 2018; Sorkin, 2018; Song et al., 2019; Bonhomme et al., 2019; Lachowska et al., 2023; Engbom et al., 2023). These papers largely focus on contemporaneous worker-firm matches, yet the effects of *past* experience at heterogeneous firms has received limited attention: Abowd et al. (2018) and Bonhomme et al. (2019) provide some evidence on dynamic implications of employment at heterogeneous firms; Abowd et al. (1999, 2006) estimate firm-varying returns to tenure, but not experience. We make progress on this front showing how firms can have long term consequences for workers by impacting their accumulation of *portable* skills.[6] We also quantify how an unexplored dimension of firm heterogeneity—on-the-job learning—meaningfully contributes to the overall variance of wages.

Our work is related to two recent papers analyzing the importance of past employers. First, Di Addario et al. (2023) examine the relative importance of workers' current employer and the employer they were hired from, finding that origin firms explain a small share of the wage variance. Di Addario et al. (2023) are guided by a sequential auction framework of poaching and bargaining, which differs from our focus on human capital accumulation. These different frameworks give rise to distinct empirical approaches—while Di Addario et al. (2023) consider the most recent employer and only the extensive margin of employment, our empirical analysis accounts for full employment histories and intensive-margin experiences. Second, Gregory (2021) builds a macro search model to quantify how much variation in life-cycle earnings profiles is explained by heterogeneity across establishments' human capital provision. While her analysis of human capital accumulation exclusively relies on stayers' wage growth, a key focus of our paper is to understand the *portability* of past experience returns through the analysis of stayers vs. movers, hiring wages, and displaced workers. Such analyses are central towards reaching a human capital interpretation of our results.

The rest of this paper is organized as follows. Section 2 describes our two datasets. Section 3 lays out our conceptual and empirical frameworks, together with the classification of firms using a clustering algorithm. Section 4 presents our baseline results on returns to heterogeneous experiences, including task-content responses. Section 5 documents heterogeneity analyses, results on the three tests for a human capital interpretation, and our joint analysis on firms and occupations. Section 6 highlights the relationship between firms' learning opportunities and pay premia, while Section 7 investigates how well firm observables predict learning opportunities. Section 8 concludes.

comparing labor markets in different countries (e.g. Dustmann and Pereira, 2008; Lagakos et al., 2018; Rucci et al., 2020; Bonhomme et al., 2023; Donovan et al., 2021).

[6] By showing that heterogeneous experience across firm classes impacts workers' task content, we contribute to previous work on the importance of tasks in the early career (Yamaguchi, 2012; Sanders, 2014; Speer, 2017).

2 Data Sources and Descriptive Statistics

2.1 Data Sources

Brazil. We use the *Relação Anual de Informações Sociais* (RAIS) dataset for the 1994–2010 period. RAIS covers matched employee-employer information from a mandatory annual survey filled out by all formal sector firms. We focus our analysis on the state of Rio de Janeiro, a large economy (population 16m in 2010) that exhibits a lower rate of informal employment vis-à-vis the rest of the country.[7] RAIS includes unique person identifiers which allow us to track workers over time along with their characteristics such as age, gender, and educational attainment.[8] We additionally observe unique establishment and firm identifiers, along with information on their sectoral classification and total annual employment.[9] We rely on unique identifiers for workers and firms in the sample, which allow us to link workers to their employers each year.

For each employment spell, we observe the starting and ending month as well as the number of weekly hours worked. We use these variables to construct measures of actual labor market experience across firms. We consider workers' annual gross earnings, which include regular salary payments, holiday bonuses, performance-based and commission bonuses, tips, and profit-sharing agreements. We use information on hours worked to construct a measure of hourly wages. Importantly, we observe information on workers' three-digit occupations, which we use to construct a mapping to occupational task content. In particular, we leverage a concordance between the Brazilian Classification of Occupations (CBO) and the Occupational Information Network (O*NET) to measure the task content of occupations. O*NET includes detailed information on work activities and work context across jobs. We use this information to construct measures of task content across occupations, which we subsequently match to occupations in RAIS using the CBO-O*NET crosswalk. We follow the existing literature (e.g., Autor et al., 2003; Acemoglu and Autor, 2011) and focus on four different dimensions of the task vector: non-routine analytic, non-routine interpersonal, routine cognitive, and routine manual tasks. For instance, the non-routine analytic task measure considers the frequency with which workers analyze data/information, think creatively, and interpret information for others.

Italy. Our second administrative data source is the Veneto Worker History (VWH) dataset, covering the years 1984–2001. VWH data is constructed from administrative records from Italy's Social Security System, covering employment histories for all workers who ever work in the Veneto region. This is one of the wealthiest Italian regions, with a popula-

[7] Our focus on the state of Rio de Janeiro rather than Brazil as a whole is also motivated by the fact that Brazil is a vast country with marked regional disparities, and that our empirical approach summarizes between-firm heterogeneity into a discrete number of firm "classes." To ensure our categorization does not merely group firms from different regions with heterogeneous development levels, we focus on one state as our unit of analysis.

[8] Given the distribution of educational attainment in Brazil, we classify workers by whether they have completed a high school degree.

[9] Following Alvarez et al. (2018) in the Brazilian context and other papers in the literature, we focus our analysis at the firm-level rather than at the establishment level.

tion of about 5 million in 2012. The dataset includes unique worker and firm identifiers, which we use to construct employment histories during our period of interest.[10]

We further observe information on workers' characteristics such as their age, gender, and nationality, along with firm characteristics, including firm size, industry, and location. For each worker, we observe the number of days worked in each job along with their total earnings (which include overtime payments). We use earnings and days worked to construct a measure of daily wages. We additionally observe a broad measure of workers' occupations, encompassing managerial positions, white- and blue-collar jobs, and apprenticeships.

Variable construction and sample selection. While the empirical strategy outlined below considers the population of workers and firms in Rio de Janeiro and Veneto, our main analysis—estimating heterogeneous returns to experiences acquired in different firm classes—focuses on young workers for whom we observe their labor market trajectories since entry. In particular, we consider workers born after 1976 in RAIS and after 1966 in VWH, which allows us to observe their labor market outcomes from age 18 through their mid-thirties.[11] We focus on workers' main job, defined as the employment spell yielding the highest total earnings each year. Our sample covers young workers who are ever employed in Rio de Janeiro or Veneto, yet in both cases we also observe their employment spells in other parts of the country and account for such spells in our analysis.

2.2 Descriptive Statistics

In Table 1, we present descriptive statistics for the sample of workers in Rio de Janeiro and Veneto. The sample is 59% male in Rio de Janeiro and 54% male in Veneto. On average, workers are about 20 years old when we observe them for the first time. The cohort we observe continuously from age 18 through their mid-30s in Rio de Janeiro spends on average 5.35 full-year equivalents employed in the formal sector and holds 3.6 jobs. Their Italian counterparts on average spend 7.25 full-year equivalents and hold 3.3 jobs.

Table 1 also shows that young workers in our sample experience an average wage increase of 0.091 and 0.036 log points in Rio de Janeiro and Veneto, respectively.[12] Wage growth is meaningful both within and between jobs, as average within- and between-firm wage increases reach 0.085 and 0.12 log points for Brazilian workers, respectively, while amounting to 0.036 and 0.041 for their counterparts in Veneto. Figure A3 shows within-firm and between-firm wage growth patterns by age. Both sources of growth play an important role during the 18–35 age range (Topel and Ward, 1992; Adda and Dustmann, 2023). In Veneto, both sources of growth are of roughly equal magnitude while in Rio de Janeiro within-firm growth is lower on average at younger ages but greater at ages 28–35.

[10] Previous papers that have used the VWH data include Card et al. (2014), Battisti (2017), Bartolucci et al. (2018), Serafinelli (2019), and Kline et al. (2020).

[11] Figure A1 shows the age distribution of these young workers in each of our two datasets.

[12] Figure A2 further presents wage profiles by age and experience.

Table 1: Summary Statistics: Rio de Janeiro and Veneto Samples

	Rio de Janeiro (1)	Veneto (2)
Share Male	0.594	0.538
Age at Entry	20.48	20.21
Cumulative (Actual) Experience	5.35	7.25
Cumulative Number of Jobs	3.59	3.30
Average Wage Growth	0.091	0.036
Within-Firm Wage Growth	0.085	0.036
Between-Firm Wage Growth	0.120	0.041
Number of Workers	3,420,113	1,019,590
Observations	17,503,326	6,723,614
Number of Firms	441,030	284,139

Notes: Summary statistics for the Rio de Janeiro and Veneto samples as described in Section 2, focusing on individuals we observe for at least two different calendar years. Wage growth statistics are averages of differences in logs at the worker-year level. Share male, age at entry, cumulative experience and cumulative jobs are averages at the worker level for the oldest cohort in each country which we can observe from age 18 to their mid-thirties (the 1976 birth cohort in Rio de Janeiro and 1966 cohort in Veneto). The oldest cohort includes 266,111 and 86,023 workers in Rio de Janeiro and Veneto, respectively. Number of firms counts private-sector firms in Rio de Janeiro and Veneto.

3 Learning On-the-Job across Firms: Conceptual and Empirical Framework

3.1 Conceptual Framework

Human Capital Accumulation. Worker i's stock of human capital in period t, H_{it}, is given by:

$$\ln\ H_{it} = \alpha_i + h_{it}, \tag{1}$$

where α_i is human capital developed prior to labor market entry, and h_{it} is the stock of human capital accumulated on-the-job since labor market entry up until period t. Following previous work (e.g., Bagger et al., 2014), and motivated by findings on small returns to tenure (e.g. Altonji and Williams, 2005; Adda and Dustmann, 2023), this framework assumes that all human capital is general. We later test the implications of this assumption in our empirical analysis.

Skill acquisition on the job occurs through learning-by-doing, i.e., as a byproduct of employment and not requiring costly investment decisions. The amount of human capital development a worker accrues depends on the type of firm where she is employed. The law of motion of learning on the job is:

$$h_{it+1} = h_{it} + \sum_{m=1}^{K} e_{it}^{m} \cdot \mu_{it}^{m}, \tag{2}$$

where $m \in \{1, \ldots, K\}$ indexes the firm classes in the economy, e_{it}^m is a binary variable that equals one when worker i is employed in firm class m during period t, and μ_{it}^m is an i.i.d. draw from the distribution F_m, with mean $\gamma_m \equiv \mathbb{E}\left[\mu_{it}^m\right]$.

Differences in distributions F_m reflect that some firms provide better on-the-job learning opportunities than others.[13] In the limit, the number of firm classes K could be equal to the number of firms in the economy. On the other hand, absent systematic differences in human-capital development across firms, K would be equal to one (an implicit assumption in much of the literature). We will take a middle-ground approach and allow for ten firm classes. Appendix B discusses the choice of $K = 10$.

This framework implies that the stock of human capital accumulated on the job depends (in expectation) on the worker's past employment history across heterogeneous firms:

$$h_{it} = \sum_{l=1}^{t-1} \sum_{m=1}^{K} e_{il}^{m} \cdot \mu_{il}^{m}, \tag{3}$$

$$\mathbb{E}\left[h_{it} | \mathbf{Exp}_{it}\right] = \sum_{l=1}^{t-1} \sum_{m=1}^{K} e_{il}^{m} \cdot \gamma_{m}, \tag{4}$$

where $\mathbf{Exp}_{it}$ is the K-dimensional vector of employment histories at firms of different classes since labor market entry up until time t (where workers' experience is measured at the beginning of the year).

Wages. The wage of worker i, employed at firm j, in period t, y_{it}, combines human capital H_{it} and a firm component ψ_j:

$$y_{it} = e^{\psi_{j(i,t)}} H_{it}. \tag{5}$$

Log wages are thus given by:

$$\ln y_{it} = \psi_{j(it)} + \alpha_i + h_{it}, \tag{6}$$

and the expected log wage conditional on the contemporaneous employer, the worker's identity, and the worker's employment history is given by:

$$\mathbb{E}\left[\ln y_{it} | j(i,t), i, \mathbf{Exp}_{it}\right] = \psi_{j(it)} + \alpha_i + \sum_{m=1}^{K} \gamma_m \cdot \mathrm{Exp}(m)_{it}, \tag{7}$$

where $\mathrm{Exp}(m)_{it} \equiv \sum_{l=1}^{t-1} e_{il}^{m}$ is the (actual) experience worker i has acquired in firms of class m up until period t.

The firm components ψ_j capture firms' pay premia in an Abowd et al. (1999) sense, possibly related to firm productivity (Card et al., 2018). Wage growth in this framework can arise from two sources: growth in general human capital or job mobility toward firms with greater pay premia. While the framework assumes away alternative sources of wage growth, we consider and test for their importance in our empirical analysis below.

[13] This stylized conceptual framework assumes that all workers in a given firm class experience similar learning opportunities. Yet in our empirical analysis we allow for and estimate the prevalence of differential learning opportunities within the same firm class for workers with distinct characteristics.

3.2 Empirical Framework

Building on the conceptual framework, we will estimate log wage regressions of the following form:

$$\ln y_{it} = \psi_{j(it)} + \alpha_i + \sum_{m=1}^{K} \gamma_m \cdot \text{Exp}(m)_{it} + X'_{it}\beta + \eta_{it}, \tag{8}$$

where ψ_j are contemporaneous firm fixed effects, α_i are person fixed effects, $\text{Exp}(m)_{it}$ is the number of years i has been employed in firms of class m up until period t,[14] X_{it} controls for age and year effects, and η_{it} is a mean zero error term.

The returns to one year of experience at firm class k—i.e., $\{\gamma_1, \gamma_2, \ldots, \gamma_K\}$—are our parameters of interest. Note that the K experience terms in equation (8) represent a generalization of a classical Mincerian experience term assuming equal returns to experience regardless of the type of firm where such experience was acquired (Mincer, 1974).[15]

We present the identification and interpretation of equation (8) in two steps. First, we discuss the identification of the returns to heterogeneous experiences, echoing classical work on returns to experience and seniority (e.g., Altonji and Shakotko, 1987; Topel, 1991; Dustmann and Meghir, 2005). Second, in Section 3.3, we present a detailed discussion on the human capital interpretation of the heterogeneous returns $\{\gamma_m\}_{m=1}^K$ vis-à-vis alternative drivers of wage growth, describing three empirical tests we develop to assess the plausibility of a human capital interpretation.

To consistently estimate heterogeneous returns to experiences $\{\gamma_m\}_{m=1}^K$ in (8) by OLS, the unobserved determinants of earnings η_{it} must be uncorrelated with experience stocks, conditional on the worker's identity, their observable characteristics, and their contemporaneous employer. We assume that η_{it} satisfies the strict exogeneity assumption:

$$\mathbb{E}[\eta_{it} | j(i,t), i, \textbf{Exp}_{it}, X_{it}] = 0. \tag{9}$$

In Appendix C, we present an extensive discussion of the intuition behind this assumption. We consider threats to the strict exogeneity assumption in the form of workers' unobserved ability to learn, the potential existence of match effects, firms learning about workers' productivity, and the implementation of up-or-out contracts.

Note that the flexible nature of equation (8)—i.e., including contemporaneous firm fixed effects, person fixed effects, and stock of heterogeneous experiences that capture full employment histories—allows for rich mobility patterns that would *not* bias our estimates of returns to experiences. For instance, the strict exogeneity assumption is not violated even if past experience at class-9 firms makes a worker more likely to be in a class-10 firm today. Similarly, our framework allows for the possibility that past experience at class-10 firms

[14] The units of $\text{Exp}(m)_{it}$ are years so that the γ_m parameters capture returns to one year of experience. However, we construct the experience variables using more granular data, taking advantage of the information on days worked in the Veneto data, and information on the length of employment spells in the Brazilian data.

[15] As a benchmark, we also estimate versions of equation (8) with such "homogeneous experience" (i.e., imposing the restriction $\gamma_m = \gamma \;\; \forall \; m$).

may lead a worker to be more likely to be in a high-paying firm (high contemporaneous AKM firm effect ψ_j) today.

In comparison to the classical literature on the returns to experience, we further highlight the importance of including two-way fixed effects in equation (8). First, person fixed effects α_i account for unobserved ability bias (i.e., the threat of unobserved baseline ability being correlated with experience). Second, firm fixed effects ψ_j capture the possibility that experience may lead workers to better matches, i.e., jobs at higher-paying firms. However, our returns to experiences could still be biased in the presence of ij-specific match effects, a concern we address in Section 3.3 below.

Assignment of firms to firm classes. The firm class $k(j)$ that each firm j belongs to is not readily observable, so, in a first step, we assign each firm to one of K classes. We classify firms using the within-firm empirical distributions of wage growth, and a clustering algorithm similar to the one used by Bonhomme et al. (2019).

For classification, we focus on stayers' wage growth, so as to net out the firm component, ψ_j, and baseline human capital, α_i. Wage growth for worker i who stays at firm j between $t-1$ and t, g_{ijt}, amounts to:

$$g_{ijt} \equiv \ln y_{it} - \ln y_{i,t-1} = h_{it} - h_{i,t-1} = \mu_{i,t-1}^{k(j)}. \tag{10}$$

We use the empirical distribution of g_{ijt} at each firm j, $\hat{G}_j(g)$, to classify the J firms in our data into K classes by solving the k-means minimization problem:

$$\min_{k(1),\ldots,k(J),F_1,\ldots,F_K} \sum_{j=1}^{J} n_j \int \left(\hat{G}_j(g) - F_{k(j)}(g)\right)^2 d\lambda(g), \tag{11}$$

where $k(1), \ldots, k(J)$ is the classification of firms into classes, F_k are the class-specific distribution functions, n_j is the number of worker-years in firm j, and λ is a measure supported on a discrete grid.[16,17]

3.3 Alternative Explanations and Sources of Wage Growth

Our estimated returns to experiences in equation (8) could arguably not only capture portable human capital, but also other determinants of wage growth—e.g., firm-specific human capital, bargaining following outside offers, pass-through effects of firm productivity shocks, or seniority-based pay schemes that back-load pay. We propose three empirical

[16] Appendix B discusses the implementation of the firm classification algorithm (11). First, we partial out worker demographics from wage growth g_{ijt}, and carry out the firm assignment to classes based on a residualized g_{ijt}. We use half of our sample for the classification problem (11), and estimate the returns to heterogeneous experiences on the other half, amounting to a split sample approach. We set the number of firm classes K equal to 10, which aligns with related literature (Bonhomme et al., 2019) and does a good job in summarizing between-firm wage growth variance.

[17] Figure A4 shows transition probabilities across firm classes conditional on switching employers. The matrices are well populated, indicating a substantial degree of mobility between all firm-class combinations. Such mobility is important for identification, and it allays concerns regarding the possibility that of our firm classification captures segmented labor markets that employ very different types of workers.

tests, well grounded on search and matching theories, that exploit settings were such alternative determinants should *not* impact wages. Estimating returns to heterogeneous experiences in these settings informs the merits of a general human capital interpretation.

Job stayers vs. job switchers. Since the baseline estimation sample of equation (8) includes firm-stayers, our estimated returns to experiences could partly reflect firm-specific human capital. As such, our first test follows the spirit of Topel (1991) and involves estimating returns to experiences that are allowed to differ between stayers and new job entrants. The logic in Topel (1991) is that returns to experience among job stayers identifies the combined returns of experience and tenure, while the returns to experience among initial wages in new jobs identifies the returns to experience alone. Even if the literature has mostly found returns to tenure to be small (Altonji and Williams, 2005; Adda and Dustmann, 2023), this approach allows us to discard *firm-specific* human capital as a driver of our main results. We estimate the following augmented version of equation (8):

$$\ln y_{it} = \psi_{j(it)} + \alpha_i + \sum_{m=1}^{K} \gamma_m^S \cdot S_{it} \cdot \text{Exp}(m)_{it} + \sum_{m=1}^{K} \gamma_m^{NJ} \cdot NJ_{it} \cdot \text{Exp}(m)_{it} + X_{it}'\beta + \eta_{it}, \quad (12)$$

where S_{it} is a dummy equal to one for worker-year observations corresponding to stayers, and NJ_{it} is instead a dummy equal to one for worker-year observations corresponding to entry wages in new jobs, which we additionally include in X_{it}.

As such, the returns to heterogeneous experiences for job switchers (γ_m^{NJ}) cannot be driven by firm-specific human capital. Note that while this test can rule out firm-specific human capital as a key driver of our results, it cannot rule out returns driven by ij-specific match effects or outside offers and bargaining dynamics.[18] Our next two tests directly address these concerns.

Hiring wages and dual wage ladder specification. Di Addario et al. (2023) show that equilibrium entry wages in the sequential auction model of Bagger et al. (2014) map into the following representation:

$$\ln y_{in} = \alpha_i + \psi_{j(i,n)} + \lambda_{h(i,n)} + g\left(\text{Exp}_{in}\right) + \eta_{in}, \quad (13)$$

where n indexes job spells, $\psi_{j(i,n)}$ and $\lambda_{h(i,n)}$ are destination- and origin-firm fixed effects, and Exp_{in} is actual labor market experience accumulated up until the start of job spell n. Crucially, all channels other than human capital that affect entry wages in Bagger et al. (2014) are captured by $\psi_{j(i,n)}$ and $\lambda_{h(i,n)}$, while $g\left(\text{Exp}_{in}\right)$ has a pure general on-the-job learning interpretation.[19] The intuition behind this result is as follows. Unconditionally,

[18] More experienced workers might have had more time to find better ij-specific matches (Altonji and Shakotko, 1987; Topel, 1991). In equation (12), if experience in certain firm classes leads switchers to better matches, the estimated γ_m^{NJ} parameters would still reflect this mechanism. Outside offers and bargaining dynamics present in sequential auction models (Postel-Vinay and Robin, 2002a,b; Cahuc et al., 2006; Bagger et al., 2014) could also be a confounder, particularly if some firms are more conducive to outside offers than others.

[19] Di Addario et al. (2023) show that $\psi_{j(i,n)}$ and $\lambda_{h(i,n)}$ map into functions of workers' bargaining power and

experience is correlated with wages through a job search channel leading to more productive firms. However, this channel is absorbed by the inclusion of destination-firm fixed effects $\psi_{j(i,n)}$. Also unconditionally, in Bagger et al. (2014), tenure in the previous employer is correlated with entry wages through its correlation with productivity at destination and origin firms. However, this channel is captured in (13) by the origin-firm and destination-firm fixed effects. Consequently, the effect on entry wages of $g\left(\text{Exp}_{in}\right)$ is driven by portable human capital accumulation.

Following this logic, we estimate returns to heterogeneous experiences in the sample of hiring wages using a modified version of equation (13):

$$\ln y_{in} = \alpha_i + \psi_{j(i,n)} + \lambda_{h(i,n)} + \sum_{m=1}^{K} \gamma_m^{DWL} \cdot \text{Exp}(m)_{in} + X'_{in}\beta + \eta_{in}. \tag{14}$$

Returns to heterogeneous experiences captured by the parameters γ_m^{DWL} are consistent with a portable human capital interpretation and are plausibly free of any effects of experience on wages coming through job ladder, bargaining, or firm-specific skills effects. However, since equation (14) includes voluntary movers, this specification would not account for potential ij-specific match effects. Another limitation of this test is that Bagger et al. (2014) assume firm productivity to be constant over time. For instance, if firm productivity shocks pass through to wages (Guiso et al., 2005; Engbom et al., 2023), time invariant origin- and destination-firm fixed effects might not account for the effects of such shocks. If these shocks were correlated with heterogeneous experiences, this would contaminate a human capital interpretation. Our third test addresses these two concerns.

Hiring wages following job displacement. We estimate a variant of equation (14) among the subset of hiring wages that follow an involuntary job displacement episode—i.e., job transitions after a mass layoff or a firm closure:

$$\ln y_{d(i)} = \alpha_i + \psi_{j(d(i))} + \sum_{m=1}^{K} \gamma_m^{D} \cdot \text{Exp}(m)_{d(i)} + X'_{d(i)}\beta + \eta_{d(i)}, \tag{15}$$

where $d(i)$ indexes the job displacement event experienced by individual i, $j(d(i))$ indexes the destination firm following the job displacement, and $\text{Exp}(m)_{d(i)}$ is the amount of experience of type m worker i holds when starting the post-displacement job. Since job displacement events are relatively rare, we estimate equation (15) relying on one post-displacement hire per individual. As such, worker fixed effects α_i are not identified in equation (15) and we replace them with a linear function of $\widehat{\alpha}_i$, where $\widehat{\alpha}_i$ are fixed effects recovered from equation (8). For similar reasons, we replace firm fixed effects $\psi_{j(d(i))}$ with a linear function of $\widehat{\psi}_j$—firm fixed effects recovered from equation (8).

This exercise can be seen as a special case of Di Addario et al. (2023) in which the origin state is unemployment for everyone in the sample. As such, all the benefits from the prior

firms' (origin and destination) productivity in the model of Bagger et al. (2014).

test in terms of isolating a portable human capital channel carry over. Moreover, these estimates account for any potential match effects, as involuntarily displaced workers are likely willing to accept any job offer that is preferable to unemployment (Kletzer, 1989; Dustmann and Meghir, 2005; Gathmann and Schönberg, 2010). This approach is also robust to other potential model misspecifications in Bagger et al. (2014). First, in the presence of firm productivity shocks, the bargaining conditions of workers who originate from the same firm in different time periods could differ. Second, in the presence of seniority-based pay schemes (Lazear, 1981; Guiso et al., 2013), the bargaining conditions of workers who originate from the same firm in the same year but with different tenure levels could also differ. Focusing on involuntarily displaced workers tackles both concerns since such workers lose all search capital and any incumbent-employer outside option. Returns to heterogeneous experiences captured by the parameters γ_m^D are thus consistent with a portable human capital interpretation and are plausibly free of any effects of experience on wages coming through moving up the job ladder, bargaining, firm-specific skills, firm productivity shocks, seniority-based pay schemes, or match effects.

All in all, these three tests will help to more convincingly establish whether our firm classification does capture differences in on-the-job learning of portable skills. The first test is robust to contamination due to firm-specific human capital. The second test is additionally robust to outside offers-bargaining dynamics. The third test is robust to the previous two confounders plus match effects, time-varying firm productivity shocks, and seniority based pay schemes. We present the results from these tests in Section 5.1.

3.4 Learning Opportunities and Firms' Pay Premia

Should we expect firms with good learning opportunities to pay lower wages? Models featuring frictionless and perfectly competitive labor markets would predict equalizing compensating differentials (e.g., Rosen, 1972; Jarosch et al., 2021). In such a case, the net present value of the contemporaneous wage plus the future wage returns from learning would be equalized across firms with varying degrees of learning opportunities. Such an equalization in a net present value sense would imply a cross-firm negative correlation in contemporaneous wages and learning opportunities.

However, a positive correlation between firm productivity and learning opportunities would work against detecting a negative correlation between wages and learning opportunities. Many models of imperfect labor market competition predict that more productive firms pay higher wages (e.g., a wage posting model like Card et al. (2018), or a search and bargaining model like Bagger et al. (2014)). More productive firms may also be more likely to offer stronger learning opportunities to their workers, in which case the observed correlation between firm-level wages and learning opportunities may not be negative. Unfortunately, our data does not feature firm productivity measures, which prevents us from computing a correlation between learning opportunity and wages that controls for productivity.

Moreover, there are a number of reasons why young workers might value learning opportunities less than the net present value of their wage returns, which would also work against a negative correlation between wages and learning opportunities. With liquidity constraints and incomplete credit markets, low contemporaneous wages will be undesirable for consumption smoothing reasons, even if compensated for by learning opportunities.[20] Moreover, risky returns to human capital accumulation (Palacios-Huerta, 2003) would make risk-averse workers value learning opportunities less than their expected flow of future returns. Additionally, firm-varying learning opportunities could be hard to observe ex-ante for young workers, and updating based on wage growth could be slow (Guvenen, 2007). Lastly, young workers could also undervalue learning opportunities if they hold incorrect beliefs about returns to skills (see Alfonsi et al., 2022, for evidence on this).

Overall, the nature of the relationship between wages and learning opportunities is an empirical question. We examine the correlation between firms' pay premia and learning opportunities in Section 6.

4 Returns to Experiences Acquired in Different Firm Classes

4.1 Baseline Results on Returns to Different Types of Experience

Figure 1 displays estimates of equation (8), which comprise our baseline results on returns to experiences acquired in different firm classes. The horizontal dashed line shows, as a benchmark, the return to one year of "homogeneous" experience. An additional year of homogeneous experience is associated with wage returns of 3% in Rio de Janeiro and 2.1% in Veneto.[21] Our main finding, however, is that these estimates mask substantial heterogeneity in the returns to experiences acquired in different firm classes. In Rio de Janeiro, one year of experience acquired at a class-1 firm is associated with a return that is close to 0%, whereas a year of experience at a class-9 or class-10 firm yields returns of 6.6% and 8.8%, respectively. In Veneto, the returns to one year of experience acquired in a class-1 firm are also close to 0%, while returns to class-10 firm experience reach 4.5%.[22]

Returns to experiences acquired in intermediate firm classes lie between class 1 (i.e., "lowest-learning" firms) and class 10 (i.e., "top learning" firms), with a gradient between returns and firm class which is generally increasing.[23] In Rio de Janeiro, returns to experiences

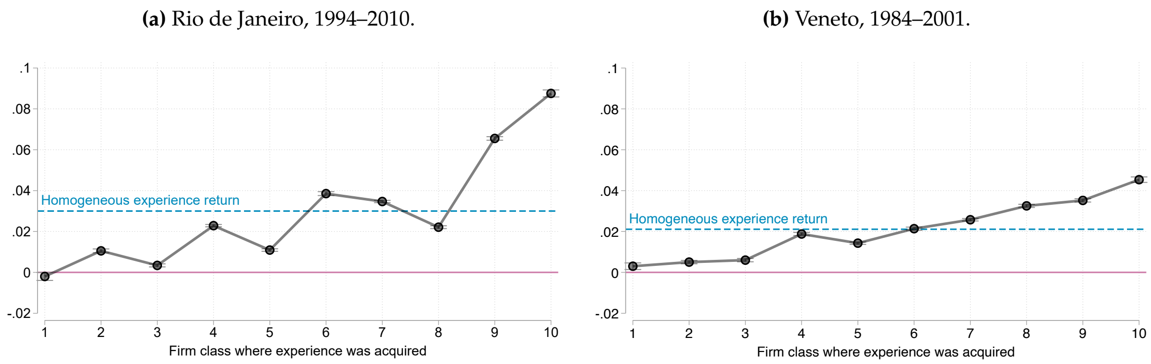
[20]Recent evidence suggests that liquidity and student debt can meaningfully impact young persons' early-career choices (Rothstein and Rouse, 2011; Coffman et al., 2019).

[21]Understanding why returns differ across these two economies is beyond the scope of this paper. Dustmann and Pereira (2008) discuss potential factors driving differential returns to experience in Germany and the UK, Rucci et al. (2020) do so across Brazil and Chile. Lagakos et al. (2018) and Donovan et al. (2021) document a positive cross-country correlation between returns to potential experience and GDP per capita. However, Italy is not part of their sample and they show that Brazil's returns are similar to those of high-income countries like France, Canada, and Australia.

[22]Tables A1 and A2 (columns (3) and (6)) show regression output corresponding to estimates presented in Figure 1 for Rio de Janeiro and Veneto, respectively. These tables also show returns to experience acquired in very small firms not categorized by our approach, in public-sector employers, and in out-of-state/region firms.

[23]The returns-firm class gradient is not monotonic likely due to the fact that we estimate equation (8) using only young workers and including firm-movers, whereas our classification methodology relies on firm stayers and includes older workers.

Figure 1: Returns to experiences acquired in different firm classes.



Notes: Estimates and 95% confidence intervals of returns to experiences acquired in different firm classes. Standard errors clustered at the person level. Blue line: returns to homogeneous experience. Black plot: returns to experiences accumulated in each of the 10 firm classes. Rio de Janeiro: outcome is log hourly wage; sample composed of private sector observations, workers born in 1976 or later while aged 18–35; N=9,168,318; number of persons = 1,568,990. Veneto: outcome is log daily wage; sample composed of private sector observations, workers born in 1966 or later while aged 18–35; N=3,608,754; number of persons = 483,799. Corresponding Appendix regression tables: Tables A1 and A2.

acquired in firm classes 6, 7, 9, and 10 are above the homogeneous benchmark, whereas the corresponding above-benchmark firm classes in Veneto are classes 6–10. While the returns to experiences in Veneto exhibit less heterogeneity in levels vis-à-vis those found in Rio de Janeiro, the pattern in relative terms is not very far apart: the returns to experience acquired in class-10 firms are roughly three times as large as the returns to homogeneous experience in Rio de Janeiro, and slightly over two times as large in Veneto. In Appendix D, we show that the heterogeneity in returns uncovered by our approach is substantially richer than the resulting one when classifying firms based on observable characteristics such as firm size, city size, or coworkers' education.

Robustness. All baseline results are robust to various ways of accounting for age effects (see Figure A5).[24,25] Additionally, the conclusions are unchanged if we relax the assumption of linear experience terms in equation (8) and instead have each type of experience enter as a quadratic function, allowing for potentially diminishing returns (see Tables A3 and A4). Results are also robust to modifying how we compute the residual wage growth measures entering the firm classification problem (11) (see Figure A6). Lastly, we show in Appendix E that our main conclusions are robust to extending the conceptual framework and estimation procedure to allow for human capital depreciation.

Contribution to Wage Inequality. We quantify how much of the variance of young work-

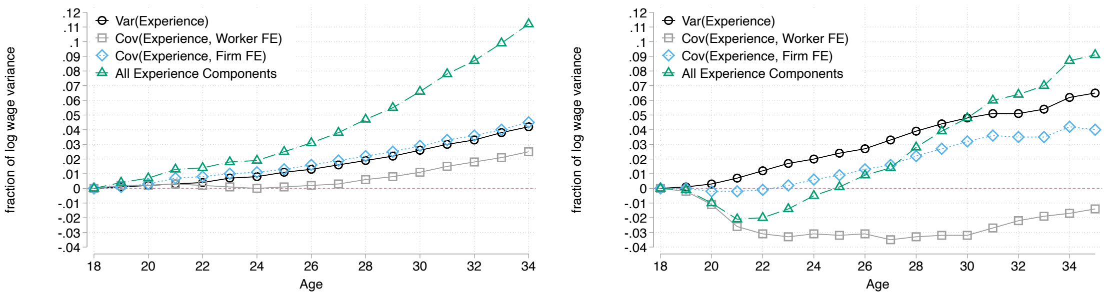
[24] A common concern in models with worker and firm fixed effects is the correct specification of age effects (Card et al., 2018). Our main specification controls for six age-category fixed effects, yet we assess the robustness of our results to alternative specifications in Figure A5. We consider specifications with an age polynomial restricting the age profile to be flat at 35, and another one with no age controls. We do not find significant differences in the estimated returns relative to our main specification.

[25] The robustness of our results to different age controls further allays potential concerns related to informality in Brazil since unobserved informal sector experience is likely correlated with age.

ers' wages is accounted for by heterogeneous experiences. We build upon the AKM literature (e.g., Card et al., 2013; Alvarez et al., 2018) and decompose the variance of wages into the variances of person effects, α_i, firm effects, ψ_j, heterogeneous experiences, $\sum_{m=1}^{K} \gamma_m \cdot Exp(m)$, and their respective covariances.[26] We estimate an age-varying variance decomposition using the OLS estimates of the parameters in equation (8), which allows us to discern the relative importance of heterogeneous experiences on earnings inequality across ages 18 through the mid-thirties.[27,28]

Figure 2: Variance decomposition: returns-to-experiences components over wage variance, by age.

(a) Rio de Janeiro, 1994–2010 **(b)** Veneto, 1984–2001



Notes: Shares of the variance of wages explained by the heterogeneous experiences components. Black dots represent the share of the variance explained by the variance of heterogeneous experiences. Gray squares represent the share of the variance explained by the covariance of heterogeneous experiences and worker fixed effects. Blue diamonds represent the share accounted for by the covariance of heterogeneous experiences and firm fixed effects. Green triangles show the sum of these three components. Panels (a) and (b) present evidence from Rio de Janeiro and Veneto, respectively. Table A5 presents the full-sample variance decomposition for Rio de Janeiro and Veneto.

Figure 2 presents the share of the wage variance explained by the heterogeneous experiences components in Rio de Janeiro and Veneto. The share of wage variance accounted for by the variance of heterogeneous experiences steadily grows in the early career, reaching about 4% and 6% at age 34 in Rio de Janeiro and Veneto, respectively. Meanwhile, the contribution of the covariance of worker fixed effects and heterogeneous experiences is positive but small in Rio de Janeiro, and negative in Veneto. The role of the covariance between firm fixed effects and heterogeneous experiences grows through the early career and accounts for an important share of the earnings variance at age 34, equal to 4.5% in Rio de Janeiro and 4% in Veneto. The growing importance of this covariance in the early career indicates that a separate mechanism through which top-learning firms improve workers' wages is by inducing mobility into higher-paying firms. Overall, the joint contribution of the heterogeneous experiences terms explains over 11% of the wage variance in Rio de Janeiro at age 34 and about 9% in Veneto. Moreover, the share of the wage variance accounted for

[26] Formally, omitting the role of covariates: $Var(\ln y_{it}) = Var(\widehat{\psi}_{j(it)}) + Var(\widehat{\alpha}_i) + Var(\sum_{m=1}^{K} \widehat{\gamma}_m \cdot Exp(m)_{it}) + 2 \cdot Cov(\widehat{\psi}_{j(it)}, \widehat{\alpha}_i) + 2 \cdot Cov(\widehat{\psi}_{j(it)}, \sum_{m=1}^{K} \widehat{\gamma}_m \cdot Exp(m)_{it}) + 2 \cdot Cov(\widehat{\alpha}_i, \sum_{m=1}^{K} \widehat{\gamma}_m \cdot Exp(m)_{it}) + Var(\widehat{\eta}_{it})$.

[27] The contributions of the heterogeneous experiences terms are lower among young workers vis-à-vis the full workforce since the former have limited amounts of experiences which, by construction, cannot be largely different from each other.

[28] Limited mobility bias implies the "plug-in" estimator of the variance decomposition yields biased estimates of the variance/covariance of worker and firm effects (Andrews et al., 2008; Kline et al., 2020; Bonhomme et al., 2023). However, the OLS estimates of $\{\gamma_m\}_{m=1}^{K}$ are consistent and precisely estimated. Thus, there is no need to correct the plug-in estimates of variance components involving $\sum_{m=1}^{K} \gamma_m \cdot Exp(m)$.

by heterogeneous experiences grows throughout the early career, which suggests an even greater importance in explaining inequality further into workers' careers.

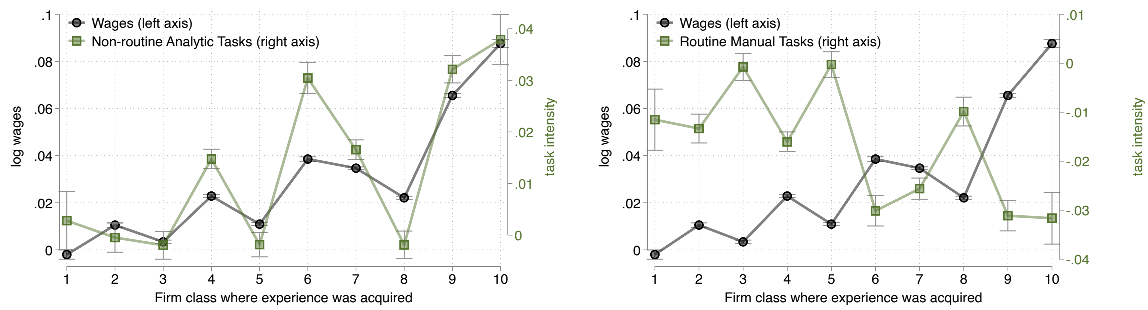
In Figure A7, we carry out a comparable variance decomposition that instead assumes all experiences to be homogeneous. The share of the variance of wages explained by homogeneous experiences reaches 6% and 4.5% by age 34 in Rio de Janeiro and Veneto, respectively. These shares, based on the conventional approach assuming homogeneous experiences, only amount to about half of the share explained in our heterogeneous experiences specification.

4.2 Heterogeneous Experiences and Subsequent Task Contents

This paper presents a number of results on wages that are consistent with portable skills accumulation driving heterogeneous returns to different types of experience. To confirm this interpretation, we would ideally observe measures of workers' skills. In the absence of such data, we turn to the types of tasks workers carry out in their jobs (Acemoglu and Autor, 2011). While not being direct measures of human capital, task contents are arguably related to workers' underlying skills.[29] We carry out this analysis in Rio de Janeiro, where we can match three-digit occupational codes to workers' task content across four dimensions: non-routine analytic, non-routine interpersonal, routine cognitive and routine manual tasks.

Figure 3: Task content returns to experiences acquired in different firm classes, Rio de Janeiro.

(a) Non-routine Analytic Tasks. **(b)** Routine Manual Tasks.



Notes: Black plot in both panels: Baseline estimates of wage returns to experiences acquired in different firm classes, described in Figure 1. Green plots: Estimates and 95% confidence intervals of task content returns to experiences acquired in different firm classes. Standard errors clustered at the person level. All task intensities are measured in standard deviations. Outcome in panel (a) is intensity of non-routine analytic tasks; in panel (b), routine manual tasks. Number of observations=8,971,906. Corresponding Appendix regression table: Table A6.

We estimate equation (8) using task intensity across the four task dimensions as outcomes instead of wages. We present the results in Figure 3, together with the baseline wage returns for comparability. The key takeaway is that experience acquired in firms that we categorize as having good learning opportunities is associated with subsequent increases in the intensity of non-routine analytic tasks. For instance, an additional year of experience

[29] Workers' non-routine task content significantly increases in the early career (Sanders, 2014; Speer, 2017), and such changes are associated with sizable wage increases (Yamaguchi, 2012; Stinebrickner et al., 2019).

at class-10 firms is associated with increases in workers' non-routine analytic task content of about 0.04 standard deviations. The second panel instead shows that our heterogeneous experience classification is negatively correlated with returns in routine manual task intensity.[30] All types of experience have associated negative returns in terms of routine tasks intensity—indicating all workers gradually shift away from these type of tasks—yet experience acquired at "top-learning" firms leads to the largest decrease in routine task intensity.[31]

5 Tests for Alternative Explanations and Heterogeneity

5.1 Test Results for Portable Human Capital vs. Alternative Explanations

We now present results of the three empirical tests detailed in Section 3.3. The aim of these tests is to estimate returns to heterogeneous experiences in settings where alternative explanations to a general human capital interpretation plausibly do not impact wages.

5.1.1 Job stayers vs. job switchers.

Figure 4 presents returns to heterogeneous experiences for job switchers and stayers in both countries, resulting from the estimation of equation (12). We find larger estimated returns to experiences for job stayers than for switchers, yet the overall magnitude of the difference is not very large—amounting to 1.2 percentage points in Rio de Janeiro and to 0.6 percentage points in the top learning classes in Veneto. As such, firm-specific components may play a small role in driving the estimated patterns presented in Figure 1. Yet, crucially, the pattern of heterogeneous returns across firm classes remains the same for stayers and for switchers, which indicates a high degree of portability across firms. Note, for instance, that the returns to a year of experience in a class 10 firm exceed 6.6% in Rio de Janeiro and 4% in Veneto for workers entering new firms, far greater than the corresponding returns to previous experiences in the lowest-learning firms. These results indicate that firm-specific human capital is not the driver of heterogeneous returns for different experience types.

5.1.2 Hiring wages and dual wage ladder specification

Figure 5 presents the estimated returns to experiences from two versions of the dual wage ladder specification (equation (14)). We first estimate a version of equation (14) that does not include origin fixed effects, capturing the returns to experiences in new jobs. We compare these returns to those in the expanded dual wage ladder specification (Di Addario et al., 2023). Across both countries, the estimated returns to experiences are very similar in the two specifications—including origin fixed effects yields no statistically significant differences in the estimates in Veneto, and only a small decrease in the magnitude of the

[30]Measures of task intensity are absolute. As such, it is not necessarily the case that an occupation with high task intensity in one dimension features lower intensity in the other three.

[31]Figure A8 shows results for non-routine interpersonal tasks (which look similar to results on non-routine analytical tasks) and routine cognitive tasks (which look similar to results on routine manual tasks).

Figure 4: Returns to experiences acquired in different firm classes: job switchers and stayers.

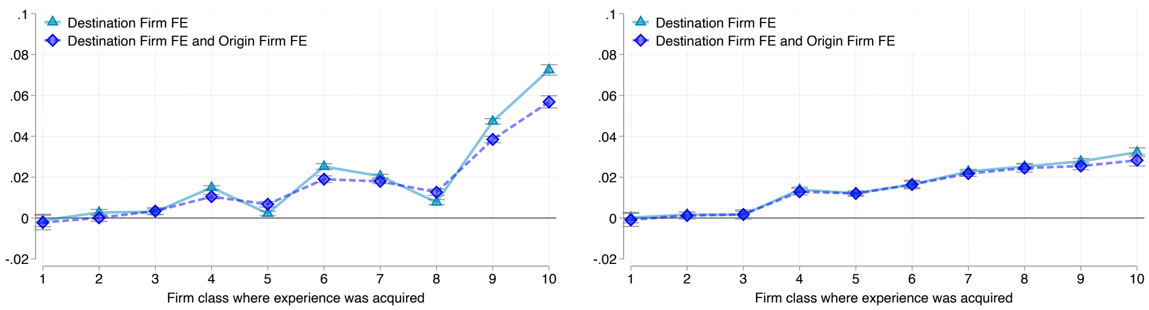
(a) Rio de Janeiro, 1994–2010. **(b)** Veneto, 1984–2001.

Notes: We present the estimated returns to heterogeneous experiences for job switchers and stayers from equation in Rio de Janeiro and Veneto in Panels (a) and (b), respectively. The orange line denotes the estimated returns to job stayers (γ_m^S), and the green line depicts the corresponding returns for switchers (γ_m^{NJ}). The outcome variable for Rio de Janeiro is log hourly wages and log daily wages for Veneto. Standard errors are clustered at the person level. Corresponding Appendix regression table: Table A7.

returns to experiences in the top learning firms in Brazil. More importantly, Figure 5 displays a pattern of heterogeneous returns that are very similar to the baseline ones presented in Figure 1. As discussed in Section 3.3, this evidence implies that outside offers and bargaining dynamics are unlikely to be the main drivers of heterogeneous returns for different experience types.

Figure 5: Returns to experiences acquired in different firm classes: hiring wages and dual wage ladder specification.

(a) Rio de Janeiro, 1994–2010. **(b)** Veneto, 1984–2001.



Notes: Returns to heterogeneous experiences in entry job observations, estimated following equation (14) in Rio de Janeiro and Veneto in Panels (a) and (b), respectively. The solid line denotes the estimated returns from equation (14) in a specification that does not include fixed effects for the origin firm, whereas the dashed line additionally includes origin firm fixed effects. Both specifications include individuals starting a new job, such that the sample includes wage observations in first jobs. The outcome variable for Rio de Janeiro is log hourly wages and log daily wages for Veneto. Standard errors are clustered at the person level. Corresponding Appendix regression table: Table A8.

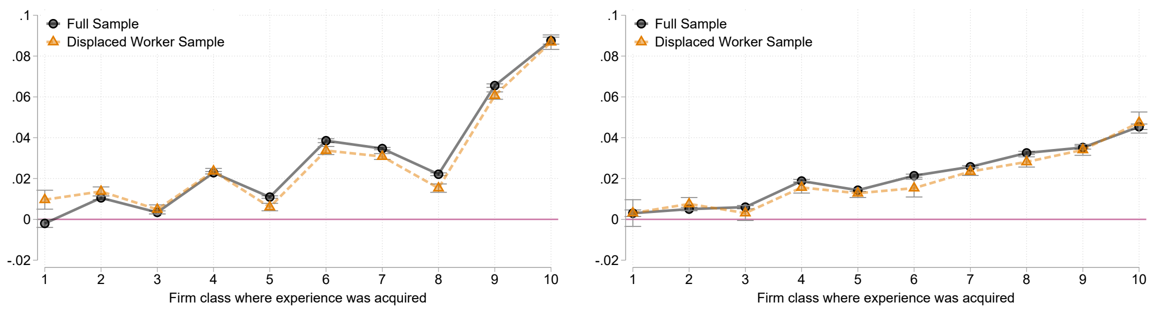
5.1.3 Hiring wages following job displacement

Displaced workers sample. To identify involuntary displacement events, we leverage the population-level coverage of both datasets and focus on firm closure and mass layoff events following the existing literature (e.g. Jacobson et al., 1993; Dustmann and Meghir, 2005; Lachowska et al., 2020).[32] Our sample includes workers who are laid off at the time of the firm closure/layoff event and do not subsequently re-enter the same firm in the following five years.[33]

Figure 6 presents returns to heterogeneous experiences resulting from the estimation of equation (15), using the sample of displaced workers' first post-displacement observation. The figure also displays baseline estimates from Figure 1 for comparison purposes. The key takeaway is that the heterogeneous returns γ_m^D, estimated in the displaced workers' sample, are extremely similar to the baseline ones. Existing search and matching theories suggest that neither firm-specific skills, outside offers and bargaining, match effects, firm productivity shocks, nor seniority based pay schemes should impact post-displacement wages. As such, we interpret the evidence as consistent with heterogeneous returns being driven by accumulation of portable skills.

Figure 6: Returns to experiences acquired in different firm classes: sample of displaced workers.

(a) Rio de Janeiro, 1994–2010. **(b)** Veneto, 1984–2001.



Notes: Black plot: Baseline estimates of returns to experiences acquired in different firm classes, described in Figure 1. Orange plot: Estimates and 95% confidence intervals of returns to experiences acquired in different firm classes, estimated using the first post-displacement observation of workers experiencing a mass layoff or firm closure. Robust standard errors. Rio de Janeiro: outcome is log hourly wage; N=292,495. Veneto: outcome is log daily wage; N=34,923. Corresponding Appendix regression table: Table A9.

5.2 Heterogeneity across workers

We now assess whether the returns to experiences acquired in different firm classes vary across workers. This exercise fulfills two purposes. First, to gain additional insights into how heterogeneous experiences impact distinct types of workers. Second, to serve as a test of our interpretation of firm-driven effects vis-à-vis an alternative interpretation based on

[32] We define firm closures as events in which large firms close down and do not subsequently reappear in the data. Mass layoffs, meanwhile, include events in which a firm's total employment drops by at least 30% in one year in firms with at least twenty employees (Bertheau et al., 2022).

[33] In Rio de Janeiro, we identify 16,115 involuntary displacement events during our period of interest, which affect 379,457 workers in our sample of young workers. In Veneto, meanwhile, 4,180 firms either shut down or undergo a mass layoff, affecting 42,523 young workers. Across Rio and Veneto, 84% and 87.4% of displaced workers eventually re-enter the sample, whereas 65.2% and 78.5% do so within one year of being displaced, respectively.

workers' unobserved heterogeneity (see the discussion in Section 3.2).[34] We posit that similar returns to heterogeneous experience for different types of workers (classified by their unobserved skills, education, or gender) would be consistent with our firm-driven interpretation, and harder to reconcile with alternative interpretations related to worker sorting.

Unobserved skills. We examine whether heterogeneous experience returns vary across the unobserved skills distribution with a similar approach to De La Roca and Puga (2017), where we use worker fixed effects as a measure of their unobserved baseline skills. We estimate the following wage equation:

$$\ln y_{it} = \psi_{j(it)} + \alpha_i + \sum_{m=1}^{K} \gamma_m \cdot \text{Exp}(m)_{it} + \sum_{m=1}^{K} \delta_m \cdot \text{Exp}(m)_{it} \cdot \alpha_i + \eta_{it}, \tag{16}$$

where α_i represents worker fixed effects, and δ_m captures whether higher-skilled workers enjoy larger returns to experience acquired at firm class m.[35] We present the results in the first two panels of Figure 7, comparing the estimated returns for individuals at the 25^{th} and 75^{th} percentiles of the unobserved skills distribution. In both countries, we find that high-skilled workers experience greater returns to all types of experience compared to low-skilled workers. Crucially, however, the pattern of heterogeneous returns for high- and low-skilled workers are quite similar. This result suggests that firms which offer good or bad learning opportunities do so *both* for high- and low-skilled workers. In particular, both types of workers enjoy the largest returns to experiences acquired at class 9 and 10 firms.

Education. In Rio de Janeiro, we estimate heterogeneous returns to experiences acquired in different firm classes separately by education level. We present the results in the third panel of Figure 7. Returns to experiences acquired across firm classes largely follow the same structure across the two groups: an additional year of experience at the "top-learning" firms results in higher hourly wages by 7.1% for workers without a high school degree, reaching 10% for their more educated peers. Similar to the heterogeneous returns by skills, the pattern of heterogeneous returns is broadly similar for the two groups of workers.

Gender. Figure A9 shows heterogeneous returns by gender. Men enjoy greater returns to experience than women, yet importantly, the relative patterns of heterogeneous returns are similar across genders, as the two profiles are parallel to each other.

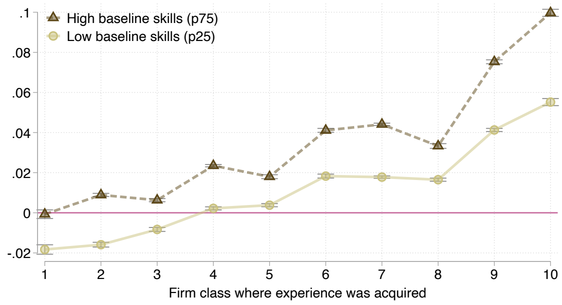
All in all, we interpret the heterogeneity analysis in this section as being consistent with

[34]Under this alternative interpretation, it is not that different types of firms present heterogeneous learning opportunities but, rather, that workers with unobserved attributes not captured by person fixed effects in our empirical analysis (e.g., learning predisposition) sort together into the same firms.

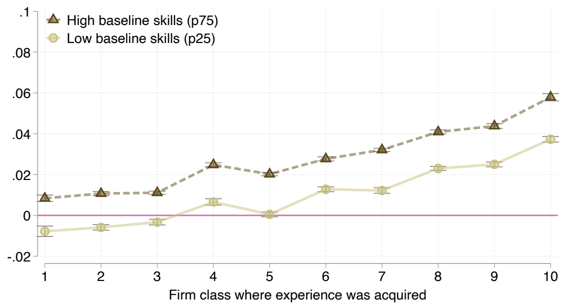
[35]We estimate equation (16) following the recursive algorithm proposed by De La Roca and Puga (2017). The first value of α_i in the interaction term follows from the estimated results of equation (8). We then estimate equation (16) and replace the interacted $\widehat{\alpha}_i$ with the fixed effect recovered in the previous iteration. We repeat this procedure until the estimated $\widehat{\alpha}_i$ parameters converge. This procedure includes an average of 5.8 and 7.5 wage observations per worker in Rio de Janeiro and Veneto, respectively.

Figure 7: Returns to experiences acquired in different firm classes: by baseline skills, education and occupation.

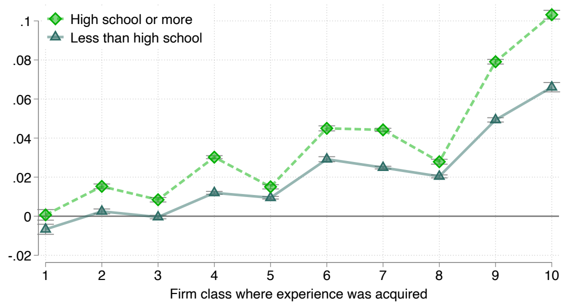
(a) Baseline skills, Rio de Janeiro, 1994–2010.



(b) Baseline skills, Veneto, 1984–2001.



(c) Education, Rio de Janeiro, 1994–2010.



Notes: Panels (a) and (b): estimates and 95% confidence intervals of returns to experiences acquired in different firm classes, separately for workers in the 25^{th} and 75^{th} percentiles of the distribution of unobserved baseline skills (worker fixed effects). Panel (c): estimates and 95% confidence intervals of returns to experiences acquired in different firm classes, separately for workers with two different education levels in Rio de Janeiro. In all panels, the outcome variable for Rio de Janeiro is log hourly wages and log daily wages for Veneto. Standard errors are clustered at the person level. Corresponding Appendix regression table for panels (a) and (b): Table A10. Corresponding Appendix regression table for panel C: Table A11.

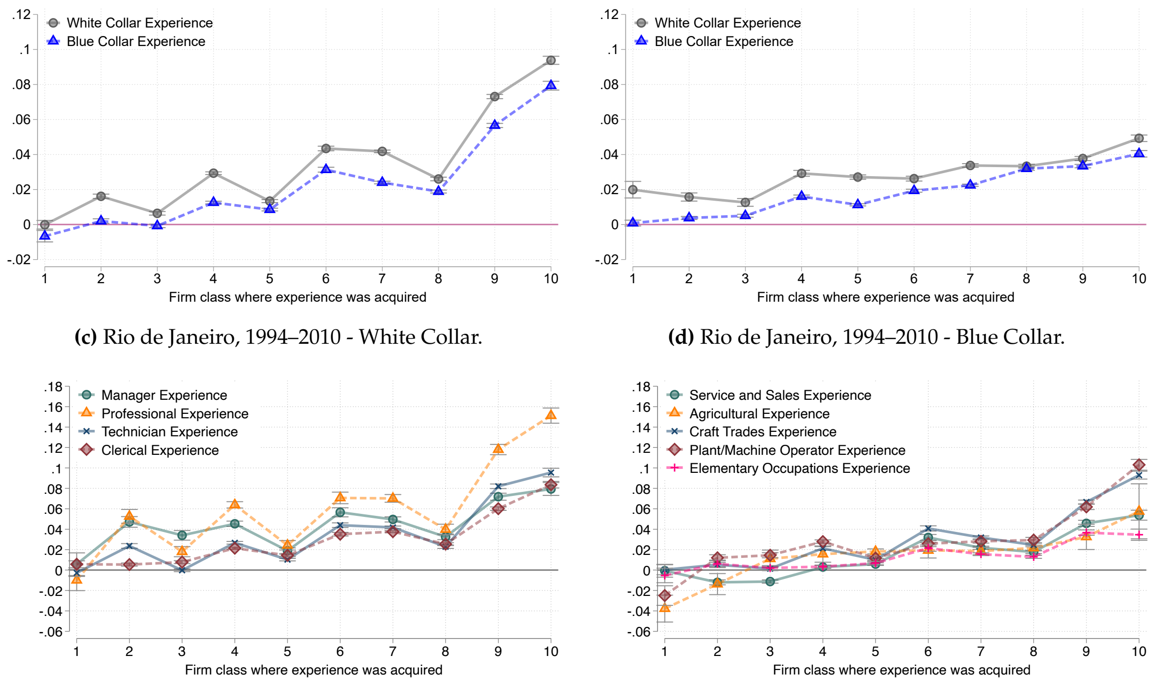
our interpretation of heterogeneous returns capturing differences in learning opportunities across firm classes compared to alternative worker-based interpretations. "Top-learning" firms are the same for high- and low-skilled workers, those with more or less education, as well as for men and women.

5.3 Occupation-specific heterogeneous returns

We assess whether firms' learning opportunities vary across occupations, estimating returns to heterogeneous experiences by occupation held *at the time during which such experience was acquired*. In both countries, we estimate heterogeneous returns to experiences across whether the worker was employed in a white- or a blue-collar occupation, implying we estimate heterogeneous returns for $2 \times K$ types of experiences. In Rio de Janeiro, we additionally estimate heterogeneous returns across the K firm classes and the nine one-digit ISCO occupations (i.e., a set of $9 \times K$ types of experiences).

We present results for blue- vs. white-collar heterogeneity in the first two panels of Figure 7. In both countries, one year of white-collar experience yields higher returns than one year of blue-collar experience, across all firm classes. However, the relative returns across

Figure 8: Returns to experiences acquired in different firm classes and occupations



(a) Rio de Janeiro, 1994–2010

(b) Veneto, 1984–2001.

(c) Rio de Janeiro, 1994–2010 - White Collar.

(d) Rio de Janeiro, 1994–2010 - Blue Collar.

Notes: Estimated γ_m^o parameters and 95% confidence intervals from log wage regressions of the form:

$$\ln y_{it} = \psi_{j(it)} + \alpha_i + \sum_{m=1}^{K} \sum_{o=1}^{O} \gamma_m^o \cdot \text{Exp}(m, o)_{it} + X_{it}'\beta + \eta_{it},$$

where $\text{Exp}(m, o)_{it}$ represents experience acquired in firm class m while being employed in occupation o. In panels (a) and (b), $O = 2$ and occupations are classified as either white or blue collar. Panels (c) and (d) refer to one single regression in which $O = 9$ and occupations are classified by their 1-digit ISCO code. The outcome variable for Rio de Janeiro is log hourly wages and log daily wages for Veneto. Standard errors are clustered at the person level. Corresponding Appendix regression tables: Table A12 for panel (a), Table A13 for panel (b), and Table A14 for panels (c) and (d).

firm classes are similar for both occupation groups. Experience acquired at "top-learning" firms has the highest returns, regardless of the type of occupation held at the time of acquiring such experience. Panels (c) and (d) disaggregate the returns across the specific one-digit occupation held by workers in Rio de Janeiro. Both panels similarly show that the profile of heterogeneous returns is rather similar across occupations and that workers employed in class-10 firms enjoy the largest estimated returns across all nine occupation groups.

Tasks. We examine further heterogeneity in the returns to experiences depending on the tasks the worker performed when employed at the firm. We present the estimated returns in Figure A10, finding that experience acquired in high non-routine content jobs leads to greater returns, yet, heterogeneity profiles are always parallel across the four types of tasks.

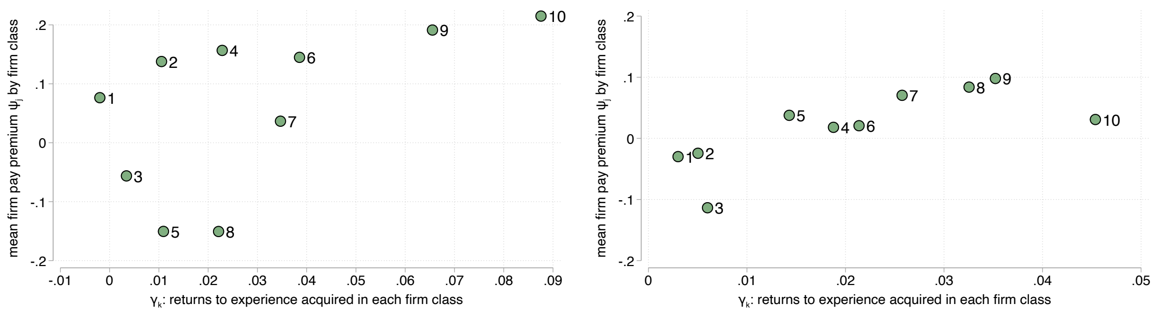
In sum, this subsection allays concerns that our firm classification and heterogeneous returns are simply driven by different occupation mixes across firm classes. We further examine the occupational composition of firm classes in Rio de Janeiro. In the first panel of Figure A11, we show that the prevalence of one-digit occupations does not vary systematically across firm classes. For instance, the prevalence of managerial jobs in class-10 firms is lower than in classes 7–9. The figure also shows that the task composition of jobs does not systematically vary across firm classes.

6 Learning Opportunities and Firm Pay Premia

We assess the empirical relationship between firms' pay premia and their learning opportunities. Each point in Figure 9 represents a firm class, the horizontal axis represents baseline estimates of γ_k (from Figure 1), and the vertical axis represents the average pay premium ψ_j in each firm class (weighted by worker-years). A negative slope would be suggestive of compensating differentials tied to learning opportunities. Yet, Figure 9 shows no evidence of such a negative relationship. If anything, firms with good learning opportunities offer slightly greater pay premiums: the correlation between ψ_j and $\gamma_{k(j)}$ is equal to around 0.18 in both Rio de Janeiro and Veneto.[36] The observed relationship could be explained by learning opportunities being positively correlated with firm productivity and more productive firms paying higher premiums (Card et al., 2018).

Figure 9: Firm pay premiums and on-the-job learning

(a) Rio de Janeiro, 1994–2010. **(b)** Veneto, 1984–2001.



Notes: Each dot represents a firm class, labeled from 1 to 10. Horizontal axis represents the baseline estimates of returns to class-specific experiences (γ_k parameters in equation (8)). Vertical axis represents the average firm pay premium in each firm class (ψ_j parameters in equation (8)). Sample includes largest connected set of firms (92.5% of firms in each of both countries). Average ψ_j in each firm class is weighted by worker-years. The correlation between the two sets of parameters, weighted by worker-years, is equal to 0.183 in Rio de Janeiro and 0.189 in Veneto.

The absence of a negative correlation between firm pay premiums and learning opportunities suggests that, from an individual's perspective, young workers do not typically face a tradeoff across employers between immediate monetary compensation and long-term compensation in terms of skill growth. The lack of such a tradeoff exacerbates the role of firms in wage inequality, as quantified in Section 4.

[36]This is consistent with recent evidence which uses data on non-wage firm attributes and employee satisfaction finding that higher-paying US firms provide *better* amenities (Sockin, 2021).

7 Are Firm Observables Predictive of Learning Opportunities?

Are firms with better learning opportunities easily recognizable by observable characteristics? We explore this question considering a wide range of firm attributes, but especially focusing on what existing work has identified as predictors of learning on the job: firm size (Arellano-Bover, 2020, 2022), large-city location (De La Roca and Puga, 2017), and coworkers' education or skills (Nix, 2020; Jarosch et al., 2021). We investigate the role of observables in two main ways: a machine learning algorithm that predicts firms' class, and a multinomial logit model rendering *ceteris paribus* associations of firm characteristics and firm class. We additionally report tables with unconditional workforce and firm mean characteristics across firm classes. We present summary results of the machine learning prediction exercise and relegate the discussion of the multinomial logit and unconditional mean tabulations to Appendix F.

How well do observables jointly predict firm class? Random forest classification

Using the data at the firm level (firm is the unit of observation, with characteristics averaged across years), we use half of the sample to train and validate a random forest classification algorithm (Athey and Imbens, 2019).[37] In the other half of the data, we use the algorithm to predict firm class and compare it against its actual classification. We feed the random forest a variety of firm characteristics, but no variables related to employees' wage growth as this is the input our clustering methodology described in Section 3.2 uses to classify firms.[38]

Table 2 shows results from the random forest prediction exercise. In both Rio de Janeiro and Veneto, the algorithm correctly classifies between 22–23% of firms. If we do the same exercise focusing only on large firms (50 employees or more), the algorithm correctly classifies 25% of large firms in Rio and 32% of large firms in Veneto. This prediction exercise indicates that firm observables are somewhat useful for predicting firms' skill-learning class, but do not suffice to accurately classify firms. Appendix F features further details on prediction accuracy.[39]

Individual firm characteristics and firm class.

Appendix F presents detailed estimates of the multinomial logit models linking observables to firm class as well as unconditional tabulations of workforce characteristics across

[37] A classification *tree* chooses how to split the training data as a function of covariates such that firm class within split is as homogeneous as possible. A random *forest* aggregates the predictions of many trees, where trees differ from each other because each one uses a different bootstrap sample and a different random subset of covariates.

[38] The firm-level characteristics we feed the random forest include mean annual earnings, firm effects $\hat{\psi}_j$ from equation (8), workforce age and gender distribution, firm size, geographic location, and 2-digit sector. For Rio de Janeiro, we additionally use the workforce education distribution, task allocation, and a dummy for export-intensive 5-digit sectors.

[39] Figure A12 shows the distribution of *actual* firm class, separately for each value of *predicted* firm class. This exhibit presents further evidence of observables having some but not substantial prediction power.

Table 2: Predicting firm class using observables: Random forest classification results.

(a) All firms

	Rio de Janeiro, 1994–2010	Veneto, 1984–2001
Number of firms to classify	63,904	38,592
Correctly classified by algorithm	23.04%	22.22%

(b) Firms with $\geq$ 50 employees

	Rio de Janeiro, 1994–2010	Veneto, 1984–2001
Number of firms to classify	4,108	1,336
Correctly classified by algorithm	25.34%	32.78%

Notes: Results from four distinct random forest classification algorithms (one for each combination of Rio de Janeiro/Veneto, and all firms/large firms). Data is at the firm level, and the goal is to correctly classify each firm into its firm class (out of a total of 10 firm classes). Firm attributes algorithm uses: Mean annual earnings, firm effects $\hat{\psi}_j$ from equation (8), workforce age and gender distribution, firm size, geographic location, and 2-digit sector (for Rio de Janeiro and Veneto); additional covariates for Rio de Janeiro: workforce education distribution, firm's task composition, and export-intensive sector dummy. Out of all firms in the data, half are set aside for prediction and the remaining half are used to train and validate the algorithm. Table shows number of firms and percent of correct predictions for the sample set aside for prediction.

firm classes.[40] The key takeaway is that, consistently with the machine learning prediction exercise, some mild associations between firm observables and learning classes emerge—e.g., larger firms in both countries are less likely to belong to the worst learning class and, in Veneto, firms in the largest cities are somewhat more likely to belong to the top learning classes—but no strong association conclusively linking a particular type of firm with a particular firm class arises.

8 Conclusion

We have documented evidence that is consistent with large disparities across firms in the human capital development opportunities afforded to their young workers. The differences in learning opportunities we find are substantial, suggesting important lifecycle implications for workers depending on which firms they match with in the early career. In fact, we show that employment experiences across firms more or less suitable for learning explain a meaningful, and growing, share of wage inequality. Our findings are notably consistent across two rather different economies in Brazil and Italy.

We have also found that firms' observable characteristics are only mildly helpful to predict learning opportunities. We reach this conclusion after considering various firm attributes, yet our analysis is limited to observables typically available in administrative la-

[40] Using the data at the firm level, the multinomial logit model is of the form $Pr\left(k(j) = k|X_j\right)$, where j indexes firms, X_j are firm characteristics, and $k = 1, \ldots, 10$ are firm classes.

bor market datasets. Future research could investigate whether important firm attributes previously considered in the literature, yet unobserved to us—e.g., productivity, technological adoption, or multinational status—might improve the identification of firms with good learning opportunities.

Altogether, it is important to understand whether workers and policymakers can recognize firms' learning opportunities. Young workers' ability to identify firms with strong learning opportunities could be critical for their long-term outcomes. For policy purposes, identifying such employers would be especially relevant if firms that embody better learning do not internalize this fact, creating positive externalities by increasing the portable skills of mobile workers. The absence of a negative correlation between firms' pay premia and learning opportunities may indicate the existence of such externalities. In any case, further research and a different framework would be needed to study such efficiency questions rigorously.

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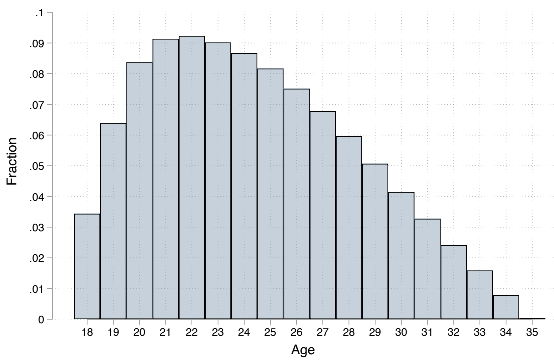
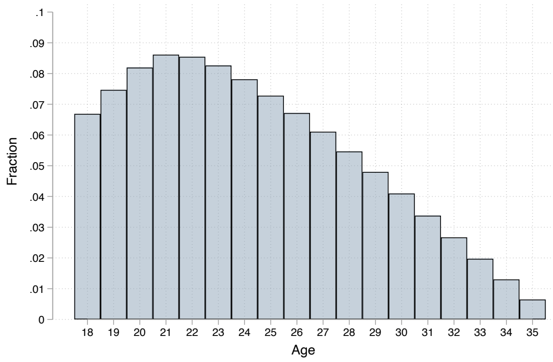
- SUPPLEMENTARY APPENDICES -
For Online Publication

A Additional Figures and Tables

A.1 Figures

Figure A1: Age distribution.

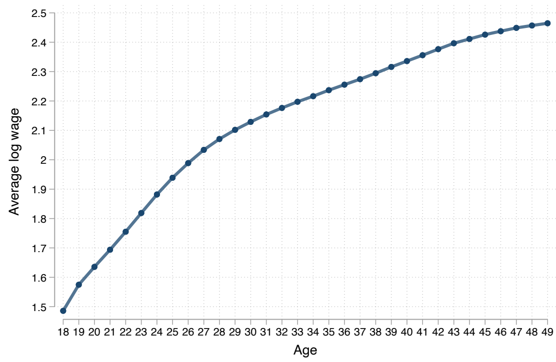




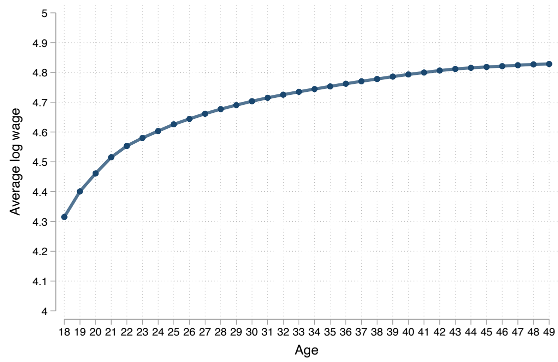
Notes: Worker-year age distribution for the samples of young workers used in our main analyses. Rio de Janeiro: workers born 1976 and after. Veneto: workers born 1966 and after.

Figure A2: Age and experience wage profiles.

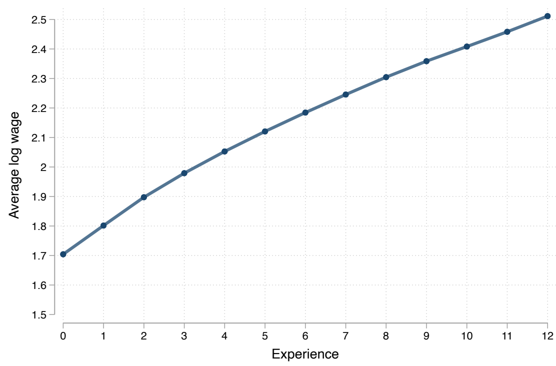
(a) Rio de Janeiro, age profile.



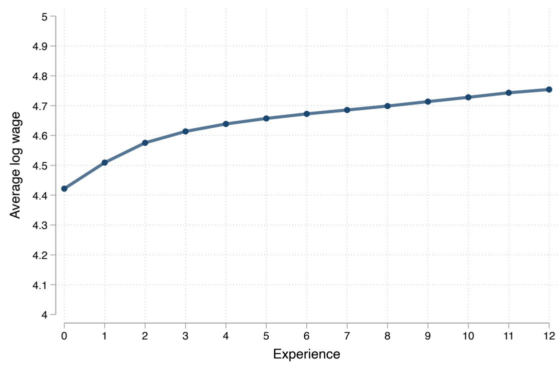
(b) Veneto, age profile.



(c) Rio de Janeiro, actual experience profile.



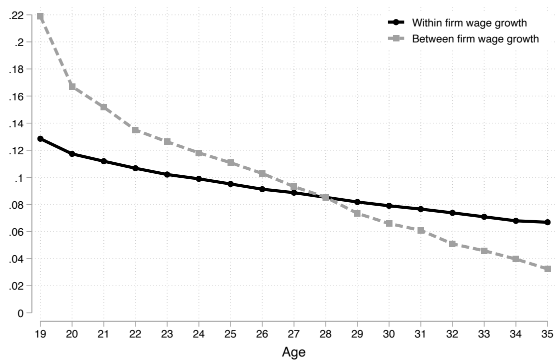
(d) Veneto, actual experience profile.



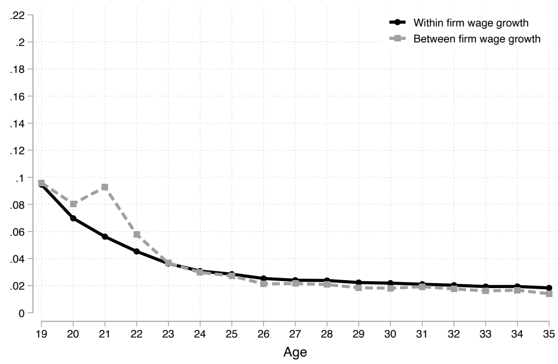
Notes: Average log wage age and years of (actual) experience profiles. Experience profiles are computed among the sample of young workers ages 18–35.

Figure A3: Within- and between-firm wage growth profiles.

(a) Rio de Janeiro, 1994–2010



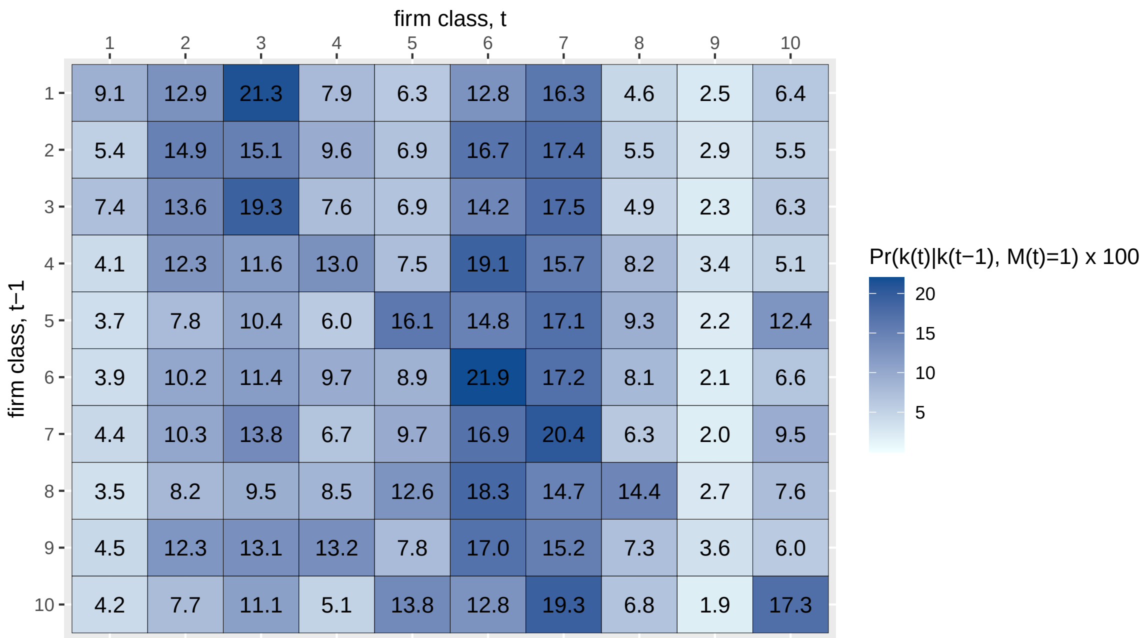
(b) Veneto, 1984–2001.



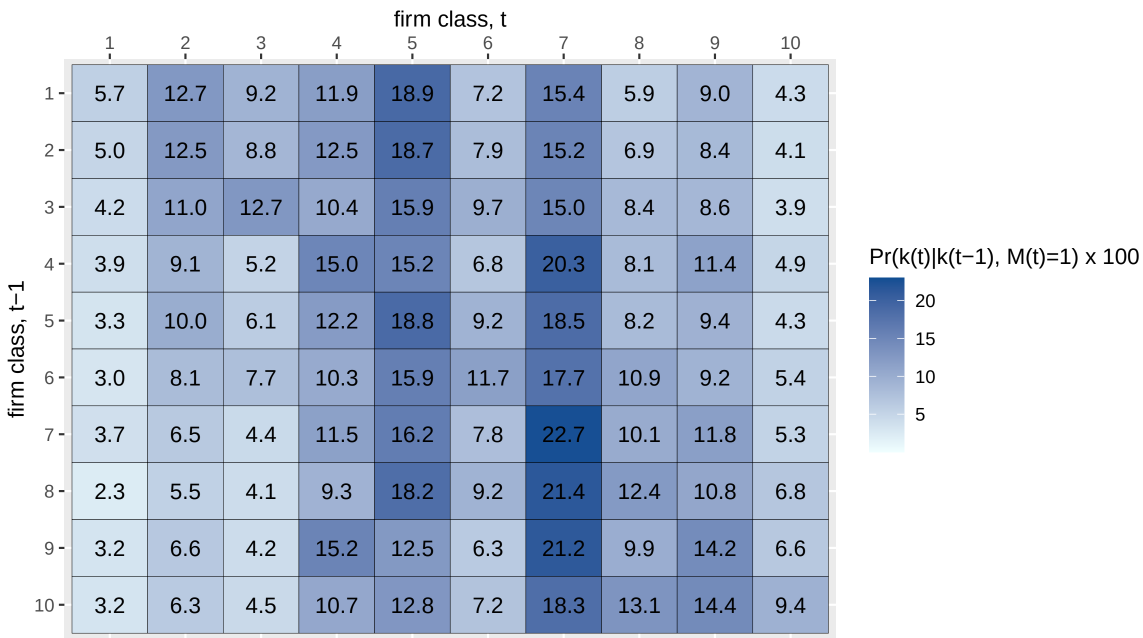
Notes: Average annual change in log wages, separately for firm stayers (within) and firm switchers (between).

Figure A4: Mobility across firm classes: Transition matrix.

(a) Rio de Janeiro, 1994–2010.



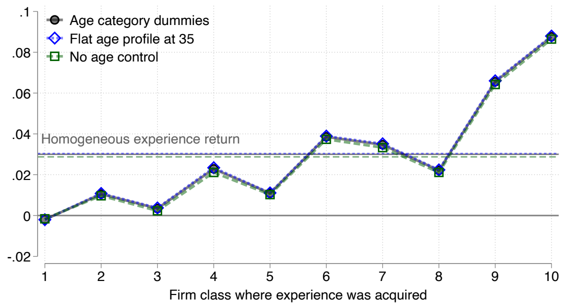
(b) Veneto, 1984–2001.



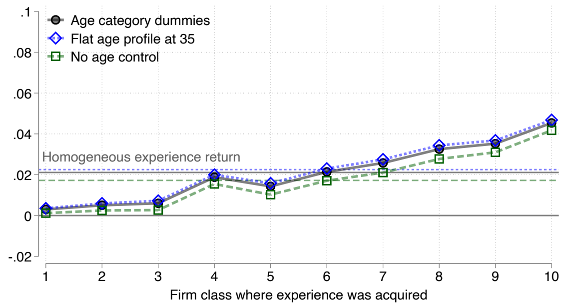
Notes: Each cell in the grid represents $100 \times Pr(k(t) \mid k(t-1), M(t) = 1)$, where $k(t)$ is firm class at period t, $k(t-1)$ is firm class at period $t-1$, and $M(t)$ is a dummy equal to one if a worker changes employers between periods $t-1$ and t.

Figure A5: Robustness by alternative age controls: returns to experiences acquired in different firm classes.

(a) Rio de Janeiro, 1994–2010.



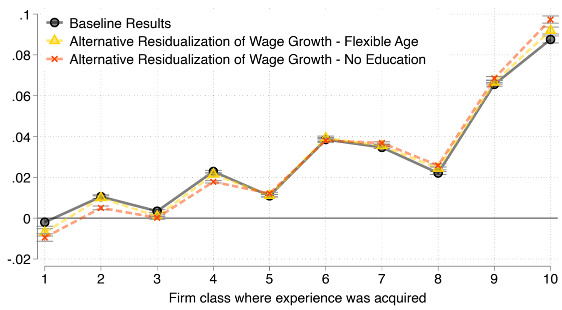
(b) Veneto, 1984–2001.



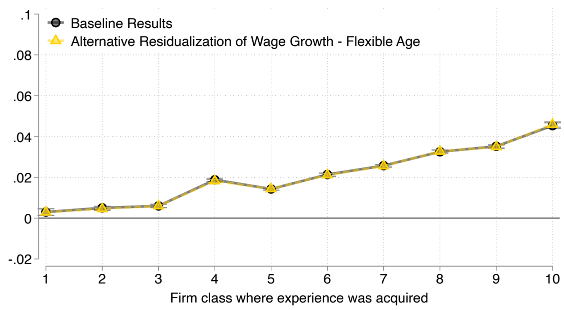
Notes: Estimates of returns to experiences acquired in different firm classes, using different ways of controlling for age effects. Black dots: baseline estimates from Figure 1, controlling for six age-category fixed effects. Blue diamonds: control for an age polynomial restricting the age profile to be flat at 35. Green squares: no age controls. Flat lines: returns to homogeneous experience for each respective age controls.

Figure A6: Robustness by alternative residualization of unexplained wage growth: returns to experiences acquired in different firm classes.

(a) Rio de Janeiro, 1994–2010.



(b) Veneto, 1984–2001.

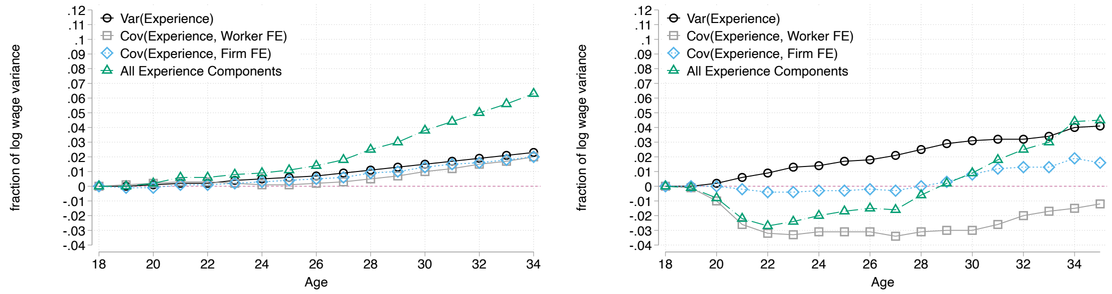


Notes: Estimates of returns to experiences acquired in different firm classes, using different ways of residualizing unexplained wage growth. Black dots: baseline estimates from Figure 1. Yellow diamonds: fully flexible specification of age effects; in Rio de Janeiro, the fully flexible age profiles are further education-specific. Orange crosses in Rio de Janeiro only: same as baseline approach but without netting out education effects (i.e., fully comparable to Veneto baseline).

Figure A7: Variance decomposition: returns-to-experiences components over wage variance, by age.

(a) Homogeneous experiences
Rio de Janeiro, 1994–2010

(b) Homogeneous experiences
Veneto, 1984–2001

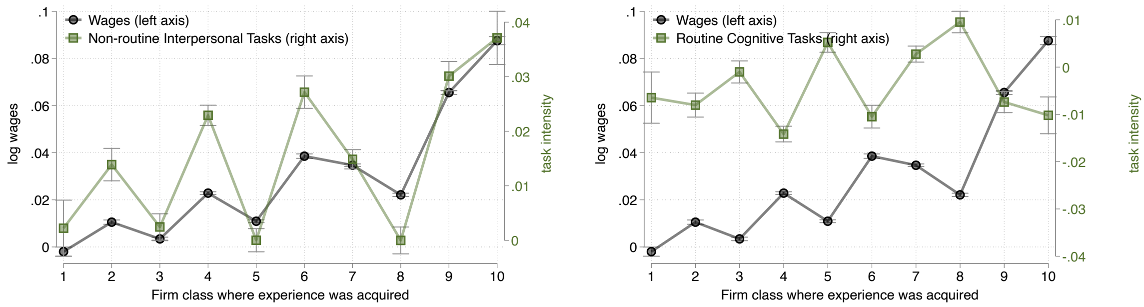


Notes: Shares of the wage variance explained by the homogeneous experiences components. Black dots represent the share of the variance explained by the variance of homogeneous experiences. Gray squares represent the share of the variance explained by the covariance of homogeneous experiences and worker fixed effects. Blue diamonds represent the share accounted for by the covariance of homogeneous experiences and firm fixed effects. Green triangles show the sum of these three components. Panels (a) and (b) present evidence from Rio de Janeiro and Veneto, respectively. Table A5 presents the full-sample variance decomposition for Rio de Janeiro and Veneto.

Figure A8: Task content returns to experiences acquired in different firm classes, Rio de Janeiro.

(a) Non-routine Interpersonal Tasks.

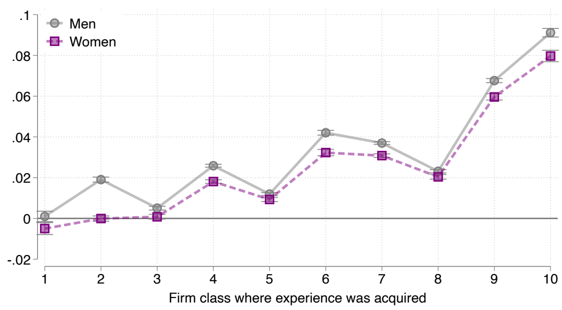
(b) Routine Cognitive Tasks.



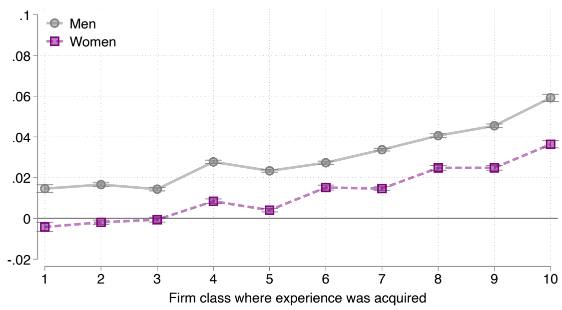
Notes: Black plot in all panels: Baseline estimates of earnings returns to experiences acquired in different firm classes, described in Figure 1. Green plots: Estimates and 95% confidence intervals of task content returns to experiences acquired in different firm classes. Standard errors clustered at the person level. All task intensities are measured in standard deviations. Outcome in panel (a) is intensity of non-routine interpersonal tasks; in panel (b), routine cognitive tasks. Number of observations=8,971,906. Corresponding Appendix regression table: Table A6.

Figure A9: Estimated separately for men and women: Returns to experiences acquired in different firm classes.

(a) Rio de Janeiro, 1994–2010.



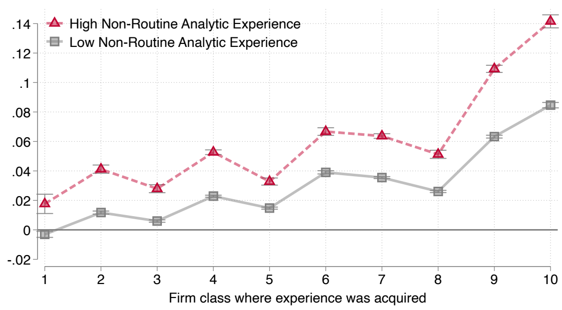
(b) Veneto, 1984–2001.



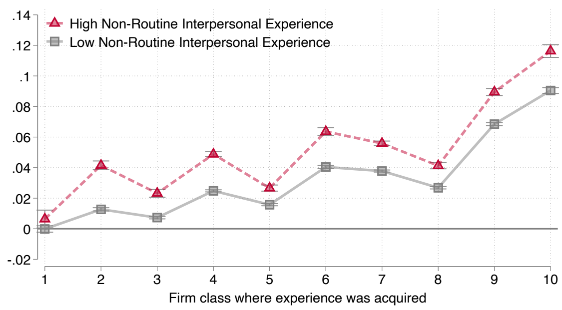
Notes: Point estimates of returns to experiences acquired in different firm classes, estimated heterogeneously for men and for women.

Figure A10: Returns to experiences acquired in different firm classes and task intensities, Rio de Janeiro

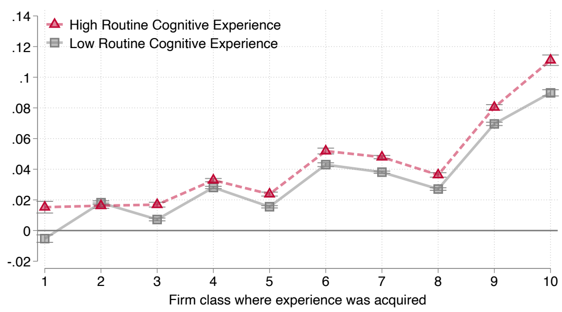
(a) Non-routine Analytic Tasks



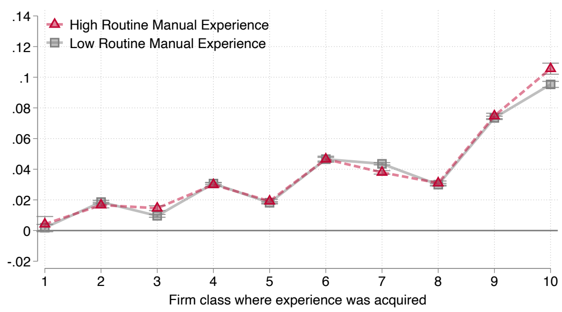
(b) Non-routine Interpersonal Tasks



(c) Routine Cognitive Tasks



(d) Routine Manual Tasks

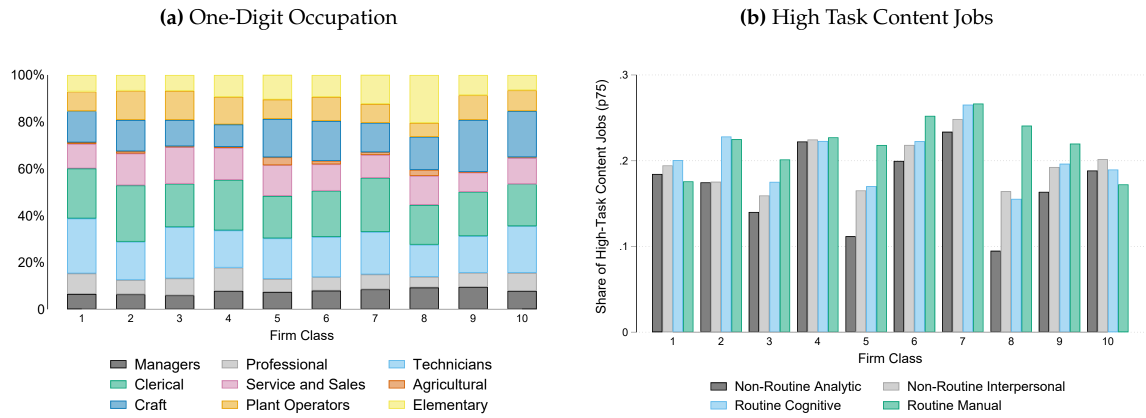


Notes: Estimated γ_m^τ parameters and 95% confidence intervals from log wage regressions of the form:

$$\ln y_{it} = \psi_{j(it)} + \alpha_i + \sum_{m=1}^{K} \sum_{\tau=1}^{T} \gamma_m^\tau \cdot \text{Exp}(m, \tau)_{it} + X_{it}'\beta + \eta_{it},$$

where $\text{Exp}(m, \tau)_{it}$ represents experience acquired in firm class m while being employed in a job with task content τ. For each panel, $T = 2$, $\tau = 1$ indexes jobs where task intensity is below the 75^{th} percentile, and $\tau = 2$ indexes jobs where task intensity is above the 75^{th} percentile. Panel (a) considers heterogeneity in the intensity of non-routine analytic tasks, panel (b) for non-routine interpersonal tasks, panel (c) for routine cognitive tasks, and panel (d) for routine manual tasks. Standard errors clustered at the person level.

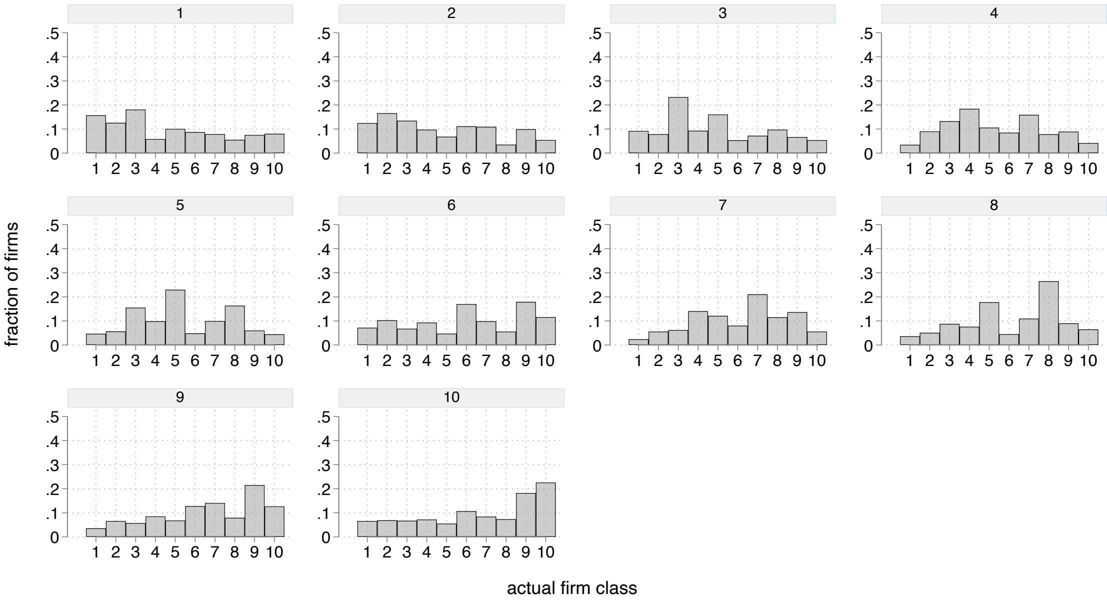
Figure A11: Occupation and task composition by firm class, Rio de Janeiro



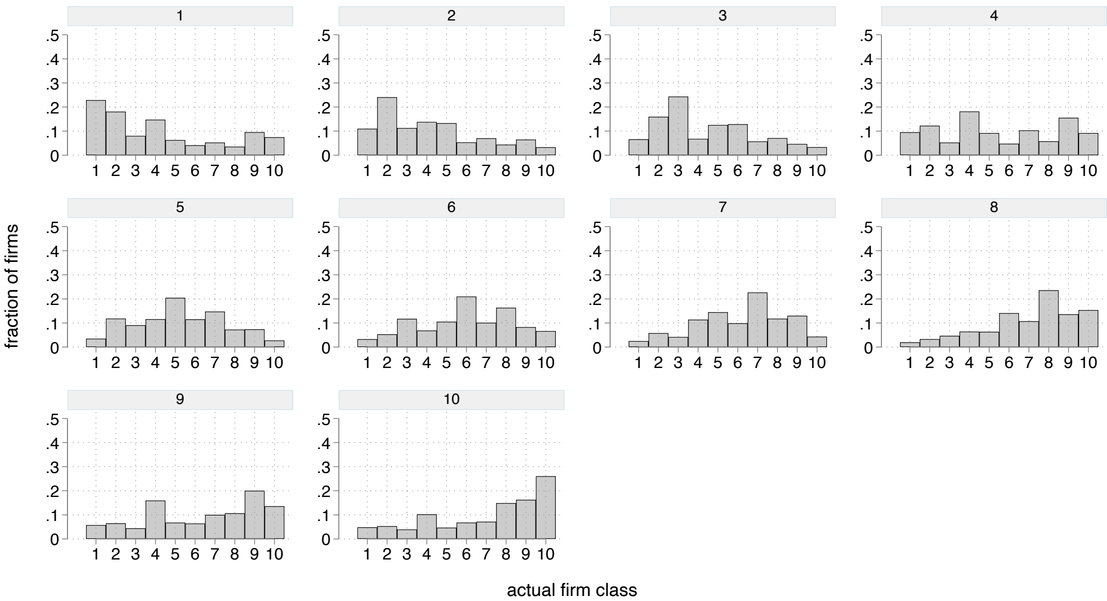
Notes: Panel (a): one-digit occupational composition across firm classes, depicting the share of jobs that belong to managerial, professional, technician, clerical, service and sales, agricultural, craft and trades, plant operators or elementary occupations across the ten firm classes in Rio de Janeiro. Panel (b): proportion of jobs with a task content above the 75^{th} percentile in the task content distribution, depicting the corresponding shares for non-routine analytic, non-routine interpersonal, routine cognitive and routine manual tasks across the ten firm classes in Rio de Janeiro. The corresponding shares in both panels are weighted by worker-years.

Figure A12: Firm-level distribution of actual firm class, separately by predicted firm class.

(a) Rio de Janeiro, 1994–2010.



(b) Veneto, 1984–2001.



Notes: Summary of the results of the random forest classification exercise described in Section 7, Table 2. Each firm j in the prediction data set is associated with its actual firm class, $k(j)$, and the one predicted by the random forest algorithm, $\hat{k}(j)$. This figure represents the firm-level distribution of $k(j)$, separately for each value of $\hat{k}(j)$. For example, the first subfigure in panel (a) shows the distribution of *actual* firm class, among firms in Rio de Janeiro that the random forest algorithm *predicted* to be of class 1.

A.2 Tables

Table A1: Returns to experiences acquired in different firm classes: Rio de Janeiro, 1994–2010.

	(1)	(2)	(3)	(4)	(5)	(6)
Experience	0.0445***	0.0357***	0.0300***			
	(0.0002)	(0.0002)	(0.0002)			
Experience: class 1				0.0024*	0.0042***	-0.0020**
				(0.0014)	(0.0012)	(0.0010)
Experience: class 2				0.0473***	0.0193***	0.0105***
				(0.0007)	(0.0006)	(0.0005)
Experience: class 3				-0.0032***	0.0029***	0.0034***
				(0.0006)	(0.0004)	(0.0004)
Experience: class 4				0.0542***	0.0314***	0.0229***
				(0.0005)	(0.0003)	(0.0003)
Experience: class 5				-0.0192***	0.0071***	0.0109***
				(0.0005)	(0.0004)	(0.0003)
Experience: class 6				0.0682***	0.0433***	0.0385***
				(0.0007)	(0.0006)	(0.0005)
Experience: class 7				0.0369***	0.0369***	0.0347***
				(0.0004)	(0.0003)	(0.0003)
Experience: class 8				-0.0124***	0.0177***	0.0221***
				(0.0006)	(0.0004)	(0.0004)
Experience: class 9				0.1006***	0.0754***	0.0655***
				(0.0007)	(0.0005)	(0.0004)
Experience: class 10				0.1305***	0.1033***	0.0876***
				(0.0015)	(0.0011)	(0.0009)
Experience: NC				-0.0143***	0.0250***	0.0203***
				(0.0007)	(0.0005)	(0.0004)
Experience: PS				0.0855***	0.0793***	0.0331***
				(0.0023)	(0.0029)	(0.0025)
Experience: non-RJ				0.0765***	0.0524***	0.0416***
				(0.0004)	(0.0003)	(0.0003)
Adj. R^2	0.259	0.662	0.759	0.286	0.665	0.761
Within adj. R^2		0.018	0.014		0.029	0.023
Person FE	no	yes	yes	no	yes	yes
Firm FE	no	no	yes	no	no	yes
SE clusters (persons)	1,928,968	1,580,092	1,568,990	1,928,968	1,580,092	1,568,990
N	9,673,897	9,326,951	9,168,318	9,673,897	9,326,951	9,168,318

Notes: Outcome is log hourly wage. Workers born in 1976 or later, ages 18–35. Private sector observations. Firm classes 1–10 represent our firm categorization based on unexplained earnings growth distributions. NC are small firms not categorized by the clustering algorithm. PS is the public sector. Non-RJ is experience acquired outside the state of Rio de Janeiro. All specifications include year fixed effects and control for age with six age-category indicators. Specifications without person fixed effects include a gender dummy and years of education (linear). Standard errors clustered at the person level. *p<0.10; **p<0.05; ***p<0.01.

Table A2: Returns to experiences acquired in different firm classes: Veneto, 1984–2001.

	(1)	(2)	(3)	(4)	(5)	(6)
Experience	0.0189***	0.0277***	0.0211***			
	(0.0001)	(0.0002)	(0.0002)			
Experience: class 1				-0.0024***	0.0057***	0.0030***
				(0.0006)	(0.0008)	(0.0008)
Experience: class 2				0.0012***	0.0087***	0.0050***
				(0.0003)	(0.0004)	(0.0004)
Experience: class 3				-0.0068***	0.0098***	0.0060***
				(0.0004)	(0.0004)	(0.0004)
Experience: class 4				0.0177***	0.0253***	0.0188***
				(0.0003)	(0.0004)	(0.0004)
Experience: class 5				0.0168***	0.0214***	0.0143***
				(0.0002)	(0.0003)	(0.0003)
Experience: class 6				0.0178***	0.0279***	0.0214***
				(0.0004)	(0.0004)	(0.0004)
Experience: class 7				0.0329***	0.0345***	0.0257***
				(0.0003)	(0.0003)	(0.0003)
Experience: class 8				0.0375***	0.0404***	0.0325***
				(0.0004)	(0.0004)	(0.0004)
Experience: class 9				0.0419***	0.0439***	0.0352***
				(0.0004)	(0.0004)	(0.0004)
Experience: class 10				0.0397***	0.0511***	0.0454***
				(0.0007)	(0.0007)	(0.0007)
Experience: NC				-0.0022***	0.0285***	0.0258***
				(0.0003)	(0.0004)	(0.0004)
Experience: PS				0.0317***	0.0329***	0.0184***
				(0.0034)	(0.0050)	(0.0045)
Experience: non-Veneto				0.0346***	0.0356***	0.0266***
				(0.0004)	(0.0004)	(0.0004)
Adj. R^2	0.149	0.464	0.602	0.174	0.469	0.606
Within adj. R^2		0.026	0.018		0.036	0.026
Person FE	no	yes	yes	no	yes	yes
Firm FE	no	no	yes	no	no	yes
SE clusters (persons)	564,332	490,376	483,799	564,332	490,376	483,799
N	3,767,051	3,693,095	3,608,754	3,767,051	3,693,095	3,608,754

Notes: Outcome is log daily wage. Workers born in 1966 or later, ages 18–35. Private sector observations. Firm classes 1–10 represent our firm categorization based on unexplained earnings growth distributions. NC are small firms not categorized by the clustering algorithm. PS is the public sector. Non-Veneto is experience acquired outside the region of Veneto. All specifications include year fixed effects and control for age with six age-category indicators. Specifications without person fixed effects include a gender dummy. Standard errors clustered at the person level. *p<0.10; **p<0.05; ***p<0.01.

Table A3: Returns to experiences acquired in different firm classes: Quadratic experience terms. Rio de Janeiro.

Firm class, k / $Exp(k)$	1	2	3	4	5	6	7	8	9	10
1	-0.006	0.015	0.003	0.030	0.006	0.053	0.039	0.018	0.079	0.106
3	-0.013	0.038	0.010	0.082	0.023	0.140	0.113	0.059	0.219	0.285
5	-0.014	0.054	0.015	0.124	0.046	0.204	0.178	0.104	0.336	0.423
10	0.012	0.060	0.026	0.181	0.130	0.259	0.309	0.240	0.525	0.582

Notes: Experience profiles evaluated at one, three, five, and ten years of experience using estimates of heterogeneous returns to different classes of experience featuring a quadratic functional form. That is, an extension of equation (8) (specification of columns (6) in Tables A1 and A2) where heterogeneous experiences, instead of entering linearly, enter as $\gamma_{1k}Exp(k) + \gamma_{2k}Exp(k)^2$. This table shows $\hat{\gamma}_{1k}e + \hat{\gamma}_{2k}e^2$ for $e \in \{1, 3, 5, 10\}$, and $k \in \{1, 2, \ldots, 10\}$.

Table A4: Returns to experiences acquired in different firm classes: Quadratic experience terms. Veneto.

Firm class, k / $Exp(k)$	1	2	3	4	5	6	7	8	9	10
1	0.005	0.012	0.011	0.024	0.019	0.026	0.033	0.042	0.045	0.058
3	0.012	0.030	0.029	0.067	0.053	0.074	0.093	0.116	0.124	0.158
5	0.015	0.041	0.041	0.102	0.081	0.115	0.143	0.178	0.190	0.239
10	0.004	0.036	0.049	0.156	0.127	0.189	0.228	0.282	0.293	0.352

Notes: Experience profiles evaluated at one, three, five, and ten years of experience using estimates of heterogeneous returns to different classes of experience featuring a quadratic functional form. That is, an extension of equation (8) (specification of columns (6) in Tables A1 and A2) where heterogeneous experiences, instead of entering linearly, enter as $\gamma_{1k}Exp(k) + \gamma_{2k}Exp(k)^2$. This table shows $\hat{\gamma}_{1k}e + \hat{\gamma}_{2k}e^2$ for $e \in \{1, 3, 5, 10\}$, and $k \in \{1, 2, \ldots, 10\}$.

Table A5: Wage variance decomposition, Rio de Janeiro and Veneto

	Rio de Janeiro		Veneto	
	Heterogeneous (1)	Homogeneous (2)	Heterogeneous (3)	Homogeneous (4)
$Var(y_{it})$	0.45247 [100.0]	0.45247 [100.0]	0.14116 [100.0]	0.14116 [100.0]
$Var(\alpha_i)$	0.14704 [32.5]	0.14923 [33.0]	0.04877 [34.5]	0.04947 [35.0]
$Var(\psi_j)$	0.11567 [25.6]	0.11700 [25.9]	0.05318 [37.7]	0.05386 [38.2]
$Var(\gamma Exp)$	0.00920 [2.0]	0.00616 [1.4]	0.00639 [4.5]	0.00477 [3.4]
$Var(X_{it}\beta)$	0.01925 [4.3]	0.01943 [4.3]	0.00404 [2.9]	0.00402 [2.8]
$2 \times Cov(\alpha_i, \psi_j)$	0.05111 [11.3]	0.05602 [12.4]	-0.01785 [-12.6]	-0.01704 [-12.1]
$2 \times Cov(\alpha_i, \gamma Exp)$	0.00779 [1.7]	0.00710 [1.6]	0.00183 [1.3]	0.00212 [1.5]
$2 \times Cov(\alpha_i, X_{it}\beta)$	-0.01431 [-3.2]	-0.01465 [-3.2]	-0.00437 [-3.1]	-0.00430 [-3.0]
$2 \times Cov(\psi_j, \gamma Exp)$	0.01264 [2.8]	0.00709 [1.6]	0.00293 [2.1]	0.00156 [1.1]
$2 \times Cov(\psi_j, X_{it}\beta)$	0.00461 [1.0]	0.00510 [1.1]	-0.00025 [-0.2]	-0.00023 [-0.2]
$2 \times Cov(\gamma Exp, X_{it}\beta)$	0.00444 [1.0]	0.00439 [1.0]	-0.00008 [-0.1]	-0.00001 [0.0]
$Var(\eta_{it})$	0.08487 [18.8]	0.08564 [18.9]	0.04383 [31.0]	0.04421 [31.3]

Notes: Shares of the (log) wage variance explained by the various components of equation (8). The first row denotes the overall wage variance. The numbers in brackets indicate the percent of the overall variance accounted for by each of the components in equation (8). Columns (1) and (3) show results using our approach with heterogeneous experiences. Columns (2) and (4) show corresponding results when making an "homogeneous experience" assumption.

Table A6: Task content returns to experiences acquired in different firm classes, Rio de Janeiro

	Non-Routine Analytic	Non-Routine Interpersonal	Routine Cognitive	Routine Manual
	(1)	(2)	(3)	(4)
Experience: class 1	0.0028	0.0022	-0.0065**	-0.0115***
	(0.0029)	(0.0026)	(0.0028)	(0.0032)
Experience: class 2	-0.0005	0.0139***	-0.0080***	-0.0133***
	(0.0014)	(0.0015)	(0.0013)	(0.0015)
Experience: class 3	-0.0020	0.0024**	-0.0010	-0.0007
	(0.0014)	(0.0012)	(0.0012)	(0.0014)
Experience: class 4	0.0148***	0.0229***	-0.0142***	-0.0160***
	(0.0010)	(0.0009)	(0.0008)	(0.0010)
Experience: class 5	-0.0018	0.0000	0.0052***	-0.0003
	(0.0012)	(0.0011)	(0.0011)	(0.0013)
Experience: class 6	0.0304***	0.0272***	-0.0105***	-0.0301***
	(0.0015)	(0.0015)	(0.0012)	(0.0016)
Experience: class 7	0.0166***	0.0149***	0.0027***	-0.0256***
	(0.0010)	(0.0009)	(0.0009)	(0.0011)
Experience: class 8	-0.0019	-0.0000	0.0095***	-0.0099***
	(0.0014)	(0.0013)	(0.0012)	(0.0015)
Experience: class 9	0.0321***	0.0301***	-0.0074***	-0.0311***
	(0.0013)	(0.0014)	(0.0011)	(0.0016)
Experience: class 10	0.0379***	0.0371***	-0.0102***	-0.0316***
	(0.0025)	(0.0025)	(0.0020)	(0.0027)
Experience: NC	-0.0029**	0.0002	0.0026**	-0.0048***
	(0.0014)	(0.0012)	(0.0012)	(0.0015)
Experience: PS	0.0759***	0.0616***	-0.0490***	-0.0476***
	(0.0069)	(0.0064)	(0.0057)	(0.0066)
Experience: non-RJ	0.0271***	0.0269***	-0.0078***	-0.0245***
	(0.0009)	(0.0009)	(0.0008)	(0.0010)
adj. R^2	0.695	0.641	0.650	0.736
Person FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
N	8,947,269	8,947,269	8,947,269	8,947,269

Notes: Outcome variables capture non-routine analytic, non-routine interpersonal, routine cognitive and routine manual task content. Task content is as defined in the text. Workers born in 1976 or later. Firm classes 1–10 represent our firm categorization based on unexplained earnings growth distributions. NC are small firms not categorized by the clustering algorithm. PS is the public sector in each data set. Specifications estimated following equation (8). All specifications include year fixed effects and control for age with six age-category indicators. Standard errors clustered at the person level. *p<0.10; **p<0.05; ***p<0.01.

Table A7: Returns to experiences acquired in different firm classes: job switchers and stayers.

	Rio de Janeiro (1)	Veneto (2)
Stayer: Experience: class 1	-0.0063***	0.0043***
	(0.0011)	(0.0009)
Switcher: Experience: class 1	-0.0073***	0.0090***
	(0.0013)	(0.0010)
Stayer: Experience: class 2	0.0065***	0.0075***
	(0.0005)	(0.0005)
Switcher: Experience: class 2	0.0020***	0.0093***
	(0.0006)	(0.0006)
Stayer: Experience: class 3	-0.0001	0.0088***
	(0.0004)	(0.0004)
Switcher: Experience: class 3	0.0014**	0.0090***
	(0.0006)	(0.0007)
Stayer: Experience: class 4	0.0185***	0.0204***
	(0.0003)	(0.0004)
Switcher: Experience: class 4	0.0136***	0.0206***
	(0.0004)	(0.0005)
Stayer: Experience: class 5	0.0083***	0.0169***
	(0.0003)	(0.0003)
Switcher: Experience: class 5	0.0062***	0.0175***
	(0.0005)	(0.0004)
Stayer: Experience: class 6	0.0340***	0.0236***
	(0.0005)	(0.0004)
Switcher: Experience: class 6	0.0229***	0.0223***
	(0.0006)	(0.0006)
Stayer: Experience: class 7	0.0388***	0.0275***
	(0.0004)	(0.0003)
Switcher: Experience: class 7	0.0279***	0.0269***
	(0.0004)	(0.0004)
Stayer: Experience: class 8	0.0186***	0.0343***
	(0.0004)	(0.0004)
Switcher: Experience: class 8	0.0149***	0.0314***
	(0.0005)	(0.0006)
Stayer: Experience: class 9	0.0609***	0.0364***
	(0.0005)	(0.0004)
Switcher: Experience: class 9	0.0473***	0.0339***
	(0.0006)	(0.0006)
Stayer: Experience: class 10	0.0788***	0.0463***
	(0.0009)	(0.0007)
Switcher: Experience: class 10	0.0666***	0.0402***
	(0.0011)	(0.0009)
Stayer: Experience: NC	0.0149***	0.0250***
	(0.0005)	(0.0005)
Switcher: Experience: NC	0.0097***	0.0216***
	(0.0006)	(0.0006)
Stayer: Experience: PS	0.0294***	0.0148***
	(0.0005)	(0.0044)
Switcher: Experience: PS	0.0447***	0.0128***
	(0.0009)	(0.0045)
Stayer: Experience: Other	0.0390***	0.0274***
	(0.0003)	(0.0004)
Switcher: Experience: Other	0.0301***	0.0273***
	(0.0003)	(0.0005)
Adj. R^2	0.780	0.602
Within adj. R^2	0.027	0.025
Person FE	yes	yes
Firm FE	yes	yes
Sample	all	all
SE clusters (persons)	1392970	424783
N	8151185	3077499

Notes: We present the estimated returns to heterogeneous experiences for job switchers and stayers from equation in Rio de Janeiro and Veneto in columns (1) and (2), respectively. The outcome variable for Rio de Janeiro is log hourly wages and log daily wages for Veneto. Standard errors are clustered at the person level. NC are small firms not categorized by the clustering algorithm. PS is the public sector in each data set. Other is experience acquired outside the state of Rio de Janeiro or outside the region of Veneto. All specifications include worker and firm fixed effects and control for age with six age-category indicators. Robust standard errors in parentheses. *p<0.10; **p<0.05; ***p<0.01.

Table A8: Returns to experiences acquired in different firm classes: hiring wages and dual wage ladder specification.

	Rio de Janeiro		Veneto	
	(1)	(2)	(3)	(4)
Experience: class 1	-0.0012	-0.0022	0.0002	-0.0009
	(0.0016)	(0.0018)	(0.0013)	(0.0016)
Experience: class 2	0.0027***	0.0001	0.0016**	0.0012
	(0.0008)	(0.0009)	(0.0007)	(0.0009)
Experience: class 3	0.0030***	0.0034***	0.0016*	0.0017
	(0.0007)	(0.0008)	(0.0008)	(0.0012)
Experience: class 4	0.0149***	0.0104***	0.0139***	0.0128***
	(0.0005)	(0.0006)	(0.0006)	(0.0008)
Experience: class 5	0.0022***	0.0067***	0.0121***	0.0120***
	(0.0006)	(0.0007)	(0.0005)	(0.0007)
Experience: class 6	0.0252***	0.0190***	0.0164***	0.0164***
	(0.0007)	(0.0008)	(0.0008)	(0.0011)
Experience: class 7	0.0205***	0.0179***	0.0228***	0.0217***
	(0.0005)	(0.0006)	(0.0005)	(0.0007)
Experience: class 8	0.0077***	0.0126***	0.0252***	0.0244***
	(0.0006)	(0.0008)	(0.0008)	(0.0010)
Experience: class 9	0.0473***	0.0384***	0.0277***	0.0254***
	(0.0007)	(0.0008)	(0.0007)	(0.0009)
Experience: class 10	0.0724***	0.0568***	0.0322***	0.0282***
	(0.0013)	(0.0015)	(0.0011)	(0.0014)
Experience: NC	0.0102***	0.0140***	0.0126***	0.0123***
	(0.0008)	(0.0011)	(0.0007)	(0.0011)
Experience: PS	0.0339***	0.0257***	0.0143**	0.0035
	(0.0027)	(0.0033)	(0.0056)	(0.0070)
Experience: non-RJ	0.0308***	0.0265***	0.0230***	0.0240***
	(0.0004)	(0.0005)	(0.0006)	(0.0009)
Adj. R^2	0.671	0.680	0.563	0.570
Within adj. R^2	0.013	0.005	0.023	0.012
Person FE	yes	yes	yes	yes
Destination Firm FE	yes	yes	yes	yes
Origin Firm FE	no	yes	no	yes
SE clusters (persons)	1,120,670	1,074,347	333,452	299,933
N	3,683,279	3,455,832	1,033,457	899,368

Notes: We present the estimated returns to heterogeneous experiences for job switchers and stayers from equation in Rio de Janeiro and Veneto in columns (1)-(2) and (3)-(4), respectively. Odd columns only include destination firm fixed effects. Even columns include *both* destination and origin firm fixed effects. The outcome variable for Rio de Janeiro is log hourly wages and log daily wages for Veneto. Standard errors are clustered at the person level. NC are small firms not categorized by the clustering algorithm. PS is the public sector in each data set. Other is experience acquired outside the state of Rio de Janeiro or outside the region of Veneto. Both specifications include individuals starting a new job, such that the sample includes wage observations in first jobs. All specifications include worker and firm fixed effects and control for age with six age-category indicators. Robust standard errors in parentheses. *p<0.10; **p<0.05; ***p<0.01.

Table A9: Returns to experiences acquired in different firm classes in first post-displacement observation: Rio de Janeiro and Veneto.

	(1)	(2)	(3)	(4)
Experience: class 1	0.0096***	0.0056**	0.0031	0.0045
	(0.0024)	(0.0024)	(0.0033)	(0.0033)
Experience: class 2	0.0137***	0.0099***	0.0075***	0.0089***
	(0.0011)	(0.0011)	(0.0016)	(0.0016)
Experience: class 3	0.0048***	0.0009	0.0031*	0.0046**
	(0.0011)	(0.0011)	(0.0019)	(0.0018)
Experience: class 4	0.0236***	0.0202***	0.0156***	0.0173***
	(0.0007)	(0.0007)	(0.0014)	(0.0014)
Experience: class 5	0.0060***	0.0020**	0.0128***	0.0143***
	(0.0009)	(0.0009)	(0.0011)	(0.0010)
Experience: class 6	0.0336***	0.0298***	0.0153***	0.0167***
	(0.0010)	(0.0010)	(0.0022)	(0.0022)
Experience: class 7	0.0308***	0.0269***	0.0234***	0.0249***
	(0.0007)	(0.0007)	(0.0010)	(0.0009)
Experience: class 8	0.0153***	0.0107***	0.0281***	0.0294***
	(0.0010)	(0.0010)	(0.0013)	(0.0013)
Experience: class 9	0.0606***	0.0564***	0.0341***	0.0356***
	(0.0009)	(0.0009)	(0.0014)	(0.0013)
Experience: class 10	0.0867***	0.0819***	0.0474***	0.0493***
	(0.0018)	(0.0018)	(0.0026)	(0.0026)
Experience: NC	0.0140***	0.0089***	0.0184***	0.0208***
	(0.0018)	(0.0018)	(0.0031)	(0.0030)
Experience: PS	0.0314***	0.0266***	-0.0223	-0.0142
	(0.0038)	(0.0038)	(0.0245)	(0.0244)
Experience: Other	0.0440***	0.0402***	0.0251***	0.0275***
	(0.0007)	(0.0007)	(0.0020)	(0.0020)
Adjusted R^2	0.730	0.729	0.536	0.536
Year FE	yes	yes	yes	yes
Time to Reentry	yes	no	yes	no
Observables	yes	yes	yes	yes
Worker FE	linear	linear	linear	linear
Firm FE	linear	linear	linear	linear
Observations	292495	292495	34923	34923

Notes: Outcome is hourly wage in Rio de Janeiro and daily wage in Veneto. Workers born in 1976 (1966) or later who were displaced in a mass layoff or firm closure event in Rio de Janeiro (Veneto). Mass layoff events and firm closures are defined in the text. Even columns present estimates that do not control for time to reentry. Firm classes 1–10 represent our firm categorization based on unexplained earnings growth distributions. NC are small firms not categorized by the clustering algorithm. PS is the public sector in each data set. Other is experience acquired outside the state of Rio de Janeiro or outside the region of Veneto. All specifications include worker and firm fixed effects from the main specification (see equation (15)) and control for age with six age-category indicators. Robust standard errors in parentheses. *p<0.10; **p<0.05; ***p<0.01.

Table A10: Returns to experiences acquired in different firm classes by workers' unobserved skills: Rio de Janeiro and Veneto.

	Rio de Janeiro (1)	Veneto (2)
Experience: class 1	-0.0075***	-0.0001
	(0.0009)	(0.0009)
Experience: class 1 $\times\alpha_i$	0.0175***	0.0173***
	(0.0015)	(0.0015)
Experience: class 2	-0.0008*	0.0020***
	(0.0004)	(0.0004)
Experience: class 2 $\times\alpha_i$	0.0248***	0.0178***
	(0.0006)	(0.0009)
Experience: class 3	0.0006*	0.0035***
	(0.0003)	(0.0004)
Experience: class 3 $\times\alpha_i$	0.0145***	0.0154***
	(0.0006)	(0.0008)
Experience: class 4	0.0152***	0.0152***
	(0.0003)	(0.0004)
Experience: class 4 $\times\alpha_i$	0.0213***	0.0194***
	(0.0004)	(0.0011)
Experience: class 5	0.0125***	0.0098***
	(0.0003)	(0.0003)
Experience: class 5 $\times\alpha_i$	0.0141***	0.0211***
	(0.0007)	(0.0009)
Experience: class 6	0.0322***	0.0198***
	(0.0004)	(0.0004)
Experience: class 6 $\times\alpha_i$	0.0228***	0.0159***
	(0.0006)	(0.0008)
Experience: class 7	0.0339***	0.0216***
	(0.0003)	(0.0003)
Experience: class 7 $\times\alpha_i$	0.0263***	0.0212***
	(0.0004)	(0.0010)
Experience: class 8	0.0268***	0.0315***
	(0.0004)	(0.0004)
Experience: class 8 $\times\alpha_i$	0.0168***	0.0191***
	(0.0007)	(0.0007)
Experience: class 9	0.0621***	0.0339***
	(0.0004)	(0.0004)
Experience: class 9 $\times\alpha_i$	0.0340***	0.0201***
	(0.0005)	(0.0010)
Experience: class 10	0.0825***	0.0470***
	(0.0008)	(0.0006)
Experience: class 10 $\times\alpha_i$	0.0444***	0.0219***
	(0.0009)	(0.0011)
Experience: NC	0.0229***	0.0274***
	(0.0004)	(0.0004)
Experience: NC $\times\alpha_i$	0.0210***	0.0060***
	(0.0006)	(0.0005)
Experience: PS	0.0230***	0.0167***
	(0.0020)	(0.0045)
Experience: PS $\times\alpha_i$	0.0166***	0.0232***
	(0.0030)	(0.0063)
Experience: Other	0.0301***	0.0233***
	(0.0003)	(0.0004)
Experience: Other $\times\alpha_i$	0.0262***	0.0179***
	(0.0003)	(0.0006)
Person FE	yes	yes
Firm FE	yes	yes
N	9,168,126	3,603,609

Notes: Outcome is log hourly wage in Rio de Janeiro and log daily wage in Veneto. Full sample of workers in Rio de Janeiro. Firm classes 1–10 represent our firm categorization based on unexplained earnings growth distributions. NC are small firms not categorized by the clustering algorithm. PS is the public sector in each data set. Other is experience acquired outside the state of Rio de Janeiro or outside the region of Veneto. All specifications include year fixed effects and control for age with six age-category indicators. We allow for returns to experiences acquired in different firm classes to differ across workers' unobserved skills recovered through the iterative method proposed by De La Roca and Puga (2017), as documented in Section 5.2. We present the estimates of the main effects, γ_m, and the interaction effects, δ_m, in equation (16). Standard errors clustered at the person level. *p<0.10; **p<0.05; ***p<0.01.

Table A11: Returns to experiences acquired in different firm classes by education: Rio de Janeiro.

	(1) Less than HS	(2) HS or more
Experience: class 1	-0.0032**	-0.0038***
	(0.0013)	(0.0014)
Experience: class 2	0.0051***	0.0116***
	(0.0007)	(0.0007)
Experience: class 3	0.0026***	0.0051***
	(0.0005)	(0.0006)
Experience: class 4	0.0148***	0.0270***
	(0.0004)	(0.0004)
Experience: class 5	0.0129***	0.0117***
	(0.0004)	(0.0006)
Experience: class 6	0.0333***	0.0414***
	(0.0007)	(0.0007)
Experience: class 7	0.0285***	0.0409***
	(0.0004)	(0.0004)
Experience: class 8	0.0242***	0.0249***
	(0.0004)	(0.0007)
Experience: class 9	0.0535***	0.0755***
	(0.0006)	(0.0006)
Experience: class 10	0.0708***	0.1004***
	(0.0013)	(0.0012)
Experience: NC	0.0171***	0.0247***
	(0.0005)	(0.0007)
Experience: PS	0.0140***	0.0332***
	(0.0048)	(0.0031)
Experience: non-RJ	0.0353***	0.0438***
	(0.0005)	(0.0004)
Adj. R^2	0.649	0.784
Within adj. R^2	0.021	0.024
Person FE	yes	yes
Firm FE	yes	yes
SE clusters (persons)	652,767	911,050
N	3,810,655	5,297,096

Notes: Outcome is hourly wage. Firm classes 1–10 represent our firm categorization based on unexplained earnings growth distributions. NC are small firms not categorized by the clustering algorithm. PS is the public sector in each data set. Other is experience acquired outside the state of Rio de Janeiro or outside the region of Veneto. All specifications include year fixed effects and control for age with six age-category indicators. We allow for returns to experiences acquired in different firm classes to differ depending on workers' educational attainment, encompassing high school dropouts and those with at least a high school degree. Standard errors clustered at the person level. *p<0.10; **p<0.05; ***p<0.01.

Table A12: Returns to experiences acquired in different firm classes, by occupation at the time experience was acquired: Rio de Janeiro.

		White Collar	Blue Collar
	(1)	(2)	(3)
Experience: White Collar	0.0354***		
	(0.0002)		
Experience: Blue Collar	0.0222***		
	(0.0002)		
Heterogeneous Experience: class 1		-0.0001	-0.0067***
		(0.0013)	(0.0017)
Heterogeneous Experience: class 2		0.0161***	0.0020***
		(0.0006)	(0.0007)
Heterogeneous Experience: class 3		0.0064***	-0.0008
		(0.0005)	(0.0005)
Heterogeneous Experience: class 4		0.0293***	0.0125***
		(0.0004)	(0.0004)
Heterogeneous Experience: class 5		0.0134***	0.0085***
		(0.0005)	(0.0004)
Heterogeneous Experience: class 6		0.0434***	0.0313***
		(0.0007)	(0.0007)
Heterogeneous Experience: class 7		0.0418***	0.0240***
		(0.0004)	(0.0004)
Heterogeneous Experience: class 8		0.0260***	0.0188***
		(0.0005)	(0.0004)
Heterogeneous Experience: class 9		0.0731***	0.0566***
		(0.0006)	(0.0006)
Heterogeneous Experience: class 10		0.0938***	0.0793***
		(0.0012)	(0.0013)
Heterogeneous Experience: NC		0.0234***	0.0131***
		(0.0006)	(0.0007)
Heterogeneous Experience: PS		0.0397***	-0.0096**
		(0.0030)	(0.0049)
Heterogeneous Experience: non-RJ		0.0488***	0.0330***
		(0.0004)	(0.0004)
Adj. R^2	0.759	0.762	
Within adj. R^2	0.155	0.163	
Person FE	yes	yes	
Firm FE	yes	yes	
SE clusters (persons)	1,568,990	1,568,990	
N	9,168,318	9,168,318	

Notes: Outcome is hourly wage. Firm classes 1–10 represent our firm categorization based on unexplained earnings growth distributions. NC are small firms not categorized by the clustering algorithm. PS is the public sector. Non-RJ is experience acquired outside the state of Rio de Janeiro. All specifications include year fixed effects and control for age with six age-category indicators. We allow for returns to experiences acquired in different firm classes to differ depending on occupation category at the time of acquiring experience. We classify occupations as either white- or blue-collar following a standard classification using occupational information at the one-digit ISCO level: We classify managers, professionals, technicians and associate professionals along with clerical support workers as white-collar occupations. Service and sales workers, skilled agricultural, forestry and fishery workers, craft and related trades workers, plant and machine operators, assemblers and workers in elementary occupations encompass blue collar occupations. The second and third columns present evidence from a single regression. Standard errors clustered at the person level. *p<0.10; **p<0.05; ***p<0.01.

Table A13: Returns to experiences acquired in different firm classes by occupation at the time experience was acquired: Veneto.

	(1)	White Collar (2)	Blue Collar (3)
Experience: White Collar	0.0317***		
	(0.0003)		
Experience: Blue Collar	0.0170***		
	(0.0002)		
Heterogeneous Experience: class 1		0.0199***	0.0008
		(0.0024)	(0.0009)
Heterogeneous Experience: class 2		0.0157***	0.0037***
		(0.0012)	(0.0004)
Heterogeneous Experience: class 3		0.0126***	0.0050***
		(0.0011)	(0.0004)
Heterogeneous Experience: class 4		0.0292***	0.0160***
		(0.0009)	(0.0004)
Heterogeneous Experience: class 5		0.0271***	0.0112***
		(0.0006)	(0.0003)
Heterogeneous Experience: class 6		0.0262***	0.0193***
		(0.0007)	(0.0004)
Heterogeneous Experience: class 7		0.0337***	0.0224***
		(0.0005)	(0.0003)
Heterogeneous Experience: class 8		0.0333***	0.0319***
		(0.0006)	(0.0005)
Heterogeneous Experience: class 9		0.0377***	0.0334***
		(0.0006)	(0.0005)
Heterogeneous Experience: class 10		0.0493***	0.0404***
		(0.0009)	(0.0009)
Heterogeneous Experience: NC		0.0246***	0.0264***
		(0.0007)	(0.0005)
Heterogeneous Experience: PS		0.0313***	0.0099
		(0.0062)	(0.0061)
Heterogeneous Experience: non-Veneto		0.0394***	0.0177***
		(0.0006)	(0.0004)
Adj. R^2	0.604	0.607	
Within adj. R^2	0.092	0.098	
Person FE	yes	yes	
Firm FE	yes	yes	
SE clusters (persons)	483,799	483,799	
N	3,608,754	3,608,754	

Notes: Outcome is daily wage. Firm classes 1–10 represent our firm categorization based on unexplained earnings growth distributions. NC are small firms not categorized by the clustering algorithm. PS is the public sector. Non-Veneto is experience acquired outside the region of Veneto. All specifications include year fixed effects and control for age with six age-category indicators. We allow for returns to experiences acquired in different firm classes to differ depending on occupation type at the time of acquiring experience. White collar jobs are those classified as either managerial or 'white collar' in the Veneto data. Blue collar jobs are those classified as 'blue collar' or apprenticeships. The second and third columns present evidence from a single regression. Standard errors clustered at the person level. *p<0.10; **p<0.05; ***p<0.01.

Table A14: Returns to experiences acquired in different firm classes, by one-digit occupation at the time experience was acquired: Rio de Janeiro.

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	NC	PS	Non-RJ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Manager Experience	0.0057	0.0471***	0.0340***	0.0453***	0.0189***	0.0566***	0.0496***	0.0325***	0.0718***	0.0794***	0.0213***	-0.0072	0.0801***
	(0.0057)	(0.0027)	(0.0024)	(0.0013)	(0.0014)	(0.0023)	(0.0013)	(0.0014)	(0.0017)	(0.0032)	(0.0014)	(0.0107)	(0.0015)
Professional Experience	-0.0099*	0.0526***	0.0180***	0.0639***	0.0243***	0.0706***	0.0702***	0.0397***	0.1180***	0.1512***	0.0219***	0.0494***	0.0952***
	(0.0052)	(0.0034)	(0.0025)	(0.0016)	(0.0024)	(0.0029)	(0.0019)	(0.0026)	(0.0026)	(0.0038)	(0.0031)	(0.0081)	(0.0016)
Technicians Experience	-0.0028	0.0236***	-0.0002	0.0267***	0.0102***	0.0440***	0.0418***	0.0229***	0.0820***	0.0955***	0.0141***	0.0315***	0.0472***
	(0.0018)	(0.0012)	(0.0007)	(0.0007)	(0.0006)	(0.0011)	(0.0007)	(0.0008)	(0.0011)	(0.0022)	(0.0007)	(0.0043)	(0.0008)
Clerical Experience	0.0057***	0.0054***	0.0078***	0.0214***	0.0144***	0.0351***	0.0376***	0.0254***	0.0601***	0.0836***	0.0352***	0.0439***	0.0343***
	(0.0017)	(0.0008)	(0.0007)	(0.0005)	(0.0006)	(0.0009)	(0.0005)	(0.0007)	(0.0009)	(0.0016)	(0.0010)	(0.0054)	(0.0006)
Service and Sales Experience	-0.0007	-0.0120***	-0.0112***	0.0030***	0.0058***	0.0320***	0.0218***	0.0177***	0.0458***	0.0537***	0.0097***	-0.0241***	0.0113***
	(0.0032)	(0.0012)	(0.0008)	(0.0007)	(0.0007)	(0.0015)	(0.0008)	(0.0008)	(0.0015)	(0.0025)	(0.0013)	(0.0092)	(0.0011)
Agricultural Experience	-0.0377***	-0.0138***	0.0111**	0.0156***	0.0182***	0.0193***	0.0186***	0.0216***	0.0325***	0.0575***	0.0112**	0.0421	0.0172***
	(0.0067)	(0.0053)	(0.0043)	(0.0040)	(0.0013)	(0.0038)	(0.0019)	(0.0014)	(0.0063)	(0.0137)	(0.0055)	(0.0481)	(0.0012)
Craft Trades Experience	0.0003	0.0052***	0.0014	0.0213***	0.0100***	0.0408***	0.0319***	0.0246***	0.0667***	0.0929***	0.0158***	0.0018	0.0516***
	(0.0025)	(0.0011)	(0.0010)	(0.0008)	(0.0007)	(0.0013)	(0.0008)	(0.0009)	(0.0009)	(0.0020)	(0.0012)	(0.0122)	(0.0008)
Plant Operators Experience	-0.0250***	0.0120***	0.0145***	0.0279***	0.0117***	0.0259***	0.0282***	0.0294***	0.0619***	0.1031***	0.0140***	0.0214*	0.0404***
	(0.0049)	(0.0015)	(0.0013)	(0.0008)	(0.0011)	(0.0015)	(0.0009)	(0.0013)	(0.0013)	(0.0027)	(0.0018)	(0.0129)	(0.0009)
Elementary Experience	-0.0053	0.0061***	0.0020*	0.0034***	0.0068***	0.0215***	0.0155***	0.0129***	0.0367***	0.0346***	0.0149***	-0.0178**	0.0108***
	(0.0036)	(0.0019)	(0.0012)	(0.0007)	(0.0009)	(0.0016)	(0.0007)	(0.0008)	(0.0013)	(0.0028)	(0.0014)	(0.0081)	(0.0010)
Adj. R^2							0.763						
Within adj. R^2							0.166						
Person FE							yes						
Firm FE							yes						
SE clusters (persons)							1,568,990						
N							9,168,318						

Notes: Outcome is hourly wage. All columns present evidence from a single regression in which we allow for returns to experiences acquired in different firm classes to differ depending on occupation category at the time of acquiring experience. Firm classes 1–10 represent our firm categorization based on unexplained earnings growth distributions. NC are small firms not categorized by the clustering algorithm. PS is the public sector. Non-RJ is experience acquired outside the state of Rio de Janeiro. All specifications include year fixed effects and control for age with six age-category indicators. Standard errors clustered at the person level. *p<0.10; **p<0.05; ***p<0.01.

B Firm Classification: Implementation

To implement the firm classification algorithm (equation 11), we partial out worker demographics from wage growth g_{ijt} and carry out the firm assignment to classes based on a residualized g_{ijt}, which we denote "unexplained wage growth." We compute unexplained wage growth using workers aged 18–49 who were employed in the same firm for at least six months in two consecutive years.[1] In this subsample, we estimate the following regression:

$$g_{ijt} = Z_{it}'\theta + \delta_t + u_{ijt}, \tag{B1}$$

where $g_{ijt} \equiv \ln y_{i,t} - \ln y_{i,t-1}$ is wage growth, δ_t are year fixed effects, and Z_{it} includes a quadratic polynomial in age and a gender dummy in Veneto; in Brazil, additionally, Z_{it} includes a quadratic polynomial of years of education and an interaction term between years of education and age.[2] The residual $\widetilde{g}_{ijt} \equiv g_{ijt} - Z_{it}'\hat{\theta} - \hat{\delta}_t$ is our measure of unexplained earnings growth entering the classification problem (11).[3]

We follow a split-sample approach in the spirit of the machine learning literature (Athey and Imbens, 2019). We split the sample introduced in Section 2 in two groups: a random half of workers is used in the classification problem (11), and we estimate the returns to heterogeneous experiences in equation (8) using the other half. In this way, the same worker is never used to both classify firms into classes and to estimate the returns from having worked in different firm classes.

The number of firm classes K is set ex-ante, without an obvious choice for it. We set $K = 10$ as we believe that ten firm classes allow for sufficient richness in firm types, while not being such a large number that makes interpreting results across firm classes too burdensome. Moreover, using ten classes implies that we do not lose too much information by not increasing K further: Figure B1 shows, for different values of K, the ratio between i) the between-firm-class variance of unexplained earnings growth, and ii) the between-firm variance. In both datasets this ratio is around 60% for $K = 10$. The gains in this ratio from increasing the number of firm classes past $K = 10$ are not large: the relationship asymptotes at about 65% for Rio de Janeiro and 70% for Veneto.

Clustering results. Figure B2 plots the ten density functions that arise from solving (11), where each firm class is labeled according to the rank of the mean of its distribution. Panel (a) presents results for Rio de Janeiro and Panel (b) for Veneto. In each panel, the density of class 1—the class with the lowest mean unexplained earnings growth—is in solid black, and the density of class 10—that with the highest mean unexplained earnings growth—is in solid orange. The dashed blue line represents the density of overall unexplained earnings growth. There is substantial variation in densities across firm classes and in comparison with the overall distribution, which illustrates systematic differences in distributions of unexplained earnings growth (see Table B1 for moments for all firm classes). There is higher dispersion of unexplained earnings growth in Rio de Janeiro than in Veneto. This is true both within and between firm classes.

Table B2 shows the proportion of person-year observations and the proportion of firms that are assigned to each firm class. In both countries, a small share of observations is assigned to class 1 (2.3-2.5%), along with a far larger share to class 7 (16.9-18.3%) and close to 10% of observations being assigned to class 9. We also show that over 50% of firms are not classified by our algorithm due to the minimum size restriction, yet these firms represent

[1] In Brazil, where we observe hours, we additionally restrict our attention to full-time workers.

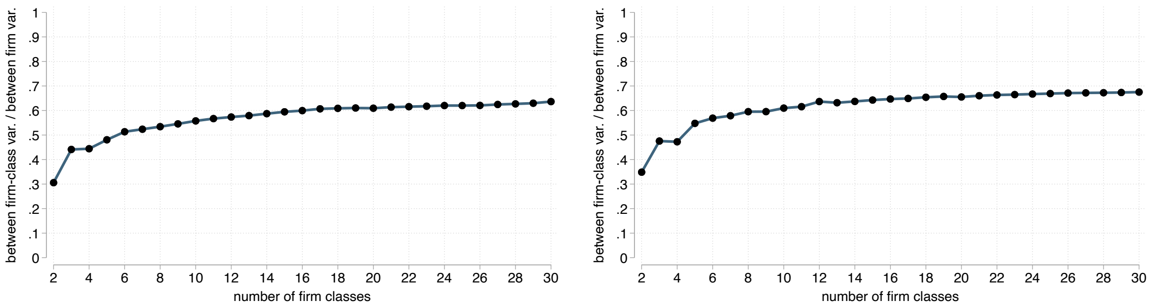
[2] We show that our results are not sensitive to alternative ways of netting out age and education.

[3] Before solving (11), we discard observations from firms for which we have, across all years, a total of less than five worker-year observations, thus not attempting to classify these very small short-lived firms.

only 7-9% of all person-year observations in both Rio de Janeiro and Veneto.

Figure B1: Ratio: between firm-class variance / between-firm variance, by number of firm classes.

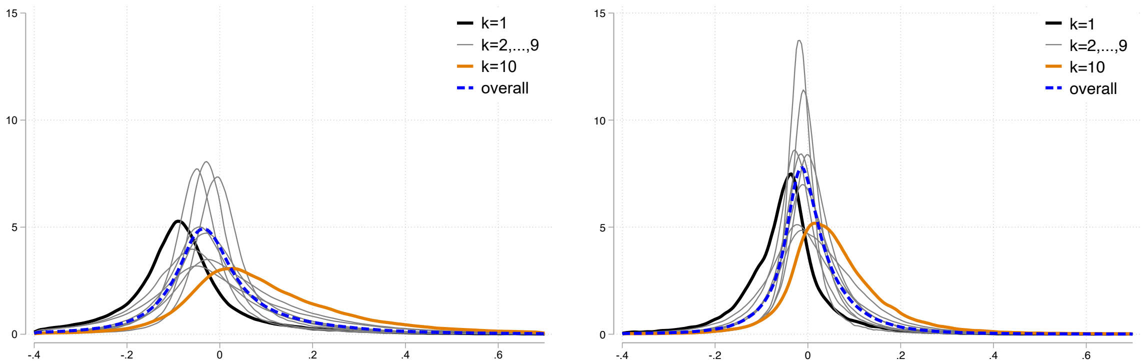
(a) Rio de Janeiro, 1994–2010. **(b)** Veneto, 1984–2001.



Notes: Ratio between i) between firm-class variance of unexplained wage growth, over ii) between-firm variance of unexplained wage growth, as a function of the number of firm classes (2–30). The logic of decomposing the variance into a within and between components comes from the law of total variance: $Var_y(Y) = \underbrace{E_x[Var_y(Y|X)]}_{\text{“within”}} + \underbrace{Var_x[E_y(Y|X)]}_{\text{“between”}}$. Denoting unexplained earnings growth by g, Figure B1 plots: $\frac{Var_k[E_g(g|\text{firm-class}=k)]}{Var_j[E_g(g|\text{firm}=j)]}$.

Figure B2: Density of unexplained earnings growth, by firm class.

(a) Rio de Janeiro, 1994–2010. **(b)** Veneto, 1984–2001.



Notes: Densities of unexplained earnings growth across firm classes. Classes ordered according to mean unexplained earnings growth. Dashed blue line marks the density of the overall distribution.

Table B1: Firm-class distributions of unexplained earnings growth.

Rio de Janeiro, 1994–2010.

Class	Mean	Median	Variance	Skewness
1	-0.093	-0.089	0.056	-1.001
2	-0.040	-0.051	0.051	-0.108
3	-0.036	-0.047	0.021	1.534
4	-0.014	-0.032	0.042	0.822
5	-0.012	-0.024	0.019	2.612
6	0.008	-0.020	0.085	0.431
7	0.012	-0.012	0.040	1.585
8	0.015	-0.000	0.022	3.045
9	0.052	0.015	0.069	1.127
10	0.121	0.073	0.079	1.216
overall	-0.000	-0.022	0.046	1.023

Veneto, 1984–2001.

Class	Mean	Median	Variance	Skewness
1	-0.056	-0.047	0.020	-0.722
2	-0.025	-0.025	0.015	-0.903
3	-0.017	-0.016	0.008	-1.419
4	-0.010	-0.013	0.023	-0.475
5	-0.009	-0.011	0.013	-0.730
6	0.001	-0.004	0.009	-0.464
7	0.004	-0.001	0.015	-0.505
8	0.017	0.010	0.011	0.042
9	0.021	0.014	0.020	-0.255
10	0.059	0.044	0.019	0.283
overall	-0.000	-0.006	0.015	-0.468

Notes: Mean, variance, and skewness of the unexplained earnings growth distributions in each of 10 firm classes and overall. Classes ordered according to the mean of unexplained earnings growth.

Table B2: Percent of observations belonging to each firm class.

Firm class	1	2	3	4	5	6	7	8	9	10	NC
					Rio de Janeiro, 1994–2010						
% person-years	2.54	8.24	6.70	18.34	8.91	9.38	16.90	7.46	10.43	3.64	7.46
% firms	2.57	2.79	5.59	3.70	6.74	2.64	4.21	6.14	3.72	2.67	59.25
					Veneto, 1984–2001						
% person-years	2.29	7.64	6.02	9.76	16.31	8.91	18.25	9.07	9.41	3.39	8.95
% firms	2.61	4.59	4.04	4.59	4.26	4.54	3.92	4.74	4.34	3.91	58.46

Notes: Table B2 presents the share of person-year observations and percent of firms belonging to each of the ten firm classes, plus non-categorized (NC) very small firms—with fewer than five worker-year observations—in both Rio de Janeiro (1994-2010) and Veneto (1984-2001).

C Exogeneity Assumptions

To guide the discussion behind the exogeneity assumption in equation (9), we consider a decomposition of the error term η_{it} into four components:

$$\eta_{it} = \sum_{m=1}^{K} \delta_{m,i} \cdot \text{Exp}(m)_{it} + \mu_{i,j(i,t)} + \zeta_{it}\left(\mathbf{Exp}_{it}, \alpha_i\right) + \varepsilon_{it}, \tag{C1}$$

where $\delta_{m,i}$ capture person-specific returns to class-m experience; $\mu_{i,j(i,t)}$ are match effects between worker i and employer j; $\zeta_{it}(\cdot)$ is a time-varying term unrelated to human capital, potentially correlated with experience profiles and baseline ability; ε_{it} is an idiosyncratic error.

The first exogeneity threat is the existence of worker heterogeneity in the form of unobserved ability to learn, captured by the parameters $\{\delta_{m,i}\}_{m=1}^{K}$ in equation (C1). Such heterogeneity would lead to biased estimates of the heterogeneous returns to experiences if it were positively correlated with, e.g., employment at high-class firms. In the most extreme form, firms would be homogeneous in their learning opportunities (i.e., $\gamma_1 = \ldots = \gamma_K$) while workers exhibit significant heterogeneity in their ability to learn. In this scenario, if unobservably similar workers sorted into the same firms, we would recover biased estimates of $\{\gamma_m\}_{m=1}^{K}$, thus incorrectly inferring heterogeneity in the returns to experiences across firm classes. Section 5.2 presents evidence showing that our estimated returns to experiences are unlikely to be biased by this type of unobserved worker heterogeneity. First, we estimate an expanded version of equation (8), which allows heterogeneity in returns to experiences across workers' unobserved ability α_i. That is, we include the term $\sum_{m=1}^{K} \delta_{m,i} \cdot \text{Exp}(m)_{it}$ in our estimating equation, where we parametrize $\delta_{m,i} = \alpha_i \cdot \delta_m$. Second, we estimate equation (8) allowing for heterogeneous returns across workers' characteristics which may be related to their learning ability—educational attainment and their blue- or white-collar occupation status. In both instances, we find that patterns of heterogeneous returns within these subgroups of workers are quite similar.

The second concern emerges through the role of match effects $\mu_{i,j(i,t)}$. If experience at certain firm classes leads workers to reach better person-firm-specific matches, such sorting could violate our exogeneity assumption. Our analysis of displaced workers addresses this concern since previous work notes that laid-off workers are likely willing to accept a job offer as long as it is preferable to unemployment (Dustmann and Meghir, 2005; Gathmann and Schönberg, 2010; Di Addario et al., 2023).[1]

Lastly, our exogeneity assumption could fail if baseline ability is unobserved by employers and wages evolve as a function of firms' learning about workers' productivity (e.g., Lange, 2007). In particular, firms may learn about workers' abilities at different speeds, and such heterogeneity could be correlated with our firm classification—a possibility captured in the term $\zeta_{it}\left(\mathbf{Exp}_{it}, \alpha_i\right)$ in (C1). However, this type of differential learning is unlikely to threaten the interpretation of our results. For instance, if the firms that we classify as offering strong learning opportunities were also adept at learning about workers' productivity, high baseline ability workers would have greater relative returns from employment at such firms whereas *low* baseline ability workers should experience the opposite. We instead find relative returns to heterogeneous experiences that are extremely similar for high and low baseline ability (α_i) workers, as well as for high/low education workers.

Relatedly, high-type firms may implement up-or-out contracts or tournaments in a way that correlates with wage growth for reasons other than human capital. First, such contracts

[1]Previous work estimating related two-way worker-firm fixed effects earnings equations has found little evidence in favor of quantitatively meaningful match effects (Card et al., 2013, 2015, 2018; Alvarez et al., 2018).

are typically found in high-skill professional occupations (Ghosh and Waldman, 2010), whereas our findings hold across the skill distribution. Moreover, such type of contractual arrangements could be positively correlated with on-the-job learning—i.e., they could be one of the "mechanisms" underlying firm heterogeneity in learning opportunities since these contracts may be implemented precisely to incentivize workers' human capital investments and effort (Lazear and Rosen, 1981; Waldman, 1990; Zabojnik and Bernhardt, 2001).

D Comparison to heterogeneous returns by firms' observable characteristics

We compare our results to those arising from an entirely different approach: categorizing firms based on their observable attributes. This alternative approach is related the literature that has examined heterogeneity in on-the-job learning across firms with specific characteristics, such as their exporter status, large-city location, size, or coworkers' education and skills (Macis and Schivardi, 2016; De La Roca and Puga, 2017; Arellano-Bover, 2020, 2022; Nix, 2020; Jarosch et al., 2021; Ma et al., 2021). Our method innovates with respect to these papers by freely allowing firms to belong to different on-the-job learning classes, regardless of their observed attributes. Following our approach, firms in the same class may have different characteristics, yet offer similar learning opportunities.

We compare the estimated returns to heterogeneous experiences following our approach to differential returns to experiences acquired in firms of different sizes, located in larger or smaller cities, and by coworkers' education.

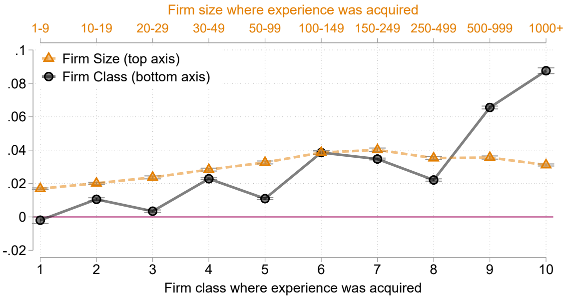
In the first two panels of Figure D1, we compare the heterogeneity in returns arising from our proposed firm classification to one arising from classifying firms based on their size—also using ten discrete categories ranging from firms with fewer than 10 workers to those with more than 1,000. Experiences acquired in firms of different sizes are differentially valuable. In Rio de Janeiro, the value of experience is initially increasing in the size of the firm where it was acquired, and then flattens for the largest size categories. Veneto presents evidence of a U-shaped relationship, with somewhat greater returns to experiences acquired in the smallest and the largest firms. All in all, our firm categorization captures heterogeneity in returns that is much richer than that captured by size in both countries (i.e., the slope of heterogeneous returns based on our proposed classification is steeper than that based on firm size).

The middle panels of Figure D1 show that a similar conclusion arises when comparing our proposed classification to one based on the size of the municipality where a firm is located. The relationship between returns to experience and size of the municipality where such experience was acquired is essentially flat in Rio de Janeiro, and increasing in Veneto. However, even in Veneto, returns based on a municipality size classification are significantly more homogeneous than those based on our proposed firm classification.

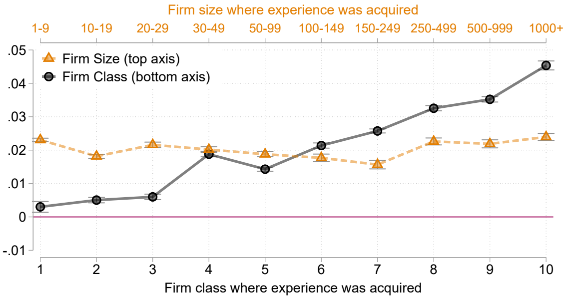
Lastly, the bottom panel of Figure D1 shows that, in Rio de Janeiro, our firm classification also captures richer heterogeneity than a classification based on level of education of the firm's workforce. Returns to experience are increasing in coworkers' education level at the firm where experience was acquired but, yet again, the slope of this gradient is flatter than the one arising from our proposed firm classification.

Figure D1: Returns to experiences acquired in different firm classes: comparison to firm categorization based on number of employees, city size and coworkers' education.

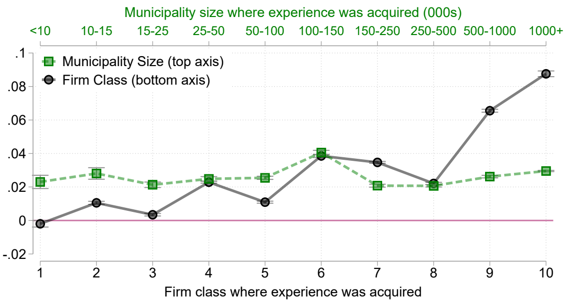
(a) Firm Size, Rio de Janeiro, 1994–2010.



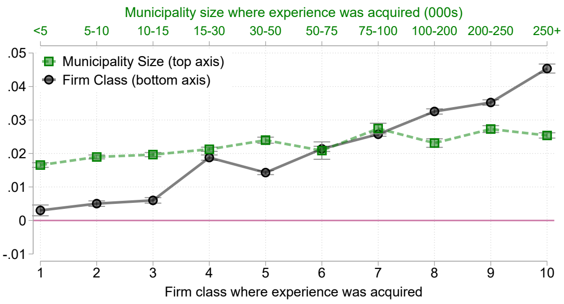
(b) Firm Size, Veneto, 1984–2001.



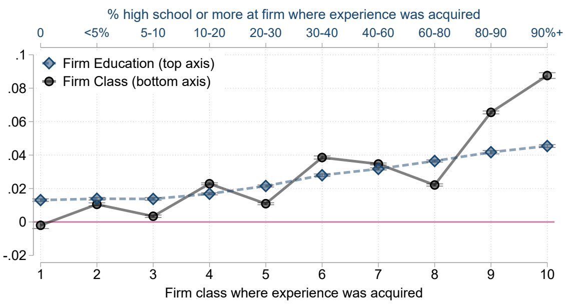
(c) City Size, Rio de Janeiro, 1994–2010.



(d) City Size, Veneto, 1984–2001.



(e) Workforce Education, Rio de Janeiro, 1994–2010.



Notes: Across all panels, the black plot presents our baseline estimates of returns to experiences acquired in different firm classes, described in Figure 1. In panels (a) and (b), the orange plot presents the estimated coefficients and 95% confidence intervals of the returns to experiences acquired in firms of different sizes. The green lines in panels (c) and (d) present corresponding evidence for experiences acquired in firms located in municipalities of different sizes. The blue plot in the panel (e) presents evidence on the returns to experiences acquired across firms categorized by the fraction of coworkers with a high school degree or more. In all panels, the outcome variable for Rio de Janeiro is log hourly wages and log daily wages for Veneto. Standard errors are clustered at the person level. Corresponding Appendix regression table: Table D1.

Table D1: Returns to experiences acquired in different firms, categorizing firms based on observables: firm size, city size, and workforce education.

	(1) Firm Size, Rio de Janeiro	(2) Firm Size, Veneto	(3) City Size, Rio de Janeiro	(4) City Size, Veneto	(5) Education, Rio de Janeiro
Experience: firm observable, group 1	0.0169***	0.0231***	0.0230***	0.0165***	0.0131***
	(0.0002)	(0.0003)	(0.0020)	(0.0004)	(0.0004)
Experience: firm observable, group 2	0.0202***	0.0182***	0.0281***	0.0190***	0.0139***
	(0.0003)	(0.0003)	(0.0018)	(0.0003)	(0.0004)
Experience: firm observable, group 3	0.0237***	0.0216***	0.0213***	0.0197***	0.0138***
	(0.0005)	(0.0004)	(0.0008)	(0.0003)	(0.0004)
Experience: firm observable, group 4	0.0283***	0.0202***	0.0248***	0.0213***	0.0168***
	(0.0004)	(0.0004)	(0.0007)	(0.0003)	(0.0003)
Experience: firm observable, group 5	0.0326***	0.0188***	0.0255***	0.0240***	0.0215***
	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0003)
Experience: firm observable, group 6	0.0385***	0.0177***	0.0405***	0.0209***	0.0280***
	(0.0006)	(0.0006)	(0.0007)	(0.0013)	(0.0004)
Experience: firm observable, group 7	0.0402***	0.0157***	0.0208***	0.0274***	0.0317***
	(0.0006)	(0.0007)	(0.0004)	(0.0008)	(0.0003)
Experience: firm observable, group 8	0.0352***	0.0226***	0.0207***	0.0231***	0.0365***
	(0.0005)	(0.0005)	(0.0004)	(0.0006)	(0.0004)
Experience: firm observable, group 9	0.0356***	0.0219***	0.0262***	0.0273***	0.0417***
	(0.0005)	(0.0006)	(0.0004)	(0.0005)	(0.0005)
Experience: firm observable, group 10	0.0311***	0.0240***	0.0295***	0.0254***	0.0454***
	(0.0003)	(0.0005)	(0.0002)	(0.0004)	(0.0004)
Adj. R^2	0.760	0.603	0.760	0.603	0.760
Within adj. R^2	0.016	0.018	0.015	0.018	0.018
Person FE	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes
SE clusters (persons)	1,568,990	483,799	1,568,990	483,799	1,568,990
N	9,168,318	3,608,754	9,168,318	3,608,754	9,168,318

Notes: Outcome is log hourly wage in Rio de Janeiro regressions and log daily wage in Veneto regressions. Estimates of heterogeneous returns to experiences acquired across firms of different observable characteristics. The ten firm size categories (in number of employees) are 1–9, 10–19, 20–29, 30–49, 50–99, 100–149, 150–249, 250–499. 500–999, and 1,000+. The ten city size categories (in 000s of people) are, in Rio de Janeiro, less than 10, 10–15, 15–25, 25–50, 50–100, 100–150, 150–250, 250–500, 500–1,000, 1,000+; in Veneto, less than 5, 5–10, 10–15, 15–30, 30–50, 50–75, 75–100, 100–200, 200–250, 250+. The ten workforce education categories (in % with high school or more) are less than 5, 5–10, 10–20, 20–30, 30–40, 40–60, 60–80, 80–90, 90+. All specifications include year fixed effects and control for age with six age-category indicators. Standard errors clustered at the person level. *p<0.10; **p<0.05; ***p<0.01.

E Human Capital Depreciation

E.1 Conceptual Framework

Human Capital Accumulation. The conceptual framework introduced in Section 3.1 can be extended to incorporate the possibility that workers' human capital may depreciate over time, as in Dinerstein et al. (2022). To this end, we slightly modify equation (1) by allowing worker i's stock of human capital, H_{it} to be given by:

$$\ln\ H_{it} = \alpha_i + \ln\ h_{it} \tag{E1}$$

where h_{it} is the stock of human capital accumulated on-the-job since labor market entry up until period t. We modify our framework to allow for depreciation, as workers' skills can atrophy with the passage of time, with workers forgetting previously acquired knowledge, or their skills becoming obsolete over time. We follow Dinerstein et al. (2022) in allowing human capital to depreciate regardless of whether, and where, a worker is employed. As such, the law of motion for workers' post-schooling human capital is given by:

$$h_{it+1} = \left[(1-\delta) + \sum_{m=1}^{K} e_{it}^{m} \cdot \mu_{it}^{m}\right] \cdot h_{it} \tag{E2}$$

where e_{it}^{m} is a binary variable that equals one if worker i spent period t working at a firm of class m, and human capital depreciates at a rate δ in period t regardless of whether the worker is employed or not. Human capital growth μ_{it}^{m} is an i.i.d. draw from the distribution F_m, with mean $\mathbb{E}\left[\mu_{it}^{m}\right] = \gamma_m$, and workers do not accumulate human capital while not employed.

The stock of human capital accumulated on the job through period t is thus given by:

$$h_{it} = \prod_{l=1}^{t-1}\left[(1-\delta) + \sum_{m=1}^{K} e_{il}^{m} \cdot \mu_{il}^{m}\right]. \tag{E3}$$

Let U_{it} capture the number of years that worker i has spent out of formal employment since labor market entry up until year t, and $\text{Exp}(m)_{it} \equiv \sum_{l=1}^{t-1} e_{il}^{m}$ capture their experience acquired in firm class m through year t. Worker i's human capital stock accumulated on the job thus depends (in expectation) on her past employment history across heterogeneous firms and the number of years in non-employment:

$$\mathbb{E}[h_{it}|\mathbf{Exp}_{it}] \;=\; \left[\prod_{m=1}^{K}\left((1-\delta)+\gamma_m\right)^{\text{Exp}(m)_{it}}\right] \cdot (1-\delta)^{U_{it}}, \tag{E4}$$

where $\mathbf{Exp}_{it}$ encompasses the vector of employment histories across firm classes and workers' time unemployed, from labor market entry through time t.

Earnings. We follow equation (5) in allowing the earnings of worker i employed at firm j in period t, y_{it}, to combine human capital H_{it} and a firm component ψ_j in:

$$y_{it} = e^{\psi_{j(i,t)}} H_{it}. \tag{E5}$$

Log earnings are thus given by:

$$\ln y_{it} = \psi_{j(it)} + \alpha_i + \ln h_{it}. \tag{E6}$$

Then, expected log earnings conditional on the contemporaneous employer, the worker's identity, and the worker's employment and unemployment history are given by:

$$\mathbb{E}\left[\ln y_{it}|j(i,t),i,\mathbf{Exp}_{it}\right] = \psi_{j(it)} + \alpha_i + \sum_{m=1}^{K} \ln\left((1-\delta)+\gamma_m\right)\cdot \text{Exp}(m)_{it} + \ln(1-\delta)\cdot U_{it} \quad \text{(E7)}$$

where $\text{Exp}(m)_{it}$ is the experience worker i has acquired in firms of class m up until period t and U_{it} denotes her total time in non-employment since labor market entry.

E.2 Empirical Evidence

We estimate versions of equation (E7) via OLS. In particular, we estimate a simplified version of (E7) that does not include person or firm fixed effects but controls for year fixed effects, six age-category fixed effects, gender, and education (in Rio de Janeiro). The coefficient on years of non-employment allows us to identify δ. Subsequently we combine the estimate of δ with the coefficients on heterogeneous experiences to recover the estimates of the γ_m parameters.

We present OLS and parameter estimates in Table E1, with odd columns refering to Rio de Janeiro and even ones to Veneto. Columns (1) and (3) present the resulting estimates when restricting the depreciation parameter, δ, to be equal to zero. Columns (2) and (4) present the resulting parameter estimates when we leave δ unrestricted. The estimated γ_m parameters are shown in square brackets.

Our main finding—evident from comparing across columns—is that the estimates of returns to heterogeneous experiences ($\hat{\gamma}_m$'s) are very similar when imposing no depreciation or when estimating it freely. For instance, the returns to one year of type-10 firm experience in Veneto is equal to 0.041 when assuming no depreciation, and equal to 0.045 when allowing for depreciation. Our second finding, stemming intuitively from the first, is that the estimated depreciation rates are not large—1.6% in Rio de Janeiro and 0.7% in Veneto. This could be related to our data being composed of young workers, as our sample is restricted to ages 18–35. Lastly, we note that both sets of γ_m estimates are quite similar to the estimates we obtain in our baseline framework in the main text.[1]

Overall, the modest estimated depreciation rates imply that the estimated returns to heterogeneous experiences in both countries are only slightly larger than those recovered in our baseline analyses in the main text. Moreover, relative returns across different experience types turn out to be unaffected by allowing for depreciation. Altogether, incorporating human capital depreciation to our framework does not change our conclusions regarding the importance of heterogeneous experiences in shaping workers' early-career labor market outcomes.

[1]The returns to experiences presented in columns (1) and (3) correspond to the estimates presented in the fourth column of Tables A1 and A2 for Rio de Janeiro and Veneto, respectively.

Table E1: Estimated Returns to Heterogeneous Experiences with Depreciation

	Rio de Janeiro		Veneto	
	(1)	(2)	(3)	(4)
Experience: class 1	0.0035***	0.0003	-0.0024***	-0.0040***
	(0.0013)	(0.0013)	(0.0006)	(0.0006)
	[0.0035]	[0.0161]	[-0.0024]	[0.0032]
Experience: class 2	0.0470***	0.0427***	0.0012***	-0.0007**
	(0.0007)	(0.0007)	(0.0003)	(0.0003)
	[0.0481]	[0.0594]	[0.0012]	[0.0064]
Experience: class 3	-0.0014**	-0.0062***	-0.0068***	-0.0088***
	(0.0005)	(0.0005)	(0.0004)	(0.0004)
	[-0.0014]	[0.0096]	[-0.0068]	[-0.0016]
Experience: class 4	0.0547***	0.0494***	0.0177***	0.0159***
	(0.0005)	(0.0005)	(0.0003)	(0.0003)
	[0.0562]	[0.0664]	[0.0179]	[0.0232]
Experience: class 5	-0.0176***	-0.0225***	0.0168***	0.0147***
	(0.0005)	(0.0005)	(0.0002)	(0.0003)
	[-0.0175]	[-0.0065]	[0.0169]	[0.022]
Experience: class 6	0.0676***	0.0634***	0.0178***	0.0157***
	(0.0006)	(0.0006)	(0.0004)	(0.0004)
	[0.0699]	[0.0812]	[0.0179]	[0.023]
Experience: class 7	0.0375***	0.0322***	0.0329***	0.0308***
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
	[0.0382]	[0.0485]	[0.0335]	[0.0384]
Experience: class 8	-0.0107***	-0.0160***	0.0375***	0.0353***
	(0.0005)	(0.0006)	(0.0004)	(0.0004)
	[-0.0107]	[-0.0001]	[0.0382]	[0.0431]
Experience: class 9	0.0998***	0.0950***	0.0419***	0.0397***
	(0.0007)	(0.0007)	(0.0004)	(0.0004)
	[0.1050]	[0.1154]	[0.0428]	[0.0477]
Experience: class 10	0.1297***	0.1259***	0.0397***	0.0375***
	(0.0015)	(0.0015)	(0.0007)	(0.0007)
	[0.1385]	[0.1499]	[0.0405]	[0.0454]
Experience: NC	-0.0118***	-0.0147***	-0.0022***	-0.0036***
	(0.0007)	(0.0007)	(0.0003)	(0.0003)
	[-0.0117]	[0.0012]	[-0.0022]	[0.0036]
Experience: PS	0.1061***	0.0986***	0.0317***	0.0329***
	(0.0024)	(0.0024)	(0.0034)	(0.0033)
	[0.1119]	[0.1194]	[0.0322]	[0.0407]
Experience: non-Province	0.0747***	0.0716***	0.0346***	0.0335***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
	[0.0775]	[0.09]	[0.0352]	[0.0412]
Unemployment Years		-0.0159***		-0.0072***
		(0.0002)		(0.0002)
Depreciation Rate (δ)	[0]	[0.0158]	[0]	[0.0072]
Adj. R^2	0.291	0.293	0.174	0.175
Person FE	no	no	no	no
Firm FE	no	no	no	no
UN Years	no	yes	no	yes
SE clusters (persons)	1928968	1928968	564332	564332
N	9,673,897	9,673,897	3,767,051	3,767,051

Notes: Outcome is hourly wage in Rio de Janeiro and daily wage in Veneto. Workers born in 1976 or later, ages 18–35. Private sector observations. Firm classes 1–10 represent our firm categorization based on unexplained earnings growth distributions. NC are small firms not categorized by the clustering algorithm. PS is the public sector. Other is experience acquired outside the state Rio de Janeiro and Veneto, respectively. All specifications include a gender dummy, years of education (Rio de Janeiro), year fixed effects and control for age with six age-category indicators. The first and third columns replicate the estimated coefficients presented in column (4) of Table A1 and Table A2, respectively. The values presented in brackets correspond to the estimated returns to heterogeneous experiences (γ_m) in equation (E7). Standard errors clustered at the person level. *p<0.10; **p<0.05; ***p<0.01.

F Key observables: Firms' pay premia, size, geography, and workforce education

Figures F1 and F2 show the estimated multinomial logit probabilities of a firm belonging to each class for Rio de Janeiro and Veneto, respectively. Each characteristic of interest is evaluated at the 25^{th} and at the 75^{th} percentiles, and the remaining variables are evaluated at the mean. Dummy variables are instead evaluated at zero and one. Each panel also includes $Pr\,(k(j) = k)$, the unconditional probability a firm belongs to a given class. For example, focusing on firm size in Figure F1, the panel corresponding to $k = 7$ indicates that keeping other firm characteristics constant, a firm in the 25^{th} size percentile has an estimated probability of around 0.08 to belong to firm class 7, while a firm in the 75^{th} percentile has a higher estimated probability of 0.125. The horizontal line reflects the unconditional probability of a firm belonging to class 7, which is approximately equal to 0.10.

Pay premia. At the firm level, and keeping other covariates constant, both countries show no systematic relationship between firms' class and firms' pay premia (Figures F1 and F2). This is consistent with the results documented in Section 6, which do not condition on other firm observables.

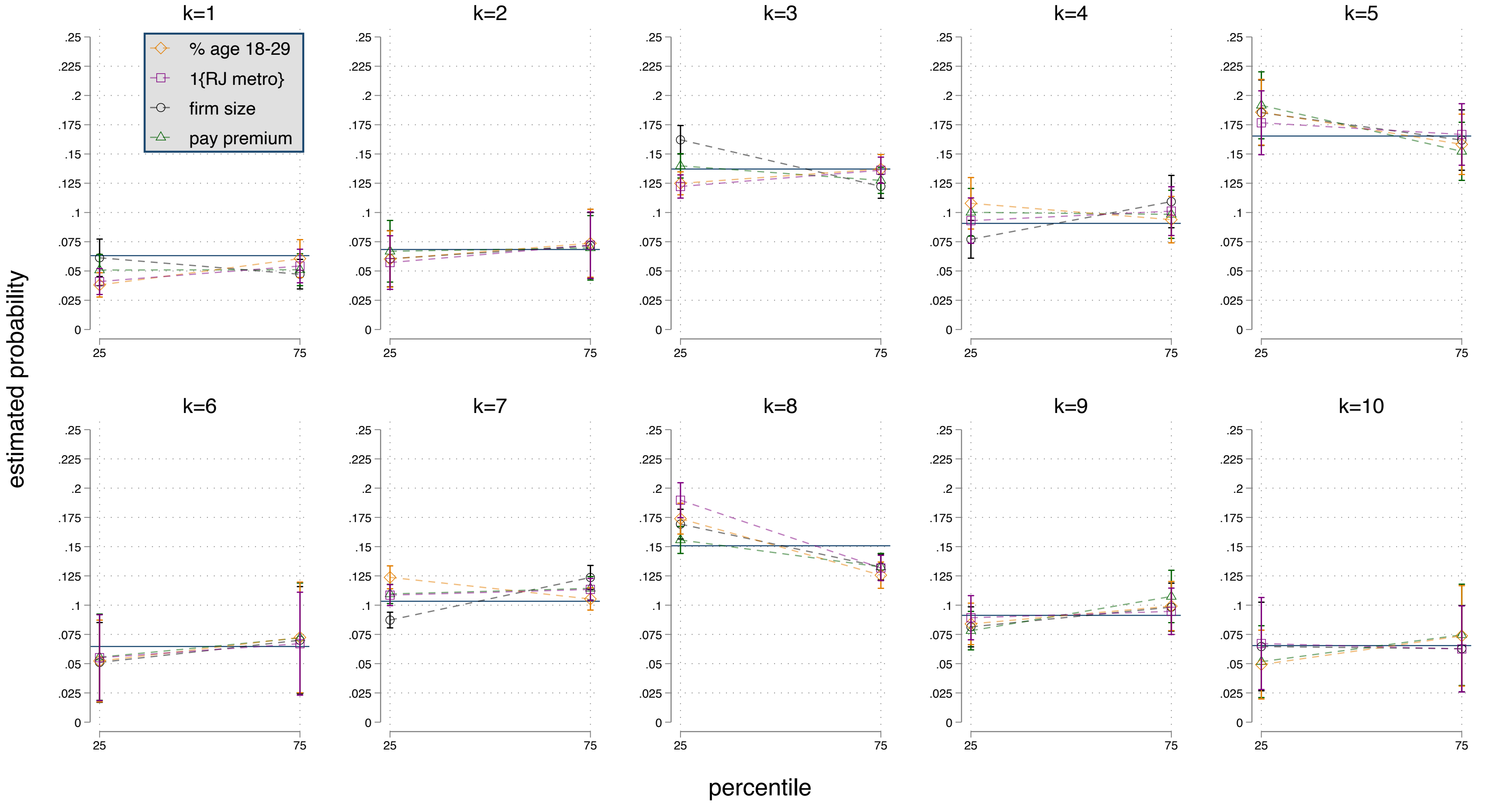
Firm size. There is no obvious pattern in employer size across firm classes. In Rio de Janeiro, workers of class-1 and class-10 firms are not employed in particularly large nor small firms (Table F1). In Veneto, while there is no clear relationship between firm classes and firm size, we find that workers in both classes 1 and 10 are employed by relatively small employers (Table F2). At the firm level, and keeping constant other covariates, we see that larger firms are less likely to belong to class 1 in Rio de Janeiro (Figure F1), and less likely to belong to class 1 and to class 10 in Veneto (Figure F2). Despite the lack of a clear-cut relationship between firm size and class, some facts are consistent with previous work suggesting greater learning opportunities for young workers in large firms (Arellano-Bover, 2020, 2022): in both Rio de Janeiro and Veneto, large firms are less likely to belong to class 1, and somewhat more likely to belong to class 9—i.e., the second-ranked category in terms of learning opportunities.

Geographic location. In Brazil, we classify firms with a dummy variable equal to one if located in the metropolitan area of Rio de Janeiro, and zero if elsewhere in the state. In Veneto, we construct a dummy equal to one if a firm is located in one of the five largest cities: Venezia, Verona, Padova, Vicenza, and Treviso. The share of the workforce employed in the Rio de Janeiro metro area is between 76–86 percent across firm classes (Table F1). Since this share equals 79 percent for firm class-10 workers, we do not find them disproportionately represented in the metro area. In Veneto, we find a positive association between large-city firms and firm class: large-city share is generally increasing in firm class. Thus, while 14 percent of the class 1 workforce is in one of the largest cities, the corresponding share for class 10 is 35 percent (Table F2). Multinomial logit results show that, keeping other firm attributes constant, metro region firms in Rio are slightly more likely to belong to class 1 and equally likely to belong to class 10 (Figure F1). In Veneto, large-city firms are less likely to belong to class 1 and more likely to belong to class 10 (Figure F2). The association we find in Veneto is consistent with De La Roca and Puga (2017), who show evidence from Spain consistent with workers learning more when employed in larger urban areas.

Workforce education. The education distribution of the workforce in Rio de Janeiro is largely comparable across firm classes, with the exception of classes 5 and 8, which disproportionately employ lower-education workers (Table F1). In spite of this moderate variation, the workforce at class 10 has the second largest share of workers with at least a high school degree, reaching 45 percent (class 4 has 49 percent). The fact that class 10 has a relatively high share of highly educated workers aligns with existing evidence on learning from highly educated (Nix, 2020) or highly paid (Jarosch et al., 2021) coworkers.

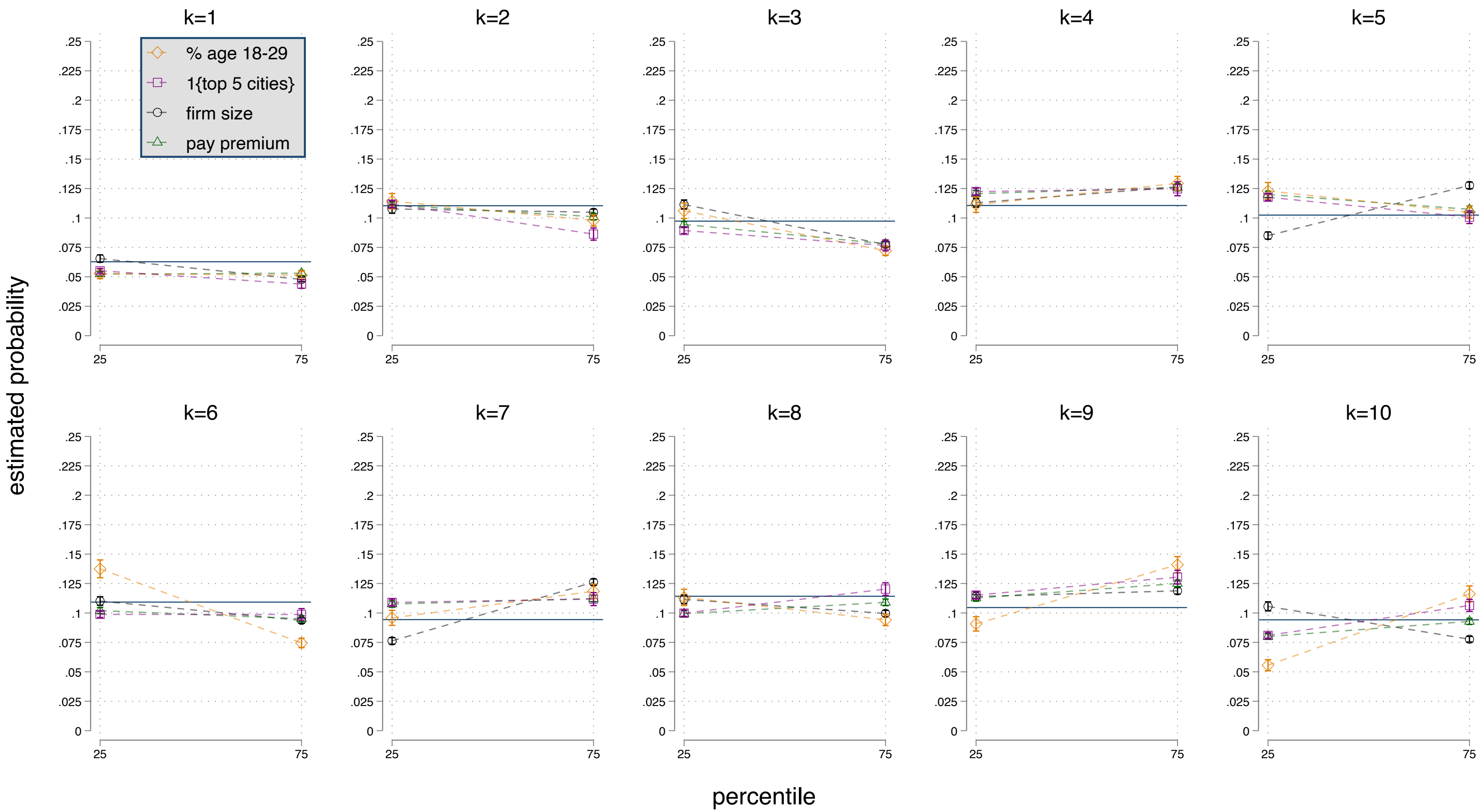
All in all, observed characteristics account for a relatively small share of the difference in firms' on-the-job learning opportunities. Learning opportunities as a dimension of firm heterogeneity may be an intrinsic attribute that is not easily identifiable with typically observed firm characteristics.

Figure F1: Multinomial Logit Estimated Probabilities: $Pr(\text{class} = k|X)$. Rio de Janeiro, 1994–2010.



Notes: Estimated probabilities and 95% confidence intervals from firm-level multinomial logit with the following explanatory variables: workforce age distribution, workforce gender distribution, workforce education distribution, log firm size, firm effects $\hat{\psi}_j$ from equation (8), 1-digit sector indicators, indicator for export-intensive 3-digit sector, indicator for being in Rio de Janeiro metropolitan area, and firm's task composition. For each firm class and each of four variables of interest, figure plots the estimated probability when said variable is evaluated at the 25th and 75th percentiles of the firm-level distribution (evaluated at 0 and 1 for the dummy variable 1{RJ metro}), while evaluating the remaining variables at their mean. Each display k shows $Pr(\text{class} = k)$, the unconditional probability of a firm belonging to a given class, with the solid horizontal line.

Figure F2: Multinomial Logit Estimated Probabilities: $Pr(\text{class} = k|X)$. Veneto, 1984–2001.



Notes: Estimated probabilities and 95% confidence intervals from firm-level multinomial logit with the following explanatory variables: workforce age distribution, workforce gender distribution, log firm size, firm effects $\hat{\psi}_j$ from equation (8), 1-digit sector indicators, indicator for being in one of the 5 largest cities of Veneto (Venezia, Verona, Padova, Vicenza, Treviso). For each firm class and each of four variables of interest, figure plots the estimated probability when said variable is evaluated at the 25th and 75th percentiles of the firm-level distribution (evaluated at 0 and 1 for the dummy variable 1{top 5 cities}), while evaluating the remaining variables at their mean. Each display k shows $Pr(\text{class} = k)$, the unconditional probability of a firm belonging to a given class, with the solid horizontal line.

Table F1: Workforce characteristics in each class of firms. Rio de Janeiro, 1994–2010.

Class	1	2	3	4	5	6	7	8	9	10	NC
Number of Worker-Years	1,322,079	4,321,475	3,474,514	9,614,276	4,600,812	4,928,916	8,849,161	3,873,003	5,475,392	1,915,013	4,348,342
Number of Firms	9,995	10,828	21,722	14,366	26,189	10,246	16,365	23,875	14,457	10,367	281,410
Firm Size: Mean	1481.09	2140.50	318.36	2652.96	194.27	742.24	1141.79	726.17	701.24	851.39	367.16
Firm Size: Median	50.08	470.25	25.67	481.58	26.08	262.58	199.42	29.17	147.67	71.50	4.00
% Firm $>$ 50 Employees	0.500	0.732	0.400	0.779	0.353	0.763	0.705	0.399	0.674	0.553	0.149
% Men	0.617	0.655	0.634	0.655	0.619	0.683	0.629	0.599	0.740	0.709	0.593
% Less than HS	0.539	0.551	0.595	0.514	0.678	0.575	0.576	0.724	0.573	0.546	0.587
% HS or more	0.460	0.449	0.405	0.486	0.322	0.424	0.424	0.275	0.426	0.453	0.412
% Age 18-29	0.413	0.373	0.411	0.346	0.393	0.414	0.376	0.363	0.407	0.418	0.448
% Age 30-39	0.271	0.290	0.293	0.311	0.292	0.300	0.298	0.293	0.296	0.290	0.260
% Age 40-49	0.197	0.221	0.190	0.225	0.197	0.188	0.205	0.214	0.192	0.185	0.175
% Age 50+	0.119	0.115	0.106	0.118	0.118	0.098	0.120	0.131	0.105	0.107	0.117
% Export-Oriented Sectors	0.015	0.023	0.006	0.036	0.025	0.017	0.018	0.019	0.030	0.029	0.006
% Rio de Janeiro Metro Region	0.858	0.859	0.818	0.844	0.772	0.856	0.830	0.756	0.794	0.790	0.776
Non-routine Cognitive Analytical	0.077	-0.004	0.016	0.074	-0.049	0.021	-0.015	-0.118	0.040	0.058	0.020
Non-routine Cognitive Interpersonal	-0.012	-0.133	-0.085	-0.027	-0.038	-0.033	-0.042	-0.070	-0.014	0.020	0.011
Routine Cognitive	0.088	0.239	0.150	0.117	-0.026	0.094	0.054	-0.098	0.066	0.046	0.043
Routine Manual	-0.013	0.086	0.007	0.018	0.111	0.107	0.092	0.190	0.141	0.090	-0.019
% Agriculture, Livestock	0.007	0.010	0.002	0.004	0.037	0.010	0.012	0.025	0.002	0.003	0.007
% Extractive Industries	0.003	0.003	0.002	0.022	0.002	0.002	0.002	0.003	0.019	0.022	0.003
% Manufacturing	0.133	0.161	0.094	0.136	0.128	0.178	0.149	0.093	0.168	0.102	0.076
% Construction	0.055	0.030	0.020	0.024	0.057	0.108	0.065	0.064	0.165	0.177	0.068
% Retail, Trade	0.238	0.166	0.334	0.200	0.310	0.225	0.217	0.231	0.183	0.194	0.368
% Accommodation, Meals	0.043	0.027	0.041	0.045	0.099	0.066	0.073	0.110	0.057	0.055	0.078
% Transportation, Storage, Communications	0.110	0.178	0.191	0.138	0.036	0.060	0.064	0.019	0.064	0.059	0.032
% Finance, Insurance	0.019	0.043	0.033	0.048	0.010	0.020	0.018	0.005	0.016	0.020	0.064
% Business Services, Real Estate	0.172	0.215	0.129	0.145	0.169	0.191	0.217	0.305	0.226	0.252	0.169
% Education	0.098	0.027	0.061	0.067	0.057	0.027	0.035	0.036	0.016	0.048	0.028
% Health, Social Services	0.022	0.025	0.031	0.073	0.030	0.057	0.075	0.033	0.021	0.017	0.034
% Other Services (e.g. Leisure, Personal)	0.068	0.044	0.058	0.087	0.062	0.051	0.064	0.071	0.054	0.034	0.060
Wages: Mean	16.11	16.72	11.15	21.74	8.81	14.94	13.37	7.75	16.50	17.41	12.20
Wages: Median	6.72	8.11	6.19	8.28	5.08	8.00	6.74	5.02	8.41	8.49	5.21
Wages: Variance	697	695	555	2,882	402	778	1,071	582	900	811	869
Firm Pay Premium: Mean	0.091	0.147	-0.041	0.160	-0.139	0.141	0.034	-0.145	0.174	0.183	-0.020

Notes: Characteristics of the workforce in each firm class. Firm classes 1–10 represent our firm categorization based on unexplained earnings growth distributions. Firm class NC are small firms not categorized by the clustering algorithm. Export-oriented sectors are those related to iron, soybeans, petroleum, sugar, poultry, plane manufacturing, coffee, woodpulp, car manufacturing, and bovine meat.

Table F2: Workforce characteristics in each class of firms. Veneto, 1984–2001.

Class	1	2	3	4	5	6	7	8	9	10	NC
Number of Worker-Years	402,252	1,331,522	1,042,484	1,732,555	2,887,408	1,554,876	3,241,346	1,591,316	1,671,299	599,965	1,940,268
Number of Firms	6,201	10,899	9,606	10,917	10,114	10,783	9,319	11,276	10,326	9,298	185,400
Firm Size: Mean	32.40	45.76	46.49	202.19	339.75	105.79	448.25	272.14	613.05	55.57	5.22
Firm Size: Median	9.16	13.69	15.27	24.42	52.63	23.40	82.30	28.26	33.10	8.80	1.88
% Firm > 50 Employees	0.145	0.203	0.238	0.365	0.510	0.338	0.598	0.406	0.445	0.156	0.011
% Men	0.577	0.560	0.602	0.627	0.643	0.612	0.660	0.597	0.622	0.514	0.523
% Age 18-29	0.557	0.513	0.429	0.463	0.383	0.344	0.387	0.376	0.444	0.534	0.564
% Age 30-39	0.218	0.247	0.288	0.263	0.287	0.302	0.299	0.312	0.288	0.279	0.215
% Age 40-49	0.134	0.144	0.180	0.168	0.208	0.223	0.201	0.202	0.172	0.125	0.122
% Age 50+	0.091	0.095	0.104	0.106	0.122	0.131	0.113	0.110	0.096	0.062	0.099
% 5 Largest Cities	0.137	0.122	0.146	0.242	0.169	0.233	0.229	0.397	0.422	0.352	0.215
% Extractive and Chemical Industries	0.033	0.048	0.054	0.045	0.085	0.073	0.068	0.072	0.050	0.026	0.018
% Manufacturing: Metal	0.136	0.134	0.106	0.247	0.235	0.180	0.321	0.182	0.194	0.197	0.094
% Manufacturing: Other	0.450	0.525	0.501	0.267	0.446	0.289	0.227	0.157	0.123	0.138	0.167
% Construction	0.172	0.146	0.053	0.149	0.056	0.032	0.036	0.023	0.054	0.040	0.136
% Trade, Retail, Hospitality	0.093	0.073	0.139	0.095	0.104	0.272	0.206	0.307	0.196	0.304	0.374
% Transportation, Communications	0.034	0.012	0.043	0.026	0.019	0.067	0.018	0.048	0.082	0.041	0.031
% Finance, Insurance, Business Services	0.031	0.026	0.024	0.080	0.019	0.029	0.053	0.115	0.210	0.144	0.075
% Other Services	0.043	0.030	0.025	0.089	0.030	0.045	0.056	0.076	0.077	0.102	0.093
Daily Wages: Mean	108.44	106.84	102.57	120.26	123.65	117.09	136.22	138.64	147.68	126.73	99.19
Daily Wages: Median	97.48	98.00	94.62	107.42	110.08	108.72	118.27	118.23	119.66	106.92	94.44
Daily Wages: Variance	202,589	18,160	528,423	53,161	228,809	13,294	30,132	62,126	56,871	148,013	93,775
Firm Pay Premium: Mean	-0.016	-0.012	-0.099	0.020	0.043	0.021	0.066	0.074	0.087	0.014	-0.054

Notes: Characteristics of the workforce in each firm class. Firm classes 1–10 represent our firm categorization based on unexplained earnings growth distributions. Firm class NC are small firms not categorized by the clustering algorithm. The five largest cities are Venezia, Verona, Padova, Vicenza, and Treviso.

Table F3: Firm-level characteristics, by firm class. Rio de Janeiro, 1994–2010.

Class	1	2	3	4	5	6	7	8	9	10
Firm Size: Mean	13.58	27.87	10.81	38.39	11.20	32.33	34.00	11.43	25.01	20.22
Firm Size: Median	4.76	6.04	4.79	7.42	5.13	6.76	7.85	4.74	6.94	6.15
% Firms > 50 Employees	0.031	0.064	0.021	0.091	0.026	0.105	0.090	0.026	0.085	0.057
% Men Employees	0.602	0.613	0.611	0.623	0.616	0.641	0.645	0.609	0.660	0.636
% Less than HS	0.602	0.641	0.613	0.639	0.677	0.638	0.665	0.700	0.628	0.594
% HS or more	0.397	0.358	0.386	0.360	0.322	0.361	0.334	0.299	0.371	0.406
% Age 18-29	0.505	0.452	0.473	0.412	0.407	0.437	0.388	0.356	0.411	0.422
% Age 30-39	0.271	0.288	0.285	0.298	0.303	0.290	0.303	0.310	0.297	0.294
% Age 40-49	0.147	0.171	0.160	0.189	0.195	0.181	0.202	0.227	0.192	0.193
% Age 50+	0.077	0.089	0.082	0.101	0.095	0.092	0.107	0.107	0.100	0.091
% Export-Oriented Sectors	0.008	0.008	0.007	0.007	0.006	0.007	0.006	0.007	0.008	0.010
% Rio de Janeiro Metro Region	0.814	0.824	0.785	0.811	0.764	0.833	0.815	0.722	0.826	0.803
% Agriculture, Livestock	0.004	0.004	0.003	0.004	0.005	0.004	0.005	0.009	0.002	0.004
% Extractive Industries	0.004	0.004	0.002	0.003	0.002	0.004	0.003	0.003	0.006	0.006
% Manufacturing	0.113	0.109	0.096	0.113	0.104	0.109	0.108	0.083	0.107	0.098
% Construction	0.032	0.030	0.019	0.027	0.025	0.042	0.032	0.026	0.039	0.047
% Retail, Trade	0.445	0.422	0.522	0.378	0.463	0.369	0.317	0.381	0.306	0.328
% Accommodation, Meals	0.067	0.076	0.057	0.085	0.087	0.086	0.101	0.110	0.078	0.078
% Transportation, Storage, Communications	0.036	0.039	0.037	0.039	0.026	0.040	0.033	0.021	0.043	0.043
% Finance, Insurance	0.016	0.019	0.011	0.017	0.006	0.018	0.012	0.006	0.015	0.018
% Business Services, Real Estate	0.133	0.151	0.130	0.183	0.170	0.204	0.249	0.233	0.290	0.272
% Education	0.044	0.038	0.037	0.039	0.026	0.032	0.028	0.021	0.022	0.017
% Health, Social Services	0.026	0.033	0.028	0.047	0.023	0.031	0.042	0.034	0.033	0.028
% Other Services (e.g. Leisure, Personal)	0.078	0.074	0.058	0.066	0.060	0.059	0.067	0.073	0.057	0.056
Firm Pay Premium	-0.152	-0.121	-0.181	-0.120	-0.207	-0.057	-0.103	-0.190	-0.037	-0.046
N	9,995	10,828	21,722	14,366	26,189	10,246	16,365	23,875	14,457	10,367

Notes: Mean firm-level characteristics of firms in each firm class. Export-oriented sectors are those related to iron, soybeans, petroleum, sugar, poultry, plane manufacturing, coffee, woodpulp, car manufacturing, and bovine meat.

Table F4: Firm-level characteristics, by firm class. Veneto, 1984–2001.

Class	1	2	3	4	5	6	7	8	9	10
Firm Size: Mean	7.21	8.47	7.38	10.34	17.45	9.10	20.37	9.63	10.93	5.87
Firm Size: Median	3.59	4.52	3.41	4.57	6.44	3.77	6.54	3.67	4.19	3.26
% Firms $>$ 50 Employees	0.014	0.017	0.016	0.026	0.059	0.022	0.070	0.025	0.020	0.007
% Men Employees	0.585	0.604	0.612	0.569	0.609	0.523	0.586	0.457	0.516	0.443
% Age 18-29	0.599	0.557	0.460	0.569	0.483	0.404	0.494	0.450	0.570	0.570
% Age 30-39	0.210	0.241	0.296	0.236	0.277	0.322	0.279	0.313	0.253	0.264
% Age 40-49	0.118	0.128	0.168	0.126	0.158	0.191	0.152	0.166	0.120	0.118
% Age 50+	0.073	0.073	0.076	0.069	0.081	0.083	0.075	0.071	0.058	0.048
% 5 Largest Cities	0.146	0.135	0.177	0.190	0.162	0.239	0.211	0.297	0.240	0.301
% Primary Sector	0.007	0.005	0.013	0.005	0.007	0.010	0.007	0.008	0.009	0.007
% Utilities	0.001	0.001	0.000	0.001	0.001	0.001	0.001	0.002	0.001	0.001
% Extractive and Chemical Industries	0.031	0.044	0.042	0.037	0.060	0.037	0.047	0.027	0.031	0.021
% Manufacturing: Metal	0.134	0.143	0.125	0.199	0.198	0.125	0.230	0.132	0.193	0.142
% Manufacturing: Other	0.386	0.409	0.352	0.280	0.326	0.203	0.227	0.128	0.188	0.145
% Construction	0.195	0.173	0.087	0.151	0.106	0.054	0.076	0.044	0.081	0.051
% Trade, Retail, Hospitality	0.126	0.134	0.269	0.160	0.197	0.391	0.243	0.383	0.248	0.324
% Transportation, Communications	0.020	0.015	0.017	0.024	0.022	0.028	0.028	0.034	0.033	0.035
% Finance, Insurance, Business Services	0.034	0.028	0.032	0.064	0.036	0.073	0.072	0.147	0.121	0.164
% Other Services	0.068	0.049	0.062	0.079	0.048	0.079	0.069	0.093	0.096	0.110
Firm Pay Premium	-0.045	-0.053	-0.081	-0.038	-0.039	-0.055	-0.020	-0.030	-0.039	-0.041
N	6,201	10,899	9,606	10,917	10,114	10,783	9,319	11,276	10,326	9,298

Notes: Mean firm-level characteristics of firms in each firm class. The five largest cities are Venezia, Verona, Padova, Vicenza, and Treviso.