Differences in On-the-Job Learning Across Firms*

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Abstract

We present evidence consistent with large disparities across firms in the on-the-job learning their young employees experience, using administrative datasets from Brazil and Italy. We discretize firm "classes" using a clustering methodology which groups together firms with similar distributions of unexplained wage growth. Equipped with this categorization of firms—which our conceptual framework interprets as skill-learning classes—we document three main results. First, Mincerian returns to experience vary substantially across experience acquired in different firm classes, and the magnitude of this type of heterogeneity is associated with significant shifts across the distribution of early-career wage growth. Second, past experience at firms with better on-the-job learning is associated with subsequent jobs featuring greater non-routine task content. Third, firm and workforce observables only mildly predict on-the-job learning opportunities across firms. Our findings hold among involuntarily displaced workers who have no seniority at their new jobs, reinforcing a human capital interpretation as opposed to seniority-based pay schemes.

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1 Introduction

A growing literature highlights the importance of firms in the labor market, mostly focusing on the role of firms' pay premia on workers' compensation levels (see Abowd et al., 1999; Card et al., 2013, 2018). More broadly, workplaces vary greatly across many dimensions that impact workers' experiences on the job, including the use of new technologies, management practices, training schemes, and coworkers' quality, among others. These differences suggest the existence of heterogeneous learning opportunities across firms, which may be particularly relevant for young workers, given the importance of on-the-job human capital accumulation in driving early career outcomes (Rubinstein and Weiss, 2006).

Previous literature has examined the importance of heterogeneous post-schooling human capital accumulation, encompassing variation across industries (Neal, 1995), occupations (Kambourov and Manovskii, 2009), tasks (Gathmann and Schönberg, 2010) and geography (De La Roca and Puga, 2017). The firm as a driver of variation in learning opportunities has received theoretical attention for some time now (Rosen, 1972; Gibbons and Waldman, 2006), but few accompanying empirical evidence.[1]

In this paper, we find evidence consistent with large disparities across firms in the on-the-job learning their employees experience. We rely on matched employer-employee records from Brazil and Italy, encompassing population data on the state of Rio de Janeiro for 1994–2010, and population data on the region of Veneto covering 1984–2001.[2] Our analysis largely focuses on cohorts observed from entry through their mid-thirties. As such, we can capture their entire employment histories across different types of firms, and estimate the returns to heterogeneous experiences during the steepest part of lifecycle wage growth. We believe 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.[3]

We start by laying out a conceptual framework in which workers accumulate human capital at work through learning-by-doing. Firms differ in the amount of learning their workers experience, as well as in their pay premia. We assume a discrete number of firm classes regarding the on-the-job learning dimension, where all employees in a firm-class draw from the same distribution of human capital growth. Earnings are determined by workers' human capital (both pre-labor market and that accumulated while working) and the firm's pay premium (common to all workers in a firm). This framework leads to two results. First, an earnings equation featuring returns to experience that vary depending on the firm class where experience was acquired—a generalization of a classical Mincerian experience term that implicitly assumes homogeneous experience. Second, the possibility of categorizing firms into learning classes using firms' distributions of stayers' earnings

[1] Theoretical work such as Rosen (1972) or Gibbons and Waldman (2006) do not feature a clear conceptual distinction between "jobs" and "firms." This is also the case in the search-and-matching models, which have recently considered varying human-capital growth across jobs/firms (e.g. Gregory, 2019).

[2] In both cases, we follow workers who move to different areas of Brazil or Italy.

[3] Additionally, we 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., 2020; Donovan et al., 2020).

growth. Assuming a discrete number of firm classes allows us to estimate richer models of earnings and mobility relative to a framework in which each firm had its own idiosyncratic type.[4]

Following the conceptual framework, the empirical approach consists of assigning firms to classes in a first step, and estimating heterogeneous returns to experience acquired in different firm classes in a second step. We implement the categorization of firms into classes using firms' distributions of stayers' unexplained earnings growth (i.e., growth net of worker demographics and year effects) as inputs in a k-means clustering algorithm similar to that of Bonhomme et al. (2019).[5] This algorithm groups firms so as to maximize within-class similarity of firms' unexplained earnings growth distributions. The number of firm classes needs to be set ex-ante, and we classify firms into ten classes.[6] To avoid issues related to overfitting, in both datasets we follow 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 experience acquired in different firm classes.

We estimate heterogeneous returns to experience acquired in different firm classes for workers aged 18–35. Our approach is to estimate log earnings regressions that—while including firm fixed effects and person fixed effects—allow for each of the ten different types of experience to have a different return.[7] Consistent with heterogeneous learning opportunities across firms, we find sizable disparities in the returns to experiences acquired in different firm classes. Our benchmark are returns to Mincerian homogeneous experience, which we find to be around 3.7% in Rio and 1.1% in Veneto. Relative to this benchmark, returns to experience acquired in the top learning firm-classes are about three times as large, in both Rio (9.8%) and Veneto (3.5%). Returns to experience acquired in firm classes offering the least learning opportunities are close to zero or even negative.

We show that heterogeneous experience results are robust to controlling for age in a variety of ways, and we also test for differing returns by workers' education, latent skills, occupation, and gender. Across education levels, the main patterns remain broadly similar (e.g. all education levels benefit the most from working at top learning firms). In relative terms, however, the highly educated benefit the most from having worked at the top learning firm-class. Workers with higher latent skills (measured by their person fixed effect) experience higher returns across all classes, but no relative differences across classes compared to those with lower latent skills. Results by type of occupation suggest learning in a firm class is highly correlated between white- and blue-collar workers. Lastly, results for men and women are largely similar, although women in Veneto experience slightly lower

[4]This includes non-linear models, and linear models of interaction effects that would be too high-dimensional with unconstrained firm types.

[5]In both datasets we net out workers' age and gender, and year fixed effects. In Rio de Janeiro, we additionally net out workers' education level (we do not observe education in Veneto). Wage growth net of these characteristics is what we call "unexplained earnings growth."

[6]In our view, ten firm classes are enough to allow sufficient richness in types, while not being such a large number that makes interpreting results too burdensome. Bonhomme et al. (2019) also select ten wage-level firm classes. In both countries, the between-firm-class variance of unexplained earnings growth is about 60% of the between-firm variance. Going beyond ten firm classes does not change this percentage substantially.

[7]Our earnings measure in Rio de Janeiro are hourly wages while in Veneto, where we do not observe hours, we analyze daily wages.

returns to experience across all firm classes.

Studying displaced workers and their first post-displacement earnings observation, we show evidence that is consistent with our estimates capturing differences in the learning of general skills, rather than returns to tenure or seniority-based pay schemes (e.g. Lazear, 1981; Guiso et al., 2013). Displaced workers who suffered a firm closure or mass layoff have firm tenure set to zero at their new job for exogenous reasons (Dustmann and Meghir, 2005), and feature a "clean" separation between their current employer and the firm(s) where they acquired experience. When focusing on this sample, we still find similarly heterogeneous returns to experiences acquired in different firm classes.[8] This result is consistent with our firm categorization capturing differences in the learning of skills that are portable beyond the firm where they were acquired, but harder to reconcile with explanations solely based on heterogeneous within-firm returns to tenure.[9] Relatedly, and taking advantage of our discrete categorization of firm classes, we further examine the generality of skills acquired across firm classes by estimating returns to different experiences when the worker is *outside* of the firm class where said experience was acquired. Results from this exercise are also consistent with skill generality.

Next, we document a relationship between past experience at different firm classes and workers' job task content. To study heterogeneous learning across firms one would ideally observe measures of workers' skills (see Arellano-Bover, 2020b), yet in absence of such data, jobs' task content carries relevant information related to workers' evolving skills. We carry out this analysis on the Brazilian data, which includes detailed information on workers' occupations. We crosswalk this information with occupational task content from the O*NET across four dimensions: non-routine analytic, non-routine interpersonal, routine cognitive, and routine manual tasks (Acemoglu and Autor, 2011). Experience acquired in the top learning firm classes yields substantial increases in workers' non-routine analytic and non-routine interpersonal task content. Moreover, these results hold in the sample of displaced workers, further highlighting how such updates in task contents hold across employers.

In light of sizable differences in firms' learning opportunities, we then consider whether firms' characteristics can predict their firm class. That is, without observing firms' wage growth distributions, how well could a worker or an econometrician predict the existence of better or worse learning opportunities? This is a policy-relevant assessment since being able to recognize better-learning firms would be valuable for young job seekers and policymakers alike.

To determine how well firm observables jointly predict firm classes, we train a random forest classification algorithm (Athey and Imbens, 2019). The goal of the algorithm is to assign each (out of sample) firm to one of the ten possible classes.[10] We then compare predicted to observed firm classes and find that, in both Rio de Janeiro and Veneto,

[8] In the full sample, we also find very similar heterogeneous returns if we directly control for firm tenure in our regressions.

[9] Regardless of whether returns to tenure are due to firm-specific skills, incentive-pay schemes, or endogenous survival of good firm-worker matches.

[10] The firm observables we feed the random forest include mean annual earnings, AKM firm effects, firm size, sector, geographic location, and workforce characteristics.

the algorithm correctly classifies 25% of firms. We further consider the importance of specific observable characteristics by estimating an unconditional tabulation of workforce/firm characteristics, and a multinomial logit model that renders *ceteris paribus* associations of firm characteristics and firm class. The results from these exercises are broadly consistent with the limited predictive power of the random forest algorithm: some mild associations emerge, but we do not find evidence of a smoking-gun predictor of better or worse on-the-job learning. For instance, we find no meaningful relation between firms' learning classes and AKM pay premia. At the same time, while large-city firms in Veneto are somewhat more likely to be top learning-class firms (consistent with De La Roca and Puga, 2017), this is not the case in Rio de Janeiro. In both Rio and Veneto, larger firms are somewhat less likely to belong to the least-learning class.

Lastly, we come back to our estimates of heterogeneous returns to different experiences and provide an additional quantification of their magnitudes using as a benchmark the distribution of early-career earnings growth. We compute the earnings growth associated with different counterfactual employment trajectories across firm classes, and place it on the observed distribution of annualized total growth between ages 18–35. Being exclusively employed in the least-learning firm class is associated with the 17th and 19th percentile of early-career growth in Rio de Janeiro and Veneto, respectively. Being employed in equal proportion across the least-learning class, the top-learning class, and the closest-to-homogeneous-returns class is associated with the 43rd and 39th percentiles. Finally, being exclusively employed in the top-learning class throughout the early career is associated with the 76th and 66th percentiles. We interpret these shifts across the distribution of early career growth as further evidence of the meaningful consequences for young workers from being employed in different learning-class firms.

This paper contributes to several strands of literature. Regarding a very large literature on post-schooling human capital accumulation (e.g. Neal, 1995; Acemoglu and Pischke, 1999; Dustmann and Meghir, 2005; Gathmann and Schönberg, 2010), we show evidence consistent with large disparities in human capital accumulation where firms are relevant units of heterogeneity. This possibility has been relatively unexplored empirically, although it has been previously postulated theoretically (Rosen, 1972; Gibbons and Waldman, 2006). A recent paper interested in a similar question but tackled through the lens of a macro search and matching model is Gregory (2019). She uses German data and, consistent with our findings, she documents that different establishments offer systematically different earnings growth, which has important implications for young workers' career trajectories.[11] Using data from Spain, Arellano-Bover (2020a) documents long-term benefits from holding the first job at a large firm and finds evidence consistent with large Spanish firms offering better human capital accumulation than small firms.

We contribute to a second related literature that studies how firm-driven wage differ-

[11]Compared to Gregory (2019), our discretization of firm types allow a number of clear empirical analyses on the effects and characteristics of firm types that would be unfeasible with idiosyncratic establishment types. We also devote special attention to the relationship between on-the-job learning opportunities and firms' observable characteristics. Finally, we show our findings are largely comparable in two very different economies.

entials shape the wage structure (Abowd et al., 1999; Card et al., 2013; Goldschmidt and Schmieder, 2017; Sorkin, 2018; Card et al., 2018; Song et al., 2019; Bonhomme et al., 2019). The focus of this literature on contemporaneous worker-firm links, contrasts with the relatively little attention devoted to effects of *past* experience at heterogeneous firms.[12] We make progress on this front and show how firms can have long term consequences for workers by impacting their human capital accumulation. By showing that heterogeneous experience across firm classes impacts workers' task content, we additionally contribute to previous work examining the importance of tasks in the early career (Yamaguchi, 2012; Sanders, 2014; Speer, 2017; Stinebrickner et al., 2019). Our key empirical approach follows the discretization and clustering methodology of Bonhomme et al. (2019), which they apply to earnings levels and we instead apply to earnings growth. Some papers have explored how learning-by-doing can vary depending on workplace characteristics such as exporter status (Macis and Schivardi, 2016), the quality of coworkers (Jarosch et al., 2020; Nix, 2020) or being in a large city (De La Roca and Puga, 2017). We add to this work by freely allowing firms—regardless of their attributes—to embody different learning opportunities. The importance of our approach is reinforced by our finding that, in our two settings, firm observables only mildly predict on-the-job learning.

The rest of this paper is organized as follows. Section 2 describes our administrative datasets from Brazil and Italy. Section 3 lays out our conceptual and empirical frameworks regarding heterogeneity across firm classes in learning opportunities, and the classification of firms using a clustering algorithm. Section 4 presents our main results on heterogeneous returns to experience acquired in different firm classes, including results for the sample of displaced workers. Section 5 documents the association between heterogeneous experiences and jobs' task content. Section 6 investigates how well can firm observables predict firms' learning class. Section 7 benchmarks the magnitude of our main findings against the distribution of early career wage growth. Section 8 concludes.

2 Data Sources

Brazil. We take advantage of *Relação Anual de Informações Sociais* (RAIS) data for the 1994-2010 period. RAIS covers matched employee-employer information from a mandatory annual survey filled out by all formal sector firms.[13] 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-a-vis the rest of the country. RAIS includes unique person identifiers which allow us to track workers over time along with important observed characteristics, including their age, gender and educational attainment.[14] We additionally observe unique

[12] Abowd et al. (2018), and Bonhomme et al. (2019) provide some evidence on dynamic implications of employment at heterogeneous firms. Abowd et al. (1999) and Abowd et al. (2006) estimate firm-varying returns to tenure, but not experience.

[13] RAIS initially covered employment across various regions in 1986, reaching complete coverage of formal sector employment in 1994.

[14] Given the distribution of educational attainment in Brazil, we classify workers as high school dropouts, high school graduates, or having gone beyond high school.

establishment and firm identifiers, along with information on their sectoral classification and total annual employment.[15] We rely on unique identifiers for workers and firms in the sample, which allow us to link workers to their employers in every year in the sample.

For each worker in the sample, we observe the number of days worked each year and the number of hours worked in each week. We use these variables to construct measures of labor market experience and tenure 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 leverage information on hours worked to construct a measure of workers' hourly wages.

Importantly, we observe detailed information on workers' three-digit occupations, which we use to construct a mapping to occupational task content. In particular, we take advantage of a concordance between the Brazilian Classification of Occupations (CBO) and the Occupational Information Network (O*NET) in the United States to measure the task content of occupations. O*NET includes detailed information on work activities and work context across jobs. We use this information to construct measures of task content across occupations, which we subsequently match to occupations in RAIS using the CBO-O*NET crosswalk.[16] We follow Autor et al. (2003); Acemoglu and Autor (2011) and focus on four different dimensions of the task vector, including non-routine analytic, non-routine interpersonal, routine cognitive and routine manual tasks.[17]

Italy. We take advantage of data from the Veneto Worker History (VWH) dataset from 1984 through 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 richest Italian regions which in 2012 had a population of about 5 million. The dataset includes unique worker and firm identifiers, which we use to construct employment histories during our period of interest. 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 we use to construct a measure of daily wages. Previous papers that have used these data include Card et al. (2014), Battisti (2017), Serafinelli (2019), and Kline et al. (2020).

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 experience acquired in different firm classes—

[15] 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.

[16] This analysis carries an underlying assumption that the task content across occupations is directly comparable across Brazil and the U.S (Almeida et al., 2018). While this is a strong assumption, we focus on workers' task content to examine moves up the job ladder rather than seeking to precisely characterize the tasks they perform at work. As such, as long as tasks are broadly similar across occupations across the two countries, this assumption should not affect the interpretation of our results.

[17] For instance, the non-routine analytic task measure considers the frequency with which workers analyze data/information, think creatively and interpret information for others.

focuses on young workers for whom we observe their labor market trajectories starting at 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. Across both countries, we focus on workers' main job, defined as the employment spell yielding the highest total earnings each year. Nonetheless, differential data availability across countries implies we consider hourly wages and daily wages as the main outcome variable in Brazil and Italy, respectively. These restrictions yield a sample of 4,196,508 unique workers in Rio de Janeiro and 1,163,473 workers in Veneto. Our main sample covers young workers who are ever employed in Rio de Janeiro or Veneto, yet in both cases we also observe their employment spells in other parts of the country and include them in our sample.

In Table 1, we present descriptive statistics for the sample of workers in Rio de Janeiro and Veneto. The sample is 58% 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. For the cohort we observe continuously from 18–35, young workers in Rio de Janeiro spend on average 6.35 years employed in the formal sector holding 3.5 jobs, compared to their Italian counterparts who on average spend 8.15 years and hold 3.3 jobs. Cross-country differences in average labor market experience are partly driven by the role of informal employment in Brazil (Ulyssea, 2018). The last two rows show that Brazilian workers in our oldest cohort enjoy mean and median annual earnings growth of 6.8% and 5.5%, respectively. In Veneto, mean and median annual earnings growth are 3.1% and 2.3%.

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 pre-labor market entry, and h_{it} is the stock of human capital accumulated on-the-job since labor market entry.

Skill acquisition on the job occurs through learning-by-doing, 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:

$$h_{i,t+1} = h_{it} + \mu_{it}^k, \tag{2}$$

where $k \in \{1, \ldots, K\}$ is the firm class where i is employed during period t, and μ_{it}^k is an i.i.d. draw from the CDF F_k, with $E\left[\mu_{it}^k\right] = \gamma_k$.

Differences in distributions F_k reflect that some firms provide better on-the-job learning

opportunities than others. In the limit, 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 a discrete number of firm classes that is greater than one but lower than the number of firms.

The above implies that the stock of human capital accumulated on the job depends on a worker's past employment history across heterogeneous firms:

$$h_{it} = \sum_{l=1}^{t-1} \mu_{il}^{k(i,l)}, \tag{3}$$

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

where $\mathbf{Exp}_{it}$ is the vector of employment histories at firms of different classes since labor market entry up until time t, and $\mathbf{1}\{k(i,l) = m\}$ is the indicator function equal to one if worker i was employed at a firm of class m during period l.

Earnings. The earnings of worker i employed at firm j in period t combine human capital H_{it} and a firm component ψ_j:[18]

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

Log earnings are thus given by:

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

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

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

3.2 Empirical Framework

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

$$\ln y_{it} = \psi_{j(it)} + \alpha_i + \sum_{m=1}^{K} \gamma_m \cdot \mathrm{Exp}(m)_{it} + \eta_{it}. \tag{8}$$

Where ψ_j are firm fixed effects, α_i are person fixed effects, $\mathrm{Exp}(m)_{it}$ is the amount of experience worker i has acquired in firms of class m up until period t, and η_{it} is a mean zero error term. The returns to different types of experiences $\{\gamma_1 \ldots \gamma_K\}$ are our parame-

[18] The firm premium ψ_j could arise from at least two different wage setting (static) models: i) a rent-sharing model where ψ_j is a combination of worker surplus share and j's average match surplus (Card et al., 2015); ii) a monopsonistic wage setting model where ψ_j is a combination of a labor supply parameter and j's value-added per worker (Card et al., 2018). We will allow each firm j to have their own idiosyncratic premium.

ters of interest. Note that the experience terms in equation (8) represent a generalization of a classical Mincerian experience term assuming equal returns to experience (Mincer, 1974), regardless of the type of firm where experience was acquired. As a benchmark, we consider versions of equation (8) with such "homogeneous experience" (i.e., imposing the restriction $\gamma_1 = \ldots = \gamma_K$). To correctly measure workers' experience across different firm types, we estimate equation (8) using a sample of workers who we observe starting at labor market entry.

Assignment of firms to classes. We do not observe the firm class $k(j)$ each firm j belongs to, so, in a first step, we assign each firm to one of K classes. We classify firms using the within-firm empirical distributions of earnings growth, and a clustering algorithm similar to Bonhomme et al. (2019) (BLM).

For classification we focus on stayers' earnings growth, so as to net out the firm component, ψ_j, and baseline human capital, α_i. Earnings growth for stayer i at firm j, g_{ijt} , amounts to:

$$g_{ij,t+1} \equiv \ln y_{i,t+1} - \ln y_{it} = h_{i,t+1} - h_{it} = \mu_{it}^{k(j)}. \tag{9}$$

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:

$$\min_{k(1),\ldots,k(J),F_1,\ldots,F_K} \sum_{j=1}^{J} n_j \int \left(\hat{G}_j(g) - F_{k(j)}(g)\right)^2 d\lambda(g), \tag{10}$$

where $k(1), \ldots, k(J)$ is the classification of firms into classes, F_k are distribution functions, n_j is the number of worker-years in firm j, and λ is a measure supported on a discrete grid. Note that classifying firms based on earnings *growth* according to (10), is akin to BLM's approach to classify firms according to earnings *levels*.

Implementation of BLM clustering algorithm. In practice, we partial out basic worker demographics from earnings growth g_{ijt}, and carry out the firm assignment to classes based on a residualized g_{ijt}, which we denote "unexplained earnings growth."

We compute unexplained earnings growth using the subsample of workers, ages 18–49, who were employed in the same firm for at least six months in two consecutive years.[19] In this subsample, we estimate the following regression:

$$g_{ijt} = \mathbf{X}_{it}'\beta + \delta_t + u_{ijt}, \tag{11}$$

where $g_{ijt} \equiv \ln y_{i,t} - \ln y_{i,t-1}$ (y is hourly wage in Brazil and daily wage in Veneto), δ_t are year fixed effects, and $\mathbf{X}_{it}$ includes a quadratic polynomial in age and a gender dummy in Veneto, and in Brazil, additionally, a quadratic polynomial of years of education and an interaction term between years of education and age. The residual $\widetilde{g}_{ijt} \equiv g_{ijt} - \mathbf{X}_{it}'\hat{\beta} - \hat{\delta}_t$ is our measure of unexplained earnings growth which enters the classification problem (10).[20]

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

[20] Before solving (10), we discard observations from firms for which we have, across all years, a total of less

Our empirical implementation follows the machine learning literature (Mullainathan and Spiess, 2017) such that we split the sample introduced in Section 2 in two groups: we include half of the workers in our data in the classification problem (11), and we estimate the returns to experience acquired in different firm types in equation (8) using the other half.

The number of firm classes K, needs to be set ex-ante and there is no obvious choice for it. We set $K = 10$ since we believe that 10 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. We check that we do not lose too much information by not increasing K further. Figure A1 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.[21] For $K = 10$ and in both Rio de Janeiro and Veneto, this ratio is around 60%. 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 1 plots the ten density functions that arise from solving (10), where each firm class is labeled according to the rank of its mean. Panel (a) plots 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 density shapes across firm classes (and in comparison with the overall distribution), illustrating systematic differences in distributions of unexplained earnings growth. Figures A2 and A3 separately plot each density in comparison to the overall distribution, and Table A1 shows the mean, median, variance, and skewness of each distribution. For instance, in Rio de Janeiro, the mean and variance of unexplained earnings growth in firm-class 1 are -0.095 and 0.053, while the equivalent moments in firm-class 10 are 0.128 and 0.080. There is higher dispersion of unexplained earnings growth in Rio de Janeiro than in Veneto. This is true both within and across firm classes.

4 Returns to Experience Acquired in Different Firm Classes

4.1 Main Results on Returns to Different Types of Experience

As discussed in Section 3, we first estimate the returns to "homogeneous" experience to provide a benchmark for heterogeneous returns across firm classes.[22] We present our

than five worker-year observations, thus not attempting to classify these small short-lived firms.

[21] 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 A1 plots: $\frac{Var_k[E_g(g|\text{firm-class}=k)]}{Var_f[E_g(g|\text{firm}=f)]}$.

[22] We exclude from the estimation of the returns to experience public sector worker-year observations. Yet we consider the experience accumulated in the public sector when calculating the returns to experience for workers employed in the private sector.

results in the first three columns of Tables 2 and 3 for Rio de Janeiro and Veneto, respectively. Our initial specification controls for workers' observed characteristics and indicates that an additional year of labor market experience is associated with wage returns in the range of 4.2% in Rio de Janeiro and 1.7% in Veneto (first column in Tables 2 and 3, respectively). It has been argued that experience accumulation may be endogenous to workers' unobserved characteristics (Dustmann and Meghir, 2005; Dustmann and Pereira, 2008). To take this concern into account, we re-estimate the returns to experience including worker fixed effects. We present the results in column (2), finding that the estimated returns to experience do not exhibit substantial changes relative to the first specification. To account for firm-specific pay premia—which may be correlated with experience for reasons other than skill accumulation—in column 3, we additionally include firm fixed effects. This last specification is equivalent to a version of equation (8) in which all experiences are assumed to be equal. The returns to experience in Rio de Janeiro reach 3.70% whereas the corresponding returns in Veneto equal 1.1%.[23]

In the last three columns of Tables 2 and 3, we present the estimated returns to experience acquired in different firm classes for Rio de Janeiro and Veneto, respectively. Our first specification thus controls for observed characteristics, and we document the results in the fourth column of these tables. In Brazil, we find a strong gradient in the estimated returns to experience by firm class: spending a year working at a class 1 firm increases wages by just 0.46%, whereas a year of experience at a class-9 or class-10 firm yields substantially larger returns, in the range of 9.7% and 12.6%, respectively. In Italy, there is less heterogeneity in levels, yet a similar pattern emerges in *relative* returns to experience across firm types, as the returns to experience in the top four firm types far exceed those at lower-ranked firms. In both countries, the estimated returns to experience at a class-10 firm are close to three times as large as the homogeneous returns discussed above.

To account for the fact that workers' unobserved characteristics may be correlated with experience acquisition at high-growth firms, we additionally include worker fixed effects and present the results in column (5). In Rio de Janeiro, the estimated returns to experience across firm types remain similar to the first specification. In Veneto, we similarly find larger returns to experience at class-10 firms (4.7%) relative to other firm classes. The estimated returns to high-class firms in both countries remain significantly larger than in the homogeneous returns specification. As such, extending the analysis to allow for heterogeneous experience increases the within adjusted R^2 of the regression in both countries from 0.016 to 0.033 in Rio de Janeiro, and from 0.020 to 0.031 in Veneto.

The results presented so far show that working at high wage-growth firms delivers sizable wage returns in both Rio de Janeiro and Veneto, respectively. The framework presented in Section 3.2 posits that this result emerges through high-growth firms providing additional learning opportunities. However, such firms may also offer high pay premia them-

[23] Our paper does not explicitly analyze why returns differ across these two countries. 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. (2020) document a cross-country *positive* correlation between returns to potential experience and GDP per capita. However, Italy is not part of their samples and, further, they show that Brazil's profile is similar to that of France, Canada, and Australia.

selves (Abowd et al., 1999; Card et al., 2018), or may lead to employment at high-paying firms. To account for the potential relationship between high wage- and high wage-growth firms, we additionally include firm fixed effects, as in equation (8) and present the results in the last column of Tables 2 and 3. In Rio de Janeiro, the estimated returns to experience at class-10 firms fall to 9.8%, yet remain significantly larger than at other firm classes, and in Veneto we similarly find that class-10 firms offer the largest estimated returns, reaching 3.5%.[24] In both countries, the estimated returns to experience in high-growth firms are 20-30% smaller than in the previous specification, suggesting that experience at such firms leads to higher wages partly through finding jobs at higher-paying firms. Nonetheless, the magnitude of the returns at class-10 firms indicates the returns are large, even upon controlling for current firm premia. This result is thus consistent with high-class firms providing better skill-development opportunities.[25] In short, while the levels in the estimated returns to experience vary across our two data sources, the relative returns to having acquired experience in a class-10 firm are three times as large vis-a-vis an empirical specification measuring "homogeneous" experience (see Figure 2).[26]

We have so far established that working at high-class firms yields high wage returns. Yet we have abstracted from the importance of firm tenure, which has been shown to yield positive returns (Topel, 1991; Altonji and Williams, 2005; Dustmann and Meghir, 2005). As such, omitting tenure from the analysis could lead to biased returns to experience acquired in different firm classes if, for instance, the returns to working at such firms are explained by longer employment spells at the same firm. To assess this consideration, we re-estimate equation (8) including tenure as a control variable. We present the results in Table A4. Across both countries, we find positive returns to firm-level tenure, reaching 1.9% and 1.1% in Rio de Janeiro and Veneto, respectively. Moreover, while the estimated returns to experience at class-10 firms are slightly smaller than those presented in Table 3 (from 9.8% to 8.4% in Rio de Janeiro, and from 3.5% to 2.5% in Veneto), we still find significant heterogeneity in returns to experience acquired in different firm classes and, broadly, a similar pattern as before.

[24] In both countries, we find far smaller returns to experience acquired at very small firms not classified by the clustering algorithm (Section 3). In Rio de Janeiro, we find significant returns to experience acquired in the public sector, reaching close to 5%, fitting in with evidence presented in Gonzaga and Firpo (2010). The returns to public sector experience in Veneto are not different from zero but still larger than returns to experience acquired in the three lowest firm-classes. Lastly, as discussed in Section 2, we consider workers' employment spells in other states. In both Rio and Veneto, experience acquired in other regions yields positive wage returns, yet the magnitudes are far below the high wage-growth firms in these states.

[25] In Tables A2 and A3, we re-estimate equation (8) including quadratic terms in experience acquired across firm classes to account for potential non-linearities in early career wage growth (Mincer, 1974). The estimated returns to one, three, five or ten years of experience across different firm classes remains similar to the findings in the main specification across both countries.

[26] A common concern in models with both worker- and firm- fixed effects is the correct specification of the effects of age (Card et al., 2018). Our main specification controls for six age-category fixed effects, yet we assess the robustness of our results to alternative specifications in Appendix Figure A4. We consider specifications with an age polynomial restricting the age profile to be flat at 35, and another one with no age controls. We do not find significant differences in the estimated returns relative to our main specification, indicating that this is not a major concern in our setting.

4.2 Returns to heterogeneous experience among displaced workers

We now estimate returns to experience acquired in different firm classes for a sample of involuntarily displaced workers (Gibbons and Katz, 1991; Neal, 1995; Dustmann and Meghir, 2005). In particular, we use the first post-displacement earnings observation. The goal of this exercise is to provide further evidence of our interpretation of heterogeneous returns capturing on-the-job learning of general skills. Alternative interpretations that wouldn't lead to returns post-displacement are wage growth due to firm-specific human capital, or seniority-based compensation schemes that back-load pay (e.g. Lazear, 1981; Guiso et al., 2013). Further, this exercise allays concerns regarding tenure effects. In this subsample, workers' tenure is exogenously set to zero and their current employer is different from the firm(s) where experience was acquired.[27]

To identify involuntary displacement events, we take advantage of our administrative data sources covering firm-level employment in both countries and focus on firm closure and mass layoff events (Jacobson et al., 1993; Dustmann and Meghir, 2005; Couch and Placzek, 2010). 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 below half of its prior three-year moving average, without subsequently recovering. In light of differences in the firm size distribution across the two data sources, we focus on firms with at least 50 and 20 employees at its pre-layoff average in Rio de Janeiro and Veneto, respectively. We take advantage of detailed information on workers' employment transitions to identify workers who are involuntarily displaced. We consider workers who are employed in the distressed firms within two years of the event, and who are laid off in within one year of the closure/layoff event. We additionally require displaced workers not to re-enter the same firm in the following three years.

In Rio de Janeiro, we identify 3,075 involuntary displacement events during our period of interest, which affect 125,065 workers in our sample of young workers. In Veneto, meanwhile, 2,844 firms either shut down or undergo a mass layoff, affecting 35,319 young workers. Across Brazil and Italy, 82.3% and 74.5% of displaced workers eventually re-enter the sample, whereas 58% and 64.5% do so within one year of being displaced, respectively.

As noted above, we estimate the returns to experience using the first wage observation for displaced workers. We control for workers' observed characteristics and time to re-entry and include measures of their experience acquired at different firm types. We present the results in the first and third columns of Table 4.[28] In both countries, we find remarkably similar returns to experience as in the full sample. In Rio de Janeiro, the returns to an additional year at a class-10 firm reach 13.6% in the first post-layoff observation, far outpacing the returns at any other firm class. In Veneto, we similarly find large returns for individuals

[27] Moreover, this approach allows us to allay concerns regarding wage growth due to endogenous survival of good matches. Further, displaced workers choose to re-enter if wages exceed the value of unemployment—removing the possibility of particularly good match effects reached through search capital accumulation (Gathmann and Schönberg, 2010).

[28] We control for time to re-entry to compare workers who took a similar amount of time to find a new job. We have alternatively estimated our empirical strategy without controlling for this variable and results are unchanged (Table A6).

who worked at high wage-growth firms, yet the returns to experience at class-10 firms are slightly smaller vis-a-vis class-8 firms. In the second and fourth columns of Table 4, we include firm fixed effects to examine whether experience accumulated at high wage growth firms increases wages beyond the post-layoff firm displaced workers match to. In Brazil, the magnitude of the estimated returns in class-10 firms falls to 7.1%, while remaining far larger than for other firm types. In Veneto, upon controlling for firm fixed effects, we find that the returns to experience at the highest wage-growth firms become larger than at all other firm classes. We thus remark that across both data sources, the returns to having worked at high wage-growth firms in the early career remain significant and economically important, even within a sample of involuntarily displaced workers. We interpret this as further evidence that our firm classification captures differences in on-the-job learning of *portable* skills.

4.3 Heterogeneous returns by education, latent skills, occupation, and gender

Education. We first use information on Brazilian workers' educational attainment to estimate heterogeneous returns to experience acquired on different firm classes separately by education level. On the one hand, greater returns to experience for more educated workers would be consistent with past work documenting steeper profiles for the more educated and hypothesizing these workers are better able to learn on the job (Mincer, 1974; Heckman et al., 2006; Kambourov and Manovskii, 2009). On the other hand, less educated workers may have the most to gain by learning general skills on the job. Importantly, these two forces could play out differently in different firms—something our framework would be able to uncover.

We estimate heterogeneous returns to experience separately for high school dropouts, high school graduates, and those with more than a high school education and present the results in Figure 3. Returns to experience acquired at firm classes largely follow the same structure across the three groups: an additional year of experience at the highest wage-growth firms increases hourly wages by close to 7% for high school dropouts, reaching close to 10% for their more educated peers. Interestingly, different education groups disproportionately benefit from different firm classes. The most educated disproportionately benefit from classes 9 and 10 employment, but relatively very little from classes 3, 5, or 8. Compared to more educated individuals, high school dropouts enjoy large relative benefits from classes 5 and 8. Thus, while in absolute terms, all workers benefit more from working at high-class firms, in relative terms, workers from different education levels disproportionately benefit from different firm classes.

Latent skills. Workers' latent skills have been shown to affect labor market outcomes beyond what is captured by observed measures of human capital, such as educational attainment (Heckman et al., 2006). In our context, we examine whether the returns to experience acquired in different firm classes varies across the latent skills distribution following De La Roca and Puga (2017) and using worker fixed effects as a proxy of their unobserved

abilities. We estimate the following earnings regression:

$$\ln y_{it} = \psi_{j(it)} + \alpha_i + \sum_{m=1}^{K} \gamma_m \cdot \text{Exp}(m)_{it} + \sum_{m=1}^{K} \delta_m \cdot \text{Exp}(m)_{it} \cdot \alpha_i + \eta_{it} \tag{12}$$

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.[29] We present the results for Rio de Janeiro and Veneto in Figure A5, comparing the estimated returns for individuals at the 25th and 75th percentile of the latent skills distribution. In both countries, we find that low- and high-skilled workers enjoy the largest returns to experience acquired at class-10 firms. While higher-skilled workers enjoy larger returns to experience acquired in all firm classes relative to their lower-skilled peers, the extent of the difference in the returns does not vary significantly across firm classes. While De La Roca and Puga (2017) find that higher-skilled workers enjoy larger returns to experience acquired in larger cities, we do not find evidence that higher skilled workers necessarily enjoy larger relative returns from working at high-growth classes.

Blue- vs. white-collar occupations. Since holding different jobs at the same firm may entail differential learning opportunities, we examine whether the returns to experience across firm classes varies across the type of occupation held at the time during which experience was acquired. We define occupations as either white- or blue-collar following a standard classification using occupational information at the one-digit ISCO level.[30] We present the estimated results in Rio de Janeiro in Figure A6. The estimated returns to experience in high-growth classes are larger for workers who held white-collar jobs, yet blue-collar workers enjoy sizable returns from having worked at those firms, too. The extent of heterogeneity in returns across firm classes is largely similar for both sets of workers, remarking that both workers employed in high- and low-wage occupations enjoy the learning opportunities available at such firms.

Gender. We check for differences in returns between men and women, and find that the returns to experience acquired in different firm classes are very similar for both genders in both countries (Appendix Figure A7).[31] We interpret this result as being consistent with our firm categorization capturing learning opportunities and there being no average differences between men and women in learning predisposition.

[29] We estimate equation (12) 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 12 and replace the interacted $\widehat{\alpha}_i$ with the fixed effect recovered in the previous iteration. We repeat this procedure until the parameters converge.

[30] We classify managers, professionals, technicians and associate professionals along with clerical support workers as'white-collar' occupations, whereas service and sales workers, skilled agricultural, forestry and fishery workers, raft and related trades workers, plant and machine operators, assemblers and workers in elementary occupations encompass 'blue collar' occupations.

[31] Returns are identical for the two genders in Rio, except for returns to experience at firm-class 2 which are slightly larger for men. In Veneto the pattern across classes is the same for men and women, with women's gradient being slightly below men's.

4.4 Allowing for richer patterns of returns

The conceptual framework in Section 3 considers a single general skill that is equally valued by all employers. Yet experience acquired in different firm classes may be valued differently across firm classes, resembling the returns to industry-specific capital (Neal, 1995), occupation-specific capital (Kambourov and Manovskii, 2009), or varying mixes of different general skills (Lazear, 2009). We test for this possibility by extending equation (8) to include an interaction term for whether workers are currently employed in the firm class in which they acquired the relevant experience. We are able to study such complementarities in a transparent and tractable way thanks to our approach that discretizes the firm-type space.

We present the results in the first two panels of Figure 4. While the returns to experience acquired at different firm classes varies by whether workers are currently employed at such firms, the pattern of relative returns across firm types remains unchanged. As such, having worked at high-class firms yields high returns regardless of the current employer type.[32] To assess whether currently employment at high wage-growth firms increases the relative returns to experience acquired in *any* firm type, we re-estimate equation (8) with an interaction term for being employed at class-10 firms. Results are in the last two panels of Figure 4. In both countries, we find that working at class-10 firms does not result in higher returns to experience acquired at lower ranked firms, while returns to experience acquired at class-10 firms are slightly higher. All in all, we conclude that returns to experience at different firm classes remain similar independently of the firm that workers are currently employed at.

5 Task Content Effects of Heterogeneous Experiences

The conceptual framework presented in Section 3 posited that the heterogeneous returns to experience across firm classes are driven by differential learning opportunities across firms. To test this theory, we would ideally observe measures of workers' human capital accumulation, or learning outcomes. Yet these measures are not generally available in the data. At the same time, previous work has shown that workers' non-routine task content significantly increases in the early career (Sanders, 2014; Speer, 2017), and such changes are associated with sizable wage increases (Yamaguchi, 2012; Stinebrickner et al., 2019). As noted above, RAIS data allows us to characterize Brazilian workers' task content across four dimensions, encompassing non-routine analytic, non-routine interpersonal, routine cognitive and routine manual tasks.

First, we estimate a wage regression encompassing occupational task content and worker fixed effects (Table A5). Increases in non-routine task content are associated with sizable wage gains in our sample, whereas corresponding increases in routine tasks lead to wage losses (Autor et al., 2003; Autor and Handel, 2013). To examine whether past experience at high-growth firms is associated with subsequent increased non-routine task content, we

[32] Interestingly, the first two panels of Figure 4 indicate that the returns to experience at low-wage firms are lower if workers are currently employed at such firms, with the opposite pattern emerging for high growth firms. These results are statistically significant in Rio de Janeiro, yet not in Veneto.

re-estimate equation (8) using task content as outcomes. We present the results in Figure 5 (see also Table A7). An additional year of experience at class-10 firms is associated with increases in workers' non-routine task content, reaching 0.027 and 0.030 standard deviations in analytic and interpersonal tasks, respectively. As with the estimated wage returns, the task-returns to experience at such firms far outpaces the benefits of having worked at all other firm classes. These results are thus consistent with a framework in which firms offer differential learning opportunities, as high-growth firms lead workers to experience wage increases, and access jobs with higher non-routine task content. Moreover, working at class-10 firms results in decreased content in routine tasks, as a year of experience at these firms reduces workers' routine cognitive task content and manual content by 0.019 and 0.027 standard deviations, respectively.

To assess the robustness of our results to endogenous mobility concerns, we re-estimate our results using the sample of involuntarily displaced workers. We present the results in Table A8. Among the sample of displaced workers, having worked at class-10 firms similarly leads to significant increases in post-layoff non-routine task content, reaching 0.04 and 0.036 standard deviations in analytic and interpersonal tasks, respectively. At the same time, past experience at such firms reduces workers' routine task content, fitting in with the full sample results. The estimated results are robust to the inclusion of post-layoff firm fixed effects. In this context, we remark that tasks represent noisy proxies of workers' human capital accumulation during their labor market careers. As such, these results provide further evidence of the existence of differential learning opportunities in Brazil across our firm-class categorization.

We next re-estimate equation (8) across the three education groups in Brazil to examine whether task effects are different across workers' baseline human capital. In Table A9, we show that the estimated returns to an additional year of experience at class-10 firms on non-routine task content are strikingly similar across workers' educational attainment. As such, spending an additional year at these firms increases analytic task content of high school dropouts, HS graduates and those beyond high school by 0.025, 0.022 and 0.022 standard deviations, respectively. We document similar results on the interpersonal dimension, as well. Remarkably, working at such firms decreases routine task content across all three educational groups. As such, these results indicate that the learning opportunities offered by these firms push workers on an upward trajectory in non-routine tasks, irrespective of their baseline educational attainment.[33]

Lastly, in light of existing evidence of gender differences in task content in the early career (Speer, 2017; Stinebrickner et al., 2018), we consider heterogeneous task returns to past experience classes by gender. We present the results in Table A10. While we find somewhat larger analytic-task-returns to experience at class-10 firms for women than for men (0.037 v. 0.025 standard deviations), these results further confirm that working at high growth firms leads to improved outcomes for workers across genders.

[33] An alternative scenario would be one in which these firms helped less educated workers move up the routine-task ladder.

6 Workforce and Firm Characteristics across Firm Classes

Are firms with better learning opportunities easily recognizable by observable characteristics? We explore this question considering a wide range of firm attributes, but focusing especially on firms' pay premia (Abowd et al., 1999; Card et al., 2018), and on what existing work has identified as predictors of learning on the job: firms' large-city location (De La Roca and Puga, 2017), firm size (Arellano-Bover, 2020a,b), and coworkers' education or skills (Nix, 2020; Jarosch et al., 2020). We investigate the role of observables in three ways: a machine learning algorithm that predicts firms' class, the unconditional characteristics of the workforce at each firm class, and a multinomial logit model rendering *ceteris paribus* associations of firm characteristics and firm class.[34]

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 aggregated 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 against true class. We feed the random forest a variety of firm characteristics, but no variables related to employees' wage growth since this is the input our clustering methodology in Section 3.2 uses to classify firms.[35]

Table 5 shows results from the random forest prediction exercise. In both Rio de Janeiro and Veneto, the algorithm correctly classifies 25% of firms. If we do the same exercise focusing only on large firms (50 employees or more), the algorithm correctly classifies 26% of large firms in Rio and 33% of large firms in Veneto. This prediction exercise indicates that firm observables are somewhat useful for predicting firms' skill-learning class, but do not allow us to classify these firms in an accurate way. Firms' skill-development opportunities appear to be an intrinsic quality not easily predicted by observables.

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

In Tables 6 and 7, we present the workforce characteristics at each firm class (person-year is the unit of observation) in Rio de Janeiro and Veneto, respectively.[36] At the same time, Figures A8–A10 (Rio) and A11 (Veneto) show the estimated multinomial logit probabilities of a firm belonging to each class, with the characteristic of interest is evaluated at the 25th and at the 75th percentiles, and the remaining variables evaluated at the mean.[37] In the following discussion we mainly comment on firm classes 1 and 10—offering the least

[34] 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 and $k = 1, \ldots, 10$ are firm classes.

[35] The firm-level characteristics we feed the random forest are mean annual earnings, AKM firm effect, workforce age and gender distribution, firm size, geographic location, and 2-digit sector. For Rio de Janeiro, we additionally use the workforce education distribution, task allocation, and a dummy for export-intensive 5-digit sectors.

[36] Tables A11 and A12 show similar information where the firm is the unit of observation.

[37] Dummy variables are 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.

and most learning opportunities, respectively.

Pay premia. Workers employed in firm classes 1 and 10 do not enjoy disproportionately low or high firm pay premia (Tables 6 and 7). The highest pay premia are enjoyed by workers in firm class 2 in Rio and class 9 in Veneto, while the lowest correspond to workers in firm class 8 in Rio and class 3 in Veneto. More generally, there is no clear relationship between pay premia and firm classes (which are ordered by mean unexplained earnings growth). At the firm level, and keeping other covariates constant, high- and low-paying firms in Rio de Janeiro are equally likely to belong to class 1, and higher-paying firms are somewhat more likely to belong to class 10 but this difference is not statistically significant (Figure A8). In Veneto, high- and low-paying firms are equally likely to belong to class 1, and high-paying firms are only slightly more likely to belong to class 10 (Figure A11).

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.[38] The share of the workforce who are employed in the metro region of Rio de Janeiro is between 75–86 percent across firm classes (Table 6). Since this shares equals 79 percent for firm class-10 workers, we do not find them disproportionately represented in the metro area. In Veneto, we find a positive association between large-city firms and firm class: the share in large cities is generally increasing in firm class. Thus, while 14 percent of the class 1 workforce is in one of the largest cities, the corresponding number for class 10 is 38 percent (Table 7). 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 A8). In Veneto, large-city firms are less likely to belong to class 1 and more likely to belong to class 10 (Figure A11). This 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.

Firm size. There is no clear pattern between the workforce employer size at different firm classes. In Rio de Janeiro, workers of class 1 and class 10 firms are not employed in particularly large nor small firms (Table 6). In Veneto, while there is no clear relationship between firm classes and firm size, we find that workers in classes 1 and 10 have the smallest employers (Table 7). 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 A8), and less likely to belong to class 1 and to class 10 in Veneto (Figure A11). 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, 2020a,b): in both Rio and Veneto, large firms are less likely to belong to class 1, and somewhat more likely to belong to class 9—the "second best" category, showing significant returns to expe-

[38] These are Venezia, Verona, Padova, Vicenza, and Treviso.

rience (see Section 4).

Workforce education. The education distribution of the workforce in Rio de Janeiro is largely comparable across firm classes, with the exception of classes 5 and 7, which disproportionately employ lower-education workers (Table 6). In spite of this moderate variation, the workforce at class 10 has the second largest share of workers with more than a high school degree, reaching 18 percent (class 4 has 20 percent). The fact that class 10 has a relatively high share of highly educated workers aligns with existing evidence on learning from highly educated (Nix, 2020) or highly paid (Jarosch et al., 2020) coworkers. We find a similar pattern at the firm level, keeping constant other covariates: Figure A9 shows that a large share of less educated workers is negatively associated with belonging to class 10 (but also negatively associated with class 1).

All in all, observed characteristics account for a relatively small share of the difference in firms' on-the-job learning opportunities, indicating that this dimension of firm heterogeneity may be a latent attribute instead of easily identifiable with typically observed firm characteristics.

7 Trajectories across Firm Classes and Early Career Wage Growth

In this section, we provide an additional quantification of the importance of human capital accumulation disparities across firm classes. We consider different counterfactual employment trajectories across firm classes and use as a benchmark the total wage growth workers experience between ages 18-35.

In each country, we first compute the person-level distribution of annualized total wage growth between ages 18–35.[39] We compute this measure of wage growth as follows. For each worker, we take the difference in log earnings between the last time (up to age 35) and first time we observe them, and divide over the number of years between such observations.[40] Figure 6 shows the empirical distributions of this measure of wage growth.

Counterfactual firm-class trajectories. Using our estimates of heterogeneous returns to experience acquired in different firm classes (i.e., columns (6) in Tables 2 and 3), we calculate where does the growth stemming from different counterfactual trajectories fall on the observed distribution of annualized total wage growth. We consider four different trajectories: employment exclusively in class-10 firms, exclusively in class-1 firms, or exclusively in the firm class closest to homogeneous returns (8 for Rio, 6 for Veneto); and a trajectory where a worker is employed one third of the time in each of the three aforementioned classes.

The results from this exercise, shown in Figure 6 and Table A13, indicate that different trajectories are associated with sizable moves across the distribution of total wage growth.

[39] We do so focusing on the birth cohort for each country that we fully observe between ages 18–35.

[40] We further restrict attention to workers who we observe for the first time before age 30, and for whom there are at least 5 years between their first and last earnings observation.

Being employed while 18–35 exclusively on the least-learning class-1 firms is associated with the 17th and 19th percentiles of total wage growth in Rio and Veneto, respectively. Instead, being employed on the top-learning class-10 firms is associated with the 76th and 66th percentiles in Rio and Veneto, respectively. Trajectories in less extreme firm classes or combining experience across firm classes, lie between the 33rd and 43rd percentiles. We interpret these results as further evidence on the quantitative importance of firm heterogeneity in skill-development and its implications for early-career wage growth.

Employment transitions across firm classes. In light of the importance of experience acquired in different firm classes for early-career wage growth, we further examine differences in workers' trajectories across firms offering heterogeneous learning opportunities. In particular, we consider the degree of persistence in working across firm classes—we examine whether a plurality of workers gain access to high-learning firms in the early career, or whether a small share of individuals are persistently employed at such firms.

We present a variety of empirical exercises in Appendix B, which show that having worked at high-growth firms increases the likelihood of subsequently moving to similar firms. This result may emerge through different channels, as workers may learn how to recognize firms with good learning opportunities and direct their search for subsequent jobs to such firms. Alternatively, high-learning firms may look for workers with experience at similar firms, as these workers would have learned more in their previous employment stints. Regardless of the specific channel, the degree of persistence in workers' employment across firm classes and the large returns offered by firms with strong learning environments further highlights the essential role played by firms as drivers of wage growth in the early career.

8 Conclusion

In this paper we have documented evidence on earnings and jobs' task content that is consistent with large disparities across firms in the human capital development opportunities their young workers enjoy. The differences in learning opportunities we find are substantial, suggesting significant lifecycle implications for workers depending on which firms they match with when young. Our findings are notably consistent across two rather different economies in Brazil and Italy.

It would be policy-relevant to ask whether firms that embody better opportunities to learn general skills internalize this fact or, on the contrary, they create positive externalities for young workers and the economy as a whole. Relatedly, being able to easily identify firms with good learning opportunities could be valuable for policymakers and young workers.

We find, however, that firm observables are only mildly helpful in predicting learning opportunities. We reach this conclusion considering a wide range of attributes, but admittedly being limited by observables that are typically available in population matched employer-employee datasets. Further research could investigate whether important firm

attributes that existing literature has measured, but are unobserved to us, might improve identifying firms with good learning opportunities. Such potential attributes include management practices, productivity, technological adoption, exporter status, and multinational status. Lastly, future work could also quantify the degree to which workers gradually learn to recognize firms' skill-development opportunities.

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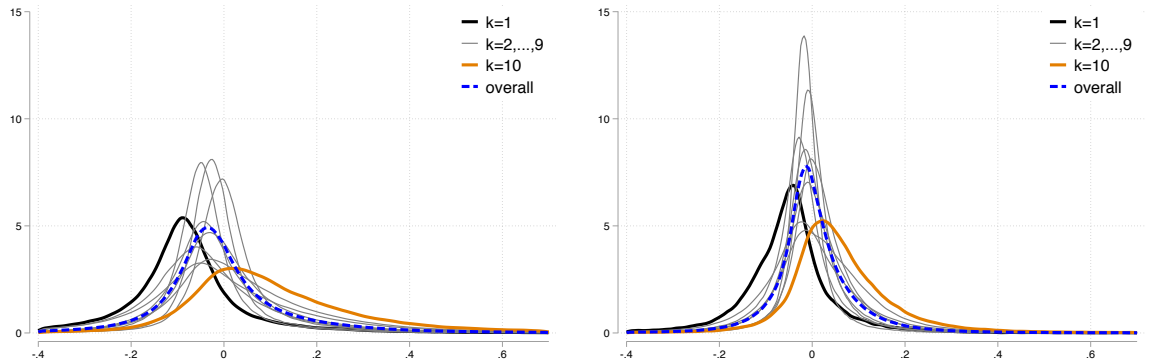
Figures and Tables

Figure 1: Density of unexplained earnings growth, by firm class.

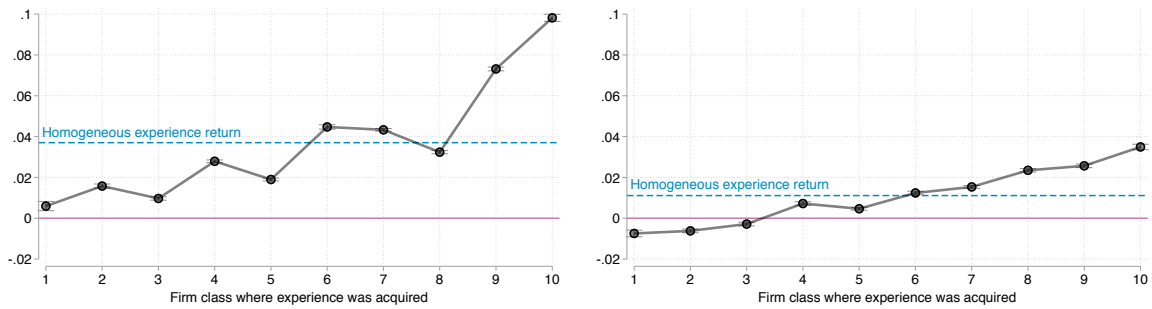
(a) Rio de Janeiro, 1994–2010. **(b)** Veneto, 1984–2001.



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.

Figure 2: Returns to experience acquired in different firm classes: coefficient plot.

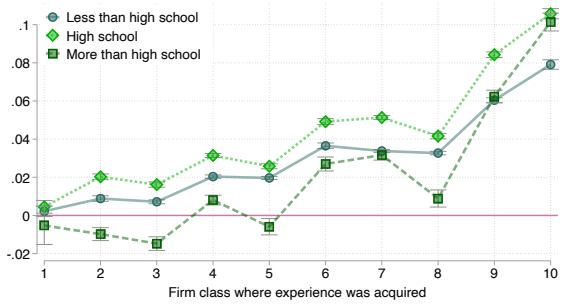
(a) Rio de Janeiro, 1994–2010. **(b)** Veneto, 1984–2001.



Notes: Point estimates and 95% confidence intervals of returns to experience acquired in different firm classes, from Tables 2 and 3. Blue line: returns to homogeneous experience, from column (5). Black plot: returns to experience accumulated in each of the 10 firm types, from column (6).

Figure 3: Returns to experience acquired in different firm classes: separately by education level.

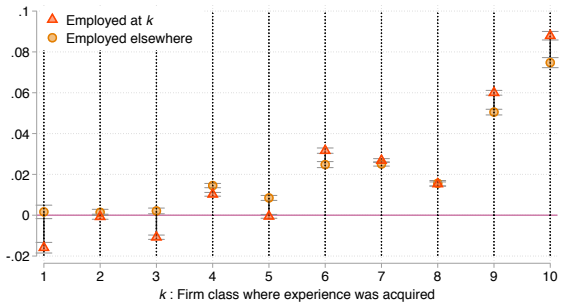
(a) Rio de Janeiro, 1994–2010.



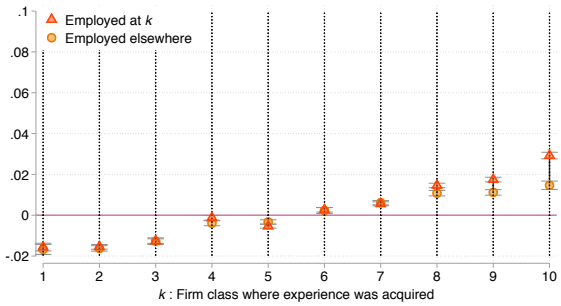
Notes: Point estimates and 95% confidence intervals of returns to experience acquired in different firm classes, estimated separately for workers with three different education levels. Flat lines: returns to homogeneous experience for each education level.

Figure 4: Returns to experience acquired in different firm classes: allowing richer returns patterns.

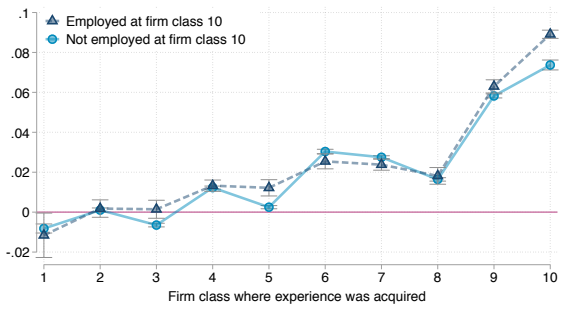
(a) Rio de Janeiro, 1994–2010.



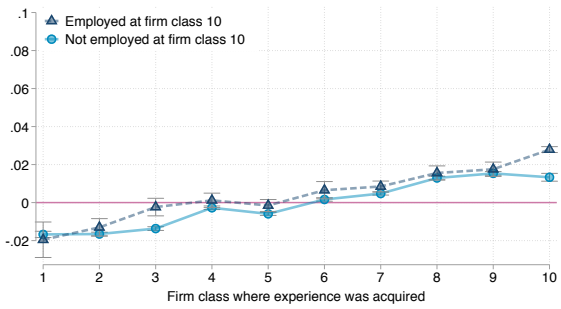
(b) Veneto, 1984–2001.



(c) Rio de Janeiro, 1994–2010.



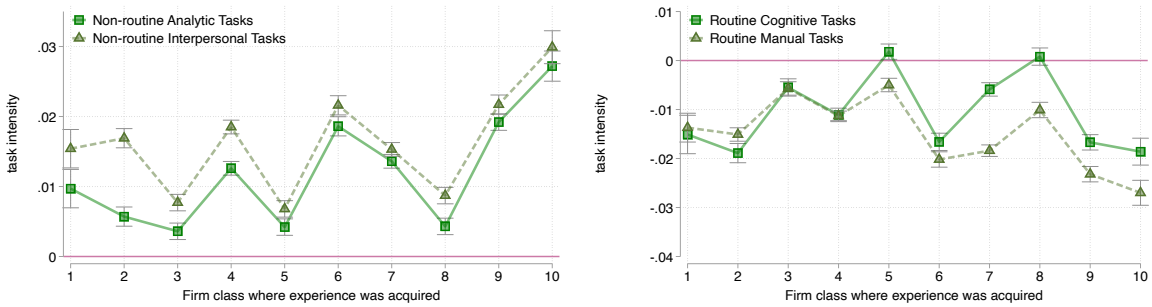
(d) Veneto, 1984–2001.



Notes: Panels (a) and (b): Point estimates and 95% confidence intervals of returns to experience acquired in different firm classes, with returns to each class of experience allowed to vary between those currently employed at that firm class and those employed elsewhere. Panels (c) and (d): Point estimates and 95% confidence intervals of returns to experience acquired in different firm classes, with returns allowed to vary between those currently employed at a class 10 firm and those employed elsewhere.

Figure 5: Returns to experience acquired in different firm classes: Task content in Rio de Janeiro.

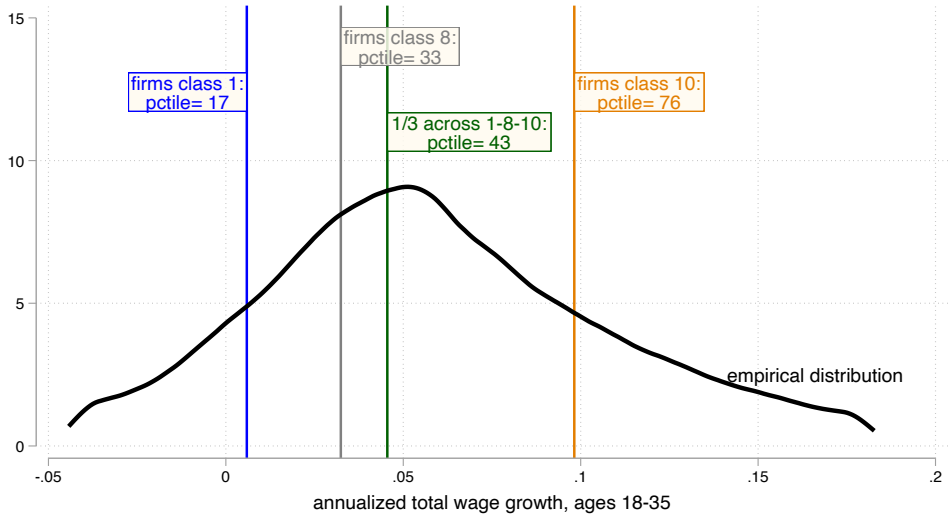
(a) Non-routine Tasks. **(b)** Routine Tasks.



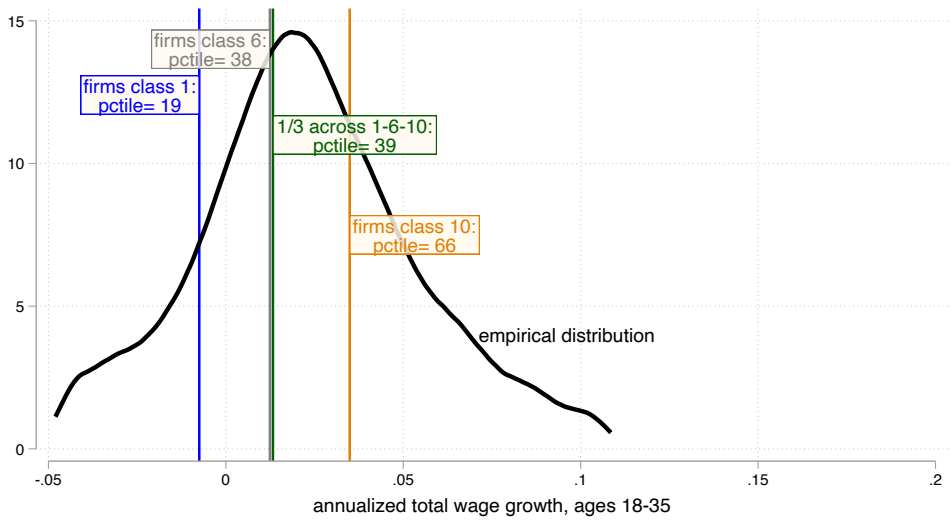
Notes: Point estimates and 95% confidence intervals of returns to experience acquired in different firm classes in term of occupational task content, from Table A7.

Figure 6: Annualized total earnings growth distribution, ages 18–35, and trajectories across firm classes

(a) Rio de Janeiro, 1994–2010.



(b) Veneto, 1984–2001.



Notes: This figure shows where does the wage growth resulting from different counterfactual trajectories across firm classes fall in the person-level distribution of annualized total wage growth between ages 18–35. The distribution of annualized total wage growth is computed for the birth cohort we fully observe between 18–35, using the difference in log earnings between the last (up to age 35) and first time we observe each worker, divided over the number of years between such observations. See Table A13 for more details. Kernel densities in this figure are truncated at the 5th and 95th percentiles for clarity.

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

	Rio de Janeiro	Veneto
	(1)	(2)
Share Male	0.582	0.540
Age at Entry	20.76	20.49
Cumulative Experience	6.35	8.15
Cumulative Number of Jobs	3.51	3.30
Annualized Wage Growth (Average)	0.068	0.031
Annualized Wage Growth (Median)	0.055	0.023
Number of Workers	4,196,508	1,163,473
Observations	20,768,019	7,866,390

Notes: Table 1 presents summary statistics for the sample of workers in the Rio de Janeiro and Veneto samples as described in Section 2. Information on cumulative experience, number of jobs and wage growth is presented for the oldest cohort in each country for whom we observe their labor market trajectories starting at age 18, covering the 1976 birth cohort in Rio de Janeiro and the 1966 cohort in Veneto.

Table 2: Returns to experience acquired in different firm classes: Rio de Janeiro, 1994–2010.

	(1)	(2)	(3)	(4)	(5)	(6)
Experience	0.0428***	0.0449***	0.0370***			
	(0.0002)	(0.0003)	(0.0002)			
Experience: class 1				0.0046***	0.0073***	0.0059***
				(0.0013)	(0.0013)	(0.0011)
Experience: class 2				0.0443***	0.0310***	0.0158***
				(0.0006)	(0.0006)	(0.0005)
Experience: class 3				-0.0026***	0.0063***	0.0097***
				(0.0005)	(0.0005)	(0.0004)
Experience: class 4				0.0425***	0.0384***	0.0279***
				(0.0004)	(0.0004)	(0.0003)
Experience: class 5				-0.0175***	0.0096***	0.0190***
				(0.0004)	(0.0004)	(0.0004)
Experience: class 6				0.0695***	0.0619***	0.0447***
				(0.0006)	(0.0006)	(0.0005)
Experience: class 7				0.0450***	0.0510***	0.0433***
				(0.0004)	(0.0004)	(0.0003)
Experience: class 8				-0.0095***	0.0227***	0.0324***
				(0.0005)	(0.0005)	(0.0004)
Experience: class 9				0.0971***	0.0943***	0.0731***
				(0.0006)	(0.0006)	(0.0005)
Experience: class 10				0.1260***	0.1256***	0.0982***
				(0.0012)	(0.0011)	(0.0009)
Experience: NC				-0.0158***	0.0227***	0.0280***
				(0.0006)	(0.0006)	(0.0005)
Experience: PS				0.0806***	0.0963***	0.0476***
				(0.0023)	(0.0033)	(0.0029)
Experience: non-RJ				0.0769***	0.0677***	0.0552***
				(0.0004)	(0.0005)	(0.0004)
Adj. R^2	0.257	0.662	0.759	0.292	0.668	0.762
Within adj. R^2		0.016	0.012		0.033	0.022
Person FE	no	yes	yes	no	yes	yes
Firm FE	no	no	yes	no	no	yes
SE clusters (persons)	1,860,420	1,520,912	1,510,168	1,860,420	1,520,912	1,510,168
N	9,234,871	8,897,238	8,754,064	9,234,871	8,897,238	8,754,064

Notes: Outcome is log hourly wage. Workers born 1976 or later, ages 18–35. Private sector observations. Firm classes 1–10 are BLM clusters ordered according to mean unexplained earnings growth. NC are small firms not categorized by BLM clustering. 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 3: Returns to experience acquired in different firm classes: Veneto, 1984–2001.

	(1)	(2)	(3)	(4)	(5)	(6)
Experience	0.0167***	0.0238***	0.0111***			
	(0.0001)	(0.0003)	(0.0003)			
Experience: class 1				-0.0020***	0.0018**	-0.0075***
				(0.0006)	(0.0009)	(0.0008)
Experience: class 2				-0.0001	0.0031***	-0.0062***
				(0.0003)	(0.0005)	(0.0005)
Experience: class 3				-0.0079***	0.0045***	-0.0028***
				(0.0004)	(0.0005)	(0.0005)
Experience: class 4				0.0151***	0.0199***	0.0072***
				(0.0003)	(0.0005)	(0.0005)
Experience: class 5				0.0153***	0.0185***	0.0046***
				(0.0002)	(0.0004)	(0.0004)
Experience: class 6				0.0173***	0.0243***	0.0124***
				(0.0003)	(0.0004)	(0.0004)
Experience: class 7				0.0304***	0.0316***	0.0153***
				(0.0002)	(0.0004)	(0.0004)
Experience: class 8				0.0367***	0.0391***	0.0235***
				(0.0004)	(0.0004)	(0.0004)
Experience: class 9				0.0367***	0.0403***	0.0257***
				(0.0004)	(0.0005)	(0.0005)
Experience: class 10				0.0350***	0.0470***	0.0349***
				(0.0006)	(0.0007)	(0.0007)
Experience: NC				-0.0067***	0.0170***	0.0126***
				(0.0003)	(0.0005)	(0.0005)
Experience: PS				0.0264***	0.0274***	-0.0011
				(0.0035)	(0.0060)	(0.0054)
Experience: non-Veneto				0.0312***	0.0313***	0.0158***
				(0.0003)	(0.0004)	(0.0004)
Adj. R^2	0.146	0.460	0.601	0.176	0.466	0.604
Within adj. R^2		0.020	0.012		0.031	0.020
Person FE	no	yes	yes	no	yes	yes
Firm FE	no	no	yes	no	no	yes
SE clusters (persons)	565,705	491,651	484,953	565,705	491,651	484,953
N	3,773,262	3,699,209	3,614,154	3,773,262	3,699,209	3,614,154

Notes: Outcome is log daily wage. Workers born 1966 or later, ages 18–35. Private sector observations. Firm classes 1–10 are BLM clusters ordered according to mean unexplained earnings growth. NC are small firms not categorized by BLM clustering. 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 4: Returns to experience acquired in different firm classes in first post-displacement observation: Rio de Janeiro and Veneto.

	Rio de Janeiro		Veneto	
	(1)	(2)	(3)	(4)
Experience: class 1	0.0433***	0.0253***	-0.0026	0.0087
	(0.0056)	(0.0070)	(0.0035)	(0.0081)
Experience: class 2	0.0522***	0.0294***	-0.0058***	0.0012
	(0.0026)	(0.0030)	(0.0019)	(0.0036)
Experience: class 3	-0.0078**	0.0126***	-0.0377***	-0.0016
	(0.0039)	(0.0045)	(0.0040)	(0.0054)
Experience: class 4	0.0274***	0.0238***	0.0048**	0.0122***
	(0.0019)	(0.0022)	(0.0021)	(0.0042)
Experience: class 5	-0.0371***	0.0044	0.0097***	0.0097**
	(0.0032)	(0.0038)	(0.0022)	(0.0041)
Experience: class 6	0.0484***	0.0328***	0.0052*	0.0005
	(0.0023)	(0.0028)	(0.0031)	(0.0068)
Experience: class 7	0.0330***	0.0219***	0.0213***	0.0260***
	(0.0022)	(0.0025)	(0.0017)	(0.0031)
Experience: class 8	-0.0338***	0.0026	0.0412***	0.0220***
	(0.0037)	(0.0046)	(0.0021)	(0.0033)
Experience: class 9	0.1024***	0.0493***	0.0279***	0.0196***
	(0.0030)	(0.0033)	(0.0024)	(0.0039)
Experience: class 10	0.1360***	0.0710***	0.0387***	0.0396***
	(0.0046)	(0.0056)	(0.0044)	(0.0099)
Experience: NC	-0.0126***	0.0085	-0.0355***	-0.0024
	(0.0046)	(0.0053)	(0.0041)	(0.0063)
Experience: PS	0.1862***	0.0705***	0.0395***	0.0013
	(0.0114)	(0.0132)	(0.0044)	(0.0072)
Experience: Other	0.0784***	0.0378***	0.0223***	0.0207***
	(0.0032)	(0.0037)	(0.0019)	(0.0035)
Adjusted R^2	0.197	0.540	0.137	0.415
Year FE	yes	yes	yes	yes
Time to Reentry	yes	yes	yes	yes
Observables	yes	yes	yes	yes
Post-ML Firm FE	no	yes	no	yes
Observations	102459	102459	26228	26228

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. Firm classes 1–10 are BLM clusters ordered according to mean unexplained earnings growth. NC are small firms not categorized by BLM clustering and PS is the public sector in each data set. 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. Robust standard errors in parentheses. *p<0.10; **p<0.05; ***p<0.01.

Table 5: 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	106,168	67,290
Correctly classified by algorithm	25.05%	24.58%
	(b) Firms with $\geq$ 50 employees	
	Rio de Janeiro, 1994–2010	Veneto, 1984–2001
Number of firms to classify	4,212	1,385
Correctly classified by algorithm	25.78%	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 AKM fixed effect, 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 6: Workforce characteristics in each class of firms. Rio de Janeiro, 1994–2010.

Class	1	2	3	4	5	6	7	8	9	10	NC
Number of Worker-Years	841,309	3,528,349	2,973,921	7,964,829	4,039,786	3,834,176	7,016,132	2,893,551	3,718,893	1,131,109	1,620,207
Number of Firms	13,623	14,598	30,200	18,897	36,441	13,609	22,020	32,040	18,570	12,287	227,552
Firm Size: Mean	1184.56	2151.91	311.76	2585.48	271.05	755.65	1043.38	708.67	662.91	926.28	595.59
Firm Size: Median	34.17	458.67	24.17	459.42	24.42	260.17	155.58	25.58	123.08	79.25	4.25
% Firm > 50 Employees	0.455	0.730	0.395	0.756	0.353	0.756	0.667	0.378	0.645	0.567	0.229
% Men	0.632	0.657	0.638	0.656	0.615	0.686	0.629	0.596	0.741	0.699	0.579
% HS Dropouts	0.542	0.546	0.594	0.505	0.658	0.563	0.578	0.727	0.564	0.518	0.524
% HS Graduates	0.298	0.281	0.280	0.296	0.240	0.285	0.279	0.212	0.295	0.299	0.302
% More than HS	0.159	0.173	0.125	0.199	0.101	0.151	0.143	0.060	0.141	0.183	0.172
% Age 18-29	0.396	0.325	0.377	0.313	0.356	0.372	0.337	0.323	0.372	0.381	0.384
% Age 30-39	0.279	0.295	0.302	0.317	0.303	0.315	0.304	0.299	0.303	0.296	0.258
% Age 40-49	0.202	0.246	0.203	0.240	0.212	0.204	0.223	0.232	0.206	0.200	0.205
% Age 50+	0.122	0.133	0.119	0.129	0.129	0.109	0.136	0.146	0.119	0.123	0.153
% Export-Oriented Sectors	0.015	0.020	0.006	0.041	0.024	0.015	0.018	0.020	0.037	0.034	0.007
% Rio de Janeiro Metro Region	0.843	0.863	0.819	0.843	0.780	0.859	0.825	0.746	0.785	0.793	0.788
Non-routine Cognitive Analytical	0.040	0.011	0.013	0.074	-0.039	0.026	-0.020	-0.118	0.037	0.060	0.034
Non-routine Cognitive Interpersonal	-0.037	-0.116	-0.089	-0.027	-0.026	-0.031	-0.039	-0.070	-0.012	0.017	0.013
Routine Cognitive	0.121	0.218	0.154	0.116	-0.017	0.096	0.042	-0.104	0.059	0.055	0.072
Routine Manual	0.038	0.066	0.012	0.017	0.092	0.104	0.094	0.190	0.145	0.089	-0.040
% Agriculture, Livestock	0.008	0.010	0.003	0.003	0.036	0.007	0.010	0.027	0.002	0.003	0.009
% Extractive Industries	0.003	0.004	0.002	0.024	0.001	0.002	0.004	0.003	0.024	0.027	0.005
% Manufacturing	0.151	0.159	0.089	0.145	0.125	0.198	0.150	0.090	0.181	0.103	0.070
% Construction	0.054	0.028	0.016	0.019	0.043	0.102	0.058	0.057	0.133	0.162	0.059
% Retail, Trade	0.246	0.153	0.322	0.201	0.300	0.226	0.200	0.230	0.190	0.191	0.312
% Accommodation, Meals	0.039	0.025	0.034	0.039	0.097	0.060	0.075	0.107	0.052	0.046	0.063
% Transportation, Storage, Communications	0.127	0.173	0.212	0.136	0.038	0.060	0.069	0.020	0.072	0.065	0.031
% Finance, Insurance	0.025	0.044	0.037	0.043	0.031	0.023	0.020	0.005	0.015	0.026	0.145
% Business Services, Real Estate	0.165	0.194	0.123	0.136	0.160	0.168	0.217	0.314	0.221	0.235	0.149
% Education	0.038	0.056	0.062	0.073	0.069	0.030	0.036	0.038	0.018	0.068	0.029
% Health, Social Services	0.026	0.025	0.035	0.078	0.031	0.064	0.083	0.032	0.022	0.015	0.049
% Other Services (e.g. Leisure, Personal)	0.080	0.045	0.061	0.092	0.063	0.056	0.069	0.072	0.061	0.034	0.058
Wages: Mean	13.03	17.59	10.87	21.35	9.40	15.22	12.93	7.29	15.95	17.77	15.31
Wages: Median	6.26	8.17	6.11	8.12	5.09	8.07	6.62	4.99	8.28	8.62	5.48
Wages: Variance	555	945	739	2,690	703	790	971	203	867	805	1,261
AKM Firm Effect: Mean	-0.023	0.121	-0.158	0.101	-0.260	0.088	-0.068	-0.308	0.084	0.097	-0.096

Notes: Characteristics of the workforce in each firm class. Firm class NC are small firms not categorized by BLM clustering. Export-oriented sectors are those related to iron, soybeans, petroleum, sugar, poultry, plane manufacturing, coffee, woodpulp, car manufacturing, and bovine meat.

Table 7: Workforce characteristics in each class of firms. Veneto, 1984–2001.

Class	1	2	3	4	5	6	7	8	9	10	NC
Number of Worker-Years	235,649	1,058,171	952,200	1,328,260	2,514,369	1,494,467	2,824,797	1,433,039	1,384,897	451,045	552,006
Number of Firms	7,416	14,842	12,767	14,480	13,368	14,808	12,370	15,998	14,362	13,868	149,860
Firm Size: Mean	32.46	40.80	42.96	191.56	320.79	109.80	425.78	255.39	586.22	53.00	6.24
Firm Size: Median	8.40	11.88	14.56	20.54	44.44	23.73	71.74	24.08	26.80	7.09	1.35
% Firm > 50 Employees	0.149	0.173	0.223	0.341	0.480	0.346	0.569	0.386	0.417	0.151	0.017
% Men	0.589	0.572	0.616	0.638	0.656	0.616	0.677	0.593	0.633	0.499	0.530
% Age 18-29	0.547	0.506	0.402	0.442	0.365	0.314	0.359	0.348	0.416	0.523	0.551
% Age 30-39	0.220	0.247	0.299	0.270	0.295	0.317	0.310	0.327	0.299	0.289	0.202
% Age 40-49	0.138	0.150	0.192	0.177	0.219	0.239	0.216	0.215	0.186	0.127	0.120
% Age 50+	0.095	0.097	0.106	0.111	0.122	0.131	0.115	0.110	0.099	0.061	0.126
% 5 Largest Cities	0.138	0.125	0.128	0.246	0.161	0.242	0.232	0.379	0.444	0.381	0.223
% Extractive and Chemical Industries	0.032	0.044	0.058	0.045	0.087	0.074	0.070	0.069	0.054	0.025	0.018
% Manufacturing: Metal	0.145	0.121	0.104	0.236	0.247	0.185	0.340	0.175	0.200	0.197	0.099
% Manufacturing: Other	0.450	0.531	0.525	0.266	0.444	0.281	0.217	0.141	0.122	0.118	0.166
% Construction	0.170	0.163	0.049	0.156	0.059	0.023	0.037	0.022	0.049	0.039	0.141
% Trade, Retail, Hospitality	0.088	0.066	0.136	0.090	0.092	0.294	0.194	0.325	0.178	0.314	0.369
% Transportation, Communications	0.033	0.012	0.032	0.026	0.019	0.052	0.020	0.044	0.086	0.040	0.032
% Finance, Insurance, Business Services	0.031	0.026	0.021	0.091	0.013	0.032	0.057	0.128	0.224	0.154	0.076
% Other Services	0.044	0.026	0.023	0.084	0.031	0.044	0.051	0.078	0.071	0.106	0.091
Daily Wages: Mean	112.76	108.73	97.61	118.09	122.21	116.37	134.86	137.99	144.79	126.34	98.48
Daily Wages: Median	97.83	96.94	94.76	106.42	108.87	108.45	117.53	117.37	117.45	105.16	93.94
Daily Wages: Variance	398,550	411,853	12,776	25,286	215,116	8,629	33,986	62,153	85,031	230,160	58,963
AKM Firm Effect: Mean	-0.042	-0.049	-0.142	-0.018	0.002	-0.031	0.034	0.031	0.044	-0.027	-0.099

Notes: Characteristics of the workforce in each firm class. Firm class NC are small firms not categorized by BLM clustering. The five largest cities are Venezia, Verona, Padova, Vicenza, and Treviso.

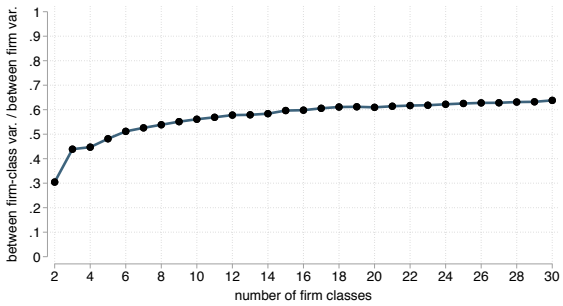
- SUPPLEMENTARY APPENDICES -

A Additional Figures and Tables

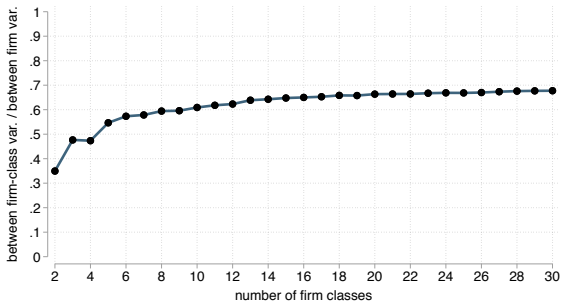
A.1 Figures

Figure A1: Ratio: between firm-class variance / between-firm variance, by number of firm classes.

(a) Rio de Janeiro, 1994–2010.

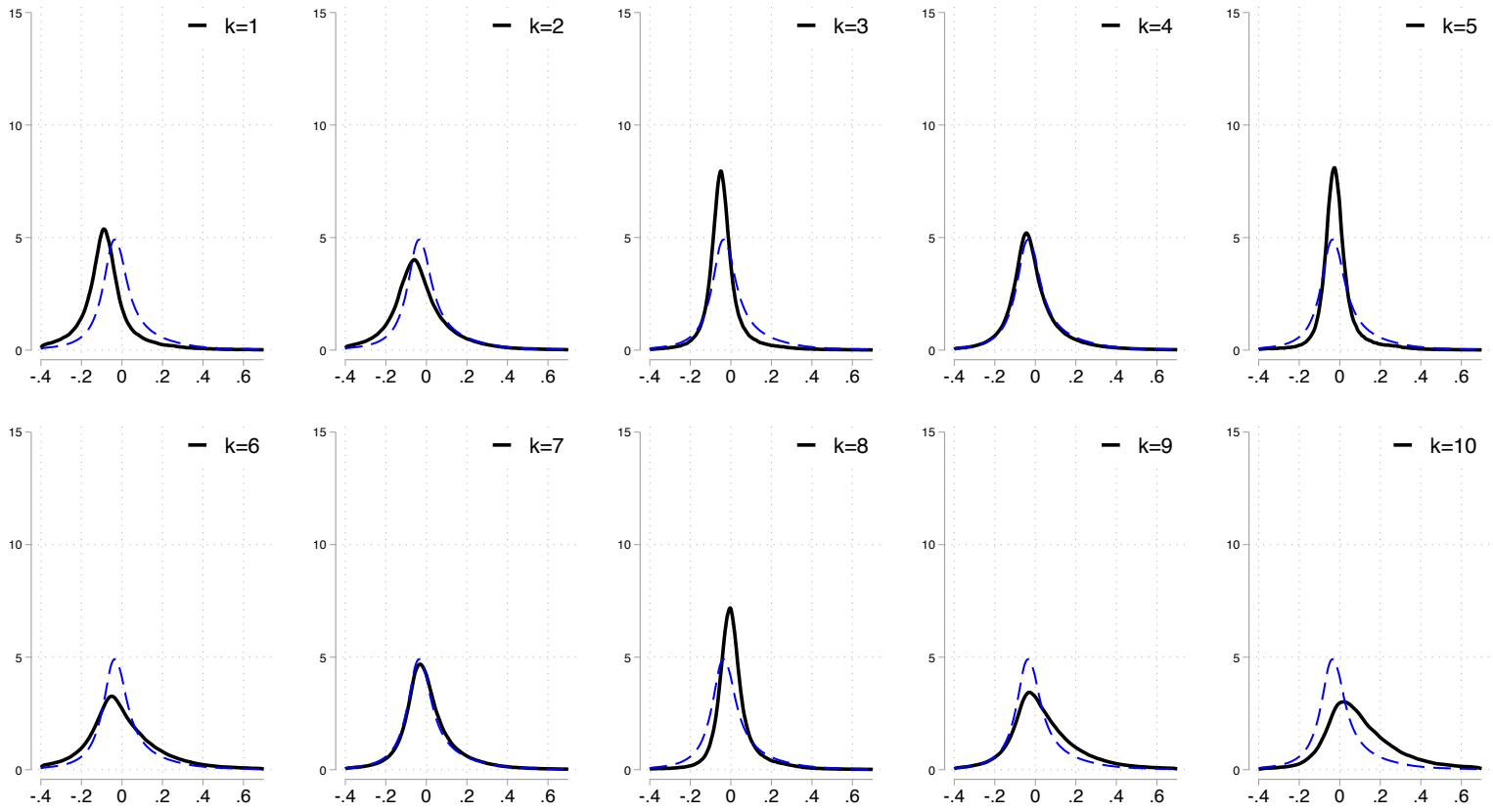


(b) Veneto, 1984–2001.



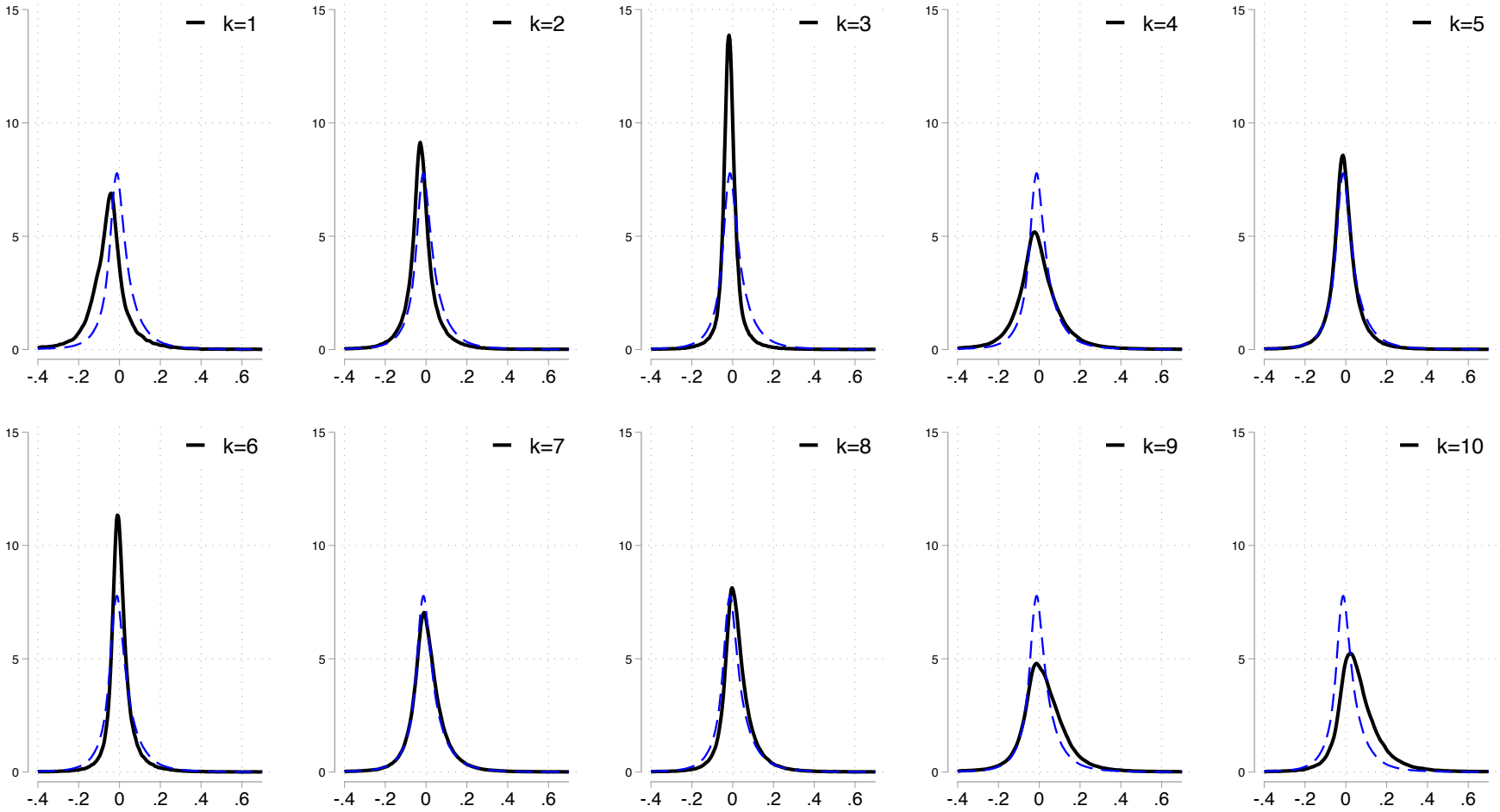
Notes: Ratio between i) between firm-class variance of unexplained earnings growth, over ii) between-firm variance of unexplained earnings growth. As a function of number of firm classes (2–30).

Figure A2: Density of unexplained earnings growth in each firm class. Rio de Janeiro, 1994–2010.



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

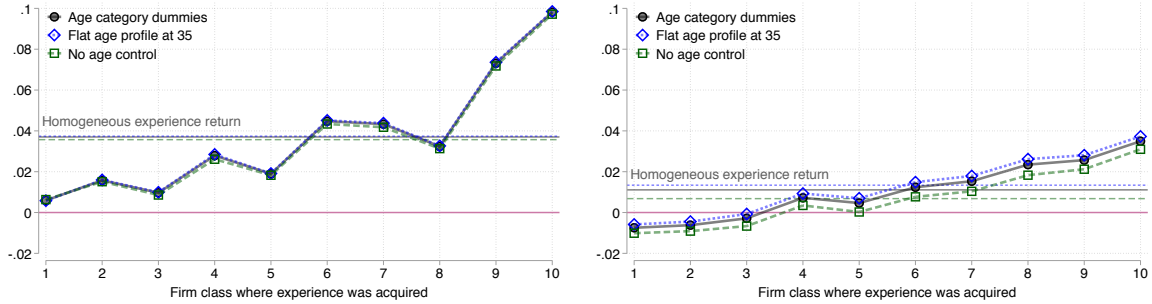
Figure A3: Density of unexplained earnings growth in each firm class. Veneto, 1984–2001.



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

Figure A4: Robustness by alternative age controls: Returns to experience acquired in different firm classes.

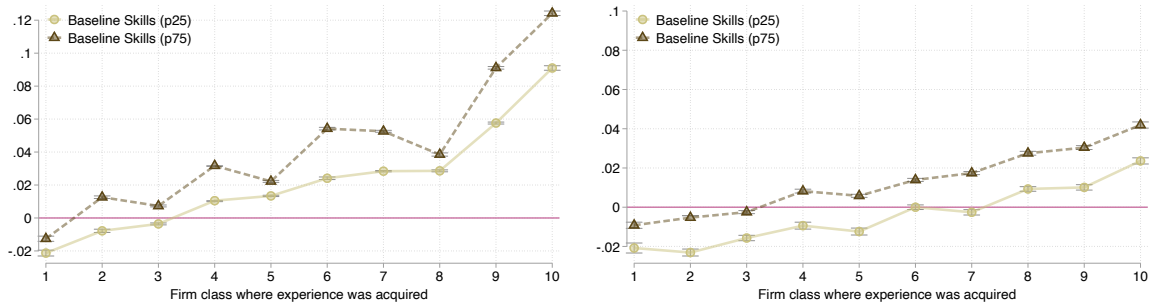
(a) Rio de Janeiro, 1994–2010. **(b)** Veneto, 1984–2001.



Notes: Point estimates of returns to experience acquired in different firm classes, using different ways of controlling for age effects. Black dots: baseline estimates from Tables 2 and 3, column (6), 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 with each age option.

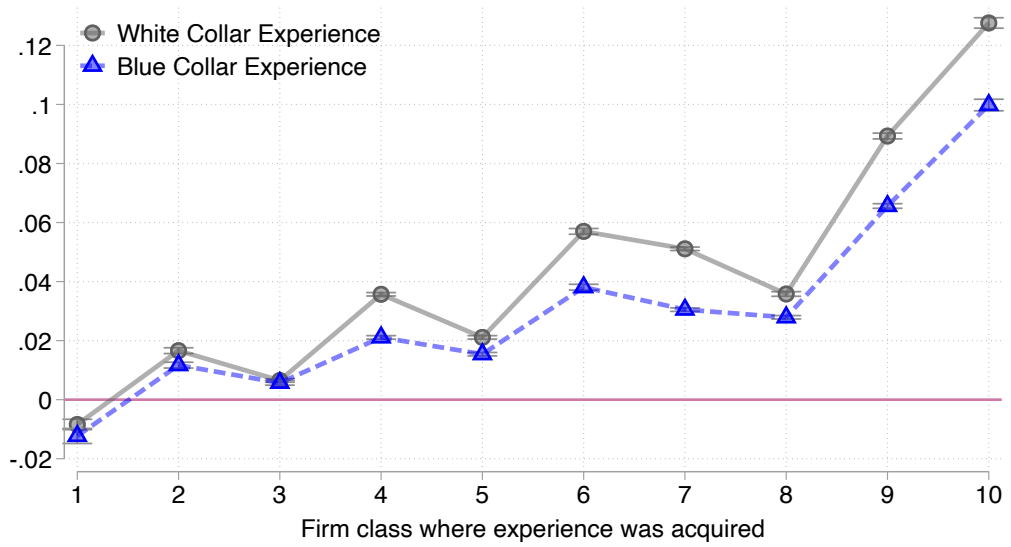
Figure A5: Returns to experience acquired in different firm classes by unobserved skills.

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



Notes: Estimated returns to experience across firm classes for workers in the 25th and 75th percentile of the distribution of unobserved skills in Rio de Janeiro and Veneto, respectively. Estimates follow from De La Roca and Puga (2017)'s specification, detailed in Section 4.3.

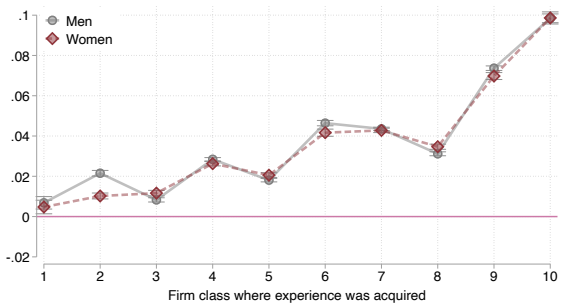
Figure A6: Returns to experience acquired in different firm classes by occupation. Rio de Janeiro.



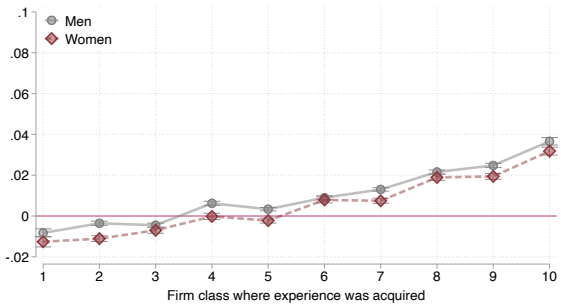
Notes: Estimated returns to experience across firm classes for workers who were employed in white- and blue-collar occupations in Rio de Janeiro. Occupational categories are defined in Section 4.3.

Figure A7: Estimated separately for men and women: Returns to experience acquired in different firm classes.

(a) Rio de Janeiro, 1994–2010.

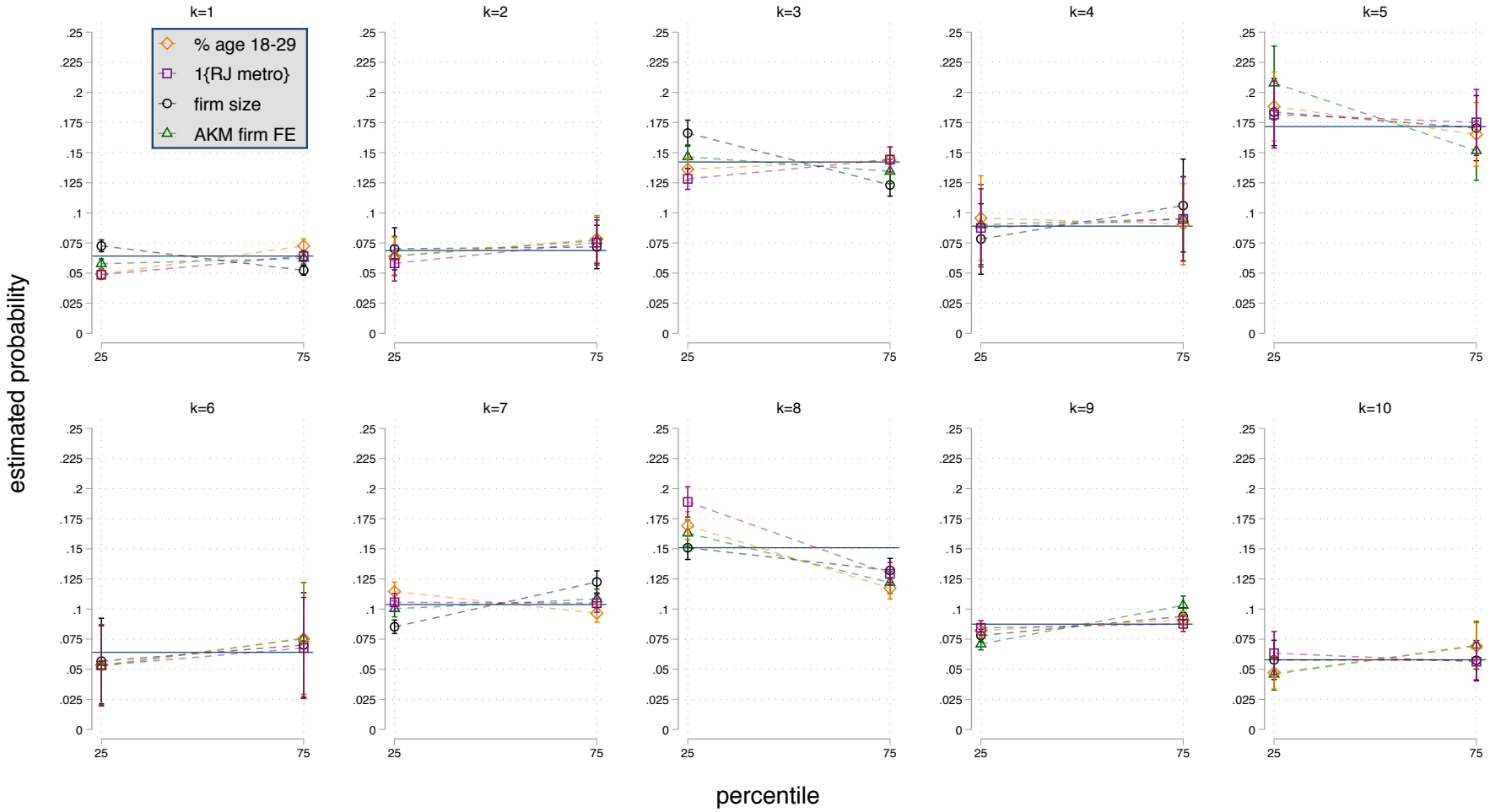


(b) Veneto, 1984–2001.



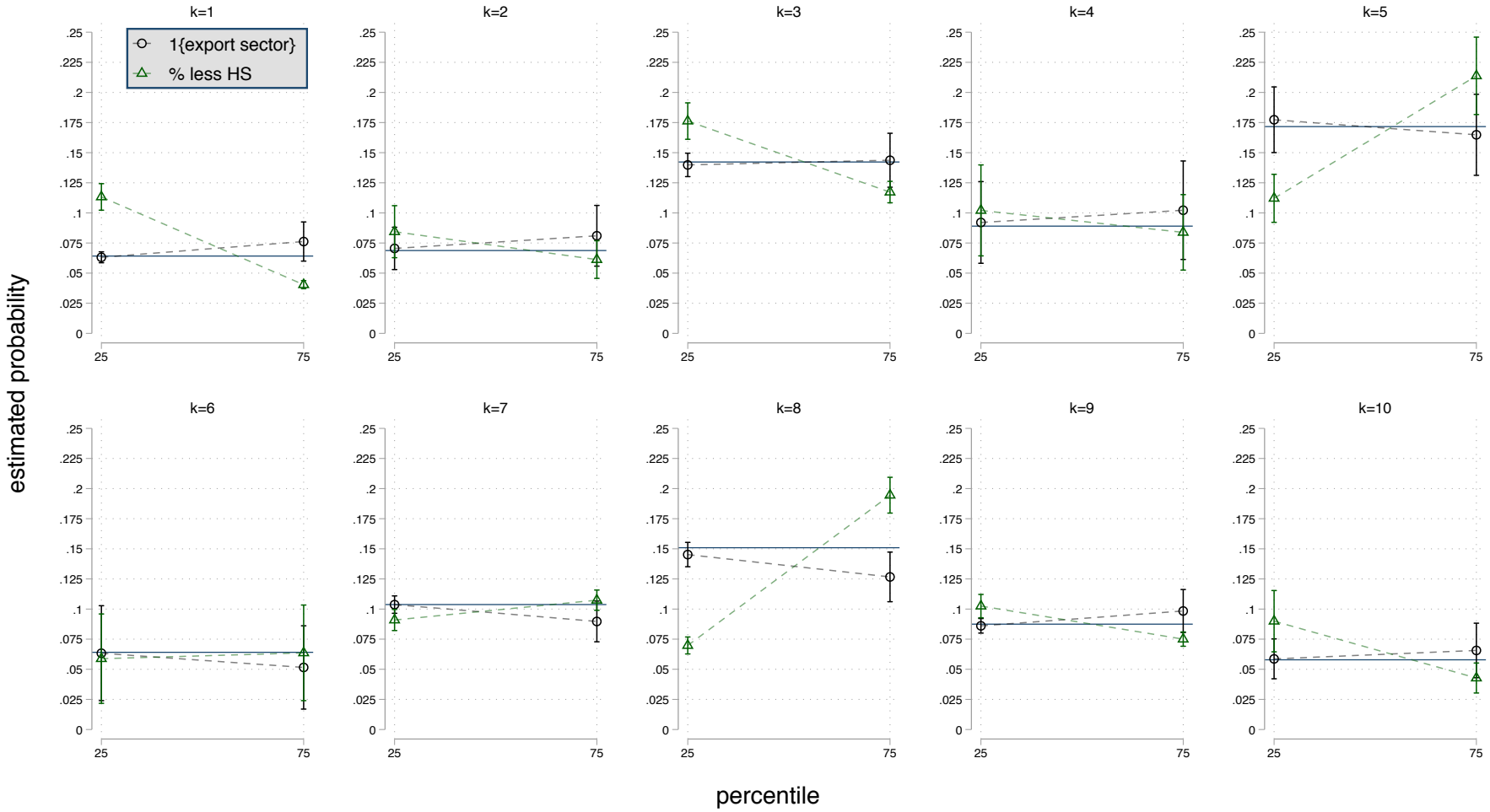
Notes: Point estimates of returns to experience acquired in different firm classes, estimated separately for men and for women. Flat lines: returns to homogeneous experience for each gender.

Figure A8: Multinomial Logit Estimated Probabilities: $Pr(\text{class} = k|X)$. Rio de Janeiro, 1994–2010.



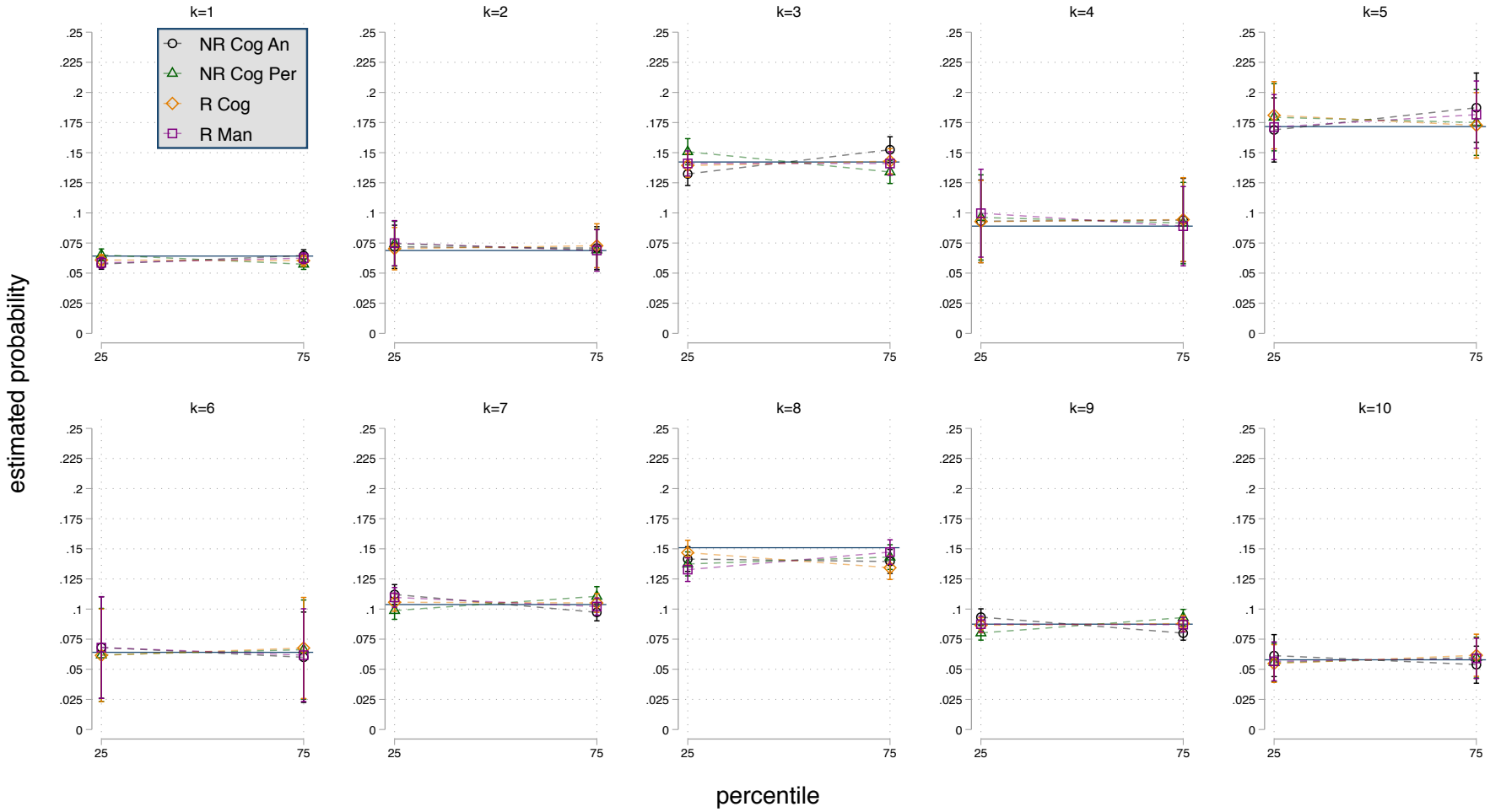
Notes: Estimated probabilities and 95% confidence intervals from firm-level multinomial logit with the following explanatory variables: workforce age distribution, workforce gender distribution, workforce education distribution, log firm size, AKM firm effect, 1-digit sector indicators, indicator for 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 A9: Multinomial Logit Estimated Probabilities: $Pr(\text{class} = k|X)$. Rio de Janeiro, 1994–2010.



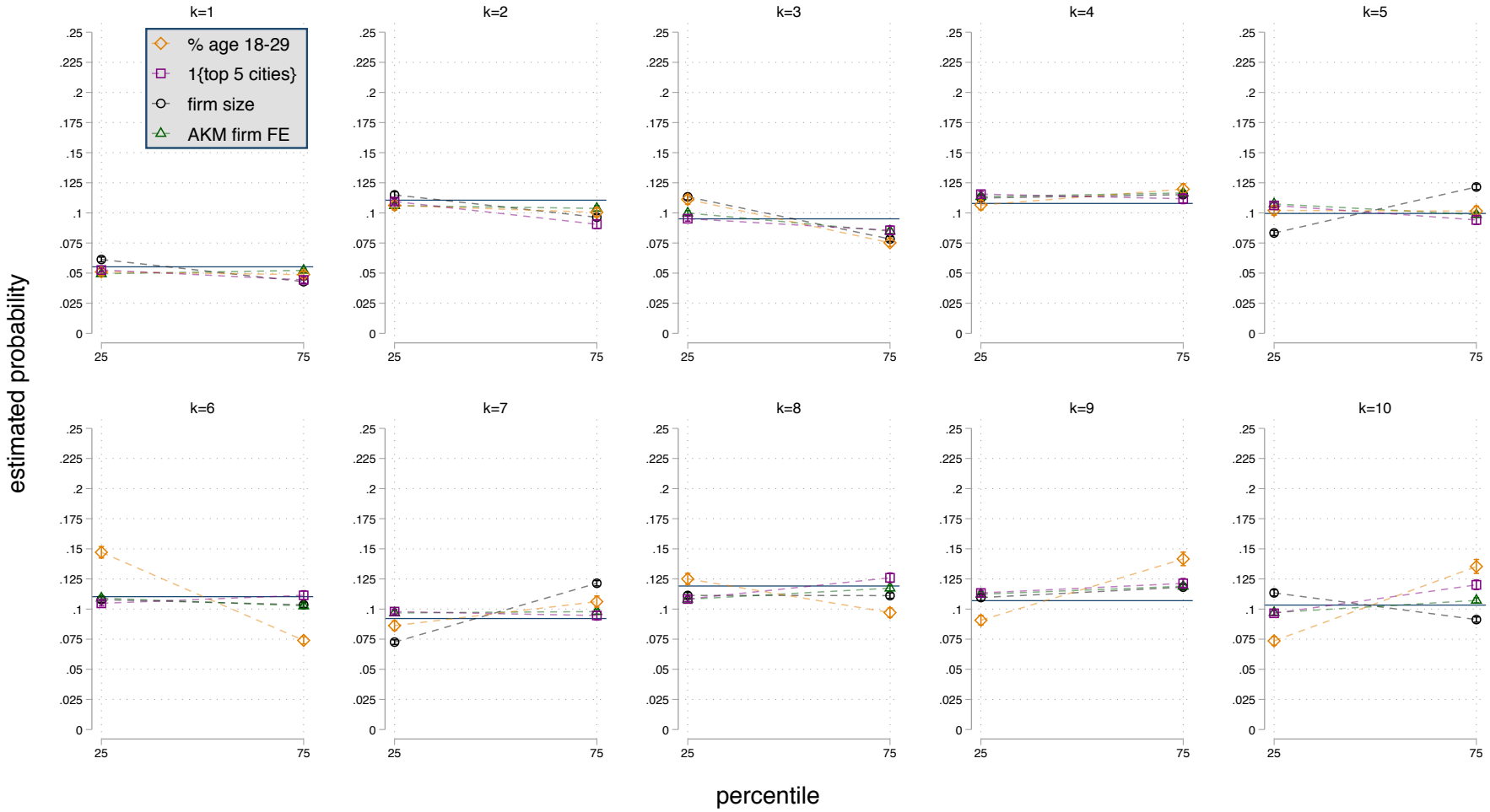
Notes: Estimated probabilities and 95% confidence intervals from firm-level multinomial logit with the following explanatory variables: workforce age distribution, workforce gender distribution, workforce education distribution, log firm size, AKM firm effect, 1-digit sector indicators, indicator for 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{export sector}), 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 A10: 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, AKM firm effect, 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, 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. NR Cog An is the prevalence of non-routine cognitive analytic tasks. NR Cog Per is the prevalence of non-routine cognitive interpersonal tasks. R Cog is the prevalence of routine cognitive tasks. R Man is the prevalence of routine cognitive tasks.

Figure A11: 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, AKM firm effect, 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.

A.2 Tables

Table A1: Firm-class distributions of unexplained earnings growth.

Rio de Janeiro, 1994–2010.

Class	Mean	Median	Variance	Skewness
1	-0.094	-0.089	0.050	-1.442
2	-0.040	-0.052	0.050	0.146
3	-0.036	-0.046	0.021	1.151
4	-0.016	-0.033	0.037	0.891
5	-0.010	-0.023	0.019	2.861
6	0.004	-0.023	0.081	0.466
7	0.010	-0.012	0.043	1.277
8	0.017	0.001	0.023	3.065
9	0.052	0.014	0.071	1.106
10	0.122	0.074	0.078	1.438
overall	-0.000	-0.022	0.046	1.049

Veneto, 1984–2001.

Class	Mean	Median	Variance	Skewness
1	-0.058	-0.050	0.020	-0.488
2	-0.026	-0.026	0.014	-0.916
3	-0.016	-0.016	0.008	-1.367
4	-0.012	-0.014	0.023	-0.489
5	-0.009	-0.011	0.013	-0.745
6	0.002	-0.003	0.009	-0.459
7	0.003	-0.002	0.015	-0.562
8	0.018	0.010	0.011	-0.052
9	0.019	0.012	0.021	-0.282
10	0.058	0.044	0.019	0.246
overall	-0.000	-0.006	0.015	-0.481

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.

Table A2: Returns to experience acquired in different firm classes: Quadratic experience terms. Rio de Janeiro.

Firm class, k	1	2	3	4	5	6	7	8	9	10
$Exp(k)$										
1	0.004	0.022	0.012	0.035	0.016	0.059	0.050	0.030	0.086	0.114
3	0.017	0.061	0.035	0.101	0.052	0.165	0.145	0.093	0.247	0.324
5	0.035	0.094	0.058	0.160	0.094	0.255	0.235	0.163	0.392	0.507
10	0.105	0.153	0.112	0.278	0.222	0.406	0.434	0.362	0.688	0.852

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. I.e., an extension of equation (8) (specification of columns (6) in Tables 2 and 3) 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 A3: Returns to experience acquired in different firm classes: Quadratic experience terms. Veneto.

Firm class, k	1	2	3	4	5	6	7	8	9	10
$Exp(k)$										
1	-0.009	0.002	0.002	0.014	0.011	0.019	0.024	0.035	0.037	0.051
3	-0.024	0.002	0.005	0.038	0.030	0.054	0.068	0.098	0.104	0.140
5	-0.034	-0.003	0.006	0.058	0.046	0.084	0.105	0.151	0.161	0.215
10	-0.041	-0.038	-0.005	0.089	0.069	0.144	0.173	0.247	0.266	0.334

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. I.e., an extension of equation (8) (specification of columns (6) in Tables 2 and 3) 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: Robustness: including tenure. Returns to experience acquired in different firm classes.

Rio de Janeiro, 1994–2010.

	(1)	(2)
Experience	0.0233***	
	(0.0003)	
Experience: class 1		-0.0084***
		(0.0012)
Experience: class 2		0.0009*
		(0.0005)
Experience: class 3		-0.0065***
		(0.0005)
Experience: class 4		0.0122***
		(0.0004)
Experience: class 5		0.0025***
		(0.0004)
Experience: class 6		0.0301***
		(0.0006)
Experience: class 7		0.0273***
		(0.0004)
Experience: class 8		0.0163***
		(0.0004)
Experience: class 9		0.0581***
		(0.0005)
Experience: class 10		0.0840***
		(0.0009)
Experience: NC		0.0108***
		(0.0005)
Experience: PS		0.0430***
		(0.0029)
Experience: non-RJ		0.0419***
		(0.0005)
Tenure	0.0165***	0.0186***
	(0.0002)	(0.0002)
Adj. R^2	0.760	0.763
Within adj. R^2	0.014	0.025
Person FE	yes	yes
Firm FE	yes	yes
SE clusters (persons)	1,510,168	1,510,168
N	8,754,064	8,754,064

Veneto, 1984–2001.

	(1)	(2)
Experience	0.0007*	
	(0.0004)	
Experience: class 1		-0.0169***
		(0.0008)
Experience: class 2		-0.0167***
		(0.0005)
Experience: class 3		-0.0138***
		(0.0005)
Experience: class 4		-0.0028***
		(0.0005)
Experience: class 5		-0.0061***
		(0.0004)
Experience: class 6		0.0015***
		(0.0005)
Experience: class 7		0.0046***
		(0.0004)
Experience: class 8		0.0128***
		(0.0005)
Experience: class 9		0.0152***
		(0.0005)
Experience: class 10		0.0249***
		(0.0007)
Experience: NC		0.0017***
		(0.0005)
Experience: PS		-0.0076
		(0.0053)
Experience: non-Veneto		0.0060***
		(0.0005)
Tenure	0.0110***	0.0112***
	(0.0002)	(0.0002)
Adj. R^2	0.602	0.605
Within adj. R^2	0.014	0.023
Person FE	yes	yes
Firm FE	yes	yes
SE clusters (persons)	484,953	484,953
N	3,614,154	3,614,154

Notes: Left panel: Same specification as that reported for Rio de Janeiro in Table 2, columns (5) and (6), adding a linear term of tenure at the current employer. Right panel: Same specification as that reported for Veneto in Table 3, columns (5) and (6), adding a linear term of tenure at the current employer.

Table A5: Estimated wage returns to task content: Rio de Janeiro.

	(1)	(2)	(3)	(4)
Non-Routine Analytic	0.0647***			
	(0.0005)			
Non-Routine Interpersonal		0.0461***		
		(0.0005)		
Routine Cognitive			-0.0109***	
			(0.0003)	
Routine Manual				-0.0079***
				(0.0004)
Experience	0.0388***	0.0387***	0.0391***	0.0391***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Year FE	yes	yes	yes	yes
Person FE	yes	yes	yes	yes
R^2	0.693	0.692	0.691	0.691
Observations		16,171,168		

Notes: Outcome is hourly wage. Full sample of workers in Rio de Janeiro. Firm classes 1–10 are BLM clusters, estimated with the remaining 50% of the original sample, ordered according to mean unexplained earnings growth. NC are small firms not categorized by BLM clustering. PS is the public sector. 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 A6: Returns to experience acquired in different firm classes in first post-displacement observation: Rio de Janeiro and Veneto.

	(1)	(2)	(3)	(4)
Experience: class 1	0.0472***	0.0256***	0.0009	0.0095
	(0.0056)	(0.0070)	(0.0035)	(0.0081)
Experience: class 2	0.0576***	0.0301***	-0.0018	0.0030
	(0.0026)	(0.0029)	(0.0019)	(0.0036)
Experience: class 3	-0.0018	0.0135***	-0.0330***	0.0003
	(0.0039)	(0.0045)	(0.0040)	(0.0054)
Experience: class 4	0.0328***	0.0245***	0.0092***	0.0140***
	(0.0019)	(0.0022)	(0.0021)	(0.0042)
Experience: class 5	-0.0305***	0.0053	0.0142***	0.0112***
	(0.0032)	(0.0038)	(0.0022)	(0.0041)
Experience: class 6	0.0531***	0.0334***	0.0095***	0.0021
	(0.0023)	(0.0028)	(0.0031)	(0.0067)
Experience: class 7	0.0392***	0.0227***	0.0262***	0.0277***
	(0.0022)	(0.0025)	(0.0016)	(0.0031)
Experience: class 8	-0.0257***	0.0038	0.0463***	0.0235***
	(0.0036)	(0.0045)	(0.0021)	(0.0032)
Experience: class 9	0.1085***	0.0500***	0.0330***	0.0213***
	(0.0029)	(0.0033)	(0.0024)	(0.0039)
Experience: class 10	0.1417***	0.0717***	0.0437***	0.0418***
	(0.0046)	(0.0056)	(0.0044)	(0.0099)
Experience: NC	-0.0063	0.0094*	-0.0307***	-0.0000
	(0.0045)	(0.0053)	(0.0041)	(0.0063)
Experience: PS	0.1890***	0.0715***	0.0472***	0.0043
	(0.0113)	(0.0132)	(0.0044)	(0.0073)
Experience: Other	0.0844***	0.0387***	0.0283***	0.0227***
	(0.0032)	(0.0037)	(0.0019)	(0.0035)
Adjusted R^2	0.196	0.540	0.130	0.413
Year FE	yes	yes	yes	yes
Time to Reentry	no	no	no	no
Observables	yes	yes	yes	yes
Post-ML Firm FE	no	yes	no	yes
Observations	102459	102459	26228	26228

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. We do not control for time to reentry. Firm classes 1–10 are BLM clusters ordered according to mean unexplained earnings growth. NC are small firms not categorized by BLM clustering and PS is the public sector in each data set. 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. Robust standard errors in parentheses. *p<0.10; **p<0.05; ***p<0.01.

Table A7: Returns to experience acquired in different firm classes: task content in Rio de Janeiro

	Non-Routine Analytic	Non-Routine Interpersonal	Routine Cognitive	Routine Manual
	(1)	(2)	(3)	(4)
Experience: class 1	0.0097***	0.0154***	-0.0151***	-0.0137***
	(0.0014)	(0.0014)	(0.0020)	(0.0015)
Experience: class 2	0.0057***	0.0169***	-0.0189***	-0.0151***
	(0.0007)	(0.0007)	(0.0010)	(0.0007)
Experience: class 3	0.0036***	0.0077***	-0.0055***	-0.0057***
	(0.0006)	(0.0006)	(0.0009)	(0.0007)
Experience: class 4	0.0126***	0.0185***	-0.0111***	-0.0113***
	(0.0005)	(0.0005)	(0.0007)	(0.0005)
Experience: class 5	0.0042***	0.0068***	0.0018**	-0.0050***
	(0.0006)	(0.0006)	(0.0008)	(0.0007)
Experience: class 6	0.0186***	0.0216***	-0.0166***	-0.0202***
	(0.0007)	(0.0007)	(0.0009)	(0.0008)
Experience: class 7	0.0136***	0.0153***	-0.0059***	-0.0184***
	(0.0005)	(0.0005)	(0.0007)	(0.0006)
Experience: class 8	0.0043***	0.0087***	0.0008	-0.0101***
	(0.0006)	(0.0006)	(0.0009)	(0.0008)
Experience: class 9	0.0192***	0.0217***	-0.0167***	-0.0232***
	(0.0006)	(0.0007)	(0.0008)	(0.0008)
Experience: class 10	0.0272***	0.0299***	-0.0186***	-0.0270***
	(0.0011)	(0.0012)	(0.0014)	(0.0013)
Experience: NC	0.0050***	0.0101***	-0.0057***	-0.0085***
	(0.0006)	(0.0007)	(0.0009)	(0.0008)
Experience: PS	0.0403***	0.0495***	-0.0373***	-0.0271***
	(0.0031)	(0.0032)	(0.0042)	(0.0032)
Experience: Other	0.0177***	0.0216***	-0.0160***	-0.0196***
	(0.0005)	(0.0005)	(0.0007)	(0.0006)
adj. R^2	0.672	0.628	0.645	0.729
Year FE	yes	yes	yes	yes
Person FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
N	8602938	8602938	8602938	8602938

Notes: Outcome variables capture non-routine analytic, non-routine interpersonal, routine cognitive and routine manual task content. Task content is as defined in the text. Workers born in 1976 or later. NC are small firms not categorized by BLM clustering and PS is the public sector in each data set. 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 A8: Estimated wage returns to task content in first post-displacement observation:: Rio de Janeiro.

	Non-Routine Analytic		Non-Routine Interpersonal		Routine Cognitive		Routine Manual	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Experience: class 1	0.0182***	0.0043	0.0075	0.0061	0.0700***	-0.0026	-0.1018***	-0.0313***
	(0.0056)	(0.0071)	(0.0059)	(0.0071)	(0.0090)	(0.0105)	(0.0079)	(0.0087)
Experience: class 2	-0.0077***	0.0155***	-0.0137***	0.0159***	0.0485***	0.0023	-0.0351***	-0.0252***
	(0.0026)	(0.0033)	(0.0027)	(0.0035)	(0.0041)	(0.0050)	(0.0037)	(0.0040)
Experience: class 3	0.0230***	0.0117**	0.0074	0.0099	0.0139**	0.0093	-0.0742***	-0.0271***
	(0.0045)	(0.0055)	(0.0052)	(0.0063)	(0.0068)	(0.0079)	(0.0066)	(0.0072)
Experience: class 4	0.0032*	0.0108***	-0.0074***	0.0077***	0.0638***	0.0166***	-0.0649***	-0.0199***
	(0.0019)	(0.0025)	(0.0020)	(0.0027)	(0.0030)	(0.0038)	(0.0026)	(0.0032)
Experience: class 5	0.0095***	-0.0000	0.0111***	-0.0002	-0.0191***	0.0040	-0.0329***	-0.0128**
	(0.0035)	(0.0044)	(0.0037)	(0.0044)	(0.0051)	(0.0060)	(0.0050)	(0.0059)
Experience: class 6	0.0175***	0.0129***	0.0023	0.0096***	0.0260***	0.0065	-0.0162***	-0.0172***
	(0.0023)	(0.0032)	(0.0024)	(0.0034)	(0.0036)	(0.0047)	(0.0034)	(0.0041)
Experience: class 7	0.0085***	0.0120***	0.0015	0.0121***	0.0034	-0.0025	-0.0315***	-0.0231***
	(0.0024)	(0.0031)	(0.0024)	(0.0032)	(0.0033)	(0.0042)	(0.0030)	(0.0039)
Experience: class 8	-0.0092**	0.0040	0.0077*	0.0045	-0.0634***	-0.0003	-0.0070	-0.0180**
	(0.0041)	(0.0055)	(0.0044)	(0.0058)	(0.0060)	(0.0074)	(0.0060)	(0.0073)
Experience: class 9	0.0367***	0.0206***	0.0231***	0.0198***	0.0040	-0.0022	-0.0084**	-0.0311***
	(0.0027)	(0.0035)	(0.0027)	(0.0037)	(0.0040)	(0.0052)	(0.0036)	(0.0046)
Experience: class 10	0.0402***	0.0332***	0.0363***	0.0354***	-0.0309***	-0.0051	-0.0010	-0.0393***
	(0.0040)	(0.0055)	(0.0042)	(0.0058)	(0.0065)	(0.0086)	(0.0058)	(0.0072)
Experience: NC	0.0290***	0.0004	0.0292***	0.0076	0.0228***	0.0142	-0.0616***	-0.0182**
	(0.0049)	(0.0060)	(0.0051)	(0.0061)	(0.0076)	(0.0092)	(0.0064)	(0.0074)
Experience: PS	0.0931***	0.0288*	0.0635***	0.0367*	-0.0931***	-0.0038	-0.2418***	-0.0468***
	(0.0099)	(0.0149)	(0.0126)	(0.0201)	(0.0131)	(0.0164)	(0.0127)	(0.0154)
Experience: Other	0.0353***	0.0113***	0.0170***	0.0102**	0.0027	-0.0010	-0.0161***	-0.0217***
	(0.0031)	(0.0040)	(0.0031)	(0.0043)	(0.0040)	(0.0052)	(0.0040)	(0.0047)
Education	0.0483***	0.0284***	0.0268***	0.0197***	0.0468***	0.0187***	-0.0887***	-0.0509***
	(0.0007)	(0.0009)	(0.0006)	(0.0009)	(0.0009)	(0.0013)	(0.0008)	(0.0012)
Male	0.0261***	0.0292***	0.0071*	0.0405***	-0.2891***	-0.2640***	0.2992***	0.1322***
	(0.0040)	(0.0053)	(0.0040)	(0.0054)	(0.0065)	(0.0086)	(0.0051)	(0.0064)
adj. R^2	0.088	0.436	0.034	0.370	0.105	0.458	0.197	0.544
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Time to Reentry	yes	yes	yes	yes	yes	yes	yes	yes
Observables	yes	yes	yes	yes	yes	yes	yes	yes
Pre-Layoff Firm Type FE	no	no	no	no	no	no	no	no
Post-ML 1-Dig Ind FE	no	no	no	no	no	no	no	no
Post-ML Firm FE	no	yes	no	yes	no	yes	no	yes
N	98860	98860	98860	98860	98860	98860	98860	98860

Notes: Outcome is non-routine analytic, non-routine interpersonal, routine cognitive and routine manual task content. Sample of workers born after 1976 in Rio de Janeiro. All specifications include year fixed effects and control for age with six age-category indicators. Robust standard errors in parentheses. *p<0.10; **p<0.05; ***p<0.01.

Table A9: Estimated task content returns to experience acquired in different firm classes by education: Rio de Janeiro.

	HS Dropouts				HS Graduates				More than HS			
	Non-Routine Analytic	Non-Routine Interpersonal	Routine Cognitive	Routine Manual	Non-Routine Analytic	Non-Routine Interpersonal	Routine Cognitive	Routine Manual	Non-Routine Analytic	Non-Routine Interpersonal	Routine Cognitive	Routine Manual
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Experience: class 1	0.0106***	0.0095***	0.0012	-0.0109***	0.0101***	0.0205***	-0.0301***	-0.0165***	-0.0186***	-0.0036	-0.0042	0.0106***
	(0.0022)	(0.0021)	(0.0032)	(0.0028)	(0.0019)	(0.0021)	(0.0030)	(0.0021)	(0.0047)	(0.0047)	(0.0061)	(0.0033)
Experience: class 2	0.0049***	0.0124***	-0.0060***	-0.0132***	0.0023**	0.0134***	-0.0227***	-0.0138***	-0.0068***	0.0167***	-0.0205***	0.0007
	(0.0010)	(0.0010)	(0.0014)	(0.0014)	(0.0009)	(0.0009)	(0.0015)	(0.0010)	(0.0022)	(0.0024)	(0.0032)	(0.0016)
Experience: class 3	0.0053***	0.0074***	0.0013	-0.0067***	0.0046***	0.0106***	-0.0180***	-0.0093***	-0.0077***	-0.0007	0.0081**	0.0122***
	(0.0008)	(0.0008)	(0.0012)	(0.0011)	(0.0010)	(0.0010)	(0.0014)	(0.0011)	(0.0026)	(0.0025)	(0.0032)	(0.0019)
Experience: class 4	0.0092***	0.0116***	0.0011	-0.0104***	0.0093***	0.0138***	-0.0086***	-0.0107***	0.0079***	0.0266***	-0.0227***	0.0016
	(0.0007)	(0.0006)	(0.0010)	(0.0009)	(0.0007)	(0.0007)	(0.0011)	(0.0008)	(0.0016)	(0.0017)	(0.0022)	(0.0012)
Experience: class 5	0.0104***	0.0092***	0.0047***	-0.0079***	0.0069***	0.0127***	-0.0108***	-0.0111***	-0.0180***	-0.0063**	0.0097***	0.0097***
	(0.0007)	(0.0007)	(0.0011)	(0.0010)	(0.0009)	(0.0009)	(0.0014)	(0.0010)	(0.0025)	(0.0025)	(0.0034)	(0.0019)
Experience: class 6	0.0216***	0.0197***	-0.0058***	-0.0218***	0.0178***	0.0224***	-0.0247***	-0.0205***	-0.0063***	0.0042*	0.0016	0.0033*
	(0.0011)	(0.0011)	(0.0013)	(0.0014)	(0.0010)	(0.0011)	(0.0014)	(0.0011)	(0.0024)	(0.0022)	(0.0029)	(0.0018)
Experience: class 7	0.0175***	0.0140***	0.0053***	-0.0196***	0.0118***	0.0161***	-0.0155***	-0.0215***	-0.0051***	0.0057***	0.0008	0.0010
	(0.0006)	(0.0007)	(0.0010)	(0.0009)	(0.0007)	(0.0007)	(0.0010)	(0.0008)	(0.0017)	(0.0016)	(0.0021)	(0.0013)
Experience: class 8	0.0113***	0.0132***	0.0004	-0.0142***	0.0065***	0.0129***	-0.0068***	-0.0150***	-0.0196***	-0.0154***	0.0188***	0.0087***
	(0.0008)	(0.0008)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0016)	(0.0012)	(0.0032)	(0.0032)	(0.0038)	(0.0022)
Experience: class 9	0.0209***	0.0188***	-0.0053***	-0.0264***	0.0171***	0.0220***	-0.0243***	-0.0236***	0.0064***	0.0186***	-0.0149***	-0.0027
	(0.0009)	(0.0010)	(0.0012)	(0.0013)	(0.0009)	(0.0010)	(0.0013)	(0.0011)	(0.0022)	(0.0022)	(0.0027)	(0.0018)
Experience: class 10	0.0248***	0.0255***	-0.0072***	-0.0286***	0.0218***	0.0229***	-0.0229***	-0.0233***	0.0225***	0.0362***	-0.0106***	-0.0117***
	(0.0016)	(0.0019)	(0.0021)	(0.0024)	(0.0016)	(0.0017)	(0.0021)	(0.0019)	(0.0033)	(0.0033)	(0.0035)	(0.0025)
Experience: NC	0.0122***	0.0113***	0.0002	-0.0113***	0.0045***	0.0119***	-0.0187***	-0.0110***	-0.0271***	-0.0051**	0.0188***	0.0163***
	(0.0010)	(0.0010)	(0.0014)	(0.0014)	(0.0010)	(0.0009)	(0.0014)	(0.0010)	(0.0022)	(0.0025)	(0.0027)	(0.0016)
Experience: PS	0.0216***	0.0313***	-0.0084	-0.0204***	0.0319***	0.0382***	-0.0277***	-0.0170***	0.0122*	0.0232***	-0.0088	0.0069
	(0.0059)	(0.0059)	(0.0081)	(0.0072)	(0.0044)	(0.0045)	(0.0059)	(0.0048)	(0.0066)	(0.0070)	(0.0094)	(0.0056)
Experience: Other	0.0168***	0.0124***	0.0011	-0.0203***	0.0121***	0.0171***	-0.0172***	-0.0188***	0.0006	0.0176***	-0.0095***	0.0031**
	(0.0008)	(0.0008)	(0.0011)	(0.0011)	(0.0008)	(0.0008)	(0.0011)	(0.0009)	(0.0017)	(0.0017)	(0.0022)	(0.0013)
adj. R^2	0.679	0.628	0.670	0.727	0.628	0.616	0.631	0.694	0.668	0.661	0.667	0.665
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Person FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
N	3587697	3587697	3587697	3587697	3852997	3852997	3852997	3852997	1076633	1076633	1076633	1076633

Notes: Outcome is hourly non-routine analytic, non-routine interpersonal, routine cognitive and routine manual task content. Sample of workers born after 1976 in Rio de Janeiro. Firm classes 1–10 are BLM clusters, estimated with the remaining 50% of the original sample, ordered according to mean unexplained earnings growth. NC are small firms not categorized by BLM clustering. PS is the public sector. 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 A10: Estimated task content returns to experience acquired in different firm classes by gender: Rio de Janeiro.

	Females				Males			
	Non-Routine Analytic	Non-Routine Interpersonal	Routine Cognitive	Routine Manual	Non-Routine Analytic	Non-Routine Interpersonal	Routine Cognitive	Routine Manual
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Experience: class 1	0.0054***	0.0150***	-0.0197***	-0.0134***	0.0122***	0.0143***	-0.0106***	-0.0124***
	(0.0020)	(0.0021)	(0.0030)	(0.0018)	(0.0019)	(0.0018)	(0.0027)	(0.0024)
Experience: class 2	0.0061***	0.0185***	-0.0245***	-0.0140***	0.0049***	0.0151***	-0.0154***	-0.0143***
	(0.0009)	(0.0011)	(0.0016)	(0.0010)	(0.0009)	(0.0009)	(0.0013)	(0.0011)
Experience: class 3	0.0040***	0.0091***	-0.0126***	-0.0080***	0.0028***	0.0073***	-0.0023**	-0.0037***
	(0.0010)	(0.0011)	(0.0015)	(0.0009)	(0.0008)	(0.0008)	(0.0010)	(0.0010)
Experience: class 4	0.0142***	0.0224***	-0.0181***	-0.0139***	0.0114***	0.0167***	-0.0085***	-0.0094***
	(0.0008)	(0.0008)	(0.0012)	(0.0007)	(0.0006)	(0.0006)	(0.0008)	(0.0008)
Experience: class 5	0.0022**	0.0070***	-0.0033**	-0.0074***	0.0056***	0.0072***	0.0034***	-0.0032***
	(0.0009)	(0.0009)	(0.0013)	(0.0009)	(0.0007)	(0.0007)	(0.0010)	(0.0010)
Experience: class 6	0.0179***	0.0232***	-0.0220***	-0.0179***	0.0194***	0.0213***	-0.0143***	-0.0214***
	(0.0012)	(0.0012)	(0.0016)	(0.0010)	(0.0009)	(0.0009)	(0.0011)	(0.0011)
Experience: class 7	0.0102***	0.0157***	-0.0136***	-0.0198***	0.0156***	0.0155***	-0.0026***	-0.0177***
	(0.0007)	(0.0007)	(0.0011)	(0.0008)	(0.0006)	(0.0006)	(0.0008)	(0.0008)
Experience: class 8	0.0000	0.0056***	-0.0014	-0.0103***	0.0070***	0.0112***	0.0001	-0.0098***
	(0.0010)	(0.0010)	(0.0014)	(0.0010)	(0.0008)	(0.0008)	(0.0011)	(0.0011)
Experience: class 9	0.0199***	0.0260***	-0.0302***	-0.0218***	0.0199***	0.0214***	-0.0131***	-0.0248***
	(0.0012)	(0.0012)	(0.0016)	(0.0011)	(0.0007)	(0.0008)	(0.0010)	(0.0010)
Experience: class 10	0.0337***	0.0394***	-0.0307***	-0.0265***	0.0246***	0.0265***	-0.0141***	-0.0275***
	(0.0021)	(0.0021)	(0.0026)	(0.0016)	(0.0013)	(0.0015)	(0.0016)	(0.0018)
Experience: NC	-0.0007	0.0079***	-0.0116***	-0.0076***	0.0082***	0.0109***	-0.0025**	-0.0080***
	(0.0009)	(0.0009)	(0.0014)	(0.0009)	(0.0009)	(0.0009)	(0.0012)	(0.0012)
Experience: PS	0.0514***	0.0621***	-0.0466***	-0.0212***	0.0303***	0.0357***	-0.0208***	-0.0290***
	(0.0047)	(0.0049)	(0.0063)	(0.0039)	(0.0042)	(0.0042)	(0.0055)	(0.0050)
Experience: Other	0.0171***	0.0274***	-0.0290***	-0.0166***	0.0178***	0.0197***	-0.0116***	-0.0213***
	(0.0009)	(0.0009)	(0.0014)	(0.0008)	(0.0006)	(0.0007)	(0.0009)	(0.0008)
adj. R^2	0.698	0.685	0.670	0.745	0.676	0.611	0.643	0.715
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Person FE	yes	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
N	3313301	3313301	3313301	3313301	5245696	5245696	5245696	5245696

Notes: Outcome is hourly non-routine analytic, non-routine interpersonal, routine cognitive and routine manual task content. Sample of workers born after 1976 in Rio de Janeiro. Firm classes 1–10 are BLM clusters, estimated with the remaining 50% of the original sample, ordered according to mean unexplained earnings growth. NC are small firms not categorized by BLM clustering. PS is the public sector. 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 A11: Firm-level characteristics, by firm class. Rio de Janeiro, 1994–2010.

Class	1	2	3	4	5	6	7	8	9	10
Firm Size: Mean	10.10	22.30	8.89	30.21	9.37	26.44	25.90	9.10	19.56	16.42
Firm Size: Median	3.71	4.57	3.76	5.89	4.11	5.27	5.94	3.76	5.33	4.92
% Firms > 50 Employees	0.021	0.050	0.016	0.068	0.020	0.083	0.068	0.019	0.064	0.043
% Men Employees	0.602	0.607	0.607	0.616	0.610	0.627	0.647	0.600	0.651	0.610
% HS Dropouts	0.598	0.642	0.603	0.637	0.671	0.642	0.670	0.698	0.629	0.585
% HS Graduates	0.308	0.269	0.322	0.273	0.275	0.268	0.251	0.255	0.271	0.304
% More than HS	0.092	0.088	0.074	0.089	0.053	0.090	0.078	0.046	0.099	0.111
% Age 18-29	0.528	0.472	0.491	0.424	0.410	0.453	0.388	0.347	0.413	0.437
% Age 30-39	0.263	0.280	0.279	0.293	0.303	0.289	0.299	0.313	0.293	0.290
% Age 40-49	0.137	0.162	0.151	0.185	0.194	0.172	0.203	0.235	0.193	0.189
% Age 50+	0.072	0.086	0.079	0.098	0.092	0.087	0.109	0.104	0.100	0.084
% Export-Oriented Sectors	0.007	0.007	0.006	0.007	0.005	0.006	0.006	0.006	0.008	0.009
% Rio de Janeiro Metro Region	0.808	0.824	0.780	0.808	0.759	0.836	0.806	0.709	0.822	0.789
% Agriculture, Livestock	0.003	0.003	0.003	0.003	0.005	0.002	0.004	0.009	0.002	0.003
% Extractive Industries	0.003	0.004	0.002	0.003	0.002	0.003	0.003	0.003	0.005	0.006
% Manufacturing	0.108	0.098	0.091	0.106	0.096	0.101	0.095	0.076	0.095	0.099
% Construction	0.033	0.028	0.019	0.027	0.023	0.040	0.031	0.025	0.037	0.046
% Retail, Trade	0.461	0.436	0.531	0.397	0.478	0.384	0.325	0.388	0.319	0.355
% Accommodation, Meals	0.067	0.083	0.054	0.083	0.083	0.086	0.096	0.109	0.076	0.077
% Transportation, Storage, Communications	0.033	0.036	0.034	0.036	0.026	0.038	0.031	0.021	0.042	0.042
% Finance, Insurance	0.016	0.018	0.010	0.018	0.006	0.018	0.013	0.005	0.014	0.019
% Business Services, Real Estate	0.136	0.147	0.130	0.178	0.170	0.204	0.273	0.230	0.295	0.239
% Education	0.037	0.039	0.034	0.036	0.024	0.030	0.025	0.019	0.020	0.018
% Health, Social Services	0.026	0.031	0.029	0.046	0.025	0.034	0.042	0.036	0.032	0.031
% Other Services (e.g. Leisure, Personal)	0.077	0.076	0.060	0.067	0.062	0.058	0.061	0.076	0.060	0.060
AKM Firm Effect	-0.302	-0.259	-0.342	-0.257	-0.368	-0.196	-0.234	-0.357	-0.166	-0.174
N	13,623	14,598	30,200	18,897	36,441	13,609	22,020	32,040	18,570	12,287

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

Table A12: Firm-level characteristics, by firm class. Veneto, 1984–2001.

Class	1	2	3	4	5	6	7	8	9	10
Firm Size: Mean	5.86	6.58	6.22	8.06	13.93	7.72	16.28	7.54	8.40	4.45
Firm Size: Median	2.75	3.20	2.58	3.28	4.87	2.91	4.84	2.76	3.02	2.35
% Firms > 50 Employees	0.011	0.011	0.013	0.019	0.044	0.019	0.054	0.018	0.013	0.005
% Men Employees	0.597	0.622	0.628	0.564	0.604	0.511	0.576	0.430	0.489	0.418
% Age 18-29	0.614	0.575	0.450	0.589	0.498	0.399	0.507	0.454	0.598	0.597
% Age 30-39	0.200	0.230	0.300	0.226	0.271	0.323	0.276	0.314	0.240	0.249
% Age 40-49	0.114	0.121	0.172	0.118	0.153	0.194	0.146	0.165	0.109	0.110
% Age 50+	0.072	0.073	0.077	0.068	0.078	0.083	0.071	0.067	0.053	0.044
% 5 Largest Cities	0.153	0.144	0.179	0.190	0.168	0.257	0.210	0.302	0.243	0.303
% Primary Sector	0.006	0.006	0.013	0.007	0.007	0.010	0.007	0.009	0.008	0.006
% Utilities	0.001	0.001	0.000	0.000	0.001	0.001	0.001	0.002	0.001	0.000
% Extractive and Chemical Industries	0.028	0.035	0.040	0.033	0.054	0.033	0.045	0.023	0.025	0.019
% Manufacturing: Metal	0.135	0.137	0.117	0.177	0.189	0.113	0.219	0.117	0.176	0.120
% Manufacturing: Other	0.348	0.383	0.341	0.263	0.313	0.176	0.205	0.113	0.179	0.132
% Construction	0.207	0.193	0.093	0.162	0.119	0.048	0.084	0.042	0.081	0.057
% Trade, Retail, Hospitality	0.140	0.145	0.282	0.172	0.200	0.423	0.249	0.405	0.259	0.343
% Transportation, Communications	0.021	0.013	0.016	0.027	0.020	0.028	0.030	0.034	0.034	0.035
% Finance, Insurance, Business Services	0.039	0.031	0.034	0.069	0.038	0.083	0.083	0.160	0.129	0.174
% Other Services	0.075	0.056	0.064	0.091	0.060	0.085	0.078	0.097	0.108	0.115
AKM Firm Effect	-0.097	-0.102	-0.139	-0.098	-0.092	-0.121	-0.079	-0.098	-0.101	-0.104
N	7,416	14,842	12,767	14,480	13,368	14,808	12,370	15,998	14,362	13,868

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

Table A13: Trajectories across firm classes and the annualized total wage growth distribution, ages 18–35

	Percentile in total wage growth distribution	
Trajectory	Rio de Janeiro	Veneto
Employed always in same firm class		
Firm class 10	76	66
Firm class 1	17	19
Firm class closest to homogeneous returns (class 8 for Rio, class 6 for Veneto)	33	38
Mixed trajectory: moves across firm classes		
1/3rd of the time across the three classes above	43	39

Notes: This table shows where does the wage growth resulting from different counterfactual trajectories across firm classes fall in the person-level distribution of annualized total wage growth between ages 18–35. The distribution of annualized total wage growth is computed for the birth cohort we fully observe between 18–35, using the difference in log earnings between the last (up to age 35) and first time we observe each worker, divided over the number of years between such observations. In the third counterfactual trajectory, class 8 is chosen for Rio de Janeiro and class 6 is chosen for Veneto because these are the classes whose returns we find are closest to the homogeneous experience benchmark (see Figure 2).

B Employment Transitions Across Firm Classes

While firms' learning opportunities may not be directly observable to workers, they may learn about them through their labor market experience. In fact, having once worked at a high-learning firm may increase the likelihood of subsequently working at other such firms. As such, examining employment transitions across firm types can inform whether firms' latent learning environments are revealed over time, and the potential persistence of career trajectories across firm classes.

In Figure B1, we document labor market transitions across firm classes. In panels (a) and (d), we show unconditional transition matrices in Rio and Veneto, respectively. Unsurprisingly, the majority of workers remain in the firm class as in the previous year, yet around one-third of Brazilian workers and one-fourth of their Italian counterparts either switch firms or leave the sample. Interestingly, we find a U-shaped pattern in cross-firm mobility in both samples (panels (b) and (e)), as workers in both low- and high-learning firms are more likely to switch firms. We lastly consider mobility patterns across the origin and destination firm class. We find that a large relative share of movers to high-growth firm classes—in particular, to classes 9 and 10—had previously worked in different firms belonging to the same class.[1]

These results provide preliminary evidence that having worked at a high-growth firm is associated with a higher likelihood of moving to other firms in the same class. While this result is consistent with a learning framework, our descriptive analysis does not incorporate workers' characteristics which may drive employment transitions. To this end, we focus on a sample of firm-movers and estimate a multinomial logit model encompassing moves to different firm classes.[2] We examine the factors leading to moves to class-10 firms. We consider the importance of extensive margin experience—capturing whether having ever worked at a class 10 firm instead of in a different firm-class increases the likelihood of moving to a high-learning firm—and intensive margin experience, which recovers whether additional experience at these firms further increases the likelihood of such transitions.

We present the results in Figure B2.[3] In Rio de Janeiro, the first year of experience at a class-10 firm—in lieu of a second year at a class-8 firm—increases the likelihood of moving to the top-learning firm class by 3 percentage points. At the same time, an increase in workers' intensive margin experience at such firms, leads to only a small increase in the likelihood of moving to class-10 firms. In the second panel, we document similar results for Veneto: while extensive-margin experience at class-10 firms significantly increases the probability of moving to a firm in the same category, additional experience at these firms does not play a significant role in driving employment transitions. These results are robust to considering experience acquired in all other firm classes (Figures B3 and B4).[4]

B.1 Figures

[1] As can be seen in panels (c) and (f), these patterns largely hold across all firm classes.

[2] Similar to the multinomial logit presented in Section 6, we estimate a model of the form $Pr\left(k(j) = k|X_i\right)$, where j indexes firms, k captures firm classes and X_i encompass worker characteristics. Since the same worker may appear in the sample of movers more than once, we cluster standard errors at the worker-level.

[3] In each country, we compare the importance of experience at class-10 firms relative to experience at firm classes where the estimated returns to experience are closest to the 'homogeneous' returns (see Tables 2 and 3).

[4] To ensure these results are not driven by endogenous job switching decisions, we re-estimate the multinomial logit on the sample of involuntarily displaced workers. We present the results in Figure B5. In both countries, the estimated coefficients fall in line with those presented for the full sample, albeit with varying statistical significance due to small sample sizes.

Figure B1: Between firm-classes transition matrices.

Rio de Janeiro, 1994–2010.

(a) $Pr\left(k(t)|k(t-1)\right)$.

firm class, t

firm class, t−1	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	51.5	2.6	1.5	3.4	1.6	2.4	3.1	1.2	2.6	0.9	1.5	0.8	4.4	22.4
2	0.5	67.5	1.3	3.1	1.2	1.9	2.5	0.8	1.8	0.7	0.9	0.5	2.3	15.0
3	0.4	1.2	71.4	2.5	1.8	1.1	2.0	1.1	1.3	0.5	1.2	0.5	1.4	13.6
4	0.3	1.3	1.1	74.8	1.2	1.3	2.2	0.9	1.5	0.5	0.8	0.5	1.7	12.1
5	0.3	0.8	1.2	1.9	72.2	1.0	2.2	1.6	1.3	0.5	1.2	0.4	1.3	14.0
6	0.5	1.6	1.0	2.9	1.2	63.7	3.0	1.0	2.5	0.9	1.0	0.4	3.7	16.7
7	0.3	0.9	0.8	2.2	1.3	1.3	72.7	1.3	1.8	0.6	0.8	0.5	2.5	13.0
8	0.3	0.7	1.0	1.8	2.0	1.1	2.8	68.8	1.6	0.6	1.3	1.0	1.7	15.5
9	0.4	1.5	1.0	2.8	1.4	2.6	3.4	1.2	62.4	1.4	1.3	0.4	4.2	16.0
10	0.5	1.6	0.9	2.6	1.3	2.5	3.3	1.3	4.2	57.5	1.5	0.9	4.9	17.1

Pr(k(t)|k(t−1)) x 100: 60, 40, 20

(b) $Pr\left(M(t)=1|k(t-1)\right)$.

Mover, t

firm class, t−1	Mover, t
1	48.7
2	34.2
3	30.4
4	27.7
5	29.9
6	38.2
7	29.3
8	33.6
9	40.6
10	43.3

Pr(M(t)=1|k(t−1)) x 100: 50, 40, 30

(c) $Pr\left(k(t)|k(t-1), M(t)=1\right)$.

firm class, t

firm class, t−1	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	1.5	5.4	3.0	7.0	3.3	5.0	6.3	2.5	5.3	1.8	3.2	1.7	7.9	46.1
2	1.6	6.0	3.9	8.9	3.5	5.7	7.3	2.4	5.3	1.9	2.8	1.4	5.4	43.9
3	1.2	3.9	6.7	8.4	5.8	3.7	6.7	3.5	4.3	1.6	3.8	1.5	4.1	44.8
4	1.0	4.6	3.9	10.4	4.2	4.8	8.1	3.1	5.3	1.8	2.7	1.8	4.8	43.5
5	1.0	2.6	4.1	6.4	7.0	3.4	7.4	5.5	4.5	1.6	4.1	1.4	4.3	46.7
6	1.3	4.3	2.5	7.5	3.1	6.7	7.8	2.5	6.6	2.3	2.6	1.1	8.0	43.6
7	0.9	3.0	2.9	7.6	4.4	4.6	9.2	4.3	6.2	2.0	2.9	1.8	5.8	44.3
8	0.8	2.2	2.9	5.5	5.9	3.2	8.2	7.4	4.7	1.7	3.8	2.9	4.6	46.1
9	1.1	3.6	2.4	6.9	3.4	6.4	8.5	3.1	9.1	3.4	3.1	0.9	8.7	39.4
10	1.1	3.6	2.1	5.9	3.0	5.9	7.5	3.0	9.6	4.1	3.5	2.1	9.1	39.5

Pr(k(t)|k(t−1), M(t)=1) x 100: 12, 8, 4

Veneto, 1984–2001.

(d) $Pr\left(k(t)|k(t-1)\right)$.

firm class, t

firm class, t−1	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	65.8	2.5	1.9	2.3	3.7	1.5	2.8	1.3	1.8	0.8	2.4	0.3	2.6	10.3
2	0.5	79.7	1.1	1.4	2.1	0.9	1.7	0.8	1.0	0.4	1.3	0.2	1.5	7.2
3	0.3	1.0	83.7	0.9	1.4	0.9	1.3	0.7	0.8	0.4	1.1	0.2	1.2	6.2
4	0.5	1.2	0.7	76.5	1.9	0.9	2.5	1.0	1.5	0.6	1.4	0.5	2.8	7.9
5	0.2	0.8	0.6	1.0	85.1	0.8	1.6	0.7	0.8	0.4	0.8	0.2	1.7	5.3
6	0.2	0.6	0.6	0.7	1.3	84.7	1.4	1.0	0.8	0.4	1.0	0.2	1.4	5.7
7	0.3	0.5	0.4	1.0	1.3	0.7	84.3	0.9	1.0	0.5	0.9	0.3	2.4	5.6
8	0.2	0.5	0.4	0.8	1.5	1.0	2.0	82.4	1.1	0.7	1.1	0.3	2.2	5.7
9	0.3	0.7	0.5	1.7	1.5	0.8	2.4	1.2	78.3	0.8	1.4	0.4	2.9	7.1
10	0.4	1.0	0.8	1.7	1.9	1.3	2.7	2.3	2.3	69.0	2.4	0.4	3.8	9.9

Pr(k(t)|k(t−1)) x 100: 80, 60, 40, 20

(e) $Pr\left(M(t)=1|k(t-1)\right)$.

Mover, t

firm class, t−1	Mover, t
1	35.2
2	21.8
3	17.5
4	25.4
5	16.6
6	16.3
7	17.6
8	19.0
9	23.3
10	32.8

Pr(M(t)=1|k(t−1)) x 100: 40, 30, 20

(f) $Pr\left(k(t)|k(t-1), M(t)=1\right)$.

firm class, t

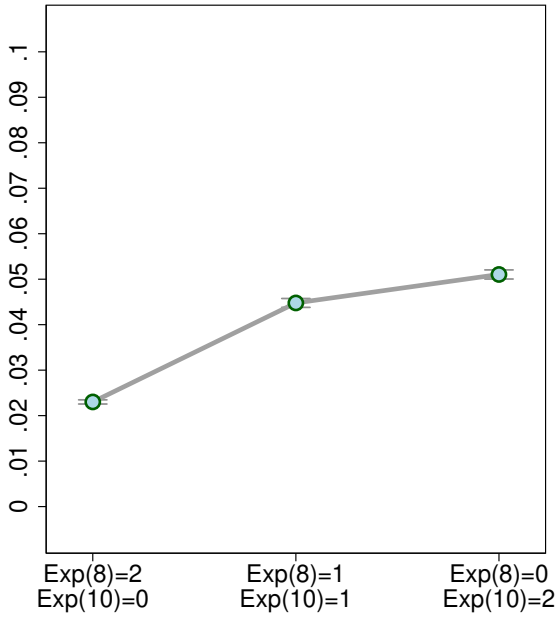
firm class, t−1	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	2.9	7.1	5.5	6.4	10.5	4.3	8.1	3.6	5.0	2.3	6.9	0.9	7.3	29.2
2	2.4	6.9	5.2	6.4	9.8	4.1	7.9	3.7	4.5	2.0	6.2	1.1	6.9	33.0
3	1.8	5.5	6.8	4.9	8.3	5.1	7.4	4.0	4.3	2.1	6.2	1.0	7.1	35.4
4	1.8	4.8	2.8	7.5	7.6	3.7	9.9	4.0	5.9	2.5	5.6	1.8	11.0	31.2
5	1.4	4.9	3.5	5.8	9.9	5.1	9.5	4.4	4.8	2.3	5.0	1.4	10.5	31.7
6	1.2	3.5	3.7	4.5	7.9	6.3	8.7	5.8	4.7	2.7	5.8	1.5	8.7	34.7
7	1.6	3.1	2.2	5.4	7.5	4.0	11.0	5.3	5.5	2.6	5.0	1.7	13.6	31.5
8	1.0	2.7	2.2	4.3	7.7	5.5	10.5	7.3	5.8	3.9	6.0	1.6	11.4	30.2
9	1.5	3.0	2.1	7.1	6.3	3.5	10.3	5.0	7.0	3.4	5.9	1.7	12.5	30.7
10	1.2	3.0	2.4	5.3	5.9	4.0	8.3	7.1	6.9	5.4	7.5	1.3	11.7	30.2

Pr(k(t)|k(t−1), M(t)=1) x 100: 12, 8, 4

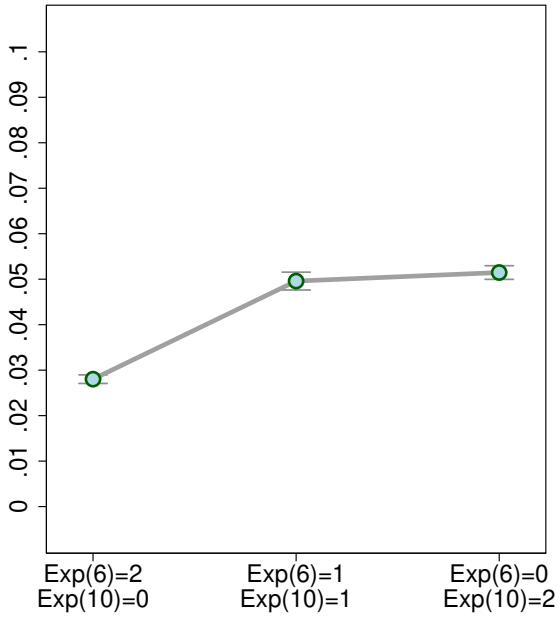
Notes: Transition matrices between firm classes. Firm class of employment at year t is denoted by $k(t)$. Firm classes 1–10 are BLM clusters ordered according to mean unexplained earnings growth. Firm class 11 are small firms not categorized by BLM clustering. Rio de Janeiro: class 12 is the public sector in Rio de Janeiro, class 13 are employers outside of Rio de Janeiro, class 14 is nonemployment. Veneto: class 12 is the public sector in Veneto, class 13 are employers outside of Veneto, class 14 is nonemployment. Movers in year t, denoted by $M(t)=1$, are those who in year t are not working in the same firm as in $t-1$.

Figure B2: Multinomial Logit Estimates: Probability of Moving to Firm Class 10.

(a) Rio de Janeiro, 1994–2010.

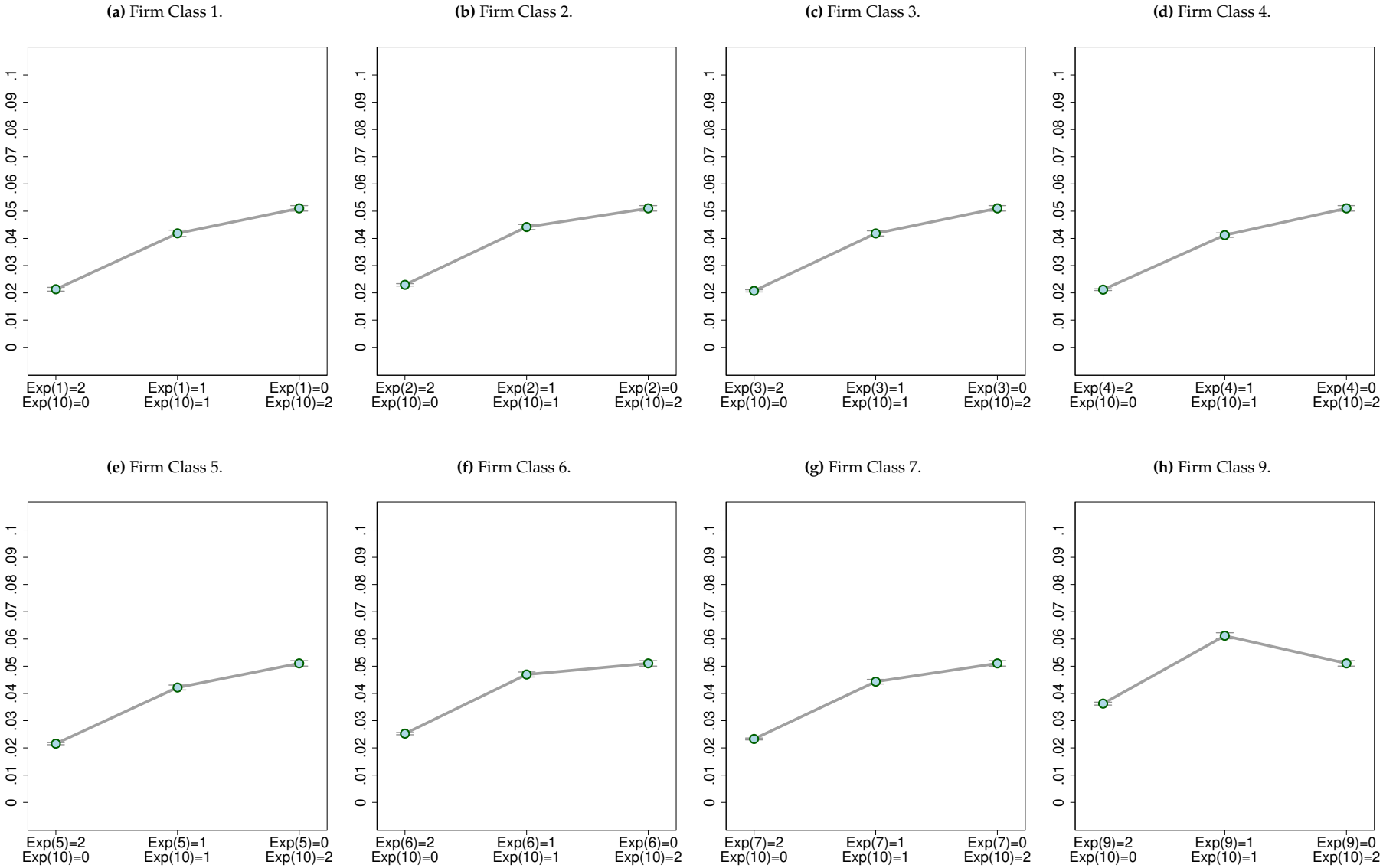


(b) Veneto, 1984–2001.



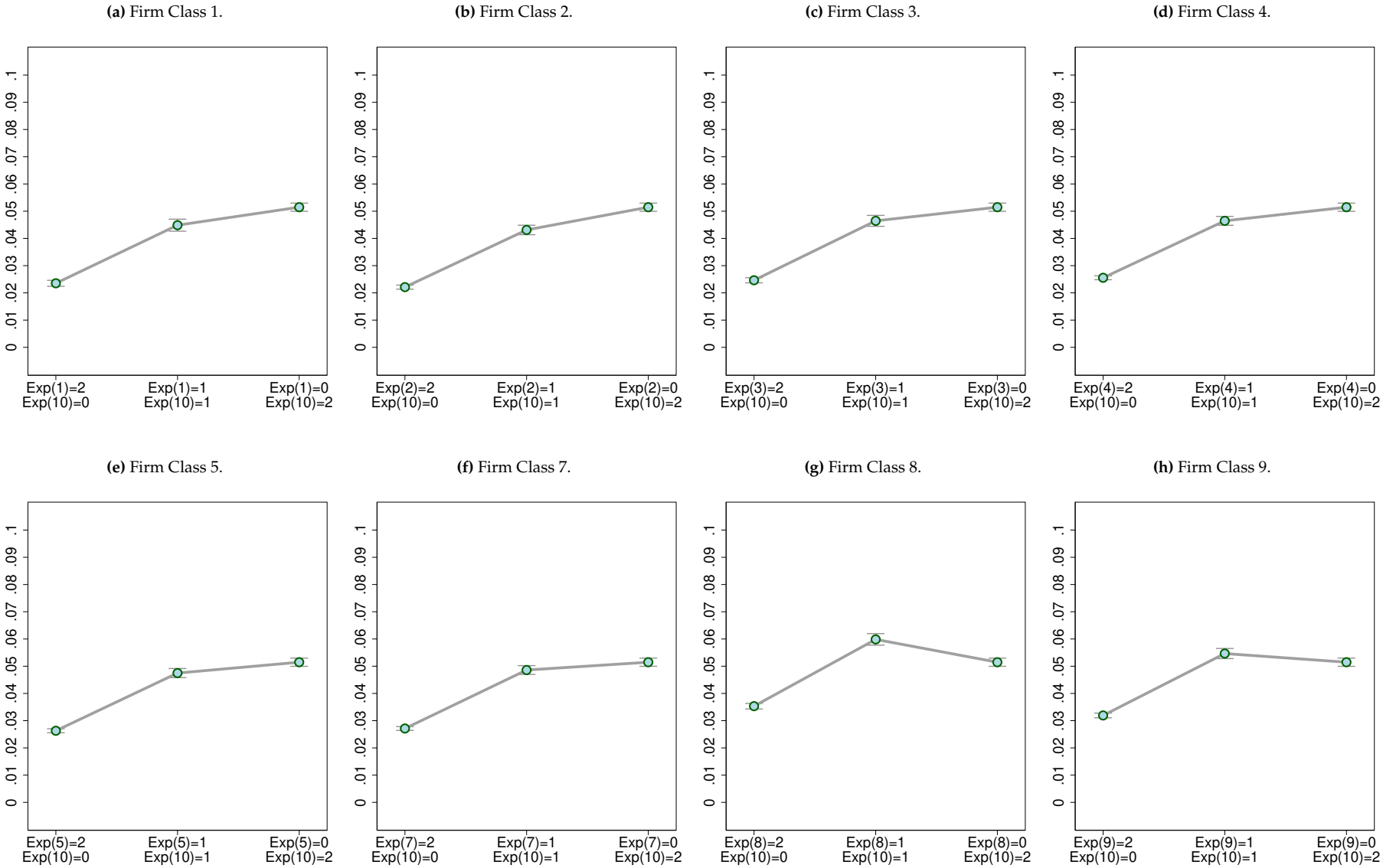
Notes: Results from multinomial logit where the unit of observation is a firm switch of a worker aged 18–35. Outcome variable is the firm class of the new firm. Explanatory variables include the amount of experience in each firm class before the move (one coefficient for extensive margin, and another one for intensive margin), and workers' age, gender, and, in Rio, education. Figure plots the estimated probabilities and 95% confidence intervals of moving to a class-10 firm, keeping total experience constant at two years, for three different combination of heterogeneous experiences. We choose class-8 for Rio and class-6 for Veneto as benchmark because these are the firm classes whose returns to experience we find closer to Mincerian homogeneous returns to experience.

Figure B3: Full Multinomial Logit Estimates: Probability of Moving to Firm Class 10 in Rio de Janeiro.



Notes: Results from multinomial logit where the unit of observation is a firm switch of a worker aged 18–35. Outcome variable is the firm class of the new firm. Explanatory variables include the amount of experience in each firm class before the move (one coefficient for extensive margin, and another one for intensive margin), and workers' age, gender, and education. Figure plots the estimated probabilities and 95% confidence intervals of moving to a class-10 firm, keeping total experience constant at two years, for three different combination of heterogeneous experiences. Each panel uses a different firm class as alternative experience to experience from class-10.

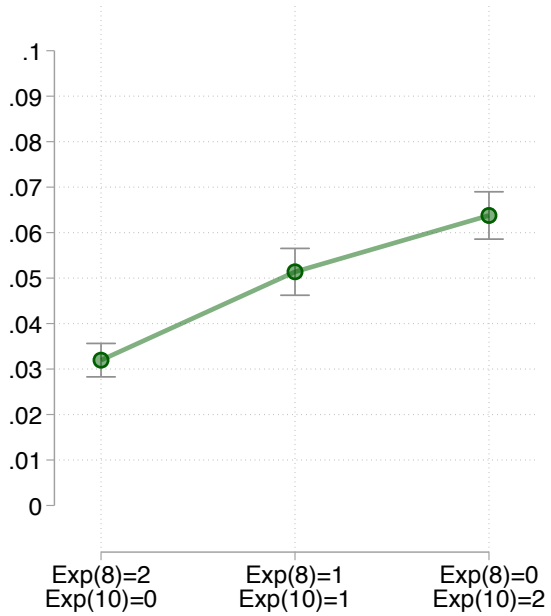
Figure B4: Full Multinomial Logit Estimates: Probability of Moving to Firm Class 10 in Veneto.



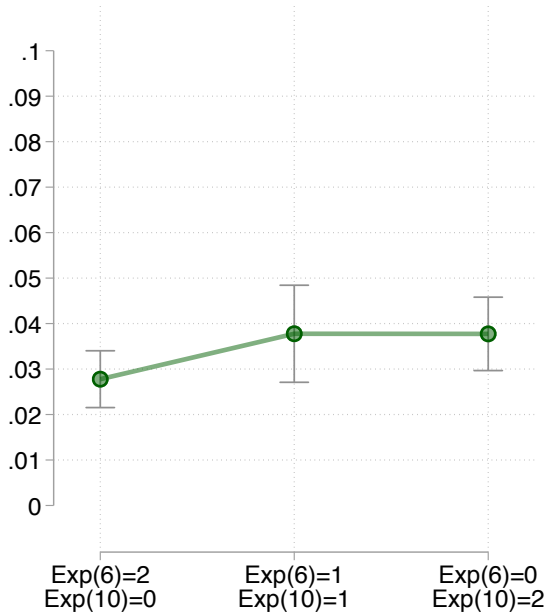
Notes: Results from multinomial logit where the unit of observation is a firm switch of a worker aged 18–35. Outcome variable is the firm class of the new firm. Explanatory variables include the amount of experience in each firm class before the move (one coefficient for extensive margin, and another one for intensive margin), and workers' age and gender. Figure plots the estimated probabilities and 95% confidence intervals of moving to a class-10 firm, keeping total experience constant at two years, for three different combination of heterogeneous experiences. Each panel uses a different firm class as alternative experience to experience from class-10.

Figure B5: Multinomial Logit Estimates, Displaced Workers: Probability of Moving to Firm Class 10.

(a) Rio de Janeiro, 1994–2010.



(b) Veneto, 1984–2001.



Notes: Results from multinomial logit where the unit of observation is a firm switch of a worker aged 18–35 following a displacement event (mass layoff or firm closure). Outcome variable is the firm class of the new firm. Explanatory variables include the amount of experience in each firm class before the move (one coefficient for extensive margin, and another one for intensive margin), and workers' age, gender, and, in Rio, education. Figure plots the estimated probabilities and 95% confidence intervals of moving to a class-10 firm, keeping total experience constant at two years, for three different combination of heterogeneous experiences. We choose class-8 for Rio and class-6 for Veneto as benchmark because these are the firm classes whose returns to experience we find closer to Mincerian homogeneous returns to experience.