CESifo WORKING PAPERS

11031
2024

March 2024

Differences in On-the-Job Learning across Firms

Jaime Arellano-Bover, Fernando Saltiel

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp

An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: https://www.cesifo.org/en/wp

CESifo *Working Paper No. 11031*

Differences in On-the-Job Learning across Firms

Abstract

We present evidence that is consistent with large disparities across firms in their on-the-job learning opportunities, 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. Four tests leveraging firm stayers and movers, occupation and industry switchers, 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. Firms' observable attributes only mildly predict on-the-job learning opportunities.

JEL-Codes: J240, J310.

Keywords: human capital, firms, on-the-job learning, wage growth.

Jaime Arellano-Bover
Yale University, New Haven / CT / USA
jaime.arellano-bover@yale.edu

Fernando Saltiel
McGill University, Montréal / Canada
fernando.saltiel@mcgill.ca

March 22, 2024
We thank Barbara Biasi, David Deming, Rafael Dix-Carneiro, Christian Dustmann, Luigi Guiso, John Eric Humphries, Patrick Kline, Fabian Lange, Elena Manresa, Costas Meghir, Claudio Michelacci, Christian Moser, Luigi Pistaferri, Tommaso Porzio, Diego Puga, Raffaele Saggio, Fabiano Schivardi, Todd Schoellman, Uta Schönberg, Daniela Scur, Isaac Sorkin, Matthew Staiger, and seminar and workshop participants at Yale University, Collegio Carlo Alberto, Università di Bologna, Universitat Autònoma de Barcelona, EIEF, CESR-USC, Tor Vergata University of Rome, Southern Methodist University, JKU Linz, St. Louis Fed and Washington University in St. Louis, SOLE 2021, CEA 2021, ECONtribute at the Universities of Bonn and Cologne, University of São Paulo, AEET Jornadas de Economía Laboral, Université Laval, Queen's University, IZA Junior/Senior Symposium, CESifo Pillars conference, Early Career Labor Economists European Symposium, England-Clark conference, University of Connecticut, University of Rochester, and Warwick University for helpful comments and suggestions. We are thankful to the participants at the NBER Wage Dynamics in the 21st Century Conference, in particular to our discussant Joe Altonji. We also thank Elena Manresa for kindly sharing code with us, Michele Battisti and Raffaele Saggio for helping us better understand the Italian data, and the Fondazione Rodolfo DeBenedetti for help with data access. Fernando Saltiel gratefully acknowledges financial support from the W.E. Upjohn Institute for Employment Research.

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. If on-the-job learning is shaped by such workplace features, this would suggest the existence of heterogeneous learning opportunities across firms. These opportunities may be particularly relevant for young workers, given the importance of on-the-job human capital accumulation in 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 their on-the-job learning opportunities and in a pay premium (wage fixed effect) à la Abowd et al. (1999). 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. 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]

We then propose four empirical tests that assess the plausibility of a general human capital interpretation of our findings. These tests address the possibility that the heterogeneous returns might be explained by other wage growth channels. Such channels include firm-, occupation-, or industry-specific human capital; outside offers and bargaining dynamics; firm productivity shocks; and seniority-based pay schemes. The four tests leverage settings where existing theories indicate that such alternative channels should not impact wages, whereas general human capital could do so instead. The first test estimates separate returns for job stayers and job switchers (Topel, 1991). The second test estimates the returns to experiences for job switchers who additionally change occupations/industries versus those who do not (Neal, 1995; Poletaev and Robinson, 2008; Kambourov and Manovskii, 2009). The third test estimates heterogeneous returns using hiring wages, combining our generalized Mincer wage equation with the models presented in Bagger et al. (2014), Di Addario et al. (2023), and Gregory (2023). The key insight of this test follows from the fact that in these sequential auction job search frameworks, the identity of a worker's employer two or more job spells ago can only impact hiring wages through human capital accumulation. Lastly, the fourth test narrows in on the subset of hiring wages that follow an involuntary job displacement event (Dustmann and Meghir, 2005). All 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 (mea-

[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.

sured 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 *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 understand 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 find some mild associations between learning opportunities and firm characteristics (e.g., a positive correlation with firm size in Rio de Janeiro and with city size in Veneto), but no strong and consistent predictors of on-the-job learning opportunities in both countries. A random forest classification algorithm leveraging the overall informational value of firm observables at our disposal confirms this interpretation, as it only correctly assigns firms to their learning class 22–23% of the time.

This paper contributes to the literature on post-schooling human capital accumulation (e.g. Neal, 1995; Acemoglu and Pischke, 1999; Dustmann and Meghir, 2005; Poletaev and Robinson, 2008; 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.[4] Furthermore, our wage equation allowing for heterogeneous types of experiences 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

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

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

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.

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 (2023) 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. Section 5 documents heterogeneity analyses, results on the four 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.

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.[5] RAIS includes unique person identifiers which

[5]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.

allow us to track workers over time along with their characteristics such as age, gender, and educational attainment.[6] We additionally observe unique establishment and firm identifiers, along with information on their sectoral classification and total annual employment.[7] 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. We further use information on workers' three-digit occupations, and also measure their task content using a concordance between the Brazilian Classification of Occupations and the Occupational Information Network (O*NET).

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 population 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.[8]

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.[9] 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

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

[7]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.

[8]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).

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

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: 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.

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

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.[11] 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:

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

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

[11] 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.

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:

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

where $\text{Exp}(m)_{it} \equiv \sum_{l=1}^{t-1} e_{il}^m$ 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, which may be 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.

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 that worker i has been employed in firms of class m up until period t,[12] 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).[13]

[12] 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.

[13] As a benchmark, we also estimate versions of equation (8) with such "homogeneous experience" (i.e., im-

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 four 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:

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

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 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

posing the restriction $\gamma_m = \gamma \;\; \forall\, m$).

$t-1$ 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.[14,15]

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, occupation- and/or industry-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 four empirical tests, well grounded on theories of human capital and search and matching, 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.

3.3.1 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 identify the combined returns of experience and tenure, while the returns to experience among initial wages in new jobs identify 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

[14] 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.

[15] 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.

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. The vector X_{it} in (12) includes NJ_{it}.

The returns to heterogeneous experiences for job switchers (γ_m^{NJ}) cannot be driven by firm-specific human capital. Yet, while this test can rule out firm-specific human capital as a key driver of our results, it does not directly rule out returns driven by other types of specific human capital, nor returns shaped by ij-specific match effects, nor outside offers and bargaining dynamics.[16] The empirical tests presented in subsections 3.3.2–3.3.4 directly address these concerns.

3.3.2 Occupation and industry specificity

An extensive literature has highlighted the importance of other types of human capital specificity, including Neal (1995); Poletaev and Robinson (2008); Kambourov and Manovskii (2009), who show that occupation- and industry-specific skills shape workers' earnings. The presence of such human capital specificity in our setting could affect our interpretation (heterogeneous accumulation of general skills) if the firm-types classification were correlated with the degree of occupation/industry-specificity of employment and accumulated skills.

To assess the empirical importance of such types of specificity, we follow this literature and estimate the differential returns to heterogeneous experiences among *firm switchers* who enter a *new* occupation/industry, relative to those who enter an occupation/industry where they had been previously employed. The returns to firm-class experiences for workers entering new occupations/industries would not be driven by this type of specificity. We estimate the following wage equation among worker-year observations corresponding to a job switch:

$$\ln y_{it} = \psi_{j(it)} + \alpha_i + \varphi_{o(it)} + \chi N_{it} + \sum_{m=1}^{K} \gamma_m^N \cdot N_{it} \cdot \text{Exp}(m)_{it} + \sum_{m=1}^{K} \gamma_m^O \cdot O_{it} \cdot \text{Exp}(m)_{it} + X_{it}'\beta + \eta_{it}, \quad (13)$$

where, O_{it} is a dummy variable that equals one for individuals entering an occupation where they had previously worked while N_{it} is a dummy that equals one for workers entering new occupations.[17] As such, χ denotes the wage difference for individuals who upon switching firms move to occupations where they have not previously worked, whereas γ_m^N and γ_m^O allow us to assess whether the returns to firm-class experiences differ for workers

[16] 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.

[17] N_{it} is equal to 1 if worker i had never been employed in one-digit occupation $o(it)$ prior to period t.

entering new/old occupations. For industry specificity, we estimate a version of equation (13) where the switchers/stayers definition is modified accordingly and where industry fixed effects are not directly included as these are subsumed by firm fixed effects.

3.3.3 Hiring wages and bargaining dynamics

The returns to heterogeneous experiences for job switchers could reflect outside offers and bargaining dynamics that are present in sequential auction models (Postel-Vinay and Robin, 2002a,b; Cahuc et al., 2006; Bagger et al., 2014), particularly if some firms are more conducive to outside offers than others. Bagger et al. (2014) introduce a job search model with human capital accumulation, where hiring wages are a function of workers' human capital and the identity of their hiring and origin employers (Di Addario et al., 2023). In this framework, all search and bargaining channels that shape hiring wages are captured by origin- and destination-firm effects, whereas workers' labor market experience reflect their on-the-job human capital accumulation.[18] To first examine whether allowing for search capital and bargaining dynamics affects our estimated returns to heterogeneous experiences, we estimate the following equation in the sample of hiring wages:

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

where n indexes job spells and ψ_j and λ_h are destination- and origin-firm fixed effects.[19] Equation (14) includes origin- and destination-firm fixed effects to capture the job search and wage bargaining channels in hiring wages (Bagger et al., 2014), such that the γ_m^{DWL}'s reflect workers' general human capital accumulation.

However, while origin- and destination-firm effects capture the search and bargaining channels in Bagger et al. (2014), this mapping need not directly apply to a framework where firms additionally differ in learning opportunities. Gregory (2023) presents a sequential auction model in which firms differ in their productivity and their learning opportunities. In this framework, hiring wages are not necessarily a separable function of origin and destination firm characteristics, as mobility decisions depend on both incumbent and poaching firms' productivities and learning opportunities. Crucially, though, it still remains true that the only firm-level characteristics that affect hiring wages through the bargaining channel are those of the incumbent and the poaching firm. As such, conditional on the current employer and the most recent past employer, the identity of the employer two spells ago *only* impacts hiring wages through human capital accumulation. Building on this insight, we estimate a more flexible version of equation (14) that allows for richer patterns of bargaining-

[18] In the Bagger et al. (2014) framework, experience is *unconditionally* correlated with wages through a job search channel leading workers to more productive firms. However, this channel is absorbed by the inclusion of destination-firm fixed effects. Note that tenure at the previous employer may also correlated with entry wages through its correlation with productivity at destination and origin firms. Yet this channel would also be captured by including origin-firm and destination-firm fixed effects in hiring wages, indicating that the effect of experience on entry wages is driven by portable human capital accumulation.

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

driven wage growth in the hiring wage sample:

$$\ln y_{in} = \alpha_i + \theta_{jh(i,n)} + \sum_{m=1}^{K} \gamma_m^{FDWL} \cdot \text{Exp}(m)_{in} + X'_{in}\beta + \eta_{in}, \tag{15}$$

where θ_{jh} represent origin-by-destination-firms effects. While in Bagger et al. (2014), voluntary switchers always move towards higher productivity firms, the two-dimensional job-ladder dynamics in Gregory (2023) are more nuanced and less tractable. Origin-by-destination effects in equation (15) thus accommodate richer patterns of bargaining that can arise when incumbent and poaching firm cannot be ranked in a single dimension. The γ_m^{FDWL} parameters can be interpreted as reflecting general human capital accumulation while allowing for more complex search and bargaining patterns than in equation (14).

3.3.4 Hiring wages following job displacement

We introduce an even stronger test of our human capital interpretation of the returns to experiences by focusing on displaced workers. 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:

$$\ln y_{d(i)} = \alpha_i + \psi_{j(d(i))} + \sum_{m=1}^{K} \gamma_m^{D} \cdot \text{Exp}(m)_{d(i)} + X'_{d(i)}\beta + \eta_{d(i)}, \tag{16}$$

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 (16) relying on one post-displacement hire per individual. As such, worker fixed effects α_i are not identified in equation (16) and we replace them with a linear function of estimated person effects $\widehat{\alpha}_i^D$. For similar reasons, we replace firm fixed effects $\psi_{j(d(i))}$ with a linear function of estimated firm effects $\widehat{\psi}_j^D$.[20]

This exercise can be seen as a special case of equations (14)-(15) in which the origin state is unemployment for everyone in the sample. As such, all the benefits from the prior tests in terms of isolating a portable human capital channel carry over. First, since displaced workers lose the outside option of their pre-displacement employer, previous employers cannot affect the hiring wages of displaced workers hired out of unemployment through a bargaining channel (Cahuc et al., 2006; Bagger et al., 2014; Di Addario et al., 2023; Gregory, 2023).[21] Moreover, these estimates account for any potential match effects, as involuntarily

[20]We avoid plugging in the firm and person fixed effects recovered from the baseline estimation of equation (8) to prevent correlation between $\eta_{d(i)}$ and estimation error in $\widehat{\alpha}_i$ and $\widehat{\psi}_j$. Instead, we estimate $\widehat{\alpha}_i^D$ and $\widehat{\psi}_j^D$ following the hold-out logic of split-sample IVs used for correcting firm fixed effects' estimation error (e.g., Schmieder et al., 2023). In particular, we recover $\widehat{\psi}_j^D$ from the estimation of equation (8) using a sample that excludes all observations from workers who enter the displaced workers' sample of equation (16); we recover $\widehat{\alpha}_i^D$ from the estimation of equation (8) using a sample that excludes worker-year observations that enter the estimation of equation (16).

[21]This insight holds even when firms exhibit two-dimensional heterogeneity as in Gregory (2023).

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) and Gregory (2023). 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 four tests will help to more convincingly establish whether our firm classification does capture differences in on-the-job learning of portable skills. The first and second tests are robust to contamination due to firm-specific and occupation/industry-specific human capital, respectively. The third test is additionally robust to outside offers-bargaining dynamics. The fourth 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); Gregory (2023)). 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.[22] Unfortunately, our data does not feature firm productivity measures, which prevents us from computing a correlation between learning opportunity and wages that

[22] Search frictions would allow low productivity and low learning firms to survive in equilibrium, even if such firms were dominated by others in these attributes (Bagger et al., 2014; Gregory, 2023).

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.[23] 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

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.[24] 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%.[25]

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.[26] In Rio de Janeiro, returns to experiences acquired in firm classes 6, 7, 9, and 10 are above the homogeneous benchmark, whereas the

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

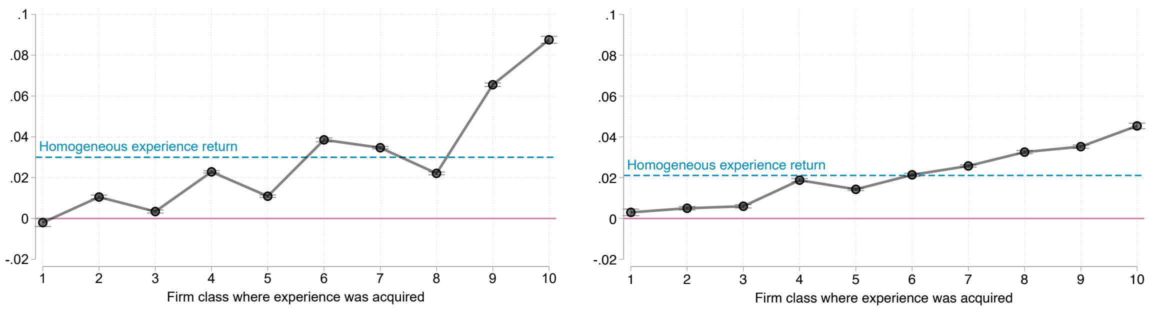
[24] Understanding why returns differ across these two economies is beyond the scope of this paper. Dustmann and Pereira (2008) discuss potential factors driving differential returns to experience in Germany and the UK, Rucci et al. (2020) do so across Brazil and Chile. Lagakos et al. (2018) and Donovan 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.

[25] 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.

[26] 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.

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



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.

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).[27,28] 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 workers' 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

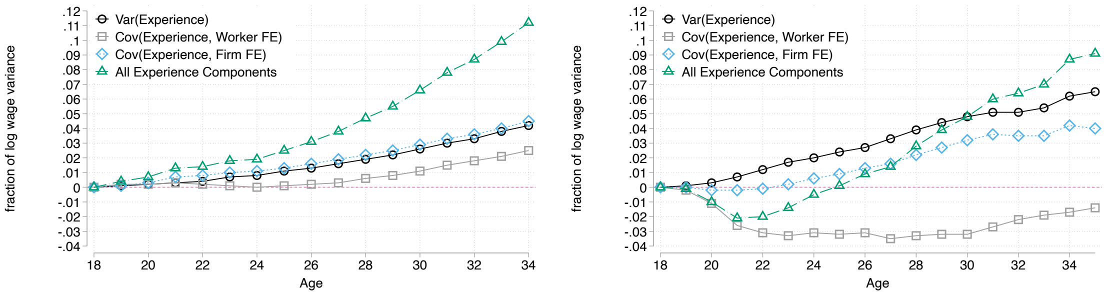
[27] A common concern in models with worker and firm fixed effects is the correct specification of age effects (Card et al., 2018). Our main specification controls for six age-category fixed effects, yet we also estimate specifications with an age polynomial restricting the age profile to be flat at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

[28] 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.

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.[29] 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.[30,31]

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.[32] 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 by heterogeneous experiences grows throughout the early career, which

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

[30]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.

[31]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 $\sum_{m=1}^{K}\gamma_m \cdot Exp(m)$.

[32]Figure A7 shows a rather flat relationship between learning opportunities and workers' fixed effects, as the correlation between α_i and heterogeneous returns equal 0.012 in Rio de Janeiro and -0.025 in Veneto.

suggests an even greater importance in explaining inequality further into workers' careers.

In Figure A8, 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.

Heterogeneous Experiences and Subsequent Task Contents. If worker skills were observed, we could validate the human capital interpretation of our results by estimating the γ_m parameters in equation (4) directly. In the absence of such data, we turn to the types of tasks workers carry out in their jobs (Acemoglu and Autor, 2011), where task contents serve as proxies of h_{it} in equation (4). In particular, we posit tasks as being vertically differentiated, where non-routine analytic tasks are a positively correlated proxy of h_{it}, and routine manual tasks are a negatively correlated proxy of h_{it}.[33] Under this lens, we estimate equation (8) in Rio de Janeiro using non-routine analytic and routine manual task intensity as outcomes instead of wages. Figure A9 shows that experience acquired in firms that we categorize as having good learning opportunities is associated with subsequent increases in non-routine analytic task intensity as well as with decreases in routine task intensity.

5 Tests for Alternative Explanations and Heterogeneity

5.1 Test Results for Portable Human Capital vs. Alternative Explanations

We now present results of the four 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 would plausibly not impact wages.

5.1.1 Job stayers vs. job switchers.

Figure 3 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—in the top learning classes, it amounts to 1.2 percentage points in Rio de Janeiro and to 0.6 percentage points 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

[33] This interpretation relies on the fact that non-routine analytic jobs tend to offer high wages and employ more highly educated workers, whereas routine manual jobs pay lower wages and employ less educated workers (Autor et al., 2003; Acemoglu and Autor, 2011; Gonzaga and Guanziroli, 2019). However, we acknowledge that the relationship between job tasks and workers' skills is more nuanced than the purely vertical interpretation of our proxy (Gathmann and Schönberg, 2010; Autor and Handel, 2013).

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.

Figure 3: Returns to experiences acquired in different firm classes: job switchers and stayers.

Notes: Estimates and 95% confidence intervals of parameters $\{\gamma_m^S, \gamma_m^{NJ}\}_{m=1}^{10}$ in equation (12). Estimates for Rio de Janeiro and Veneto in panels (a) and (b), 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. Corresponding Appendix regression table: Table A7.

5.1.2 Occupation and industry specificity

Figure 4 presents the estimated parameters of equation (13) for occupation switchers and stayers in Rio de Janeiro and for industry switchers/stayers in both countries. The first panel shows that the estimated returns to firm-class experiences in Rio de Janeiro are largely equivalent for workers entering new jobs, regardless of whether they are entering a new or old occupation. Meanwhile, the second and third panels show corresponding evidence for the heterogeneous returns for workers entering new/old industries in Rio de Janeiro and Veneto, respectively. Both occupation and industry switchers suffer wage penalties in the range of 1.4–1.7% (Table A8), suggesting the existence of some degree of occupation and industry specificity. Nonetheless, since the returns to firm-class experiences are quite similar for occupation/industry switchers and stayers, we conclude that the existence of industry/occupation specificity does not threaten our main results and interpretation.

5.1.3 Hiring wages and bargaining dynamics

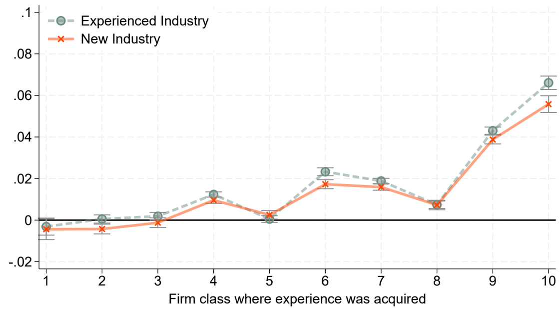
Figure 5 presents the estimated returns to experiences in a sample of hiring wages from equations (14)-(15). In both Rio de Janeiro and Veneto, the returns to experiences acquired in different firm classes exhibit significant heterogeneity in a hiring wage equation that accommodates richer patterns of firm heterogeneity (equation (15)). Moreover, the estimated coefficients on the returns to experiences are largely indistinguishable from those in equation (14) with separable origin- and destination-firm effects in both countries.[34] Crucially, Figure 5 displays a pattern of heterogeneous returns that are very similar to the baseline

[34]The estimation sample in equation (15) includes workers in origin-by-destination transitions made by at least another individual. The results are similar using the same sample for both equations (14)-(15) (Table A9).

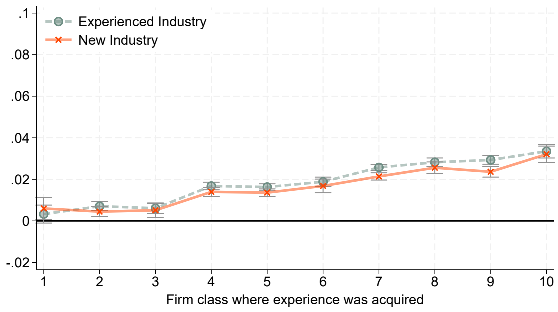
Figure 4: Returns to experiences acquired in different firm classes: occupation and industry switchers vs. stayers, among firm switchers.

(a) Occupation, Rio de Janeiro, 1994–2010

(b) Industry, Rio de Janeiro, 1994–2010



(c) Industry, Veneto, 1984–2001



Notes: Panel (a): estimates and 95% confidence intervals of parameters $\{\gamma_m^N, \gamma_m^O\}_{m=1}^{10}$ in equation (13), estimated in Rio de Janeiro. Panels (b) and (c): estimates and 95% confidence intervals of parameters $\{\gamma_m^N, \gamma_m^O\}_{m=1}^{10}$ in equation (13) for industry switchers (which does not include occupation fixed effects), estimated in Rio de Janeiro and Veneto, respectively. 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 A8.

ones presented in Figure 1. These results imply that outside offers and bargaining dynamics are unlikely to be the main drivers of heterogeneous returns to experiences acquired across firm classes.

5.1.4 Hiring wages following job displacement

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).[35] 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.[36]

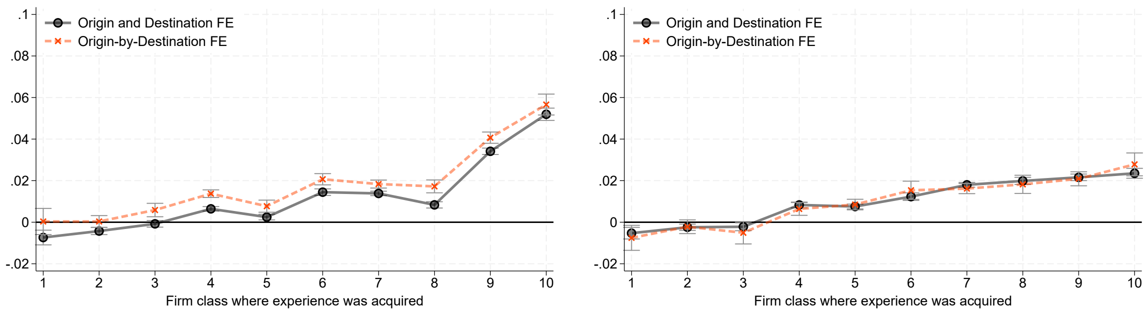
Figure 6 presents returns to heterogeneous experiences resulting from the estimation of

[35] 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).

[36] 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.

Figure 5: Returns to experiences acquired in different firm classes: hiring wages.

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

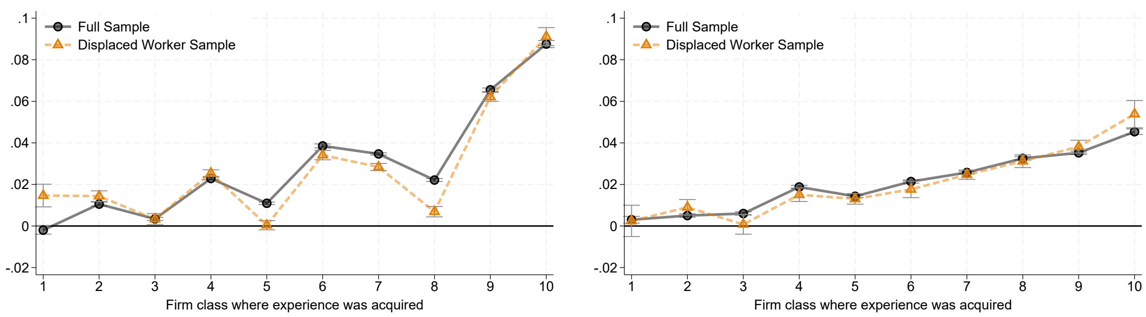


Notes: Estimates and 95% confidence intervals of parameters $\{\gamma_m^{DWL}\}_{m=1}^{10}$ and $\{\gamma_m^{FDWL}\}_{m=1}^{10}$ in equations (14)-(15). Coefficients labeled "'Origin and Destination FE" plot estimates from a version of the equation that includes origin and destination fixed effects separately. Coefficients labeled "Origin-by-Destination FE" plot estimates from a version of the equation that includes origin-by-destination fixed effects. Standard errors are clustered at the person level. Regression table presented in Table A9.

equation (16), 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=268,467. Veneto: outcome is log daily wage; N=31,182. Corresponding Appendix regression table: Table A10.

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 workers' unobserved heterogeneity (see the discussion in Section 3.2).[37] 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:

$$\ln y_{it} = \psi_{j(it)} + \alpha_i + \sum_{m=1}^{K} \gamma_m \cdot \text{Exp}(m)_{it} + \sum_{m=1}^{K} \delta_m \cdot \text{Exp}(m)_{it} \cdot \alpha_i + \eta_{it}, \tag{17}$$

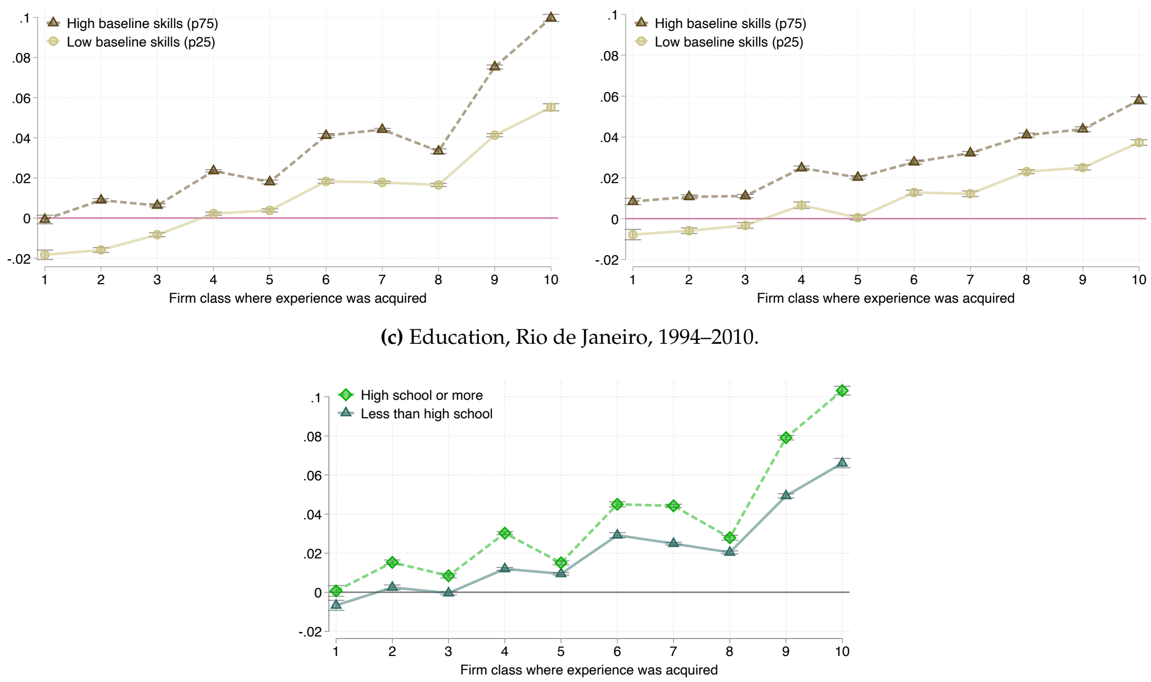
where α_i represents worker fixed effects, and δ_m captures whether higher-skilled workers enjoy larger returns to experience acquired at firm class m.[38] We present the results in the first two panels of Figure 7, comparing the estimated returns for individuals at the 25^{th} and 75^{th} percentiles 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.

[37] 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.

[38] We estimate equation (17) 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 (17) 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 and education.



(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 A11. Corresponding Appendix regression table for panel C: Table A12.

Gender. Figure A10 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.

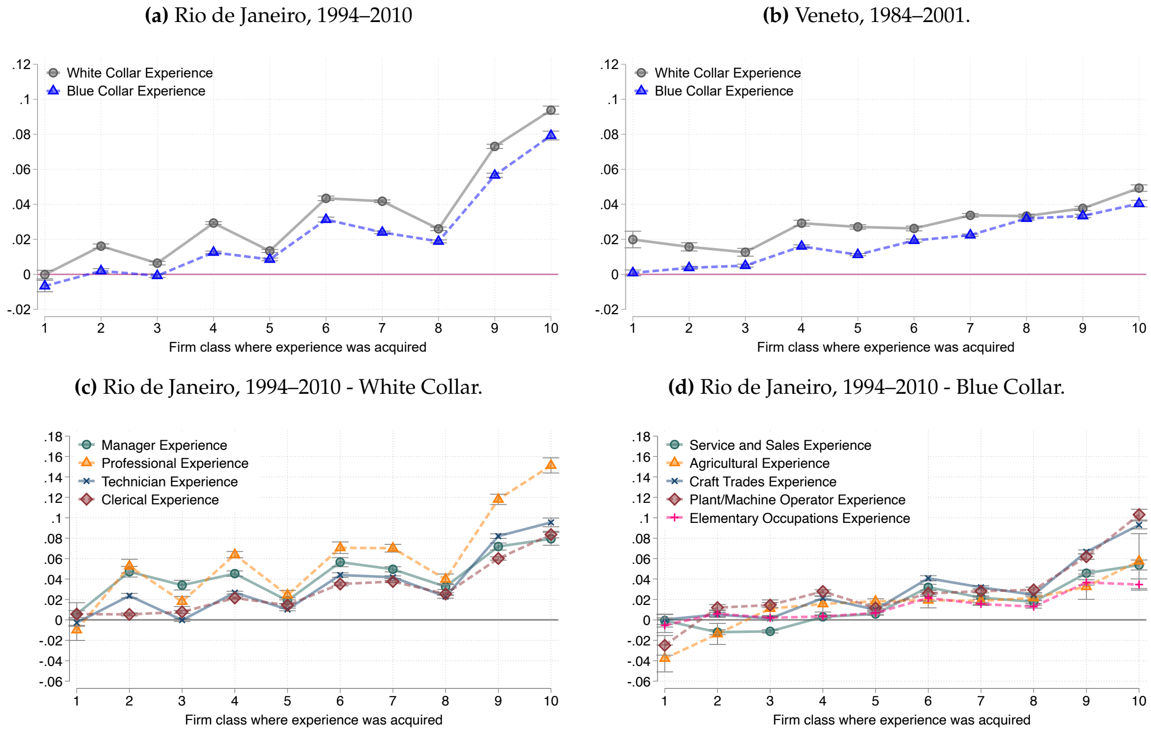
All in all, we interpret the heterogeneity analysis in this section as being consistent with our interpretation of heterogeneous returns capturing differences in learning opportunities across firm classes compared to alternative worker-based interpretations. "Top-learning" firms are the same for high- 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).

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



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 A13 for panel (a), Table A14 for panel (b), and Table A15 for panels (c) and (d).

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 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 A11. We find that experience acquired in high non-routine analytic content jobs leads to greater returns, yet, importantly, within task-group heterogeneity patterns in returns to experiences are very similar for all task groups.

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 A12, 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.

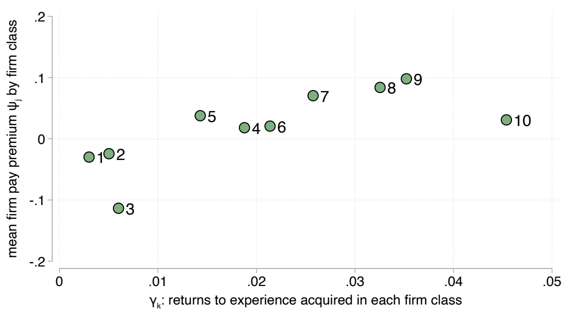
6 Learning Opportunities and Firm Pay Premia

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.[39] 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

[39]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).

tradeoff across employers between immediate monetary compensation and long-term compensation in terms of skill growth.[40] The lack of such a tradeoff exacerbates the role of firms in wage inequality, as quantified in Section 4.

7 Are Firm Observables Predictive of Learning Opportunities?

Are firms with better learning opportunities easily recognizable by their 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 first examine the role of observables by presenting mean firm-level characteristics across firm classes in Table 2. In general, we find some modest associations between firm observables and their learning opportunities, but there is no strong relationship linking a particular firm characteristic to learning opportunities in a consistent manner in both countries. For instance, while firms in the largest cities are more likely to belong to strong learning classes in Veneto (consistent with De La Roca and Puga, 2017), this is not the case in Rio de Janeiro when comparing firms within and outside the Rio de Janeiro metropolitan area. In Rio de Janeiro, firms with better learning opportunities tend to be larger (in line with Arellano-Bover, 2020, 2022), yet this is not the case in Veneto. Lastly, there is no consistent pattern between learning opportunities and the shares of male, young, and highly educated employees.[41]

Table 2: Firm-level average characteristics, by firm class.

Firm Class	1	2	3	4	5	6	7	8	9	10
Panel A. Rio de Janeiro, 1994–2010										
Firm Size: Mean	13.98	28.01	10.90	38.70	11.31	31.14	30.83	11.48	24.84	20.37
% RJ Metro Region	0.813	0.822	0.785	0.811	0.763	0.831	0.813	0.721	0.824	0.801
% Workers Aged 18-29	0.515	0.467	0.487	0.430	0.425	0.452	0.407	0.377	0.429	0.440
% Men	0.602	0.614	0.610	0.623	0.616	0.642	0.646	0.611	0.662	0.638
% More than HS	0.394	0.357	0.385	0.359	0.322	0.359	0.334	0.300	0.371	0.404
Number of Firms	9,995	10,828	21,722	14,366	26,189	10,246	16,365	23,875	14,457	10,367
Panel B. Veneto, 1984–2001										
Firm Size: Mean	7.21	8.47	7.38	10.34	17.45	9.10	20.37	9.63	10.93	5.87
% 5 Largest Cities	0.146	0.135	0.177	0.190	0.162	0.239	0.211	0.297	0.240	0.301
% Workers Aged 18-29	0.612	0.573	0.478	0.586	0.504	0.426	0.516	0.472	0.588	0.586
% Men	0.584	0.603	0.609	0.570	0.608	0.521	0.585	0.457	0.517	0.445
Number of Firms	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. Observations are weighted at the firm level. Sample of firms as described in Section 2 and firm-level variables as described in Section 7.

To assess the robustness of these patterns, we carry out two additional exercises, described in further detail in Appendix F. First, we use data on firm-level characteristics to implement a random forest classification algorithm, using half of the sample of firms to

[40] We do not find strong sorting between high baseline-skill workers and high-learning firms (Figure A7).

[41] Tables F2 and F3 present an expanded version of Table 2, showing information on additional firm characteristics across firm classes in both countries.

train and validate the model and the other half to predict firm classes.[42] In both countries, the algorithm correctly classifies between 22–23% of firms (see Table F1), indicating that firm observables are somewhat useful for predicting firms' skill-learning class, but do not suffice to accurately classify firms.[43] Lastly, Figures F2-F3 present results form a multinomial logit that renders *ceteris paribus* associations of firm characteristics and firm classes, which confirm the modest association between between firm observables and learning classes.

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 labor 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.

References

Abowd, J. M., F. Kramarz, and D. N. Margolis (1999). High wage workers and high wage firms. *Econometrica 67*(2), 251–333.

[42] We include mean earnings, firm effects $\hat{\psi}_j$ from eq. (8), workforce age and gender, firm size, firm location, and 2-digit sector. In Rio, we also include workforce education, task contents and export-intensive sectors.

[43] Figure F1 presents the distribution of *actual* firm class, separately for each value of *predicted* firm class, showing that observables have some, yet not substantial prediction power.

Abowd, J. M., F. Kramarz, and S. Roux (2006). Wages, mobility and firm performance: Advantages and insights from using matched worker–firm data. *The Economic Journal 116*(512), F245–F285.

Abowd, J. M., K. L. McKinney, and N. L. Zhao (2018). Earnings inequality and mobility trends in the United States: Nationally representative estimates from longitudinally linked employer-employee data. *Journal of Labor Economics 36*(S1), S183–S300.

Acemoglu, D. and D. Autor (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of Labor Economics*, Volume 4, pp. 1043–1171. Elsevier.

Acemoglu, D. and J.-S. Pischke (1999). The structure of wages and investment in general training. *Journal of Political Economy 107*(3), 539–572.

Adda, J. and C. Dustmann (2023). Sources of wage growth. *Journal of Political Economy 131*(2), 456–503.

Alfonsi, L., M. Namubiru, and S. Spaziani (2022). Meet your future: Experimental evidence on the labor market effects of mentors. Mimeo, UC Berkeley, BRAC Uganda, and Brown University.

Altonji, J. G. and R. A. Shakotko (1987). Do wages rise with job seniority? *The Review of Economic Studies 54*(3), 437–459.

Altonji, J. G. and N. Williams (2005). Do wages rise with job seniority? A reassessment. *ILR Review 58*(3), 370–397.

Alvarez, J., F. Benguria, N. Engbom, and C. Moser (2018). Firms and the decline in earnings inequality in Brazil. *American Economic Journal: Macroeconomics 10*(1), 149–89.

Andrews, M. J., L. Gill, T. Schank, and R. Upward (2008). High wage workers and low wage firms: negative assortative matching or limited mobility bias? *Journal of the Royal Statistical Society: Series A (Statistics in Society) 171*(3), 673–697.

Arellano-Bover, J. (2020). Career consequences of firm heterogeneity for young workers: First job and firm size. Discussion Paper 12969, IZA Institute of Labor Economics.

Arellano-Bover, J. (2022). The effect of labor market conditions at entry on workers' long-term skills. *Review of Economics and Statistics 104*(5), 1028–1045.

Athey, S. and G. W. Imbens (2019). Machine learning methods that economists should know about. *Annual Review of Economics 11*, 685–725.

Autor, D. H. and M. J. Handel (2013). Putting tasks to the test: Human capital, job tasks, and wages. *Journal of labor Economics 31*(S1), S59–S96.

Autor, D. H., F. Levy, and R. J. Murnane (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics 118*(4), 1279–1333.

Bagger, J., F. Fontaine, F. Postel-Vinay, and J.-M. Robin (2014). Tenure, experience, human capital, and wages: A tractable equilibrium search model of wage dynamics. *American Economic Review 104*(6), 1551–96.

Bartolucci, C., F. Devicienti, and I. Monzón (2018). Identifying sorting in practice. *American Economic Journal: Applied Economics 10*(4), 408–38.

Battisti, M. (2017). High wage workers and high wage peers. *Labour Economics 46*, 47–63.

Bertheau, A., E. M. Acabbi, C. Barcelo, A. Gulyas, S. Lombardi, and R. Saggio (2022). The unequal cost of job loss across countries. Technical report, National Bureau of Economic Research.

Bonhomme, S., K. Holzheu, T. Lamadon, E. Manresa, M. Mogstad, and B. Setzler (2023). How much should we trust estimates of firm effects and worker sorting? *Journal of Labor Economics 41*(2), 291–322.

Bonhomme, S., T. Lamadon, and E. Manresa (2019). A distributional framework for matched employer employee data. *Econometrica 87*(3), 699–739.

Cahuc, P., F. Postel-Vinay, and J.-M. Robin (2006). Wage bargaining with on-the-job search: Theory and evidence. *Econometrica 74*(2), 323–364.

Card, D., A. R. Cardoso, J. Heining, and P. Kline (2018). Firms and labor market inequality: Evidence and some theory. *Journal of Labor Economics 36*(S1), S13–S70.

Card, D., A. R. Cardoso, and P. Kline (2015). Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women. *The Quarterly Journal of Economics 131*(2), 633–686.

Card, D., F. Devicienti, and A. Maida (2014). Rent-sharing, holdup, and wages: Evidence from matched panel data. *Review of Economic Studies 81*(1), 84–111.

Card, D., J. Heining, and P. Kline (2013). Workplace heterogeneity and the rise of West German wage inequality. *The Quarterly Journal of Economics 128*(3), 967–1015.

Coffman, L. C., J. J. Conlon, C. R. Featherstone, and J. B. Kessler (2019). Liquidity affects job choice: Evidence from Teach for America. *The Quarterly Journal of Economics 134*(4), 2203–2236.

De La Roca, J. and D. Puga (2017). Learning by working in big cities. *The Review of Economic Studies 84*(1), 106–142.

Di Addario, S., P. Kline, R. Saggio, and M. Sølvsten (2023). It ain't where you're from, it's where you're at: Hiring origins, firm heterogeneity, and wages. *Journal of Econometrics 233*(2), 340–374.

Dinerstein, M., R. Megalokonomou, and C. Yannelis (2022). Human capital depreciation and returns to experience. *American Economic Review 112*(11), 3725–62.

Donovan, K., W. J. Lu, and T. Schoellman (2021). Labor market dynamics and development. Mimeo, Yale School of Management.

Dustmann, C. and C. Meghir (2005). Wages, experience and seniority. *The Review of Economic Studies 72*(1), 77–108.

Dustmann, C. and S. C. Pereira (2008). Wage growth and job mobility in the United Kingdom and Germany. *ILR Review 61*(3), 374–393.

Engbom, N., C. Moser, and J. Sauermann (2023). Firm pay dynamics. *Journal of Econometrics 233*(2), 396–423.

Gathmann, C. and U. Schönberg (2010). How general is human capital? A task-based approach. *Journal of Labor Economics 28*(1), 1–49.

Gendron-Carrier, N. (2021). Prior work experience and entrepreneurship: The careers of young entrepreneurs. Mimeo, McGill University.

Ghosh, S. and M. Waldman (2010). Standard promotion practices versus up-or-out contracts. *The RAND Journal of Economics 41*(2), 301–325.

Gibbons, R. and M. Waldman (2006). Enriching a theory of wage and promotion dynamics inside firms. *Journal of Labor Economics 24*(1), 59–107.

Gonzaga, G. and T. Guanziroli (2019). Returns to experience across tasks: Evidence from Brazil. *Applied Economics Letters 26*(20), 1718–1723.

Gregory, V. (2023). Firms as learning environments: Implications for earnings dynamics and job search. Mimeo, Federal Reserve Bank of St. Louis.

Guiso, L., L. Pistaferri, and F. Schivardi (2013). Credit within the firm. *Review of Economic Studies 80*(1), 211–247.

Guvenen, F. (2007). Learning your earning: Are labor income shocks really very persistent? *American Economic Review 97*(3), 687–712.

Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan (1993). Earnings losses of displaced workers. *The American Economic Review 83*(4), 685–709.

Jarosch, G., E. Oberfield, and E. Rossi-Hansberg (2021). Learning from coworkers. *Econometrica 89*(2), 647–676.

Kambourov, G. and I. Manovskii (2009). Occupational specificity of human capital. *International Economic Review 50*(1), 63–115.

Kletzer, L. G. (1989). Returns to seniority after permanent job loss. *American Economic Review 79*(3), 536–543.

Kline, P., R. Saggio, and M. Sølvsten (2020). Leave-out estimation of variance components. *Econometrica 88*(5), 1859–1898.

Lachowska, M., A. Mas, R. Saggio, and S. A. Woodbury (2023). Do firm effects drift? Evidence from Washington administrative data. *Journal of Econometrics 233*(2), 375–395.

Lachowska, M., A. Mas, and S. A. Woodbury (2020). Sources of displaced workers' long-term earnings losses. *American Economic Review 110*(10), 3231–66.

Lagakos, D., B. Moll, T. Porzio, N. Qian, and T. Schoellman (2018). Life cycle wage growth across countries. *Journal of Political Economy 126*(2), 797–849.

Lange, F. (2007). The speed of employer learning. *Journal of Labor Economics 25*(1), 1–35.

Lazear, E. P. (1981). Agency, earnings profiles, productivity, and hours restrictions. *American Economic Review 71*(4), 606–620.

Lazear, E. P. and S. Rosen (1981). Rank-order tournaments as optimum labor contracts. *Journal of Political Economy 89*(5), 841–864.

Ma, X., M.-A. Muendler, and A. Nakab (2021). Learning by exporting and wage profiles: New evidence from Brazil. Mimeo, Peking University, UC San Diego, and Universidad Torcuato Di Tella.

Macis, M. and F. Schivardi (2016). Exports and wages: Rent sharing, workforce composition, or returns to skills? *Journal of Labor Economics 34*(4), 945–978.

Mincer, J. (1974). *Schooling, Experience, and Earnings*. National Bureau of Economic Research; distributed by Columbia University Press.

Neal, D. (1995). Industry-specific human capital: Evidence from displaced workers. *Journal of Labor Economics 13*(4), 653–677.

Nix, E. (2020). Learning spillovers in the firm. Mimeo, University of Southern California.

Palacios-Huerta, I. (2003). An empirical analysis of the risk properties of human capital returns. *American Economic Review 93*(3), 948–964.

Poletaev, M. and C. Robinson (2008). Human capital specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984–2000. *Journal of Labor Economics 26*(3), 387–420.

Postel-Vinay, F. and J.-M. Robin (2002a). The distribution of earnings in an equilibrium search model with state-dependent offers and counteroffers. *International Economic Review 43*(4), 989–1016.

Postel-Vinay, F. and J.-M. Robin (2002b). Equilibrium wage dispersion with worker and employer heterogeneity. *Econometrica 70*(6), 2295–2350.

Rosen, S. (1972). Learning and experience in the labor market. *Journal of Human Resources 7*(3), 326–342.

Rothstein, J. and C. E. Rouse (2011). Constrained after college: Student loans and early-career occupational choices. *Journal of Public Economics 95*(1-2), 149–163.

Rubinstein, Y. and Y. Weiss (2006). Post schooling wage growth: Investment, search and learning. *Handbook of the Economics of Education 1*, 1–67.

Rucci, G., F. Saltiel, and S. Urzúa (2020). Should I stay or should I go? Career choices for young workers in Latin America. *Economic Inquiry 58*(3), 1430–1449.

Schmieder, J. F., T. Von Wachter, and J. Heining (2023). The costs of job displacement over the business cycle and its sources: Evidence from Germany. *American Economic Review 113*(5), 1208–1254.

Serafinelli, M. (2019). "Good" firms, worker flows, and local productivity. *Journal of Labor Economics 37*(3), 747–792.

Sockin, J. (2021). Show me the amenity: Are higher-paying firms better all around? Mimeo, University of Pennsylvania.

Song, J., D. J. Price, F. Guvenen, N. Bloom, and T. von Wachter (2019). Firming up inequality. *The Quarterly Journal of Economics 134*(1), 1–50.

Sorkin, I. (2018). Ranking firms using revealed preference. *The Quarterly Journal of Economics 133*(3), 1331–1393.

Topel, R. (1991). Specific capital, mobility, and wages: Wages rise with job seniority. *Journal of Political Economy 99*(1), 145–176.

Topel, R. H. and M. P. Ward (1992). Job mobility and the careers of young men. *The Quarterly Journal of Economics 107*(2), 439–479.

Waldman, M. (1990). Up-or-out contracts: A signaling perspective. *Journal of Labor Economics 8*(2), 230–250.

Zabojnik, J. and D. Bernhardt (2001). Corporate tournaments, human capital acquisition, and the firm size-wage relation. *The Review of Economic Studies 68*(3), 693–716.

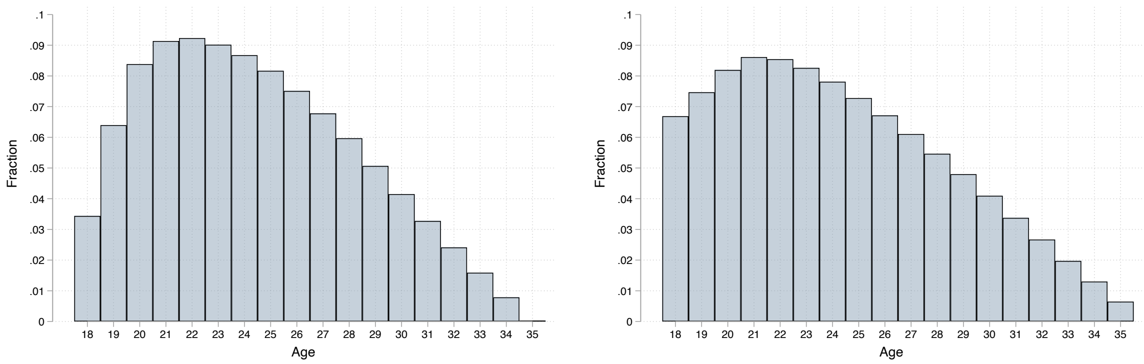
- SUPPLEMENTARY APPENDICES -
For Online Publication

A Additional Figures and Tables

A.1 Figures

Figure A1: Age distribution.

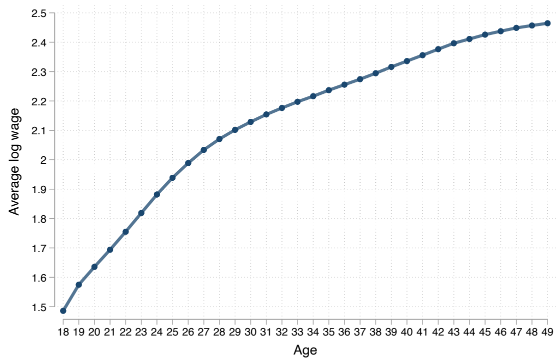
(a) Rio de Janeiro, 1994–2010. **(b)** Veneto, 1984–2001.



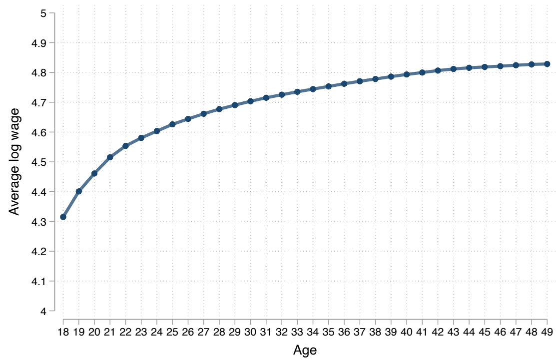
Notes: Worker-year age distribution for the samples of young workers used in our main analyses. Rio de Janeiro: workers born 1976 and after. Veneto: workers born 1966 and after.

Figure A2: Age and experience wage profiles.

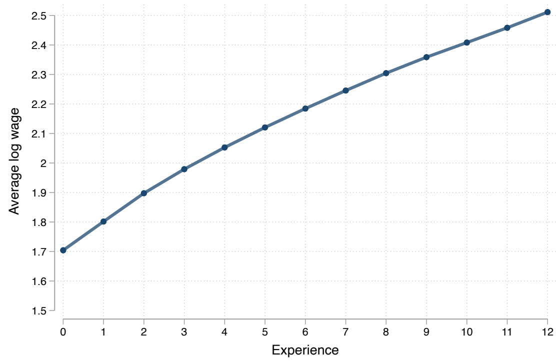
(a) Rio de Janeiro, age profile.



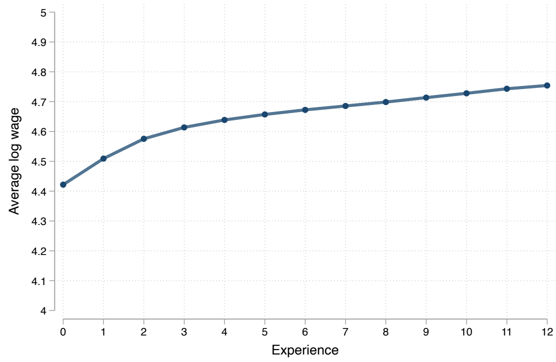
(b) Veneto, age profile.



(c) Rio de Janeiro, actual experience profile.



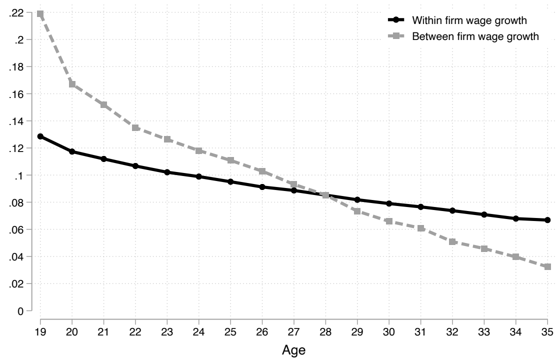
(d) Veneto, actual experience profile.



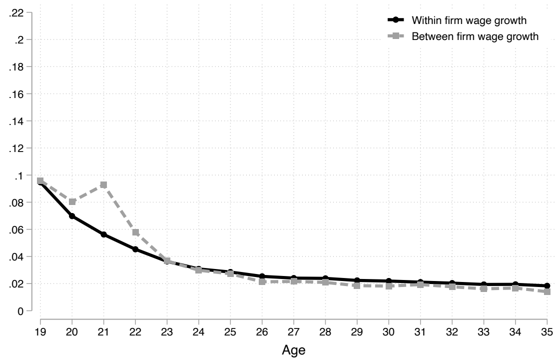
Notes: Average log wage age and years of (actual) experience profiles. Experience profiles are computed among the sample of young workers ages 18–35.

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

(a) Rio de Janeiro, 1994–2010



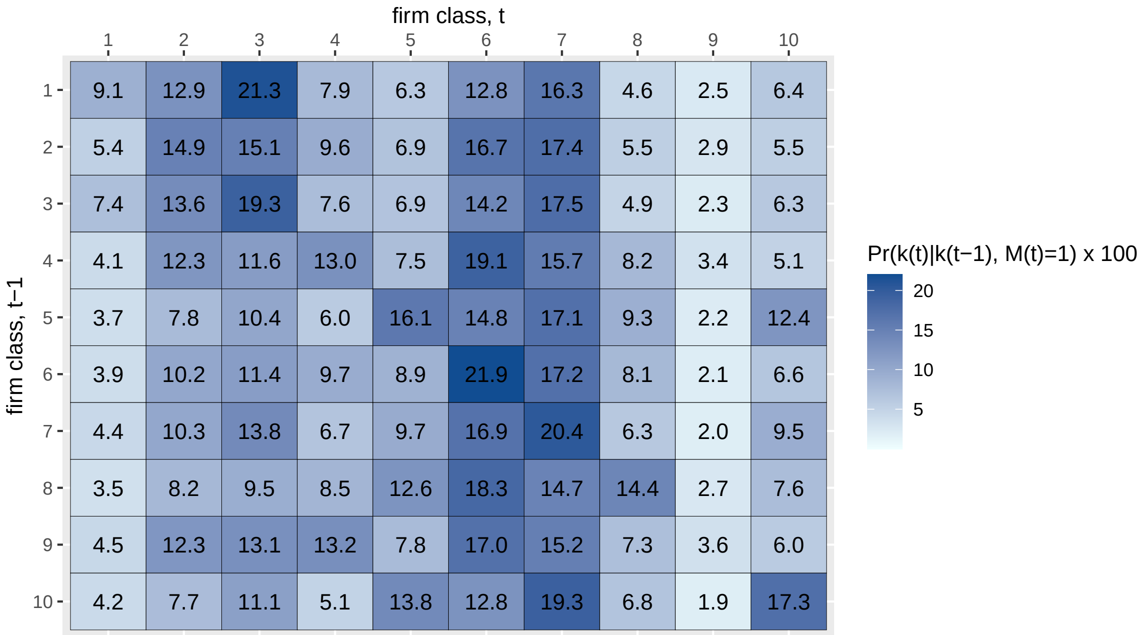
(b) Veneto, 1984–2001.



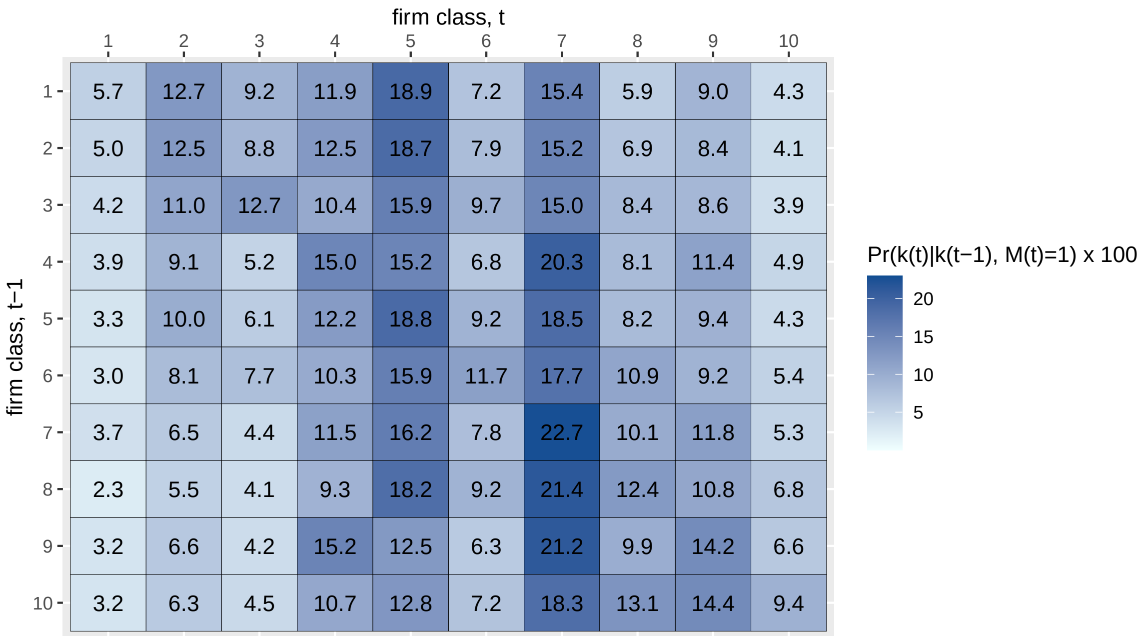
Notes: Average annual change in log wages, separately for firm stayers (within) and firm switchers (between).

Figure A4: Mobility across firm classes: Transition matrix.

(a) Rio de Janeiro, 1994–2010.



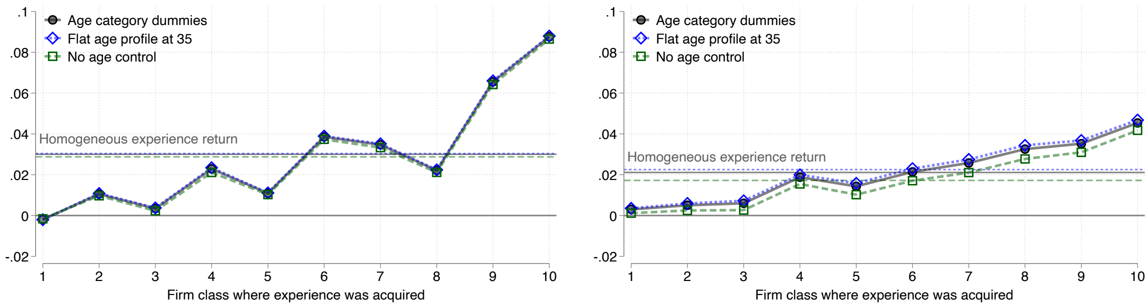
(b) Veneto, 1984–2001.



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.

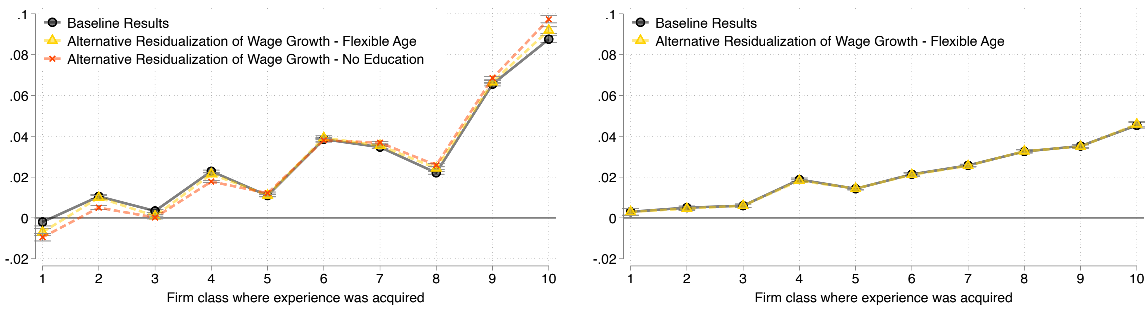
(a) Rio de Janeiro, 1994–2010. **(b)** Veneto, 1984–2001.



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.

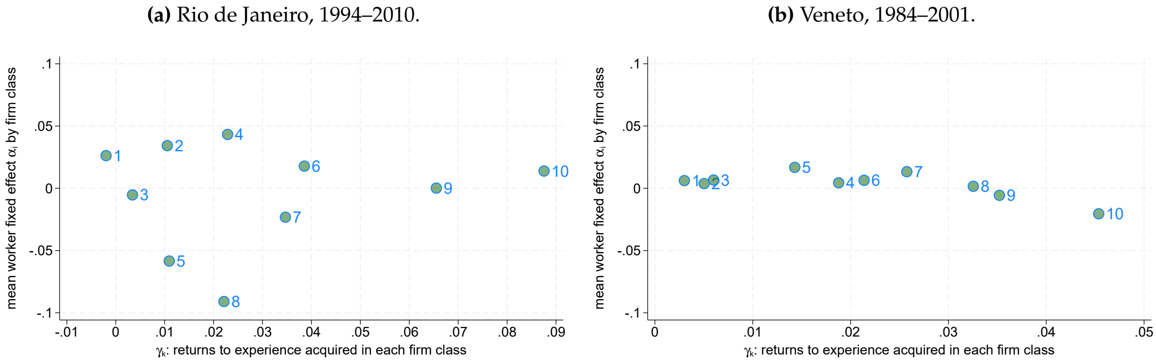
Figure A6: Robustness by alternative residualization of unexplained wage growth: returns to experiences acquired in different firm classes.

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



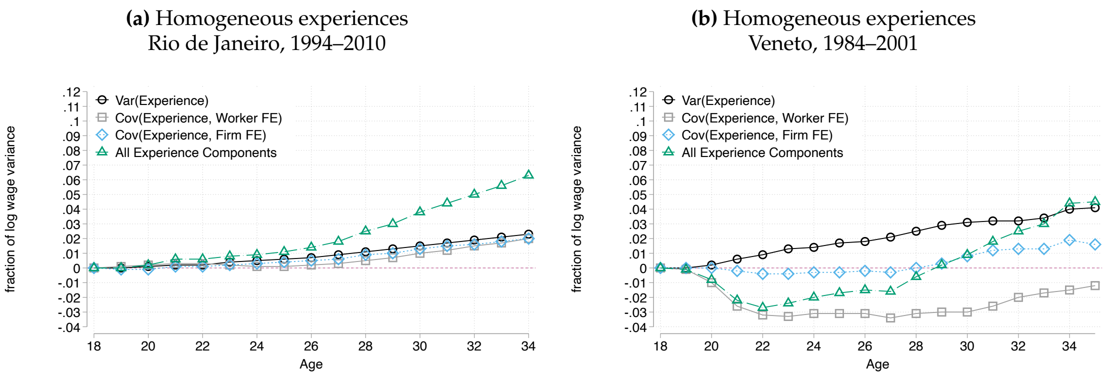
Notes: Estimates of returns to experiences acquired in different firm classes, using different ways of residualizing unexplained wage growth. Black dots: baseline estimates from Figure 1. Yellow diamonds: fully flexible specification of age effects; in Rio de Janeiro, the fully flexible age profiles 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: Firm-class learning opportunities and worker fixed effects



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 worker fixed effect in each firm class (α_i parameters in equation (8)). Sample includes largest connected set of firms (92.5% of firms in each of both countries). The correlation between the two sets of parameters is equal to 0.012 in Rio de Janeiro and -0.025 in Veneto.

Figure A8: Variance decomposition: returns-to-experiences components over wage variance, by age.

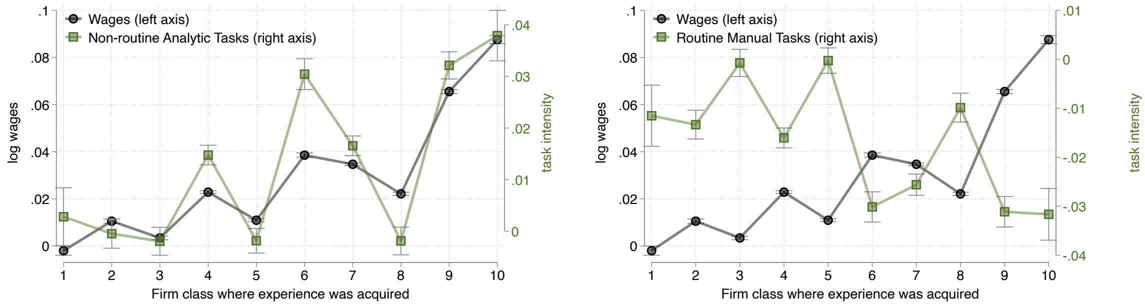


Notes: Shares of the wage variance explained by the homogeneous experiences components. Black dots represent the share of the variance explained by the variance of homogeneous experiences. Gray squares represent the share of the variance explained by the covariance of homogeneous experiences and worker 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 A9: Task content returns to experiences acquired in different firm classes, Rio de Janeiro.

(a) Non-routine Analytic Tasks.

(b) Routine Manual Tasks.

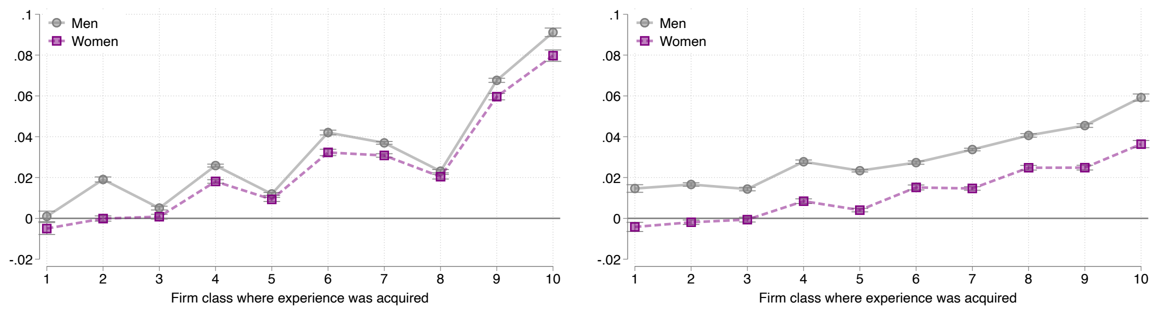


Notes: Black plot in both panels: Baseline estimates of wage returns to experiences acquired in different firm classes, described in Figure 1. Green plots: Estimates and 95% confidence intervals of task content returns to experiences acquired in different firm classes. Standard errors clustered at the 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.

Figure A10: Estimated separately for men and women: Returns to experiences acquired in different firm classes.

(a) Rio de Janeiro, 1994–2010.

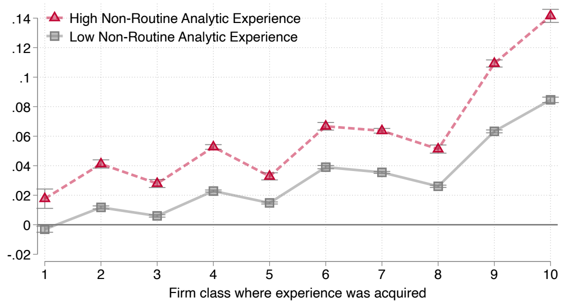
(b) Veneto, 1984–2001.



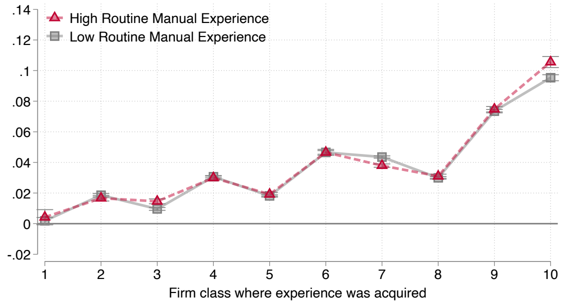
Notes: Point estimates of returns to experiences acquired in different firm classes, estimated heterogeneously for men and for women.

Figure A11: Returns to experiences acquired in different firm classes and task intensities, Rio de Janeiro

(a) Non-routine Analytic Tasks



(b) Routine Manual Tasks

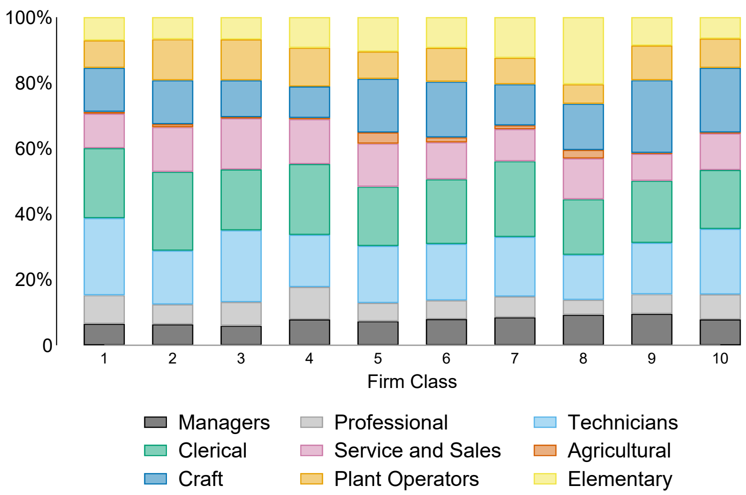


Notes: Estimated γ_m^τ parameters and 95% confidence intervals from log wage regressions of the form:

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

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 and panel (b) for routine manual tasks. Standard errors clustered at the person level.

Figure A12: Occupation composition by firm class, Rio de Janeiro



Notes: We present the 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. These shares are weighted by worker-years.

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 (1)	Routine Manual (2)
Experience: class 1	0.0028	-0.0115***
	(0.0029)	(0.0032)
Experience: class 2	-0.0005	-0.0133***
	(0.0014)	(0.0015)
Experience: class 3	-0.0020	-0.0007
	(0.0014)	(0.0014)
Experience: class 4	0.0148***	-0.0160***
	(0.0010)	(0.0010)
Experience: class 5	-0.0018	-0.0003
	(0.0012)	(0.0013)
Experience: class 6	0.0304***	-0.0301***
	(0.0015)	(0.0016)
Experience: class 7	0.0166***	-0.0256***
	(0.0010)	(0.0011)
Experience: class 8	-0.0019	-0.0099***
	(0.0014)	(0.0015)
Experience: class 9	0.0321***	-0.0311***
	(0.0013)	(0.0016)
Experience: class 10	0.0379***	-0.0316***
	(0.0025)	(0.0027)
Experience: NC	-0.0029**	-0.0048***
	(0.0014)	(0.0015)
Experience: PS	0.0759***	-0.0476***
	(0.0069)	(0.0066)
Experience: non-RJ	0.0271***	-0.0245***
	(0.0009)	(0.0010)
adj. R^2	0.695	0.736
Person FE	yes	yes
Firm FE	yes	yes
N	8,947,269	8,947,269

Notes: Outcome variables capture non-routine analytic 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 for occupation/industry switchers in new jobs.

	Rio de Janeiro		Veneto
	(1)	(2)	(3)
Switcher	-0.0144***	-0.0169***	-0.0146***
	(0.0009)	(0.0009)	(0.0014)
Stayer: Experience: class 1	-0.0026	-0.0031	0.0033
	(0.0021)	(0.0021)	(0.0022)
Switcher: Experience: class 1	-0.0039	-0.0044*	0.0060**
	(0.0028)	(0.0025)	(0.0027)
Stayer: Experience: class 2	-0.0009	0.0006	0.0071***
	(0.0010)	(0.0010)	(0.0011)
Switcher: Experience: class 2	0.0015	-0.0043***	0.0045***
	(0.0013)	(0.0012)	(0.0012)
Stayer: Experience: class 3	0.0016	0.0019**	0.0061***
	(0.0010)	(0.0009)	(0.0013)
Switcher: Experience: class 3	0.0011	-0.0012	0.0051***
	(0.0013)	(0.0012)	(0.0017)
Stayer: Experience: class 4	0.0113***	0.0123***	0.0168***
	(0.0006)	(0.0006)	(0.0009)
Switcher: Experience: class 4	0.0097***	0.0096***	0.0140***
	(0.0008)	(0.0008)	(0.0011)
Stayer: Experience: class 5	0.0012	0.0005	0.0163***
	(0.0008)	(0.0008)	(0.0008)
Switcher: Experience: class 5	0.0025**	0.0025**	0.0136***
	(0.0011)	(0.0010)	(0.0009)
Stayer: Experience: class 6	0.0204***	0.0233***	0.0188***
	(0.0009)	(0.0010)	(0.0011)
Switcher: Experience: class 6	0.0183***	0.0173***	0.0168***
	(0.0012)	(0.0011)	(0.0017)
Stayer: Experience: class 7	0.0184***	0.0188***	0.0257***
	(0.0006)	(0.0006)	(0.0007)
Switcher: Experience: class 7	0.0175***	0.0159***	0.0214***
	(0.0009)	(0.0008)	(0.0009)
Stayer: Experience: class 8	0.0089***	0.0074***	0.0282***
	(0.0009)	(0.0009)	(0.0011)
Switcher: Experience: class 8	0.0084***	0.0073***	0.0256***
	(0.0013)	(0.0012)	(0.0014)
Stayer: Experience: class 9	0.0386***	0.0430***	0.0293***
	(0.0009)	(0.0009)	(0.0010)
Switcher: Experience: class 9	0.0373***	0.0388***	0.0237***
	(0.0012)	(0.0011)	(0.0013)
Stayer: Experience: class 10	0.0590***	0.0661***	0.0335***
	(0.0016)	(0.0016)	(0.0017)
Switcher: Experience: class 10	0.0575***	0.0558***	0.0321***
	(0.0022)	(0.0021)	(0.0020)
Adj. R^2	0.688	0.684	0.581
Year FE	yes	yes	yes
Person FE	yes	yes	yes
Firm FE	yes	yes	yes
Sample	firm switchers	firm switchers	firm switchers
Switchers	occupation	industry	industry
SE clusters (persons)	726410	756879	193631
N	2274553	2412701	566665

Notes: The first column presents estimates of the estimated parameters in equation (13) for occupation switchers in Rio de Janeiro. The next two columns present the corresponding estimated parameters for industry switchers (which does not include occupation fixed effects), estimated in Rio de Janeiro and Veneto, respectively. In all columns, 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 and presented in parentheses. *p<0.10; **p<0.05; ***p<0.01.

Table A9: Returns to experiences acquired in different firm classes: hiring wages.

	Rio de Janeiro			Veneto		
	(1)	(2)	(3)	(4)	(5)	(6)
Experience: class 1	0.0004	-0.0074***	0.0016	-0.0075**	-0.0053***	-0.0085***
	(0.0032)	(0.0018)	(0.0032)	(0.0031)	(0.0014)	(0.0030)
Experience: class 2	0.0004	-0.0042***	0.0002	-0.0022	-0.0024***	-0.0016
	(0.0014)	(0.0009)	(0.0013)	(0.0017)	(0.0008)	(0.0017)
Experience: class 3	0.0059***	-0.0008	0.0071***	-0.0051*	-0.0022**	-0.0053**
	(0.0016)	(0.0008)	(0.0016)	(0.0027)	(0.0010)	(0.0026)
Experience: class 4	0.0137***	0.0064***	0.0128***	0.0064***	0.0083***	0.0074***
	(0.0009)	(0.0006)	(0.0009)	(0.0016)	(0.0007)	(0.0015)
Experience: class 5	0.0077***	0.0025***	0.0062***	0.0085***	0.0075***	0.0087***
	(0.0015)	(0.0007)	(0.0015)	(0.0013)	(0.0006)	(0.0013)
Experience: class 6	0.0207***	0.0145***	0.0198***	0.0154***	0.0123***	0.0153***
	(0.0014)	(0.0008)	(0.0013)	(0.0022)	(0.0009)	(0.0021)
Experience: class 7	0.0184***	0.0139***	0.0195***	0.0162***	0.0180***	0.0170***
	(0.0010)	(0.0005)	(0.0009)	(0.0012)	(0.0006)	(0.0012)
Experience: class 8	0.0172***	0.0083***	0.0151***	0.0182***	0.0199***	0.0189***
	(0.0016)	(0.0008)	(0.0015)	(0.0022)	(0.0009)	(0.0023)
Experience: class 9	0.0407***	0.0341***	0.0404***	0.0209***	0.0216***	0.0227***
	(0.0014)	(0.0008)	(0.0013)	(0.0017)	(0.0008)	(0.0017)
Experience: class 10	0.0566***	0.0519***	0.0581***	0.0278***	0.0235***	0.0274***
	(0.0026)	(0.0015)	(0.0025)	(0.0028)	(0.0012)	(0.0027)
Experience: NC	0.0142***	0.0073***	0.0168***	0.0062***	0.0074***	0.0059**
	(0.0023)	(0.0011)	(0.0023)	(0.0024)	(0.0008)	(0.0024)
Experience: PS	0.0199***	0.0214***	0.0180***	0.0006	-0.0031	-0.0035
	(0.0057)	(0.0033)	(0.0058)	(0.0130)	(0.0067)	(0.0125)
Experience: non-VE	0.0234***	0.0217***	0.0266***	0.0231***	0.0188***	0.0227***
	(0.0009)	(0.0005)	(0.0008)	(0.0016)	(0.0008)	(0.0016)
Adj. R^2	0.705	0.680	0.688	0.608	0.568	0.576
Person FE	yes	yes	yes	yes	yes	yes
Firm FE	joint	yes	yes	joint	yes	yes
Last Firm FE	joint	yes	yes	joint	yes	yes
Sample	origin-by-dest	origin+dest	origin-by-dest	origin-by-dest	origin+dest	origin-by-dest
SE clusters (persons)	673,247	1,074,371	673,247	131,182	315,720	131,182
N	1,701,070	3,455,945	1,701,070	303,122	962,751	303,122

Notes: Estimates and 95% confidence intervals of parameters $\{\gamma_m^{DWL}\}_{m=1}^{10}$ and $\{\gamma_m^{FDWL}\}_{m=1}^{10}$ in equations (14)-(15) presented in the first three columns for Rio de Janeiro and in the last three columns for Veneto. The coefficients presented in columns (1) and (4) present estimates from the main version of equation (15), including origin-by-destination fixed effects. The coefficients presented in columns (2) and (5) present estimates from equation (14), that includes origin and destination fixed effects separately; those presented in columns (3) and (6) present evidence from the same specification but using the sample included in the main version of equation (15). Standard errors are clustered at the person level and presented in parentheses. *p<0.10; **p<0.05; ***p<0.01.

Table A10: 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	0.0147***	0.0120***	0.0024	0.0041
	(0.0028)	(0.0028)	(0.0038)	(0.0038)
Experience: class 2	0.0144***	0.0119***	0.0090***	0.0106***
	(0.0013)	(0.0013)	(0.0019)	(0.0019)
Experience: class 3	0.0033**	0.0007	0.0008	0.0025
	(0.0014)	(0.0013)	(0.0024)	(0.0024)
Experience: class 4	0.0255***	0.0232***	0.0150***	0.0170***
	(0.0008)	(0.0008)	(0.0017)	(0.0016)
Experience: class 5	0.0004	-0.0022**	0.0131***	0.0149***
	(0.0011)	(0.0011)	(0.0013)	(0.0013)
Experience: class 6	0.0341***	0.0316***	0.0176***	0.0192***
	(0.0011)	(0.0011)	(0.0020)	(0.0020)
Experience: class 7	0.0284***	0.0258***	0.0247***	0.0263***
	(0.0009)	(0.0009)	(0.0011)	(0.0011)
Experience: class 8	0.0069***	0.0039***	0.0312***	0.0326***
	(0.0013)	(0.0013)	(0.0016)	(0.0015)
Experience: class 9	0.0621***	0.0594***	0.0382***	0.0400***
	(0.0011)	(0.0011)	(0.0016)	(0.0015)
Experience: class 10	0.0911***	0.0880***	0.0538***	0.0559***
	(0.0022)	(0.0022)	(0.0034)	(0.0034)
Experience: NC	0.0101***	0.0068***	0.0098***	0.0126***
	(0.0021)	(0.0021)	(0.0035)	(0.0035)
Experience: PS	0.0286***	0.0254***	-0.0306	-0.0215
	(0.0052)	(0.0052)	(0.0274)	(0.0274)
Experience: Other	0.0492***	0.0467***	0.0247***	0.0276***
	(0.0009)	(0.0008)	(0.0025)	(0.0025)
Adjusted R^2	0.630	0.630	0.420	0.419
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	268467	268467	31182	31182

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 linear worker and firm fixed effects from the main specification, as described in Section 3.3.4, where the firm effect follows from a modified version of equation (8) that uses a sample that excludes workers who enter the estimation of equation (16) and the worker effect comes from a version of equation (8) that excludes worker-year observations entering the estimation of equation (16). We control for age with six age-category indicators. Robust standard errors in parentheses. *p<0.10; **p<0.05; ***p<0.01.

Table A11: 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 (17). 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 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 A13: Returns to experiences acquired in different firm classes, by occupation at the time experience was acquired: Rio de Janeiro.

	(1)	White Collar (2)	Blue Collar (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 A14: 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 A15: Returns to experiences acquired in different firm classes, by one-digit occupation at the time experience was acquired: Rio de Janeiro.

	Class 1 (1)	Class 2 (2)	Class 3 (3)	Class 4 (4)	Class 5 (5)	Class 6 (6)	Class 7 (7)	Class 8 (8)	Class 9 (9)	Class 10 (10)	NC (11)	PS (12)	Non-RJ (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.

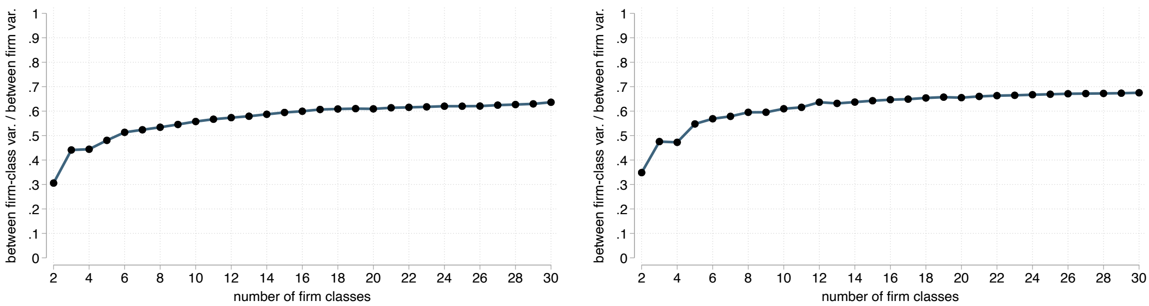
[2] We show that our results are not sensitive to alternative ways of netting out age and education.

[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.

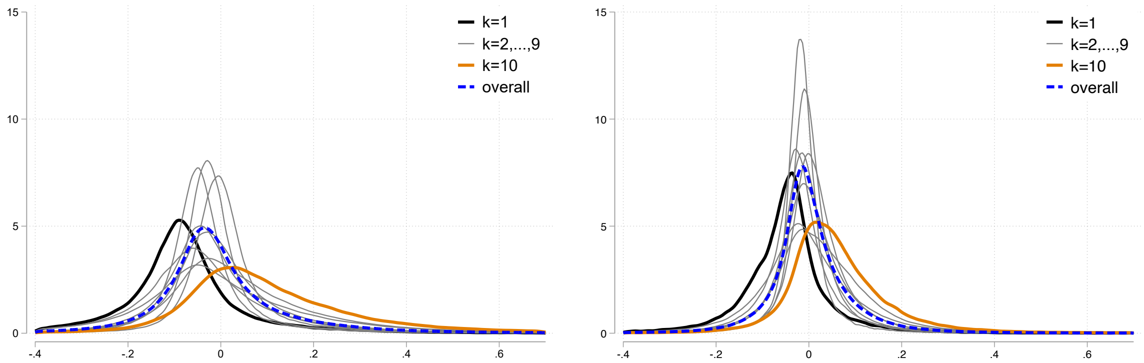
(a) Rio de Janeiro, 1994–2010. **(b)** Veneto, 1984–2001.



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 $\zeta_{it}(\mathbf{Exp}_{it}, \alpha_i)$ 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.

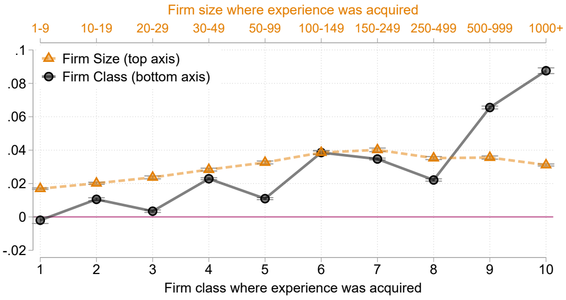
In the first two panels of Figure D1, we compare the heterogeneity in returns arising from our proposed firm classification to one arising from classifying firms based on their size—also using ten discrete categories ranging from firms with fewer than 10 workers to those with more than 1,000. Experiences 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.

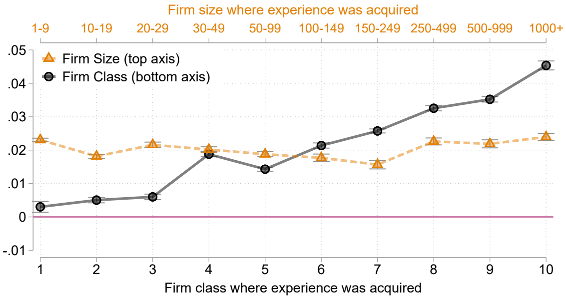
Lastly, the bottom panel of Figure D1 shows that, in Rio de Janeiro, our firm classification also captures richer heterogeneity than a classification based on level of education of the firm's workforce. Returns to experience are increasing in coworkers' education level at the firm where experience was 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.

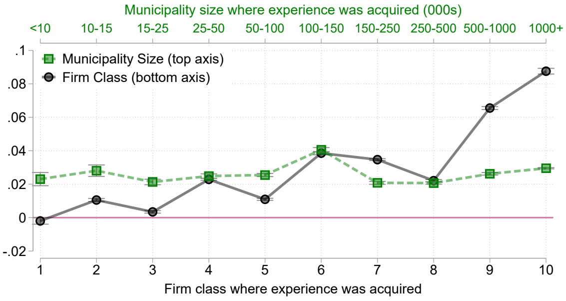
(a) Firm Size, Rio de Janeiro, 1994–2010.



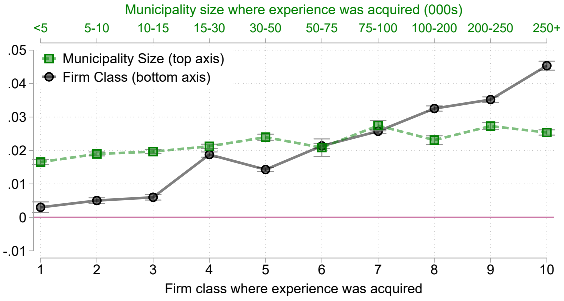
(b) Firm Size, Veneto, 1984–2001.



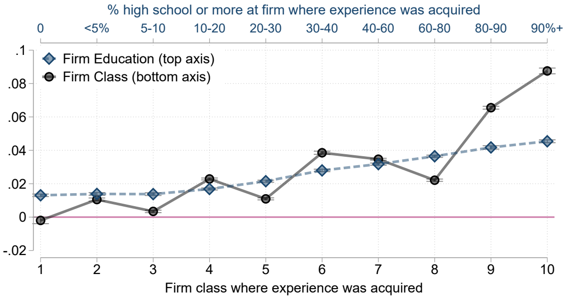
(c) City Size, Rio de Janeiro, 1994–2010.



(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:

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

where $\textbf{Exp}_{it}$ 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 Firm Characteristics and Learning Classes

F.1 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). 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.

Table F1: Predicting firm class using observables: Random forest classification results.

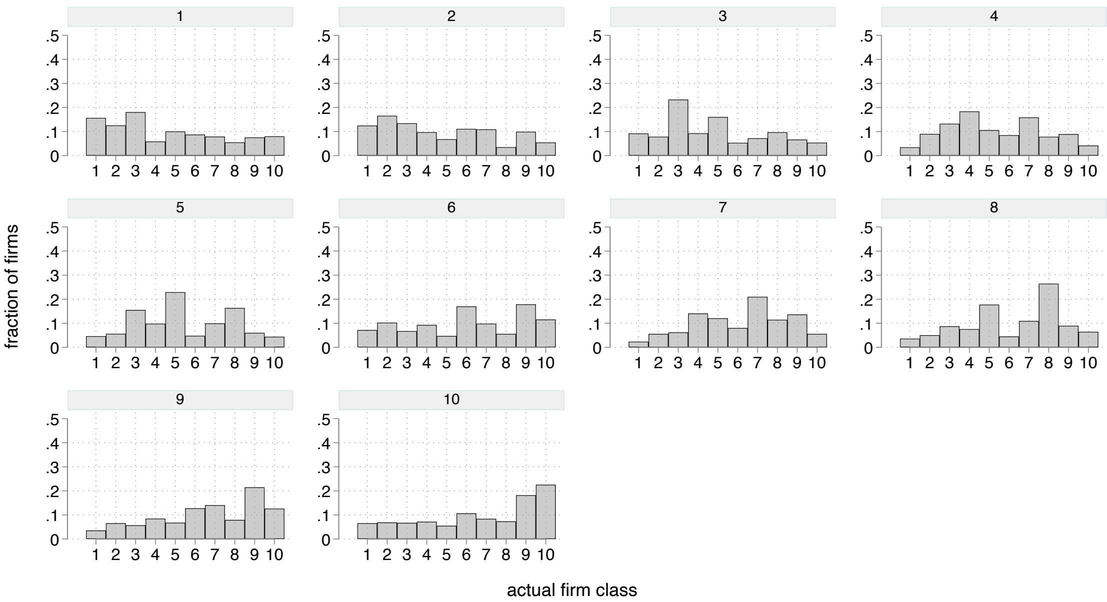
	(a) All firms	
	Rio de Janeiro, 1994–2010	Veneto, 1984–2001
Number of firms to classify	63,904	38,592
Correctly classified by algorithm	23.04%	22.22%
	(b) Firms with $\geq$ 50 employees	
	Rio de Janeiro, 1994–2010	Veneto, 1984–2001
Number of firms to classify	4,108	1,336
Correctly classified by algorithm	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.

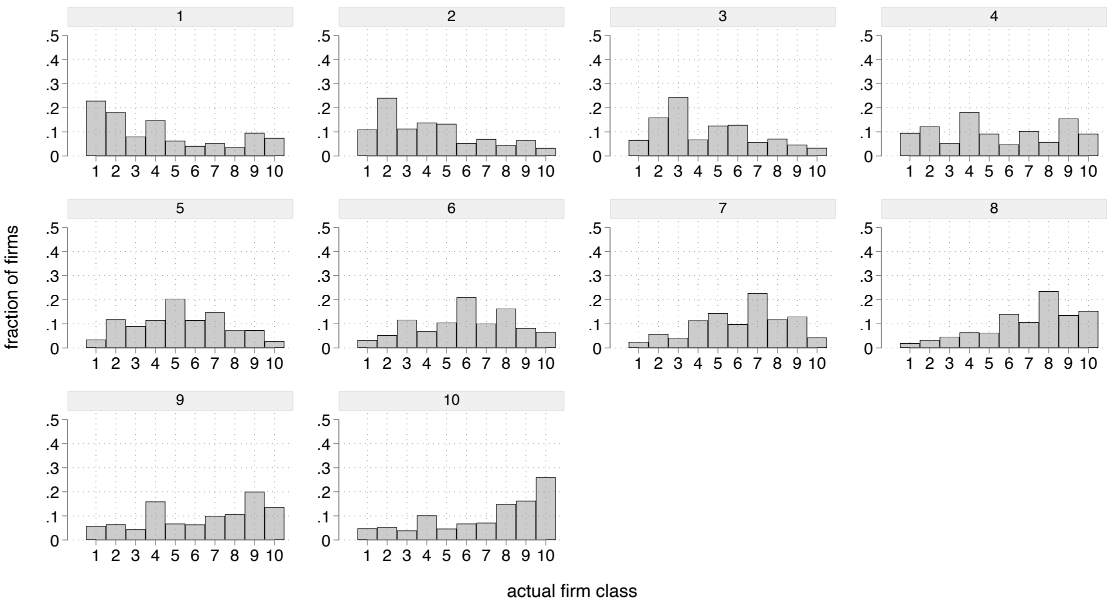
Table F1 shows results from the random forest prediction exercise. In both Rio de Janeiro and Veneto, the algorithm correctly classifies between 22–23% of firms. If we do the same exercise focusing only on large firms (50 employees or more), the algorithm correctly classifies 25% of large firms in Rio 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. Figure F1 provides additional details on this exercise by showing the distribution of *actual* firm class, separately for each value of *predicted* firm class.

Figure F1: 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 in Table F1. 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.

F.2 Multinomial Logit and Firm Observables

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 $k = 1, \dots, 10$ are firm classes. Figures F2 and F3 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, while the remaining variables are evaluated at the mean. Dummy variables are instead evaluated at zero and one. Each panel also includes $Pr\left(k(j) = k\right)$, the unconditional probability a firm belongs to a given class. For example, focusing on firm size in Figure F2, 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.

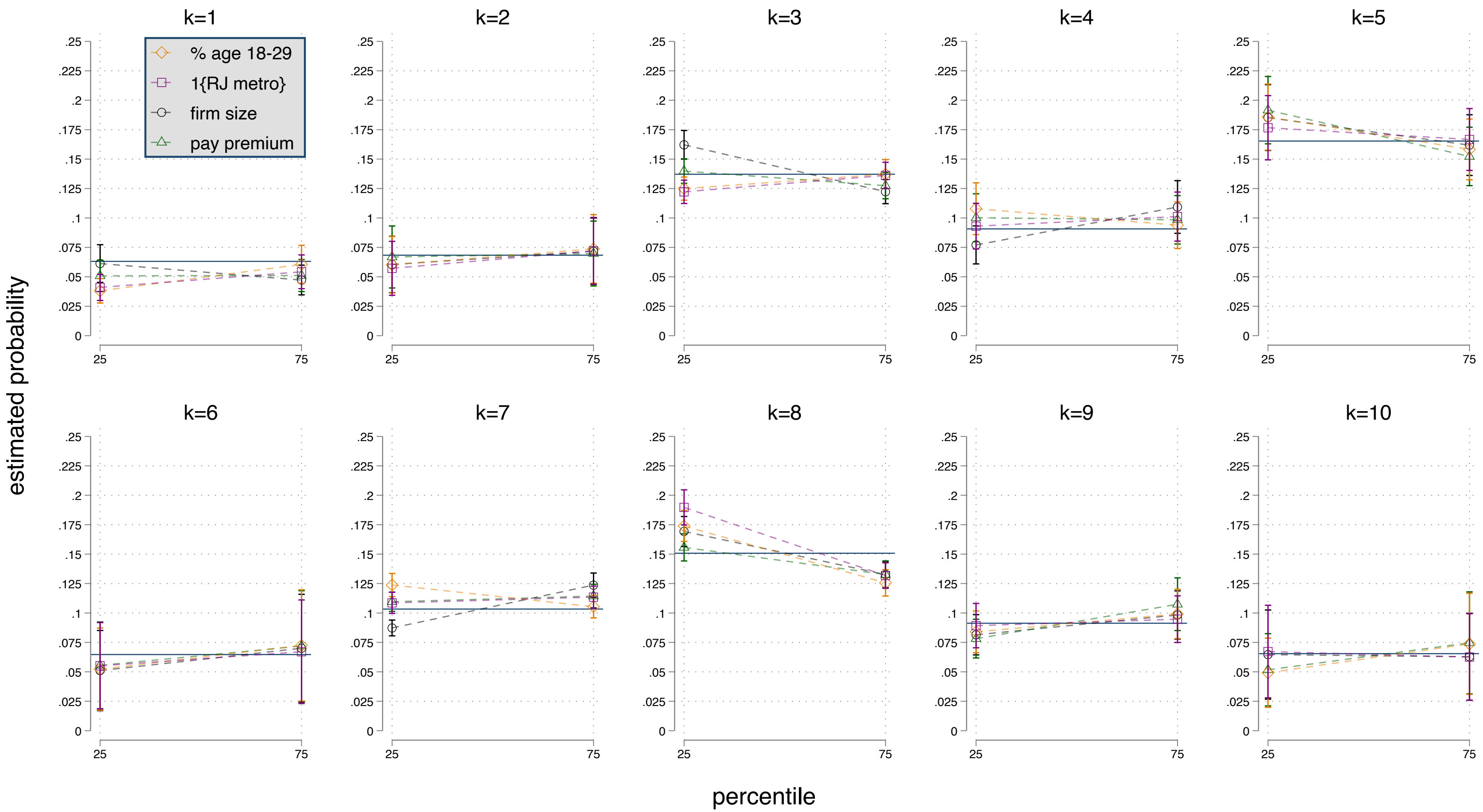
Pay premia. At the firm level, and keeping other covariates constant, both countries show no systematic relationship between firms' class and firms' pay premia (Figures F2 and F3). This is consistent with the results documented in Section 6, which do not condition on other firm observables.

Firm size. 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 F2), and less likely to belong to class 1 and to class 10 in Veneto (Figure F3). 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. 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 F2). In Veneto, large-city firms are less likely to belong to class 1 and more likely to belong to class 10 (Figure F3). 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.

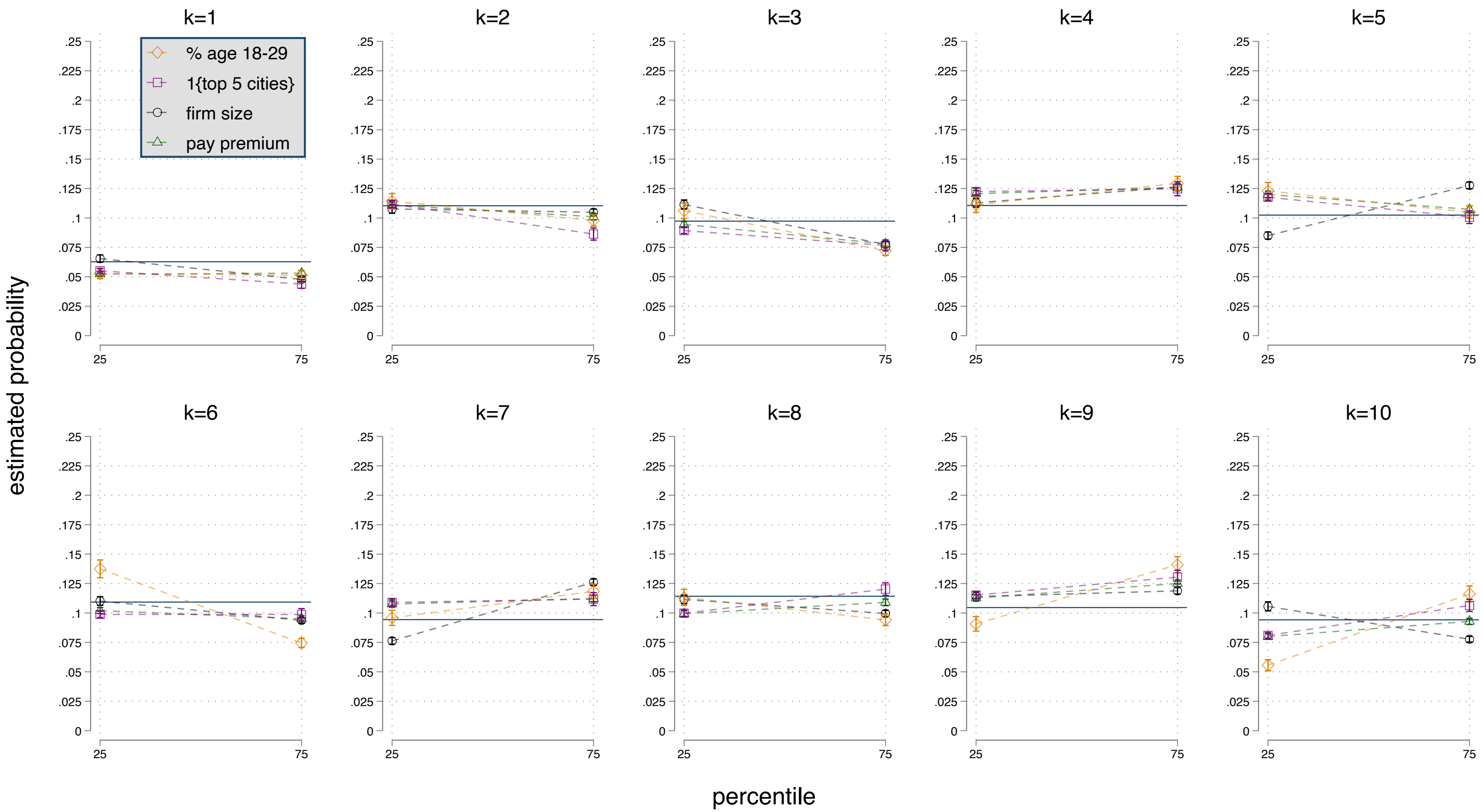
All in all, observed characteristics account for a relatively small share of the difference in firms' on-the-job learning opportunities. Learning opportunities as a dimension of firm heterogeneity may be an intrinsic attribute that is not easily identifiable with typically observed firm characteristics.

Figure F2: 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 F3: 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 F2: Firm-level average characteristics, by firm class. Rio de Janeiro, 1994–2010.

Class	1	2	3	4	5	6	7	8	9	10	NC
Firm Size: Mean	13.98	28.01	10.90	38.70	11.31	31.14	30.83	11.48	24.84	20.37	2.70
Firm Size: Median	4.80	6.09	4.83	7.51	5.18	6.83	7.96	4.80	7.01	6.19	1.27
% Men	0.602	0.614	0.610	0.623	0.616	0.642	0.646	0.611	0.662	0.638	0.553
% Age 18-29	0.515	0.467	0.487	0.430	0.425	0.452	0.407	0.377	0.429	0.440	0.501
% Age 30-39	0.264	0.280	0.277	0.289	0.294	0.283	0.294	0.301	0.289	0.286	0.251
% Age 40-49	0.142	0.163	0.153	0.179	0.185	0.172	0.191	0.214	0.182	0.183	0.149
% Age 50+	0.079	0.090	0.083	0.102	0.096	0.093	0.108	0.108	0.100	0.091	0.099
% RJ Metro Region	0.813	0.822	0.785	0.811	0.763	0.831	0.813	0.721	0.824	0.801	0.740
% Primary Sector	0.004	0.003	0.003	0.004	0.005	0.004	0.005	0.008	0.003	0.003	0.004
% Extractive Industries	0.004	0.004	0.002	0.003	0.002	0.004	0.003	0.003	0.006	0.007	0.002
% Manufacturing	0.113	0.108	0.097	0.112	0.105	0.109	0.106	0.084	0.105	0.098	0.072
% Construction	0.031	0.030	0.019	0.026	0.025	0.042	0.032	0.026	0.039	0.047	0.036
% Trade, Retail, Hospitality	0.442	0.419	0.518	0.375	0.461	0.367	0.317	0.380	0.305	0.326	0.479
% Accommodation, Meals	0.066	0.076	0.056	0.083	0.087	0.084	0.100	0.109	0.077	0.077	0.082
% Transportation, Storage, Communications	0.036	0.038	0.037	0.039	0.026	0.039	0.033	0.021	0.043	0.043	0.031
% Finance, Insurance	0.016	0.018	0.011	0.017	0.007	0.018	0.012	0.006	0.015	0.018	0.012
% Business Services, Real Estate	0.132	0.151	0.131	0.183	0.170	0.203	0.248	0.232	0.289	0.272	0.154
% Education	0.043	0.037	0.036	0.038	0.025	0.032	0.027	0.021	0.022	0.017	0.020
% Health, Social Services	0.026	0.033	0.028	0.047	0.023	0.031	0.042	0.035	0.033	0.028	0.030
% Other Services	0.078	0.075	0.059	0.066	0.061	0.059	0.069	0.073	0.058	0.056	0.066
% HS or more	0.394	0.357	0.385	0.359	0.322	0.359	0.334	0.300	0.371	0.404	0.405
Firm Pay Premium: Mean	-0.166	-0.129	-0.194	-0.124	-0.216	-0.052	-0.101	-0.194	-0.019	-0.017	-0.188
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

Notes: Mean firm-level characteristics of firms in each firm class in Rio de Janeiro. Sample of firms as described in Section 2, firm-level variables as described in Section 7 and in Appendix F 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.

Table F3: Firm-level average characteristics, by firm class. Veneto, 1984–2001.

Class	1	2	3	4	5	6	7	8	9	10	NC
Firm Size: Mean	7.21	8.47	7.38	10.34	17.45	9.10	20.37	9.63	10.93	5.87	1.42
Firm Size: Median	3.59	4.52	3.41	4.57	6.44	3.77	6.54	3.67	4.19	3.26	0.89
% Men	0.584	0.603	0.609	0.570	0.608	0.521	0.585	0.457	0.517	0.445	0.514
% Age 18-29	0.612	0.573	0.478	0.586	0.504	0.426	0.516	0.472	0.588	0.586	0.618
% Age 30-39	0.205	0.234	0.287	0.229	0.268	0.311	0.269	0.302	0.243	0.256	0.200
% Age 40-49	0.113	0.121	0.160	0.118	0.149	0.180	0.142	0.157	0.113	0.111	0.104
% Age 50+	0.071	0.072	0.075	0.067	0.080	0.082	0.073	0.069	0.056	0.047	0.078
% 5 Largest Cities	0.146	0.135	0.177	0.190	0.162	0.239	0.211	0.297	0.240	0.301	0.234
% Extractive and Chemical Industries	0.031	0.044	0.042	0.037	0.060	0.037	0.047	0.027	0.031	0.021	0.015
% Manufacturing: Metal	0.134	0.143	0.125	0.199	0.198	0.125	0.230	0.132	0.193	0.142	0.091
% Manufacturing: Other	0.386	0.409	0.352	0.280	0.326	0.203	0.227	0.128	0.188	0.145	0.151
% Construction	0.195	0.173	0.087	0.151	0.106	0.054	0.076	0.044	0.081	0.051	0.143
% Trade, Retail, Hospitality	0.126	0.134	0.269	0.160	0.197	0.391	0.243	0.383	0.248	0.324	0.367
% Transportation, Communications	0.020	0.015	0.017	0.024	0.022	0.028	0.028	0.034	0.033	0.035	0.030
% Finance, Insurance, Business Services	0.034	0.028	0.032	0.064	0.036	0.073	0.072	0.147	0.121	0.164	0.091
% Other Services	0.068	0.049	0.062	0.079	0.048	0.079	0.069	0.093	0.096	0.110	0.101
Firm Pay Premium: Mean	-0.058	-0.065	-0.092	-0.041	-0.045	-0.055	-0.017	-0.023	-0.031	-0.027	-0.096
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

Notes: Mean firm-level characteristics of firms in each firm class in Veneto. Sample of firms as described in Section 2, firm-level variables as described in Section 7 and in Appendix F 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.