# 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 categorize firms into discrete "classes"—which our conceptual framework interprets as skill-learning classes—using a clustering methodology that groups together firms with similar distributions of unexplained earnings growth. Mincerian returns to experience vary widely across experiences acquired in different firm classes. Moreover, past experiences at firms with better on-the-job learning lead to subsequent jobs featuring greater non-routine task content. Our findings hold among involuntarily displaced workers with no seniority at their post-displacement jobs, consistent with a portable skills interpretation. Overall, we show that heterogeneous employment experiences explain an important share of wage inequality by age 35, this share grows with age, and is significantly underestimated if all experiences are instead assumed to be homogeneous. Lastly, we show that firms' observable attributes only mildly predict on-the-job learning opportunities.

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# 1 Introduction

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

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

We start by introducing a conceptual framework in which workers accumulate general 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 in the on-the-job learning dimension, where employees across different firm classes draw from class-specific distributions of human capital growth. Earnings are determined by workers' human capital and the firm's pay premium, which is 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 such experience was acquired—a generalization of the classical Mincerian experience term which implicitly assumes homogeneous experience. Second, the possibility of categorizing firms into learning classes using firms' distributions of stayers' earnings growth.

Following the conceptual framework, our empirical approach consists of assigning firms to classes in a first step, and estimating heterogeneous returns to experiences acquired across different firm classes in a second step. We carry out these two steps following a split sample approach: we use half of the workers in our data to categorize firms into classes, and the other half to estimate returns to heterogeneous experiences. We implement the categorization of firms into classes using firms' distributions of stayers' unexplained 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)). This algorithm groups firms so as to maximize the 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.[1] Assuming a discrete number of firm classes allows us to estimate richer models relative to a framework in which each firm has its own idiosyncratic type.

We estimate heterogeneous returns to experiences acquired in different firm classes for workers aged 18–35. In particular, we estimate log 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. Consistent with heterogeneous learning opportunities across firms, we find sizable disparities in the returns to experiences acquired in different firm classes. We use the returns to Mincerian homogeneous experience as our benchmark, which equal 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 lowest learning opportunities are close to zero or even negative. We further show that these results are robust to controlling for age in a variety of ways.

To allay concerns related to a worker-driven interpretation of our results (e.g., sorting on unobserved ability to learn not captured by worker fixed effects) rather than a firm-driven explanation, we assess whether the returns to experiences across firm classes vary by workers' unobserved skills, education, and occupation. Workers with higher unobserved skills (measured by their person fixed effect) have higher returns across *all* firm classes, yet we find no meaningful differences in the *relative* returns across classes, compared to their lower-skilled counterparts. Across education levels, we also find that high- and low-education workers benefit similarly from working at the same firm classes. Results by occupation type indicate that white-collar experience is more valuable than blue-collar experience, but relative returns across firm classes remain, again, comparable. In sum, we find level differences in the returns to experiences across different types of workers, but patterns of relative returns that are quite similar, thus reinforcing our firm-driven interpretation.

We tackle threats to a human capital interpretation of our results by studying a sample of displaced workers. Such threats include seniority-based pay schemes (e.g. Lazear, 1981; Guiso et al., 2013), pass-through effects of productivity shocks (e.g. Guiso et al., 2005; Engbom and Moser, 2020), or heterogeneous retention policies—all of which could result in heterogeneous wage growth patterns across firms. By studying displaced workers' first post-displacement earnings observation, we ensure that firm seniority is set to zero for exogenous reasons (Kletzer, 1989; Dustmann and Meghir, 2005). Moreover, we exploit a "clean" separation between workers' current, post-displacement employer and the firm(s) where they acquired their pre-displacement experience. In this sample, we find heterogeneous returns to experiences acquired in different firm classes that are very similar to the ones estimated in the full sample. We argue that this result is consistent with our firm cate-

[1] 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 and going beyond ten firm classes does not change this percentage substantially.

gorization capturing differences in the learning of *portable* skills, but hard to reconcile with the within-firm alternative explanations discussed above.

As further evidence of a human capital channel, we go beyond earnings and document a relationship between past experiences acquired at different firm classes and workers' job task content. To study heterogeneous learning across firms one would ideally observe measures of workers' skills, yet in absence of such data, task contents carry relevant information related to workers' evolving skills. We perform this analysis on the Brazilian data—featuring detailed information on workers' occupations—which we crosswalk with occupational task content from the O*NET.[2] We find that experience acquired in top learning firm classes is associated with subsequent increases in workers' non-routine analytic and non-routine interpersonal task contents.

We present a number of additional results to address the potential concern that our firm classification based on stayers' earnings growth might capture non-general (e.g., firm-specific) skills in addition to general ones. First, our analyses on displaced workers show that the differences in skill-acquisition we capture are portable across firms. Second, in the full sample, we estimate an expanded version of our earnings equation that controls for tenure at the current employer, finding similar returns to heterogeneous experiences as in our main specification. Third, taking advantage of our discrete firm classification, we estimate returns to heterogeneous experiences allowing different returns based on whether the worker is employed *outside* the firm class where said experience was acquired. Results from this exercise leveraging between-class movers are also consistent with skill generality.

After documenting on-the-job learning disparities across firms, we quantify the contribution of this dimension of firm heterogeneity to wage inequality. We carry out a wage variance decomposition in the spirit of the two-way fixed-effects literature (e.g., Abowd et al., 1999; Card et al., 2013; Alvarez et al., 2018), which results in three main findings. First, for young workers in their mid-30s, variance components involving heterogeneous experiences explain 13% and 8% of wage variance in Rio de Janeiro and Veneto, respectively. Second, the age patterns we uncover show that these shares grow throughout the early career. Third, the traditional approach assuming all experiences to be homogeneous significantly underestimates the share of the variance accounted for by experience returns in both countries. As such, we uncover a novel channel through which firm heterogeneity shapes earnings inequality.

We additionally analyze whether compensating differentials arise in exchange for learning opportunities. That is, firms with plentiful on-the-job learning may pay lower wages, making workers effectively trade off earnings today for earnings tomorrow (Rosen, 1972). We find, however, no support for this possibility: on average, firms with better learning opportunities do not feature lower pay premia. If anything, the correlation between these two dimensions of firm heterogeneity is slightly positive.

In light of sizable differences in firms' learning opportunities, we then consider whether firms' observable characteristics can predict their firm class. That is, without observing

[2] O*NET is a database of worker attributes and job characteristics across detailed occupation categories (Acemoglu and Autor, 2011).

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.[3] We then compare predicted to observed firm classes and find that, in both Rio de Janeiro and Veneto, the algorithm correctly classifies 22–23% 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 clear predictor of better or worse on-the-job learning. First, in both Rio and Veneto, larger firms are somewhat less likely to belong to the lowest-learning class. Second, while large-city firms in Veneto are somewhat more likely to belong to the top-learning class (consistent with De La Roca and Puga, 2017), this is not the case in the state of Rio de Janeiro.

This paper contributes to various strands of the literature. First, our work adds to an extensive literature on post-schooling human capital accumulation (e.g. Neal, 1995; Acemoglu and Pischke, 1999; Dustmann and Meghir, 2005; Kambourov and Manovskii, 2009; Gathmann and Schönberg, 2010) by presenting evidence consistent with large disparities in human capital accumulation where firms are relevant units of heterogeneity. In this context, other work has explored how learning on-the-job varies depending on workplace characteristics such as exporter status (Macis and Schivardi, 2016; Ma et al., 2021), the quality of coworkers (Nix, 2020; Jarosch et al., 2021), firm size (Arellano-Bover, 2020a) or being in a large city (De La Roca and Puga, 2017). We add to this work by freely allowing firms—regardless of their observed attributes—to embody different learning opportunities. The importance of our approach is reinforced by our finding that, in the two distinct economies we study, firm observables only mildly predict on-the-job learning.[4]

We also contribute to a literature that studies how firm-driven wage differentials shape the wage structure (e.g., Abowd et al., 1999; Card et al., 2013; Goldschmidt and Schmieder, 2017; Sorkin, 2018; Card et al., 2018; Song et al., 2019; Bonhomme et al., 2019; Lachowska et al., 2020; Engbom and Moser, 2020). These papers have largely focused on contemporaneous worker-firm matches, yet the effects of *past* experience at heterogeneous firms has received limited attention: Abowd et al. (2018) and Bonhomme et al. (2019) provide some evidence on dynamic implications of employment at heterogeneous firms;[5] Abowd et al.

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

[4]By carrying out our empirical strategy in Rio de Janeiro and in Veneto, we also contribute to previous work comparing labor markets in different countries (e.g. Dustmann and Pereira, 2008; Lagakos et al., 2018; Rucci et al., 2020; Bonhomme et al., 2020; Donovan et al., 2021).

[5]Our empirical strategy employs the discretization and clustering methodology of Bonhomme et al. (2019),

(1999, 2006) estimate firm-varying returns to tenure, but not experience. We make progress on this front showing how firms can have long term consequences for workers by impacting their accumulation of portable skills.[6] Furthermore, we quantify how an unexplored dimension of firm heterogeneity—on-the-job learning—meaningfully contributes to overall wage variance.

Our work is also related to two recent papers analyzing the importance of past employers. First, Di Addario et al. (2021) examine the relative importance of workers' current employer and the firm they were hired from, finding that origin firms explain a small share of the variance of earnings. They are guided by a sequential auction framework of poaching and bargaining, which differs from our focus on human capital accumulation. These different frameworks give rise to distinct empirical approaches—while Di Addario et al. (2021) consider the most recent employer and only the extensive margin of employment, our empirical analysis accounts for workers' full employment histories and their intensive-margin experiences. Gregory (2021) builds a macro search model to quantify how much variation in life-cycle earnings profiles is explained by heterogeneity across establishments in human capital provision. While her analysis with respect to human capital accumulation exclusively relies on stayers' earnings growth, our results on displaced workers and job tasks are critical towards i) reaching a human capital interpretation vis-à-vis other sources of heterogeneous within-firm earnings growth, and ii) understanding the portability and nature of such human capital development. Further, we are able to carry out a comprehensive analysis on how firm learning opportunities are associated with a wide range of firm characteristics and do so separately for the population of two very different labor markets.

The rest of this paper is organized as follows. Section 2 describes our Brazilian and Italian datasets. Section 3 lays out our conceptual and empirical frameworks, together with the classification of firms using a clustering algorithm. Section 4 presents our results on heterogeneous returns to experiences acquired in different firm classes, including results among displaced workers. Section 5 documents the link between heterogeneous experiences and tasks. Section 6 describes the wage variance decomposition exercise. Section 7 tests for compensating differentials. Section 8 investigates how well firm observables predict firms' learning opportunities. Section 9 concludes.

## 2 Data Sources

**Brazil.** We use the *Relação Anual de Informações Sociais* (RAIS) dataset for the 1994–2010 period. RAIS covers matched employee-employer information from a mandatory annual survey filled out by all formal sector firms. We focus our analysis on the state of Rio de Janeiro, a large economy (population 16m in 2010) that exhibits a lower rate of informal employment vis-à-vis the rest of the country.[7] RAIS includes unique person identifiers which

which they apply to earnings levels. We modify their approach to group firms based on earnings growth.

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

[7] In addition to its large size and lower rate of informality, our focus on the state of Rio de Janeiro rather than Brazil as a whole is motivated by the fact that Brazil is a vast country with marked regional disparities, and that

allow us to track workers over time along with their characteristics such as age, gender, and educational attainment.[8] We additionally observe unique establishment and firm identifiers, along with information on their sectoral classification and total annual employment.[9] We rely on unique identifiers for workers and firms in the sample, which allow us to link workers to their employers in every year in the sample.

For each worker, 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 use information on hours worked to construct a measure of workers' hourly wages. Importantly, we observe information on workers' three-digit occupations, which we use to construct a mapping to occupational task content. In particular, we leverage a concordance between the Brazilian Classification of Occupations (CBO) and the Occupational Information Network (O*NET) to measure the task content of occupations. O*NET includes detailed information on work activities and work context across jobs. We use this information to construct measures of task content across occupations, which we subsequently match to occupations in RAIS using the CBO-O*NET crosswalk. We follow the existing literature (e.g., Autor et al., 2003; Acemoglu and Autor, 2011) and focus on four different dimensions of the task vector: non-routine analytic, non-routine interpersonal, routine cognitive, and routine manual tasks. For instance, the non-routine analytic task measure considers the frequency with which workers analyze data/information, think creatively, and interpret information for others.

**Italy.** Our second administrative data source is the Veneto Worker History (VWH) dataset, covering the years 1984–2001. VWH data is constructed from administrative records from Italy's Social Security System, covering employment histories for all workers who ever work in the Veneto region. This is one of the wealthiest Italian regions, with a population of about 5 million in 2012. The dataset includes unique worker and firm identifiers, which we use to construct employment histories during our period of interest.[10]

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

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our empirical approach summarizes between-firm heterogeneity into a discrete number of firm "classes." To ensure our categorization does not merely group firms from different regions with heterogeneous development levels, we focus on one state as our unit of analysis.

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

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

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

**Variable construction and sample selection.** While the empirical strategy outlined below considers the population of workers and firms in Rio de Janeiro and Veneto, our main analysis—estimating heterogeneous returns to experiences acquired in different firm classes—focuses on young workers for whom we observe their labor market trajectories since entry. In particular, we consider workers born after 1976 in RAIS and after 1966 in VWH, which allows us to observe their labor market outcomes from age 18 through their mid-thirties. In both countries, we focus on workers' main job, defined as the employment spell yielding the highest total earnings each year. These restrictions yield a sample of 4,215,247 unique workers in Rio de Janeiro and 1,163,480 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 such spells in our analysis.

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. The cohort we observe continuously from age 18 through their mid-30s in Rio de Janeiro spends on average 6.39 full-year equivalents employed in the formal sector and holds 3.6 jobs. Their Italian counterparts on average spend 8.15 full-year equivalents and hold 3.3 jobs. The last two rows show that Brazilian workers in our oldest cohort have 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%.

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

| | Rio de Janeiro<br>(1) | Veneto<br>(2) |
|---|---|---|
| Share Male | 0.582 | 0.540 |
| Age at Entry | 20.64 | 20.49 |
| Cumulative Experience | 6.39 | 8.15 |
| Cumulative Number of Jobs | 3.58 | 3.30 |
| Annualized Wage Growth (Average) | 0.068 | 0.031 |
| Annualized Wage Growth (Median) | 0.055 | 0.023 |
| Number of Workers | 4,215,247 | 1,163,480 |
| Observations | 21,590,327 | 7,866,407 |

*Notes*: Summary statistics for the sample of workers in the Rio de Janeiro and Veneto samples as described in Section 2. All statistics are sample means at the worker level except when stated otherwise. 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. The oldest cohort includes 301,444 and 94,028 workers in Rio de Janeiro and Veneto, respectively.

**Displaced workers sample.** We analyze a sample of involuntarily displaced workers in Section 4.2. To identify involuntary displacement events, we leverage our population coverage in both datasets and focus on firm closure and mass layoff events following the existing literature (e.g. Jacobson et al., 1993; Dustmann and Meghir, 2005; Lachowska et al., 2020). 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 consider workers who are employed in the distressed firms within two years of the event, and who are laid off within one year of the closure/layoff event. We additionally require displaced workers to not re-enter the same firm in the following three years.

In Rio de Janeiro, we identify 2,989 involuntary displacement events during our period of interest, which affect 255,637 workers in our sample of young workers. In Veneto, meanwhile, 2,023 firms either shut down or undergo a mass layoff, affecting 42,021 young workers. Across Rio and Veneto, 89.1% and 90.8% of displaced workers eventually re-enter the sample, whereas 64.5% and 80.2% do so within one year of being displaced, respectively.

# 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 $\alpha_i$ is human capital developed prior to labor market entry, and $h_{it}$ is the stock of human capital accumulated on-the-job since labor market entry up until period $t$.

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

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

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

Differences in distributions $F_k$ reflect that some firms provide better on-the-job learning opportunities than others.[11] In the limit, the number of firm classes $K$ could be equal to the number of firms in the economy. On the other hand, absent systematic differences in human-capital development across firms, $K$ would be equal to one (an implicit assumption in much of the literature). We will take a middle-ground approach and allow for a discrete number of firm classes that is greater than one but lower than the number of firms.

This framework implies that the stock of human capital accumulated on the job depends

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

(in expectation) on the worker's past employment history across heterogeneous firms:

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

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

where $\mathbf{Exp}_{it}$ is the $K$-dimensional 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 which equals 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 $t$, $y_{it}$, combine human capital $H_{it}$ and a firm component $\psi_j$:

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

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's identity, and the worker's employment history are given by:

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

where $\text{Exp}(m)_{it}$ is the experience worker $i$ has acquired in firms of class $m$ up until period $t$.

Lastly, we remark that while the conceptual framework assumes that post-schooling human capital is both general in nature and equally valued across firms, in our empirical analyses we relax this assumption and carry out tests that allow for several departures from purely general human capital.

## 3.2 Empirical Framework

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

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

where $\psi_j$ are firm fixed effects, $\alpha_i$ are person fixed effects, $\text{Exp}(m)_{it}$ is the number of days $i$ has been employed in firms of class $m$ up until period $t$,[12] $X_{it}$ controls for age and year fixed effects, and $\eta_{it}$ is a mean zero error term.

The returns to one year of experience at firm class $k$ ($\{\gamma_1 \ldots \gamma_K\}$) represent our parame-

[12]The $\text{Exp}(m)_{it}$ terms are measured in days and then its units transformed into years.

ters of interest. Note that the $K$ experience terms in equation (8) represent a generalization of a classical Mincerian experience term that assumes equal returns to experience regardless of the type of firm where such experience was acquired (Mincer, 1974). As a benchmark, we also estimate versions of equation (8) with such "homogeneous experience" (i.e., imposing the restriction $\gamma_1 = \ldots = \gamma_K$). In order to be able to measure workers' actual experience across different firm types, we estimate equation (8) using a sample of workers who we can observe since their labor market entry.[13]

Person fixed effects $\alpha_i$ ensure that sorting of workers across firm classes on the basis of the baseline component of worker ability (or other time-invariant unobserved worker attributes) does not bias our results. The inclusion of firm fixed effects $\psi_j$ implies that we are intuitively estimating $\{\gamma_m\}_{m=1}^K$ by comparing workers who are employed in the same firm today, but who had acquired their past experiences in different firm classes. Our empirical approach thus accounts for the possibility that experience in a particular firm type may lead to moves up the firm-effect ladder, such that this channel is not included in the estimated $\gamma_m$'s.

**Exogeneity assumptions.** In Section 4, we estimate variants of equation (8) by OLS. In order to consistently estimate heterogeneous returns to experiences $\{\gamma_m\}_{m=1}^K$, the unobserved determinants of earnings $\eta_{it}$—that is, components not already captured by person fixed effects $\alpha_i$ nor contemporaneous employer fixed effects $\psi_j$—must be uncorrelated with experience stocks across firm classes. That is, we assume that $\eta_{it}$ satisfies the strict exogeneity assumption:

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

To guide the discussion behind this assumption, we consider a decomposition of the error term $\eta_{it}$ into three components:

$$\eta_{it} = \sum_{m=1}^{K} \delta_{m,i} \cdot \mathrm{Exp}(m)_{it} + \mu_{i,j(i,t)} + \varepsilon_{it}, \tag{10}$$

where $\delta_{m,i}$ capture person-specific returns to class-$m$ experience, $\mu_{i,j(i,t)}$ are match effects between worker $i$ and employer $j$, and $\varepsilon_{it}$ is an idiosyncratic error term.

The first potential channel for the exogeneity assumption to fail would be the existence of worker heterogeneity in the form of unobserved ability to learn, captured by the parameters $\{\delta_{m,i}\}_{m=1}^K$ in equation (10). Such heterogeneity would lead to biased estimates of the heterogeneous returns to experiences if it were positively correlated with, for instance, employment at high-class firms. In the most extreme form, firms would be homogeneous in their learning opportunities (i.e., $\gamma_1 = \ldots = \gamma_K$), whereas workers would exhibit significant heterogeneity in their ability to learn. In this scenario, if workers with similar levels of $\{\delta_{m,i}\}_{m=1}^K$ sorted into the same firm classes, we would recover biased estimates of $\{\gamma_m\}_{m=1}^K$,

[13] We exclude public sector worker-year observations from the estimation of the returns to experiences. Yet we consider the experience accumulated in the public sector as an additional experience type when estimating equation (8).

thus incorrectly inferring heterogeneity in the returns to experiences across firm classes.

In Section 4.3, we present evidence from two exercises which show that our estimated returns to experiences are unlikely to be biased by this type of unobserved worker heterogeneity. First, we estimate an expanded version of equation (8), which allows heterogeneity in returns to experiences across workers' unobserved ability $\alpha_i$. That is, we include the term $\sum_{m=1}^{K} \delta_{m,i} \cdot \text{Exp}(m)_{it}$ in our estimating equation, where we parametrize $\delta_{m,i} = \alpha_i \cdot \delta_m$. Second, we estimate equation (8) allowing for heterogeneous returns across workers' characteristics which may be related to their learning ability, including their educational attainment and their blue- or white-collar occupation status. In both instances, we find that patterns of heterogeneous returns within these subgroups of workers are quite similar.

The second concern emerges through the role of match effects $\mu_{i,j(i,t)}$. If experience at certain firm classes leads workers to reach better person-firm-specific matches, such sorting would represent a threat to our exogeneity assumption. We address this concern by re-estimating our analysis using a sample of involuntarily displaced workers. In doing this, we follow previous work (Dustmann and Meghir, 2005; Gathmann and Schönberg, 2010; Di Addario et al., 2021) which notes that laid-off workers are willing to accept a job offer as long as it is preferable to unemployment, which breaks the link between pre-displacement experience and the first post-displacement job match. As such, we re-estimate $\{\gamma_m\}_{m=1}^{K}$ only using displaced workers' first post-displacement earnings observation. Additionally, we remark that previous work estimating related two-way worker-firm fixed effects earnings equations has found little evidence in favor of quantitatively meaningful match effects (e.g., Card et al., 2013, 2015, 2018; Alvarez et al., 2018).

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

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

$$g_{ijt} \equiv \ln y_{it} - \ln y_{i,t-1} = h_{it} - h_{i,t-1} = \mu_{i,t-1}^{k(j)}. \tag{11}$$

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:

$$\min_{k(1),\ldots,k(J),F_1,\ldots,F_K} \sum_{j=1}^{J} n_j \int \left(\hat{G}_j(g) - F_{k(j)}(g)\right)^2 d\lambda(g), \tag{12}$$

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 $\lambda$ is a measure supported on a discrete grid. Note that classifying firms based on earnings *growth* according to equation (12), is a modification of the approach of Bonhomme et al. (2019), as they instead classify firms according to earnings *levels*.

**Unexplained earnings growth.** In practice, we partial out 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, aged 18–49, who were employed in the same firm for at least six months in two consecutive years.[14] In this subsample, we estimate the following regression:

$$g_{ijt} = Z'_{it}\theta + \delta_t + u_{ijt}, \tag{13}$$

where $g_{ijt} \equiv \ln y_{i,t} - \ln y_{i,t-1}$ ($y$ is hourly wage in Brazil and daily wage in Veneto), $\delta_t$ are year fixed effects, and $Z_{it}$ includes a quadratic polynomial in age and a gender dummy in Veneto; in Brazil, additionally, $Z_{it}$ includes a quadratic polynomial of years of education and an interaction term between years of education and age.[15] The residual $\widetilde{g}_{ijt} \equiv g_{ijt} - Z'_{it}\hat{\theta} - \hat{\delta}_t$ is our measure of unexplained earnings growth entering the classification problem (12)).[16]

**Split-sample approach.** A key aspect of our empirical implementation—in the spirit of the machine learning literature (e.g., Athey and Imbens, 2019)—is that we split the sample introduced in Section 2 in two groups: we include a random half of workers in the classification problem (12), and we estimate the returns to experiences acquired in different firm types in equation (8) using the other half. In this way, data from the same worker is never used to both classify firms into classes and to estimate the returns from having worked in different firm classes.

**Choice of number of classes $K$.** The number of firm classes $K$ is set ex-ante, without an obvious choice for it. We set $K = 10$ as we believe that ten firm classes allow for sufficient richness in firm types, while not being such a large number that makes interpreting results across firm classes too burdensome.[17] Moreover, using ten classes implies 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.[18] In both Rio de Janeiro and Veneto, this ratio is

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

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

[16] Before solving (12), we discard observations from firms for which we have, across all years, a total of less than five worker-year observations, thus not attempting to classify these very small short-lived firms.

[17] For completeness, our empirical approach allows for three more types of experience: experience acquired in (i) very small firms not categorized by our approach, (ii) public-sector employers, and (iii) out-of-state/region firms.

[18] The logic of decomposing the variance into a within and between components comes from the law of total variance:

$$Var_y(Y) = \underbrace{E_x[Var_y(Y|X)]}_{\text{"within"}} + \underbrace{Var_x[E_y(Y|X)]}_{\text{"between"}}.$$

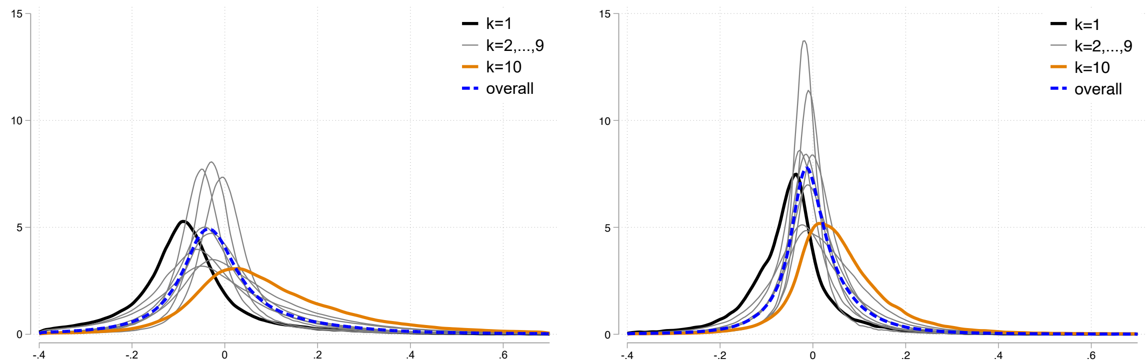
Denoting unexplained earnings growth by $g$, Figure A1 plots: $\frac{Var_k[E_g(g|\text{firm-class}=k)]}{Var_j[E_g(g|\text{firm}=j)]}$.

around 60% for $K = 10$. The gains in this ratio from increasing the number of firm classes past $K = 10$ are not large: the relationship asymptotes at about 65% for Rio de Janeiro and 70% for Veneto.

**Clustering results.** Figure 1 plots the ten density functions that arise from solving (12), where each firm class is labeled according to the rank of the mean of its distribution. Panel (a) presents results for Rio de Janeiro and Panel (b) for Veneto. In each panel, the density of class 1—the class with the lowest mean unexplained earnings growth—is in solid black, and the density of class 10—that with the highest mean unexplained earnings growth—is in solid orange. The dashed blue line represents the density of overall unexplained earnings growth.

**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.

There is substantial variation in density shapes across firm classes and in comparison with the overall distribution, which illustrates systematic differences in distributions of unexplained earnings growth.[19] For instance, in Rio de Janeiro, the mean and variance of unexplained earnings growth in firm-class 1 are -0.093 and 0.056, while the equivalent moments in firm-class 10 are 0.121 and 0.079 (see Table A1 for moments for all firm classes). There is higher dispersion of unexplained earnings growth in Rio de Janeiro than in Veneto. This is true both within and between firm classes.

In Table 2, we show the proportion of person-year observations and the proportion of firms that are assigned to each firm class. In both countries, a small share of observations is assigned to class 1 (2.3-2.5%), along with a far larger share to class 7 (16.9-18.3%) and close to 10% of observations being assigned to class 9. We also show that over 50% of firms are not classified by our algorithm in both countries due to the minimum size restriction, yet these firms represent only 7-9% of all person-year observations in both Rio de Janeiro and Veneto.

[19] Figures A2 and A3 separately plot each density in comparison to the overall distribution.

**Table 2:** Percent of observations belonging to each firm class.

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

*Notes*: Table 2 presents the share of person-year observations and percent of firms belonging to each of the ten firm classes, plus non-categorized (NC) very small firms—with fewer than five worker-year observations—in both Rio de Janeiro (1994-2010) and Veneto (1984-2001).

# 4 Returns to Experiences Acquired in Different Firm Classes

## 4.1 Baseline Results on Returns to Different Types of Experience

Figure 2 displays estimates of equation (8), which comprise our baseline results showing the returns to experiences acquired in different firm classes. The horizontal dashed line shows, as a benchmark, the return to one year of "homogeneous" experience. This specification shows that an additional year of experience is associated with earnings returns of 3.7% in Rio de Janeiro and 1.1% in Veneto.[20] Our main finding, however, is that these estimates mask substantial heterogeneity in the returns to experiences acquired in different firm classes. In Rio de Janeiro, one year of experience acquired at a class-1 firm is associated with a return of 0.2%, whereas a year of experience at a class-9 or class-10 firm yields returns of 7.4% and 9.8%, respectively. In Veneto, the returns to one year of experience acquired in a class-1 firm are negative (in real terms), equal to -0.9%, while returns to class-10 firm experience reach 3.5%.[21]

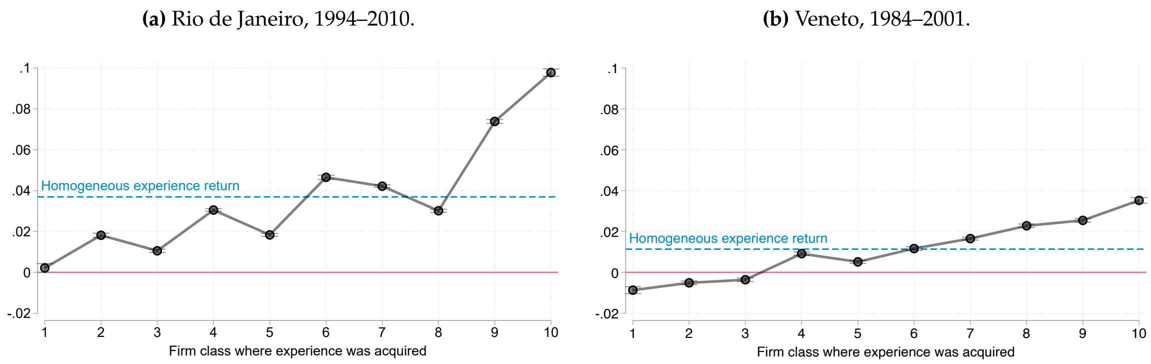
In both Rio de Janeiro and Veneto, the returns to experiences acquired in intermediate firm classes lie between class 1 (i.e., "lowest-learning" firms) and class 10 (i.e., "top learning" firms), with a gradient between returns and firm class which is generally increasing.[22] In Rio de Janeiro, returns to experiences acquired in firm classes 6, 7, 9, and 10 are above the homogeneous benchmark, whereas the corresponding above-benchmark firm classes in Veneto are classes 6–10. While the returns to experiences in Veneto exhibit less heterogene-

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

[21]Tables A2 and A3 (columns (3) and (6)) show regression output corresponding to estimates presented in Figure 2 for Rio de Janeiro and Veneto, respectively. These tables also show returns to experience acquired in very small firms not categorized by our approach, in public-sector employers, and in out-of-state/region firms.

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

**Figure 2:** Returns to experiences acquired in different firm classes.




*Notes:* Estimates and 95% confidence intervals of returns to experiences acquired in different firm classes. Standard errors clustered at the person level. Blue line: returns to homogeneous experience. Black plot: returns to experiences accumulated in each of the 10 firm classes. Rio de Janeiro: outcome is log hourly wage; sample composed of private sector observations, workers born in 1976 or later while aged 18–35; $N$=9,168,318; number of persons = 1,568,990. Veneto: outcome is log daily wage; sample composed of private sector observations, workers born in 1966 or later while aged 18–35; $N$=3,608,754; number of persons = 483,799. Corresponding Appendix regression tables: Tables A2 and A3.

ity in levels vis-à-vis those found in Rio de Janeiro, a similar pattern arises in relative terms: in both contexts, the returns to experience acquired in class-10 firms are roughly three times as large as the returns to homogeneous experience. In Appendix B, we show that the heterogeneity in returns uncovered by our approach is substantially richer than the resulting one when classifying firms based on observable characteristics such as firm size, city size, or coworkers' education.

**Robustness.** All baseline results are robust to various ways of accounting for age effects (see Figure A4).[23,24] Additionally, the conclusions are unchanged if we relax the assumption of linear experience terms in equation (8) and instead have each type of experience enter as a quadratic function, allowing for potentially diminishing returns (see Tables A4 and A5). Finally, results are unchanged when we modify how we compute unexplained earnings growth in equation (13) (see Figure A5).[25]

## 4.2 Returns to heterogeneous experiences among displaced workers

We now estimate returns to experiences acquired in different firm classes for the sample of involuntarily displaced workers described in Section 2. In particular, we focus on displaced workers' first post-displacement earnings observation. Among these observa-

[23]A common concern in models with both worker- and firm- fixed effects is the correct specification of the age effects (Card et al., 2018). Our main specification controls for six age-category fixed effects, yet we assess the robustness of our results to alternative specifications in Figure 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.

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

[25]Figure A5 shows robustness of results for two alternatives: netting out fully flexible age effects (instead of the baseline quadratic function), and, in Rio, not netting out education effects and thus making it fully comparable to the approach in Veneto.

tions, firm seniority is exogenously set to zero, and there is a clean dissociation between the firm or firms where experience was acquired in the past and the firm currently employing the worker. As such, finding similar estimated returns to heterogeneous experiences as in Figure 2 would be consistent with our interpretation of workers learning portable skills (i.e., past experiences being rewarded at the new employer), but hard to reconcile with alternative potential sources of heterogeneous wage growth patterns across firms. These alternative sources include firm-specific skills, seniority-based schemes that back-load pay (e.g. Lazear, 1981; Guiso et al., 2013), heterogeneous retention policies (e.g., "up or out"), or pass-through effects to wages of firm productivity shocks (e.g. Guiso et al., 2005; Engbom and Moser, 2020).

We estimate the following regression using displaced workers' first post-displacement earnings observation:

$$\ln y_i = \psi_{j(i)} + X_i'\beta + \sum_{m=1}^{K} \gamma_m^D \cdot \text{Exp}(m)_i + \lambda_{t(i)} + v_i, \tag{14}$$

where $i$ indexes displaced workers, $y_i$ is the first post-displacement wage, $\psi_{j(i)}$ are fixed effects for the firm where worker $i$ re-enters employment, $X_i$ are workers' observed characteristics and time to re-entry, $\text{Exp}(m)_i$ is the amount of experience worker $i$ had acquired in firms of class $m$ prior to displacement, $\lambda_{t(i)}$ are year of re-entry fixed effects, and $v_i$ is a mean zero error term.[26]

Figure 3 presents the estimated returns to experience for displaced workers $\{\gamma_1^D \ldots \gamma_K^D\}$ along with the baseline estimates from the full sample for comparison purposes. In Rio de Janeiro, we find that the two sets of returns are very highly correlated despite not being exactly equal. In particular, the returns to experiences acquired in classes 9 and 10 are still the most valuable among displaced workers, reaching 5.7% and 7.0%, respectively, and outpacing the returns at any other firm class. In Veneto, the displaced- and full-sample estimates show an even stronger correlation. For instance, among displaced workers in Veneto, returns to one year of experience at a class-9 or class-10 firm reach 2.9% and 3.9%, respectively, not different from the full sample returns. We emphasize that the heterogeneous returns estimated among displaced workers cannot be driven by firm seniority schemes or other within-firm dynamic compensation mechanisms. As such, we interpret the similarity between the two sets of estimates as being consistent with an interpretation in which our firm classification captures differences in on-the-job learning of portable skills.[27]

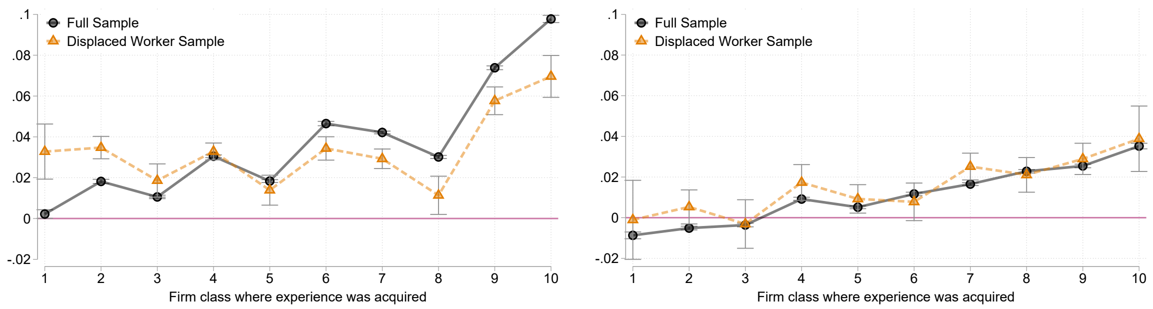
**Tenure.** The analysis on displaced workers allays potential concerns of tenure effects confounding our estimates of heterogeneous experience returns (Topel, 1991; Altonji and Williams,

[26] In Rio de Janeiro, we control for workers' educational attainment and gender. In Veneto, we control for their nationality and their gender. In both samples 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 time to re-entry and results are unchanged (see Tables A7 and A8).

[27] Table A9 presents the proportion of worker observations and of firms in the displaced sample. All firm classes are represented in the displaced sample.

**Figure 3:** Returns to experiences acquired in different firm classes: sample of displaced workers.

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




*Notes:* Black plot: Baseline estimates of returns to experiences acquired in different firm classes, described in Figure 2. Orange plot: Estimates and 95% confidence intervals of returns to experiences acquired in different firm classes, estimated using the first post-displacement observation of workers experiencing a mass layoff or firm closure. Robust standard errors. Regressions control for time to re-entry after displacement, worker demographics—gender in both countries, education in Brazil and nationality in Italy—, and post-displacement firm fixed effects. Rio de Janeiro: outcome is log hourly wage; $N$=109,995. Veneto: outcome is log daily wage; $N$=18,601. Corresponding Appendix regression table: Table A7.

2005; Dustmann and Meghir, 2005), as displaced workers' tenure is exogenously set to zero. To further assess the robustness of these findings, we re-estimate equation (8) in the full sample including tenure at the current firm as an additional variable. Results from this estimation, together with baseline results, can be found in Figure A6. The specifications which control for tenure indicate a slight *parallel* downwards shift in the heterogeneous returns to experiences vis-à-vis our baseline estimates. As such, our key result—heterogeneous returns to experiences acquired across firm classes—remains unchanged when explicitly controlling for tenure in the full sample.

### 4.3 Heterogeneous returns by unobserved skills, education, and occupation

We now assess whether the returns to experiences acquired in different firm classes vary across workers. This exercise fulfills two purposes. First, to gain additional insights into how employment at heterogeneous firm classes differentially impacts distinct types of workers. Second, this analysis serves a test of our interpretation of firm-driven effects vis-à-vis an alternative interpretation based on workers' unobserved heterogeneity (see the discussion in Section 3.2). Under this alternative interpretation, it is not that different types of firms present heterogeneous learning opportunities but, rather, that workers with unobserved attributes not captured by person fixed effects in our empirical analysis (e.g., time-varying heterogeneity or learning predisposition) sort together into the same firms. In this setting, we posit that similar returns to heterogeneous experience for different types of workers (classified by their unobserved skills, education, type of occupation, or gender) would be consistent with our firm-driven interpretation, and harder to reconcile with an interpretation related to worker sorting.

**Unobserved skills.** We examine whether the returns to experiences acquired in different firm classes varies across the unobserved skills distribution with a similar approach to De La Roca and Puga (2017), where we use worker fixed effects as a measure of their unobserved baseline skills. We estimate the following earnings regression:

$$\ln y_{it} = \psi_{j(it)} + \alpha_i + \sum_{m=1}^{K} \gamma_m \cdot \text{Exp}(m)_{it} + \sum_{m=1}^{K} \delta_m \cdot \text{Exp}(m)_{it} \cdot \alpha_i + \eta_{it}, \tag{15}$$

where $\alpha_i$ represents worker fixed effects, and $\delta_m$ captures whether higher-skilled workers enjoy larger returns to experience acquired at firm class $m$.[28] We present the results in the first two panels of Figure 4, comparing the estimated returns for individuals at the $25^{th}$ and $75^{th}$ percentiles of the unobserved skills distribution. In both countries, we find that high-skilled workers experience greater returns to all types of experience compared to low-skilled workers. Crucially, however, the pattern of heterogeneous returns for high-skilled workers represents an almost-parallel shift with respect to heterogeneous returns for their less-skilled counterparts. This result suggests that firms which offer good or bad learning opportunities do so *both* for high- and low-skilled workers. In particular, both types of workers enjoy the largest returns to experience acquired at class-10 firms.

**Education.** In Rio de Janeiro, we estimate heterogeneous returns to experiences acquired in 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 more educated workers and hypothesizing these individuals are better able to learn on the job (Heckman et al., 2006). On the other hand, less educated young people may have the most to gain from learning general skills on the job. Importantly, these two forces could play out differently in different types of firms—something our framework would be able to uncover.

We estimate returns to heterogeneous experiences by educational attainment and present the results in the third panel of Figure 4. Returns to experiences acquired across firm classes largely follow the same structure across the two groups: an additional year of experience at the "top-learning" firms results in higher hourly wages by 7.9% for workers without a high school degree, reaching 11% for their more educated peers. Similar to the heterogeneous returns by skills, the pattern of heterogeneous returns is broadly similar for the two groups of workers.

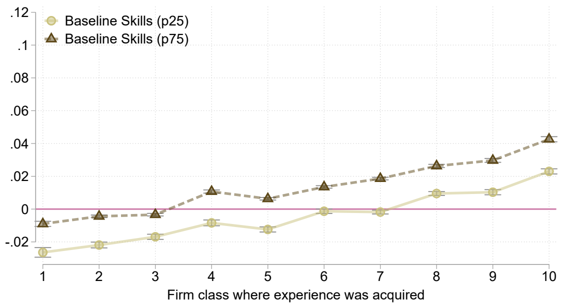
**Blue- vs. white-collar occupations.** Since different jobs within a firm could entail differential learning opportunities, we examine whether the returns to heterogeneous experiences vary across the type of occupation held *at the time during which such experience was acquired*. In practice, this implies estimating heterogeneous returns for $2 \times K$ types of experiences.

[28] We estimate equation (15) following the recursive algorithm proposed by De La Roca and Puga (2017). The first value of $\alpha_i$ in the interaction term follows from the estimated results of equation (8). We then estimate equation (15) and replace the interacted $\widehat{\alpha}_i$ with the fixed effect recovered in the previous iteration. We repeat this procedure until the estimated $\widehat{\alpha}_i$ parameters converge.

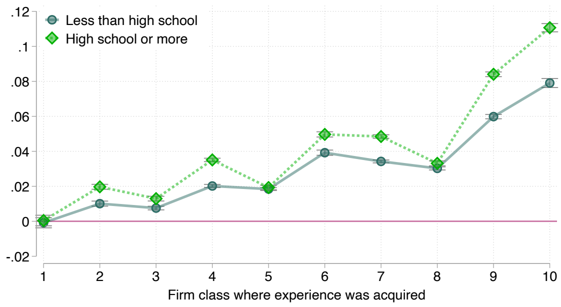
**Figure 4:** Returns to experiences acquired in different firm classes: by baseline skills, education and occupation.

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

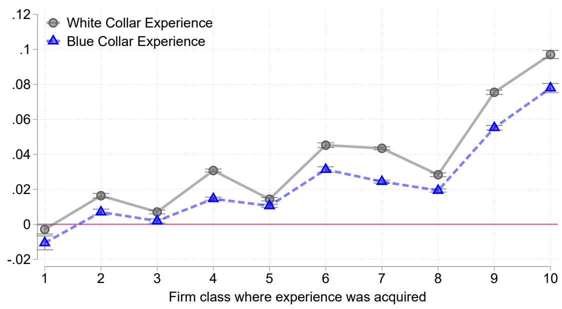

**(b)** Baseline skills, Veneto, 1984–2001.



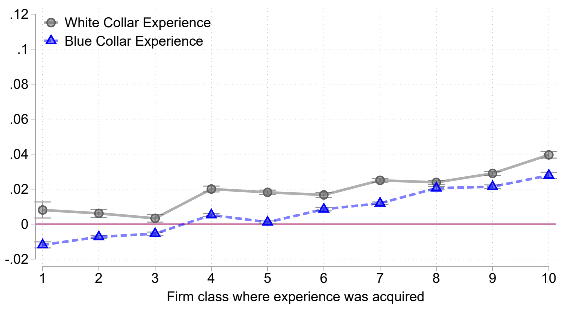

**(c)** Education, Rio de Janeiro, 1994–2010.




**(d)** Occupation, Rio de Janeiro, 1994–2010.




**(e)** Occupation, Veneto, 1984–2001.




*Notes:* Panels (a) and (b): estimates and 95% confidence intervals of returns to experiences acquired in different firm classes, separately for workers in the $25^{th}$ and $75^{th}$ percentiles of the distribution of unobserved baseline skills (worker fixed effects). Panel (c): estimates and 95% confidence intervals of returns to experiences acquired in different firm classes, separately for workers with two different education levels in Rio de Janeiro. Panels (d) and (e): estimates and 95% confidence intervals of returns to experiences acquired in different firm classes which are allowed to further differ depending on the occupation category at the time of acquiring experience. In all panels, the outcome variable for Rio de Janeiro is log hourly wages and log daily wages for Veneto. Standard errors are clustered at the person level. Corresponding Appendix regression table for panels (a) and (b): Table A10. Corresponding Appendix regression table for panel C: Table A11. Corresponding Appendix regression tables for panels (d) and (e): Tables A12 and A13.

We define occupations as either white- or blue-collar following a standard classification using occupational information at the one-digit ISCO level in Brazil.[29] In Veneto, we classify managers and white-collar workers into white-collar occupations and apprentices along

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

with blue-collar workers into blue-collar jobs. We present the estimated results in Rio de Janeiro and Veneto in the fourth and fifth panels of Figure 4. In both countries, one year of white-collar experience yields higher returns than one year of blue-collar experience, across all firm classes. However, the relative returns across firm classes are similar for both occupation groups. As such, experience acquired at "top-learning" firms has the highest returns, regardless of the type of occupation held at the time of acquiring experience. This suggests that workers employed in white- and blue-collar occupations both benefit from on-the-job learning opportunities at such firms.

Overall, we interpret the heterogeneity analysis in this section as being consistent with our interpretation of heterogeneous returns capturing differences in learning opportunities across firm classes, rather than sorting of workers with unobserved characteristics not captured with worker fixed effects. We conclude that "top-learning" firms are the same for high- and low-skilled workers, those with more or less education, those who were employed as white- or blue-collar workers, as well as for men and women.[30]

### 4.4 Allowing for richer patterns of returns

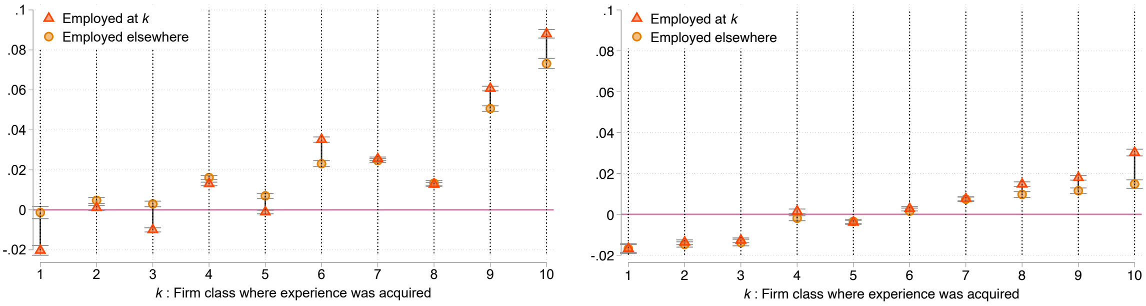
The conceptual framework in Section 3 considers a single general skill, equally valued by all employers. Yet experience acquired in different firm classes may be valued differently across firm classes, resembling the returns to industry-specific capital (Neal, 1995), occupation-specific capital (Kambourov and Manovskii, 2009), or varying mixes of different general skills (Lazear, 2009). We test for this possibility extending equation (8) by including an interaction term for each type of experience, indicating whether a worker is currently employed in the same firm class in which said experience was acquired.[31] We present the results in Figure 5. While the returns to experiences 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. In Figure A8, we show that the returns to all experience types are largely similar regardless of whether the worker is currently employed at a "top learning" class-10 firm or not. Overall, we conclude that returns to experiences at different firm classes remain quite similar, independently of the firm that workers are currently employed at.

[30]Figure A7 shows that returns to heterogeneous experiences are very similar for both genders.

[31]Note that we are able to study such complementarities in a transparent and tractable way thanks to our empirical approach which discretizes the firm-type space. In order to account for firm-specific returns when studying firm class-times firm class interactions, we additionally control for firm tenure.

**Figure 5:** Returns to experiences acquired in different firm classes: allowing richer returns patterns.

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




*Notes:* Estimates and 95% confidence intervals of returns to experiences acquired in different firm classes, with returns to each class of experience allowed to vary between those currently employed at that same firm class and those employed elsewhere. The outcome variable for Rio de Janeiro is log hourly wages and log daily wages for Veneto. Standard errors are clustered at the person level. Corresponding Appendix regression table: Table A14.

# 5 Task Content Effects of Heterogeneous Experiences

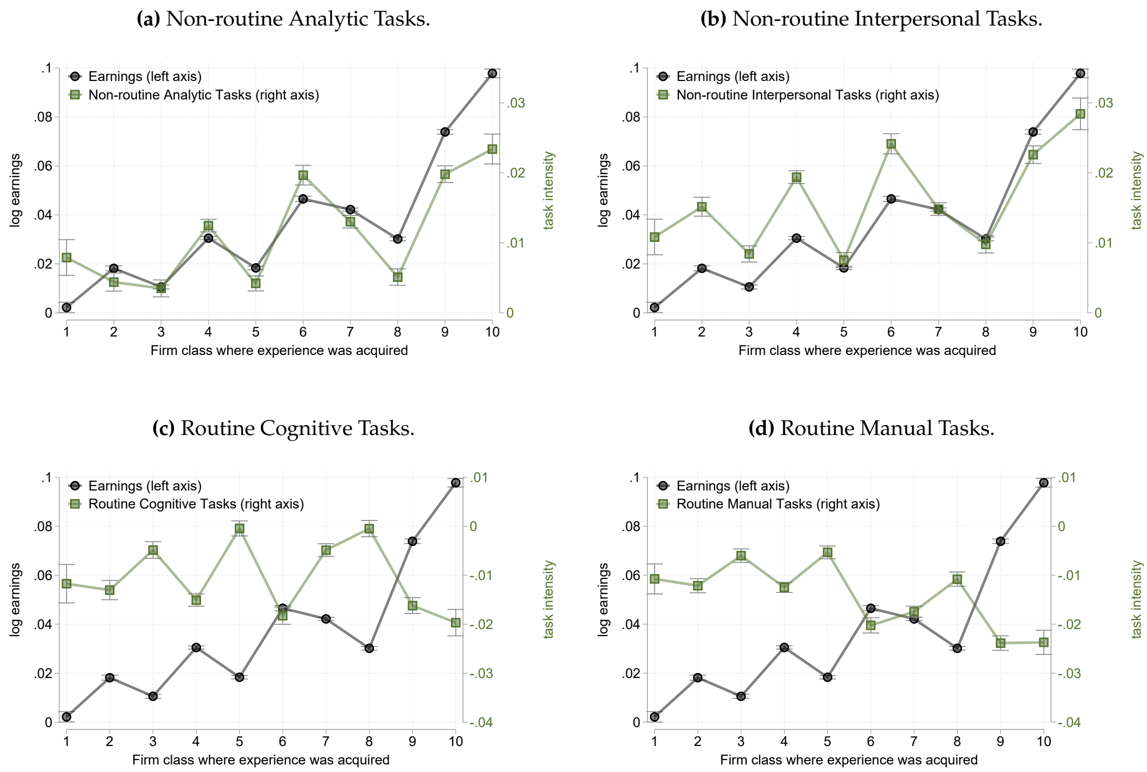
As further evidence of our human capital interpretation, in this section we go beyond earnings and study how heterogeneous experiences shape workers' evolving task contents. So far, we have presented a number of results on earnings that are consistent with portable skills accumulation driving heterogeneous returns to different types of experience. To confirm this interpretation, we would ideally observe measures of workers' skills. In the absence of such data, we turn to the types of tasks workers carry out in their jobs. While not being direct measures of human capital, task contents are arguably related to workers' underlying skills.[32] We carry out this analysis in Rio de Janeiro, where the data allow us to match detailed occupational codes to workers' task content across four dimensions: non-routine analytic, non-routine interpersonal, routine cognitive and routine manual tasks.

We thus estimate equation (8) using task intensity across the four task dimensions as outcomes instead of earnings. We present the results in Figure 6, together with the baseline earnings returns for comparability. The key takeaway—visible in the top panels—is that experience acquired in firms that we categorize as having good learning opportunities is associated with subsequent increases in the intensity of non-routine tasks. In fact, heterogeneous returns in terms of earnings are strongly correlated with the corresponding returns in terms of non-routine task intensity—both for non-routine analytic and non-routine interpersonal tasks. For instance, an additional year of experience at class-10 firms is associated with increases in workers' non-routine task content that equal 0.023 and 0.028 standard deviations in analytic and interpersonal tasks, respectively. The task-returns to experience at such firms far outpaces the benefits of having worked at all other firm classes.

The bottom two panels of Figure 6 show that our heterogeneous experience classification—

[32]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).

**Figure 6:** Task content returns to experiences acquired in different firm classes, Rio de Janeiro.




*Notes:* Black plot in all panels: Baseline estimates of earnings returns to experiences acquired in different firm classes, described in Figure 2. Green plots: Estimates and 95% confidence intervals of task content returns to experiences acquired in different firm classes. Standard errors clustered at the person level. All task intensities are measured in standard deviations. Outcome in panel (a) is intensity of non-routine analytic tasks; in panel (b), non-routine interpersonal tasks; in panel (c), routine cognitive tasks; in panel (d), routine manual tasks. Number of observations=8,971,906. Corresponding Appendix regression table: Table A15.

which is positively correlated with non-routine task intensity—is negatively correlated with routine task intensity.[33] All types of experience have associated negative returns in terms of routine tasks intensity—indicating all workers gradually shift away from these type of tasks—yet experience acquired at "top-learning" firms leads to the largest decrease in routine task intensity. In Table A15, we further show the the task-returns to heterogeneous experiences in the displaced sample are quite similar to the main sample estimates. Overall, we take results on tasks as providing further evidence of the existence of differential learning opportunities across our firm-class categorization in Rio de Janeiro.

# 6 Implications for Earnings Inequality

We have so far established that one year of experience can have widely different returns depending on the type of firm where such experience was acquired. To further show how heterogeneous experiences shape early-career outcomes, we now quantify how much of the variance of young workers' earnings is accounted for by heterogeneous experiences.

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

From our estimated earnings equation (8), we follow Abowd et al. (1999); Card et al. (2013); Alvarez et al. (2018) and decompose the variance of earnings into the variances of person effects, $\alpha_i$, firm effects, $\psi_j$, heterogeneous experiences, $\sum_{m=1}^{K}\gamma_m \cdot Exp(m)$, and their respective covariances in:[34]

$$\begin{aligned} Var\left(\ln y_{it}\right) &= Var\left(\widehat{\psi}_{j(it)}\right) + Var\left(\widehat{\alpha}_i\right) + Var\left(\sum_{m=1}^{K}\widehat{\gamma}_m \cdot Exp(m)_{it}\right) + 2 \times Cov\left(\widehat{\psi}_{j(it)}, \widehat{\alpha}_i\right) + \\ & \quad 2 \times Cov\left(\widehat{\psi}_{j(it)}, \sum_{m=1}^{K}\widehat{\gamma}_m \cdot Exp(m)_{it}\right) + 2 \times Cov\left(\widehat{\alpha}_i, \sum_{m=1}^{K}\widehat{\gamma}_m \cdot Exp(m)_{it}\right) + \\ & \quad Var\left(\widehat{\eta}_{it}\right) \end{aligned} \tag{16}$$

We estimate the variance components in (16) using the OLS estimates of the parameters in equation (8). Previous work (Andrews et al., 2008; Kline et al., 2020; Bonhomme et al., 2020) has shown that limited mobility bias—where firm effects $\psi_j$ are identified off a limited number of movers across firms—implies that the "plug-in" estimator of equation (16) will yield upward-biased estimates of $Var(\alpha_i)$ and $Var(\psi_j)$, and downward-biased estimates of $Cov(\alpha_i, \psi_j)$. However, our focus is on the share of the variance that is explained by the experiences term $\sum_{m=1}^{K}\gamma_m \cdot Exp(m)$. Since the OLS estimates of $\{\gamma_m\}_{m=1}^{K}$ are consistent and precisely estimated there is no need to correct the plug-in estimates of variance components involving $\sum_{m=1}^{K}\gamma_m \cdot Exp(m)$.

We carry out the variance decomposition in equation (16) for our sample of young workers—those used to estimate $\{\gamma_m\}_{m=1}^{K}$ in equation (8)—for whom we observe actual experiences since labor market entry. The contributions of $Var\left(\sum_{m=1}^{K}\gamma_m \cdot Exp(m)\right)$ and $Cov\left(\sum_{m=1}^{K}\gamma_m \cdot Exp(m), \cdot\right)$ are likely lower among young workers vis-à-vis the full workforce since the former have limited amounts of experiences which, by construction, cannot be largely different from each other. We thus estimate an age-varying version of (16), which allows us to discern the relative importance of heterogeneous experiences on earnings inequality across ages 18 through the mid-thirties.[35] We also compare these estimated shares to the corresponding ones that arise under a "homogeneous experience" assumption.

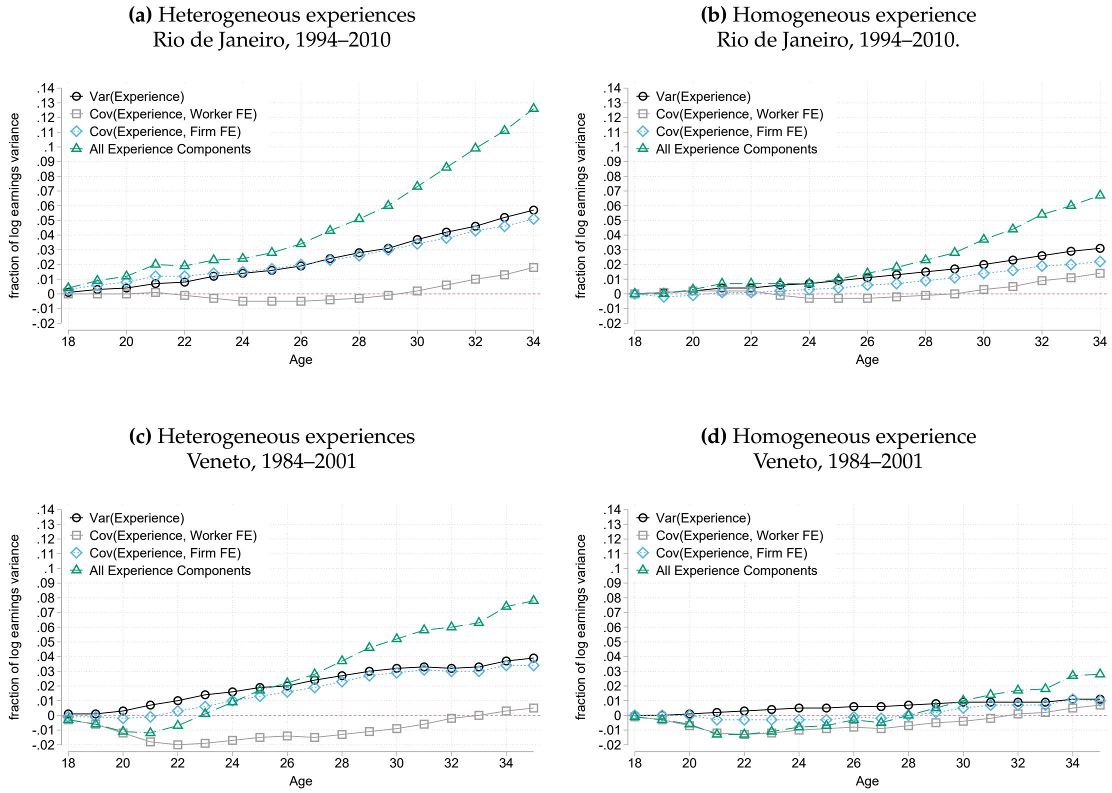
Figure 7 presents the share of the earnings variance in Rio de Janeiro explained by the heterogeneous experiences components (panel (a)), and by the equivalent components when homogeneous experience is assumed (panel (b)).[36] The black circles in panel (a) show that the share of earnings variance accounted for by the variance of heterogeneous experiences steadily grows in the early career, reaching 5.7% at age 34. This share far outpaces the corresponding one when assuming homogeneous experience (3.1%, shown in panel (b)).

[34] For notational simplicity, we omit age and time effects, $X_{it}'\beta$, from equation (16).

[35] We compute the terms in (16) for the birth cohort we observe for the longest, age by age, since age 18. In Rio de Janeiro, this cohort is born in 1976 and we observe ages 18–34. In Veneto, the birth cohort is 1966 and we observe their ages 18-35.

[36] The first two columns of Table A16 present the full-sample variance decomposition for Rio de Janeiro. 3.3% of the earnings variance is explained by the variance of $\sum_{m=1}^{K}\gamma_m \cdot Exp(m)$, along with an additional 1.4%, 3.7%, and 0.9% through its covariances with worker effects, firm effects and covariates, respectively. The joint contribution of the heterogeneous experiences terms explains 9.3% of the earnings variance compared to 6.6% when assuming homogeneous experience.

**Figure 7:** Variance decomposition: returns-to-experiences components over earnings variance, by age.




*Notes:* Shares of the wage variance explained by the heterogeneous experiences components, following an age-varying version of equation (16). Black dots represent the share of the variance explained by the variance of heterogeneous experiences Gray squares represent the share of the variance explained by the covariance of heterogeneous experiences and worker fixed effects. Blue diamonds represent the share accounted for by the covariance of heterogeneous experiences and firm fixed effects. Green triangles show the sum of these three components. Panels (a) and (b) present evidence from Rio de Janeiro in the heterogeneous and "homogeneous" experience specifications, respectively. Panels (c) and (d) present corresponding evidence from Veneto.

Meanwhile, the contribution of the covariance of worker fixed effects and heterogeneous experiences is small in magnitude and not significantly different than in the homogeneous experience specification. At the same time, the role of the covariance between firm fixed effects and heterogeneous experiences grows through the early career and accounts for an important share of the earnings variance at age 34, equal to 5.1%. The growing importance of this covariance in the early career indicates that an additional mechanism through which top-learning firms improve workers' earnings is by leading them to higher-paying firms. Overall, the joint contribution of the heterogeneous experiences terms explains 12.6% of the earnings variance at age 34, almost doubling the share explained when homogeneous experience is assumed (6.7%).

Panels (c) and (d) in Figure 7 present evidence for Veneto.[37] The share of the earnings variance accounted for by the variance of heterogeneous experiences reaches 3.9% by age 35, compared to just 1.1% in the homogeneous experience specification. On the other hand,

[37] The full-sample variance decomposition in Veneto (columns 3 and 4 of Table A16) shows that the variance of heterogeneous experiences explains 2.4% of the earnings variance along with 1.4%, 1.6%, and 1.0% through the covariance with worker effects, firm effects and covariates, respectively.

the covariance between heterogeneous experiences and worker fixed effects accounts for a small, even negative, share of the variance of earnings. Meanwhile, as in Rio de Janeiro, the covariance of firm effects and heterogeneous experiences grows through the early career, explaining an additional 3.4% of the earnings variance at age 35. In Veneto, the heterogeneous experiences components altogether explain 7.8% of the earnings variance at age 35, almost tripling the share explained when assuming homogeneous experience (2.8%).

We conclude that the conventional approach assuming all experiences to be homogeneous substantially underestimates the fraction of earnings inequality that is accounted for by varying employment experiences across workers. Our analysis on young workers shows that the share of the earnings variance accounted for by heterogeneous experiences grows throughout the early career, which suggests an even greater importance in explaining inequality further into workers' careers. In any case, our findings show that heterogeneous experiences account for a sizable share of the earnings variance as workers enter their mid-thirties, close to 13% in Rio de Janeiro and 8% in Veneto. All in all, we quantify a new and meaningful channel through which firm heterogeneity shapes earnings inequality, beyond the importance of wage-level pay policies examined extensively in the literature.

# 7 Learning Opportunities and Compensating Differentials

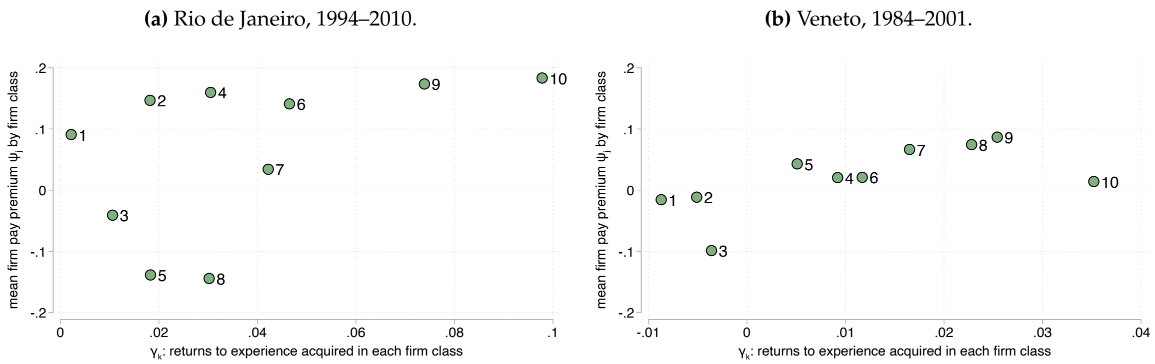
In our framework leading up to equation (8), each firm $j$ is categorized by the on-the-job learning class it belongs to, $k(j)$, and its firm pay premium $\psi_j$. One possibility is that workers are willing to accept a lower pay premium (paid today) in exchange for better learning opportunities (with long-term payoffs). Under this scenario, compensating differentials arise in exchange for learning opportunities, and we would expect a negative relationship between firm pay premiums and on-the-job learning.

We evaluate the possibility of such compensating differentials by analyzing the joint distribution of firms' pay premium, $\psi_j$, and the on-the-job learning parameter corresponding to their class, $\gamma_{k(j)}$. In Figure 8, each dot represents a firm class, the horizontal axis represents baseline estimates of $\gamma_k$ (from Figure 2), and the vertical axis represents the average pay premium $\psi_j$ in each firm class (weighted by worker-years). A negative slope would be suggestive of compensating differentials tied to learning opportunities. However, we find no evidence of such a negative relationship. If anything, firms with good learning opportunities offer slightly greater pay premiums: the correlation between $\psi_j$ and $\gamma_{k(j)}$ is equal to 0.15 in both Rio de Janeiro and Veneto.[38]

The absence of a negative correlation between firm pay premiums and learning opportunities has important implications. First, such an absence suggests that, from an individual's perspective, young workers do not typically face a tradeoff across employers between immediate monetary compensation and long-term compensation in terms of skill growth. The lack of such a tradeoff exacerbates the role of firms in wage inequality, as quantified in Section 6.

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

**Figure 8:** Compensating differentials? Firm pay premiums and on-the-job learning




*Notes:* Each dot represents a firm class, labeled from 1 to 10. Horizontal axis represents the baseline estimates of returns to class-specific experiences ($\gamma_k$ parameters in equation (8)). Vertical axis represents the average firm pay premium in each firm class ($\psi_j$ parameters in equation (8)). Average $\psi_j$ in each firm class is weighted by worker-years. The correlation between the two sets of parameters, weighted by worker-years, is equal to 0.152 in Rio de Janeiro and 0.154 in Veneto.

Second, a long tradition of models of costly on-the-job training posit that workers bear at least some of these costs (e.g. Becker, 1964; Acemoglu and Pischke, 1999). The evidence above does not align with the implications of these models. This could be either because learning is not very costly (e.g., occurs through learning-by-doing, while workers produce) and/or firms do not price learning opportunities into wages—at least not to a degree in which it would be detected in the cross-firms comparisons above. Altogether, since firms that offer good learning opportunities do not seem to enjoy lower labor costs, employment in these firms could be lower than optimal.

# 8 Are Firm Observables Predictive of Learning Opportunities?

Are firms with better learning opportunities easily recognizable by observable characteristics? We explore this question considering a wide range of firm attributes, but especially focusing on 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: firm size (Arellano-Bover, 2020a,b), large-city location (De La Roca and Puga, 2017), and coworkers' education or skills (Nix, 2020; Jarosch et al., 2021). We investigate the role of observables in two main ways: a machine learning algorithm that predicts firms' class, and a multinomial logit model rendering *ceteris paribus* associations of firm characteristics and firm class.[39] We additionally report tables with unconditional workforce and firm mean characteristics across firm classes in the Appendix (see Tables A17–A20).

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

Using the data at the firm level (firm is the unit of observation, with characteristics averaged across years), we use half of the sample to train and validate a random forest

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

classification algorithm (Athey and Imbens, 2019).[40] In the other half of the data, we use the algorithm to predict firm class and compare it against its actual classification. We feed the random forest a variety of firm characteristics, but no variables related to employees' wage growth as this is the input our clustering methodology in Section 3.2 uses to classify firms.[41]

**Table 3:** 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 | 71,364 | 38,592 |
| Correctly classified by algorithm | 23.04% | 22.34% |

**(b) Firms with $\geq$ 50 employees**

| | Rio de Janeiro, 1994–2010 | Veneto, 1984–2001 |
|---|---|---|
| Number of firms to classify | 4,139 | 1,336 |
| Correctly classified by algorithm | 24.55% | 32.19% |

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

Table 3 shows results from the random forest prediction exercise. In both Rio de Janeiro and Veneto, the algorithm correctly classifies between 22–23% of firms. If we do the same exercise focusing only on large firms (50 employees or more), the algorithm correctly classifies 25% of large firms in Rio and 32% of large firms in Veneto. This prediction exercise indicates that firm observables are somewhat useful for predicting firms' skill-learning class, but do not suffice for accurately classifying these firms. The online appendix features further details on prediction accuracy.[42]

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

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

[42] Figure A9 shows the distribution of *actual* firm class, separately for each value of *predicted* firm class. Table A21 shows the correlation, in wage space, of the parameters $\gamma_k$ associated with firms' *actual* and *predicted* classes. We interpret both exhibits as further evidence of observables having some but not substantial prediction power.

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

Figures 9 and 10 show the estimated multinomial logit probabilities of a firm belonging to each class for Rio de Janeiro and Veneto, respectively (see Figures A10 and A11 for additional variables in Rio de Janeiro, including workforce education). Each characteristic of interest is evaluated at the $25^{th}$ and at the $75^{th}$ percentiles, and the remaining variables are evaluated at the mean. Dummy variables are instead evaluated at zero and one. Each panel also includes $Pr\,(k(j) = k)$, the unconditional probability a firm belongs to a given class.

**Pay premia.** At the firm level, and keeping other covariates constant, both countries show no systematic relationship between firms' class and firms' pay premia (Figures 9 and 10). This is consistent with the results documented in Section 7, which do not condition on other firm observables.

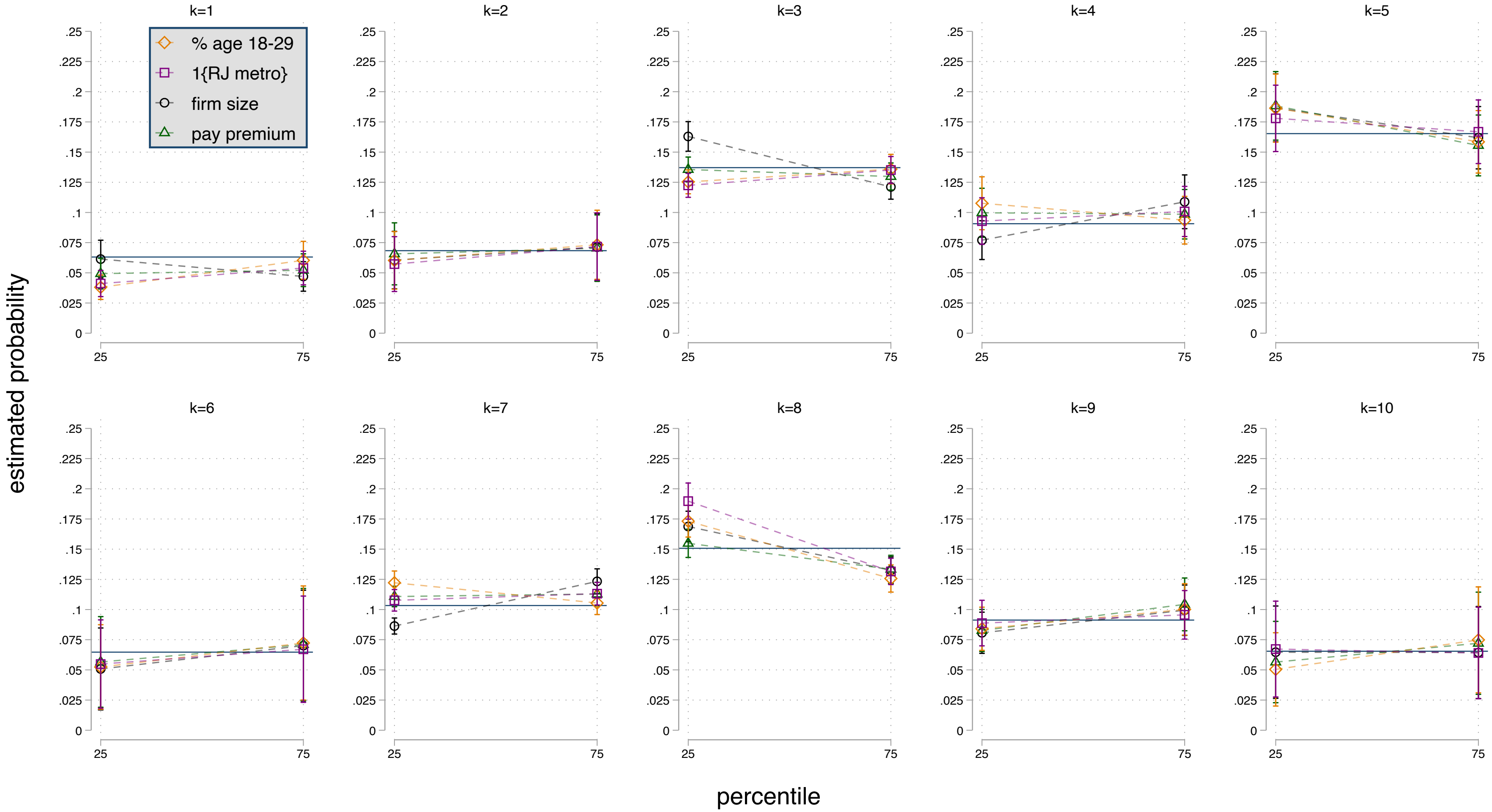
**Firm size.** There is no obvious pattern in employer size across firm classes. In Rio de Janeiro, workers of class-1 and class-10 firms are not employed in particularly large nor small firms (Table A17). In Veneto, while there is no clear relationship between firm classes and firm size, we find that workers in both classes 1 and 10 are employed by relatively small employers (Table A18). 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 9), and less likely to belong to class 1 and to class 10 in Veneto (Figure 10). 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 de Janeiro and Veneto, large firms are less likely to belong to class 1, and somewhat more likely to belong to class 9—i.e., the second-ranked category in terms of learning opportunities.

**Geographic location.** In Brazil, we classify firms with a dummy variable equal to one if located in the metropolitan area of Rio de Janeiro, and zero if elsewhere in the state. In Veneto, we construct a dummy equal to one if a firm is located in one of the five largest cities: Venezia, Verona, Padova, Vicenza, and Treviso. The share of the workforce employed in the Rio de Janeiro metro area is between 76–86 percent across firm classes (Table A17). Since this share equals 79 percent for firm class-10 workers, we do not find them disproportionately represented in the metro area. In Veneto, we find a positive association between large-city firms and firm class: large-city share is generally increasing in firm class. Thus, while 14 percent of the class 1 workforce is in one of the largest cities, the corresponding share for class 10 is 35 percent (Table A18). 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 9). In Veneto, large-city firms are less likely to belong to class 1 and more likely to belong to class 10 (Figure 10). The association we find in Veneto is consistent with De La Roca and Puga (2017), who show evidence from Spain consistent with workers learning more when employed in larger urban areas.

**Workforce education.** The education distribution of the workforce in Rio de Janeiro is largely comparable across firm classes, with the exception of classes 5 and 8, which disproportionately employ lower-education workers (Table A17). In spite of this moderate variation, the workforce at class 10 has the second largest share of workers with at least a high school degree, reaching 45 percent (class 4 has 49 percent). The fact that class 10 has a relatively high share of highly educated workers aligns with existing evidence on learning from highly educated (Nix, 2020) or highly paid (Jarosch et al., 2021) coworkers. We find a similar pattern at the firm level, keeping constant other covariates: Figure A10 shows that a large share of low-educated workers is negatively associated with belonging to class 10 (but also negatively associated with class 1).

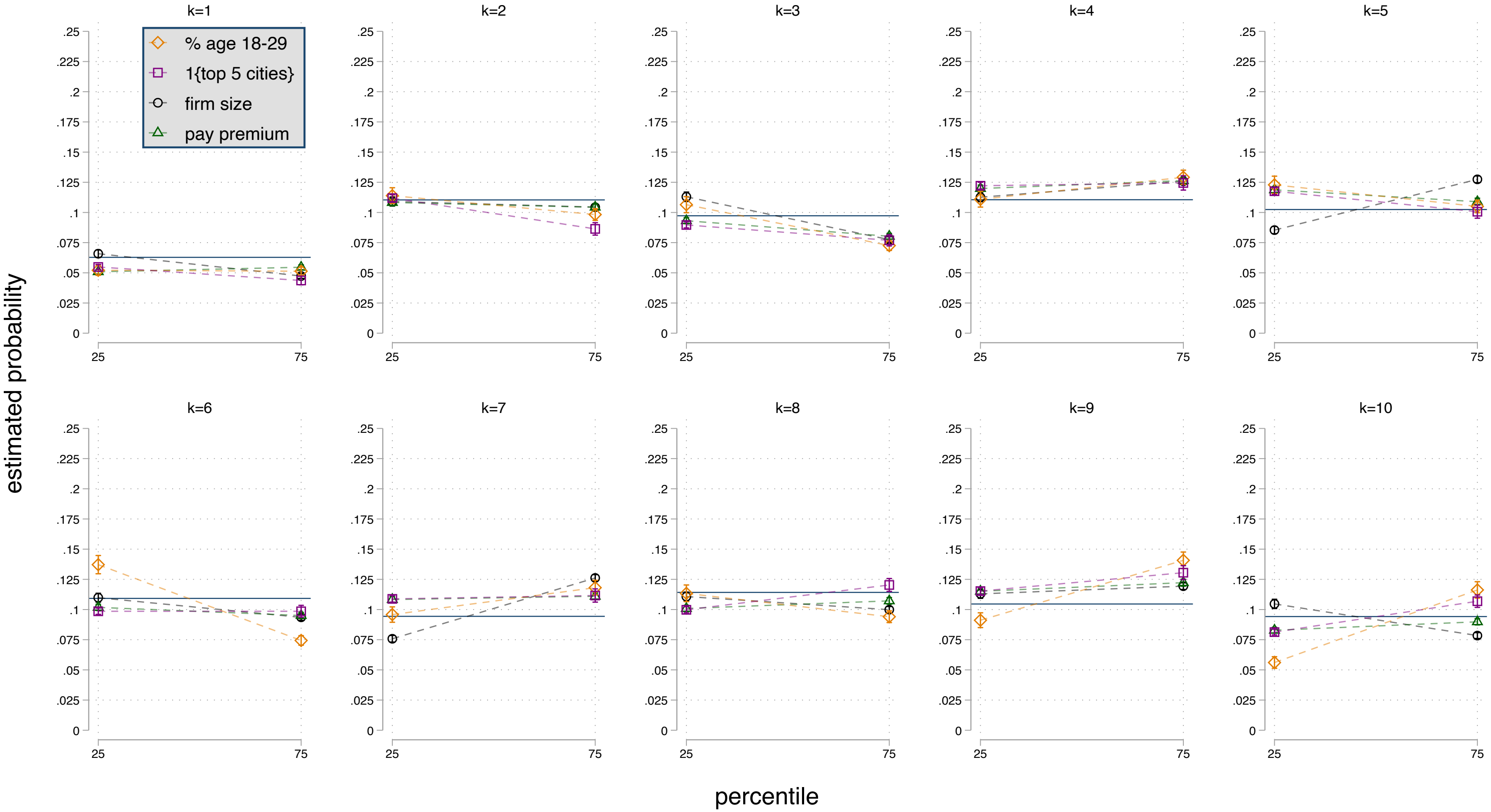
All in all, observed characteristics account for a relatively small share of the difference in firms' on-the-job learning opportunities. In Appendix C, we additionally show that—at least among a small fraction of our sample—firms' management practices are not strongly correlated with the learning opportunities they offer. We thus remark that learning opportunities as a dimension of firm heterogeneity may be an intrinsic attribute that is not easily identifiable with typically observed firm characteristics.

**Figure 9:** Multinomial Logit Estimated Probabilities: $Pr(\text{class} = k|X)$. Rio de Janeiro, 1994–2010.




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

**Figure 10:** Multinomial Logit Estimated Probabilities: $Pr(\text{class} = k|X)$. Veneto, 1984–2001.




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

# 9 Conclusion

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

We have also found that firms' observable characteristics are only mildly helpful to predict learning opportunities. We reach this conclusion after considering various firm attributes, yet our analysis is limited to observables typically available in administrative labor market datasets. Future research could investigate whether important firm attributes previously considered in the literature, yet unobserved to us—e.g., productivity, technological adoption, or multinational status—might improve the identification of firms with good learning opportunities.

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

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# - SUPPLEMENTARY APPENDICES -
# For Online Publication

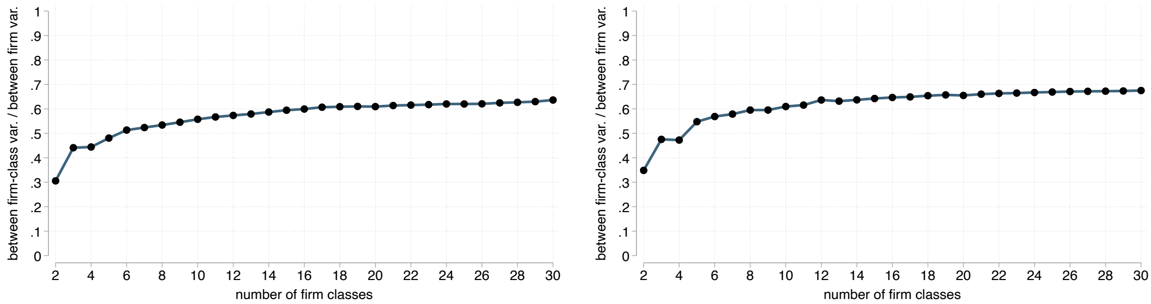
# A Additional Figures and Tables

## A.1 Figures

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

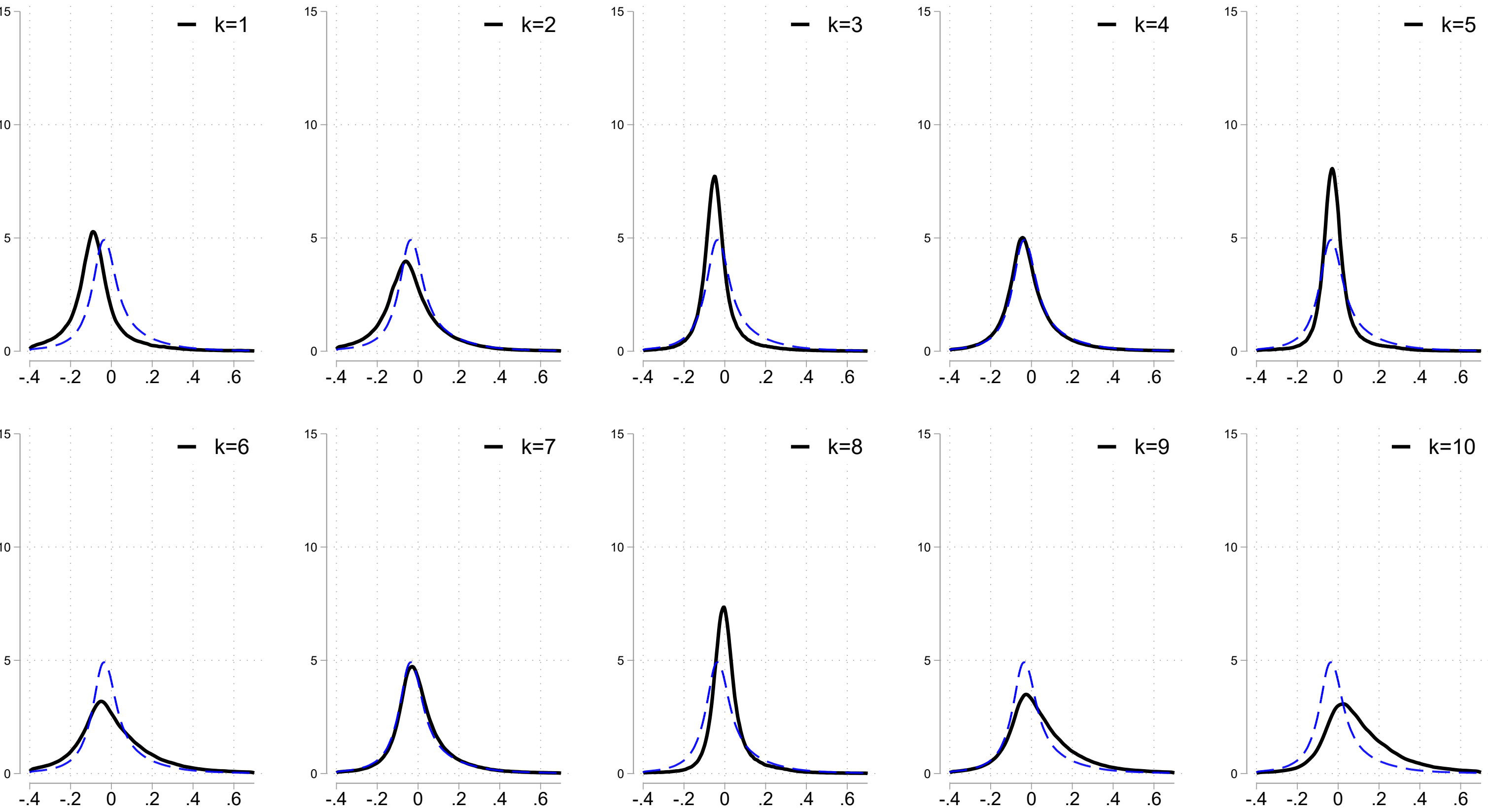
**(a)** Rio de Janeiro, 1994–2010.

**(b)** Veneto, 1984–2001.



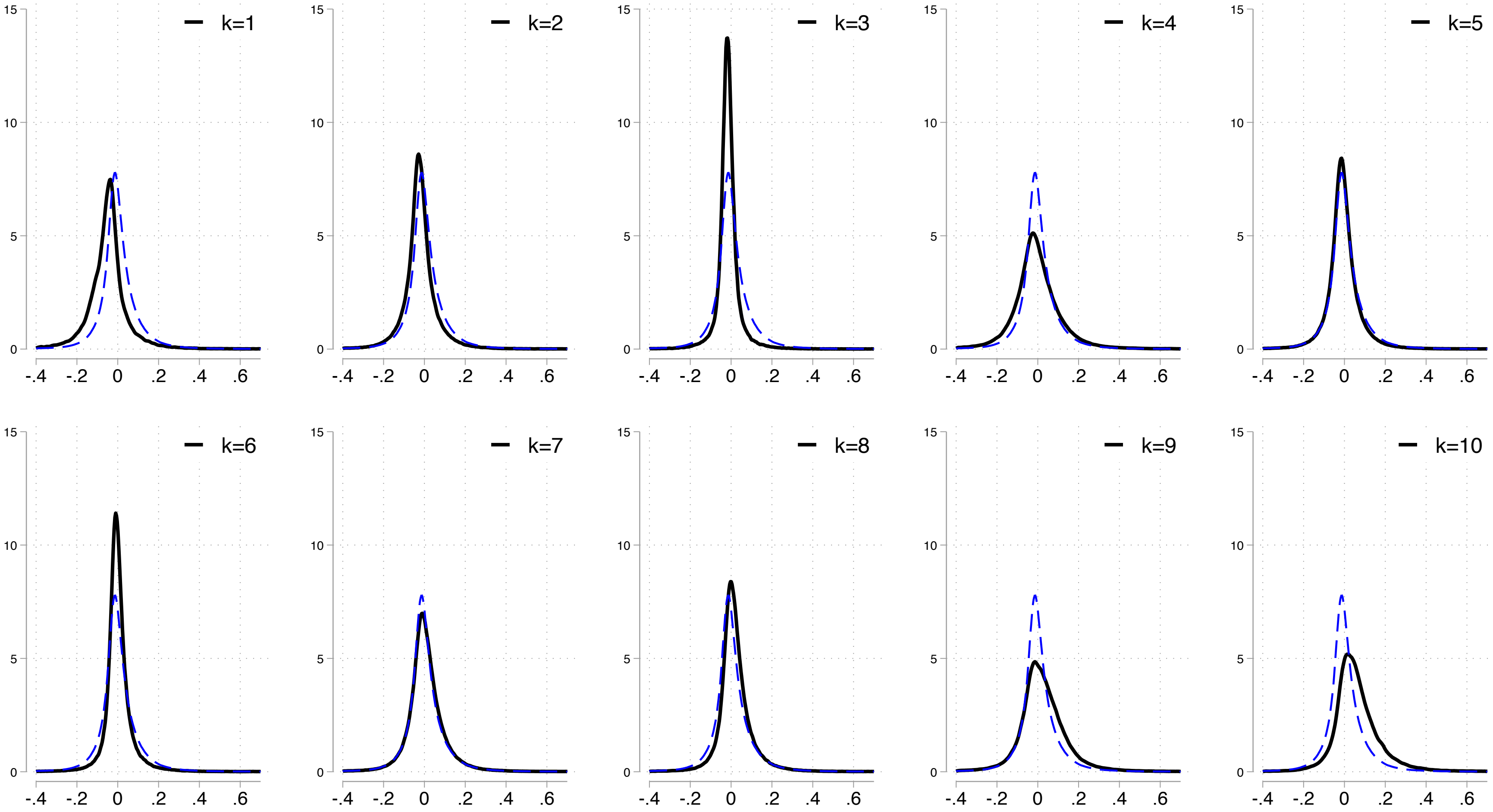

*Notes:* Ratio between i) between firm-class variance of unexplained earnings growth, over ii) between-firm variance of unexplained earnings growth, as a function of the number of firm classes (2–30).

**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.

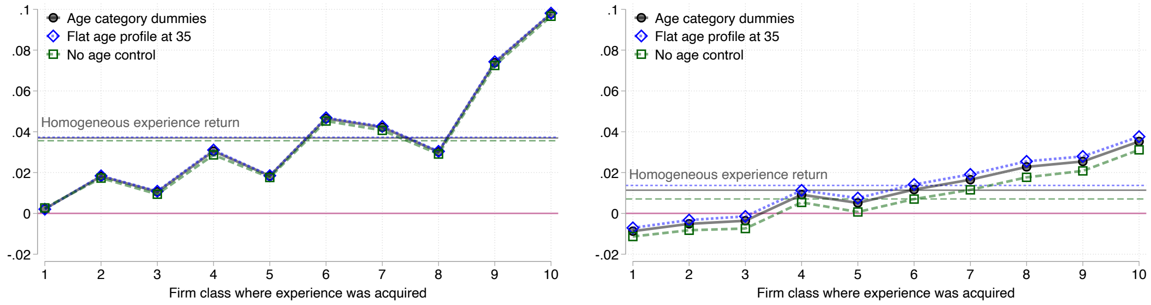
**Figure A3:** Density of unexplained earnings growth in each firm class. Veneto, 1984–2001.




*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 experiences acquired in different firm classes.

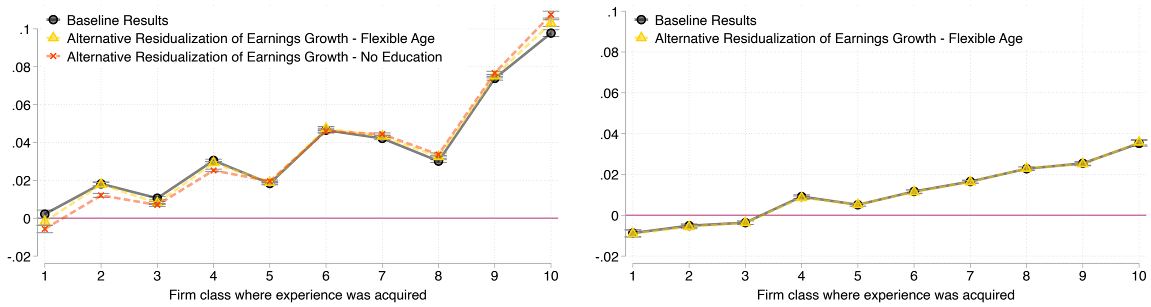
**(a)** Rio de Janeiro, 1994–2010. **(b)** Veneto, 1984–2001.




*Notes:* Estimates of returns to experiences acquired in different firm classes, using different ways of controlling for age effects. Black dots: baseline estimates from Figure 2, controlling for six age-category fixed effects. Blue diamonds: control for an age polynomial restricting the age profile to be flat at 35. Green squares: no age controls. Flat lines: returns to homogeneous experience for each respective age controls.

**Figure A5:** Robustness by alternative residualization of unexplained earnings growth: returns to experiences acquired in different firm classes.

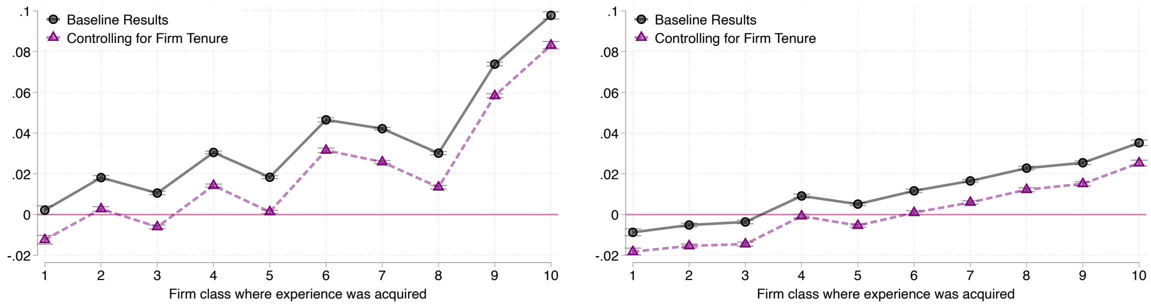
**(a)** Rio de Janeiro, 1994–2010. **(b)** Veneto, 1984–2001.




*Notes:* Estimates of returns to experiences acquired in different firm classes, using different ways of residualizing unexplained earnings growth. Black dots: baseline estimates from Figure 2. Yellow diamonds: fully flexible specification of age effects (interacted with education in Rio de Janeiro). Orange crosses in Rio only: baseline approach without netting out education effects (i.e., fully comparable to Veneto).

**Figure A6:** Robustness controlling for tenure: returns to experiences acquired in different firm classes.

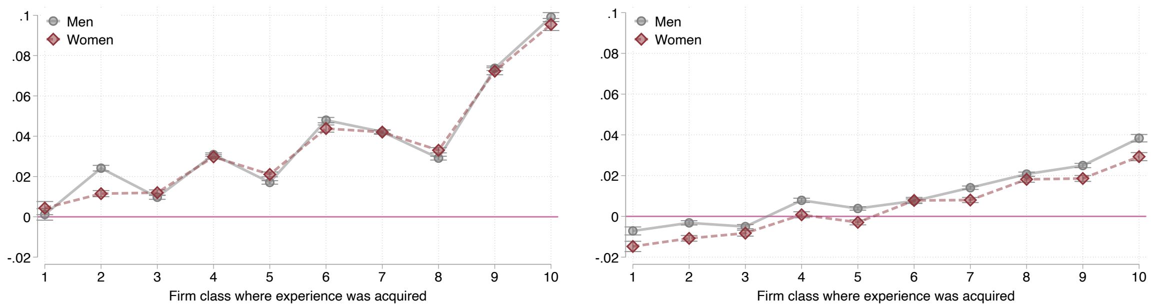
**(a)** Rio de Janeiro, 1994–2010. **(b)** Veneto, 1984–2001.




*Notes:* Estimates of returns to experiences acquired in different firm classes. Baseline estimates (black dots, described in Figure 2), and estimates which further control for tenure at the current employer (purple triangles). Corresponding Appendix regression table: Table A6.

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

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

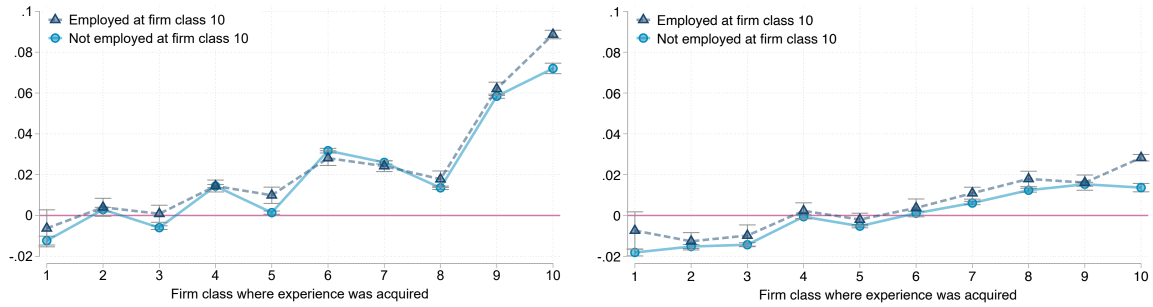



*Notes:* Point estimates of returns to experiences acquired in different firm classes, estimated separately for men and for women.

**Figure A8:** Returns to experiences acquired in different firm classes: interaction by firm 10 employment.

**(a)** Rio de Janeiro, 1994–2010.

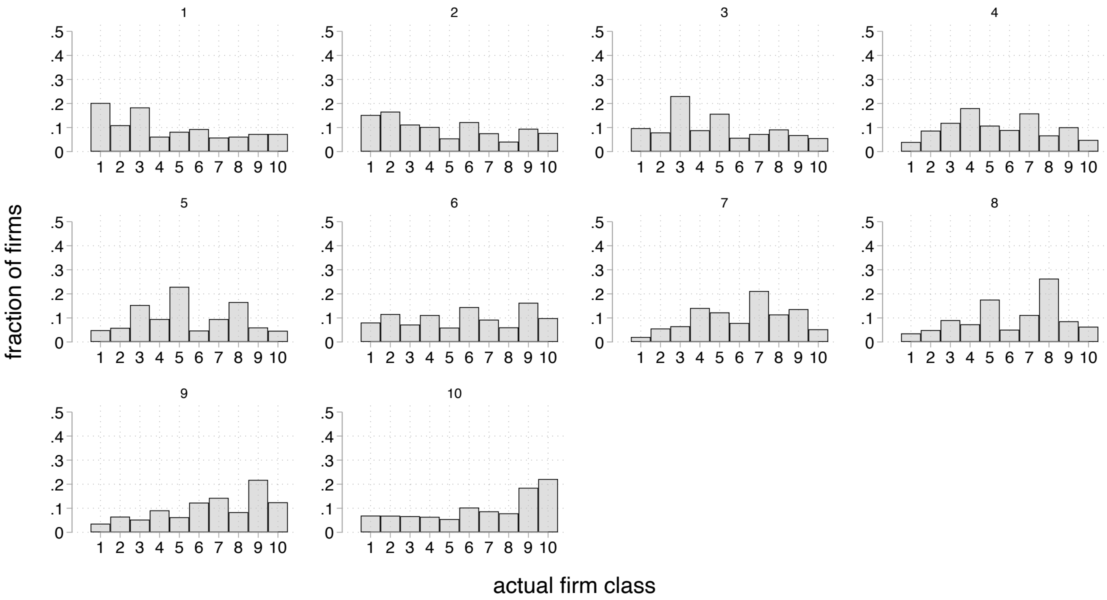
**(b)** Veneto, 1984–2001.



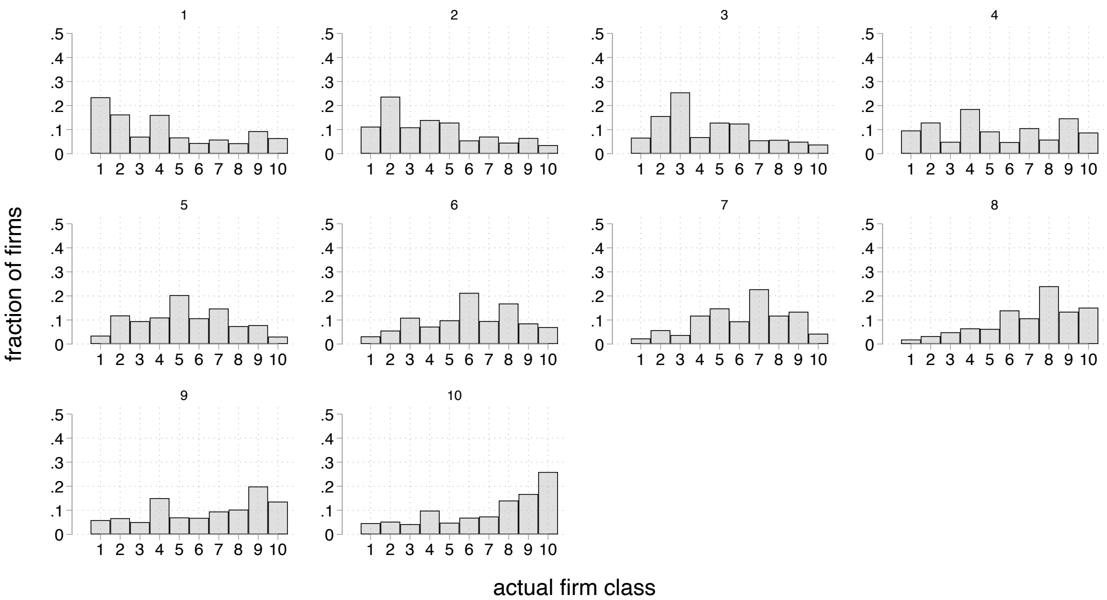

*Notes:* Estimates and 95% confidence intervals of returns to experiences acquired in different firm classes, with returns allowed to vary between those currently employed at a class 10 firm and those employed elsewhere. Rio de Janeiro: outcome is log hourly wage. Veneto: outcome is log daily wage. Across all specifications, the outcome variable for Rio de Janeiro is log hourly wages and log daily wages for Veneto. Standard errors are clustered at the person level. Corresponding Appendix regression table: Table A14.

**Figure A9:** Firm-level distribution of actual firm class, separately by predicted firm class.

**(a)** Rio de Janeiro, 1994–2010.

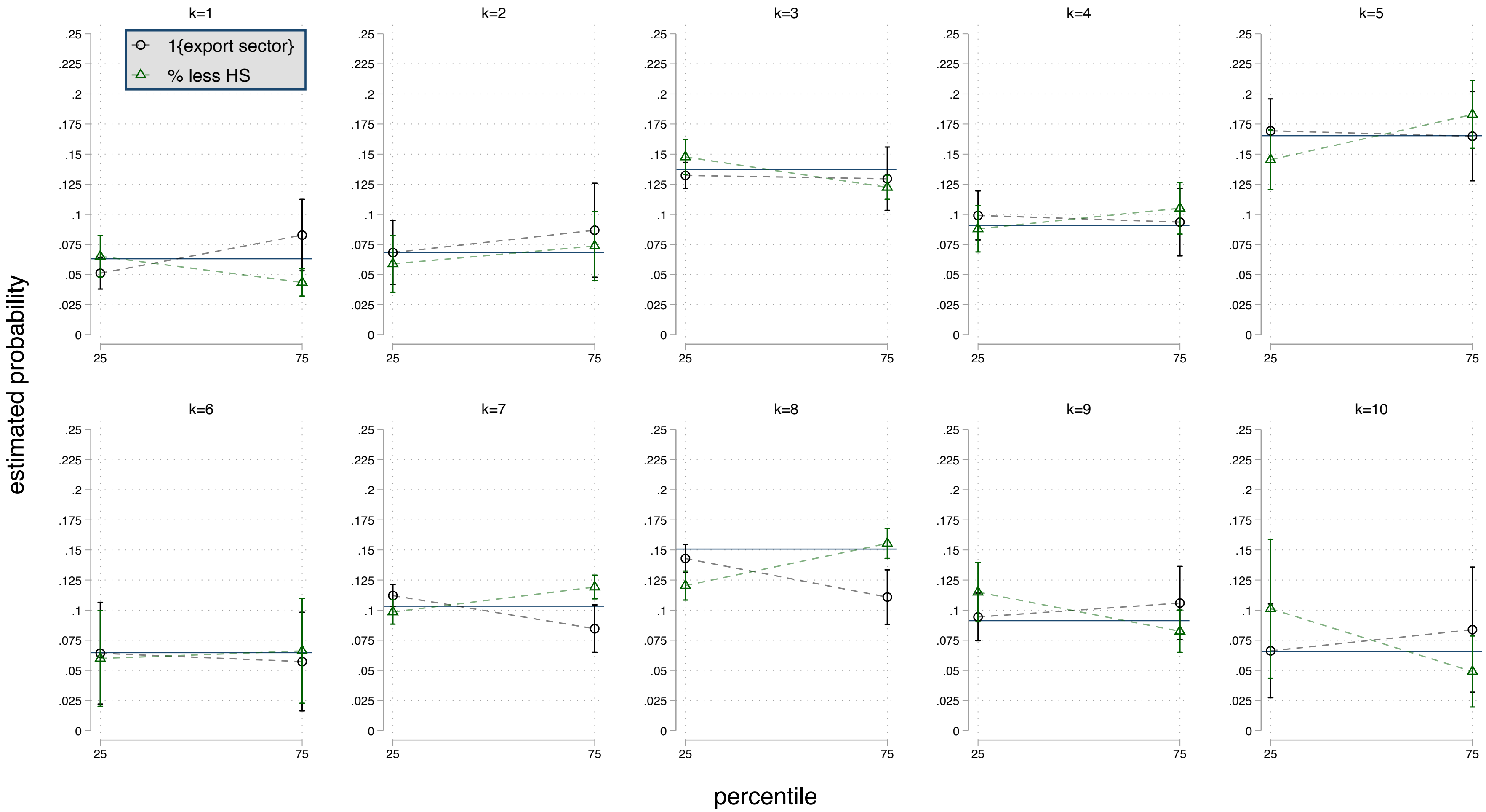



**(b)** Veneto, 1984–2001.



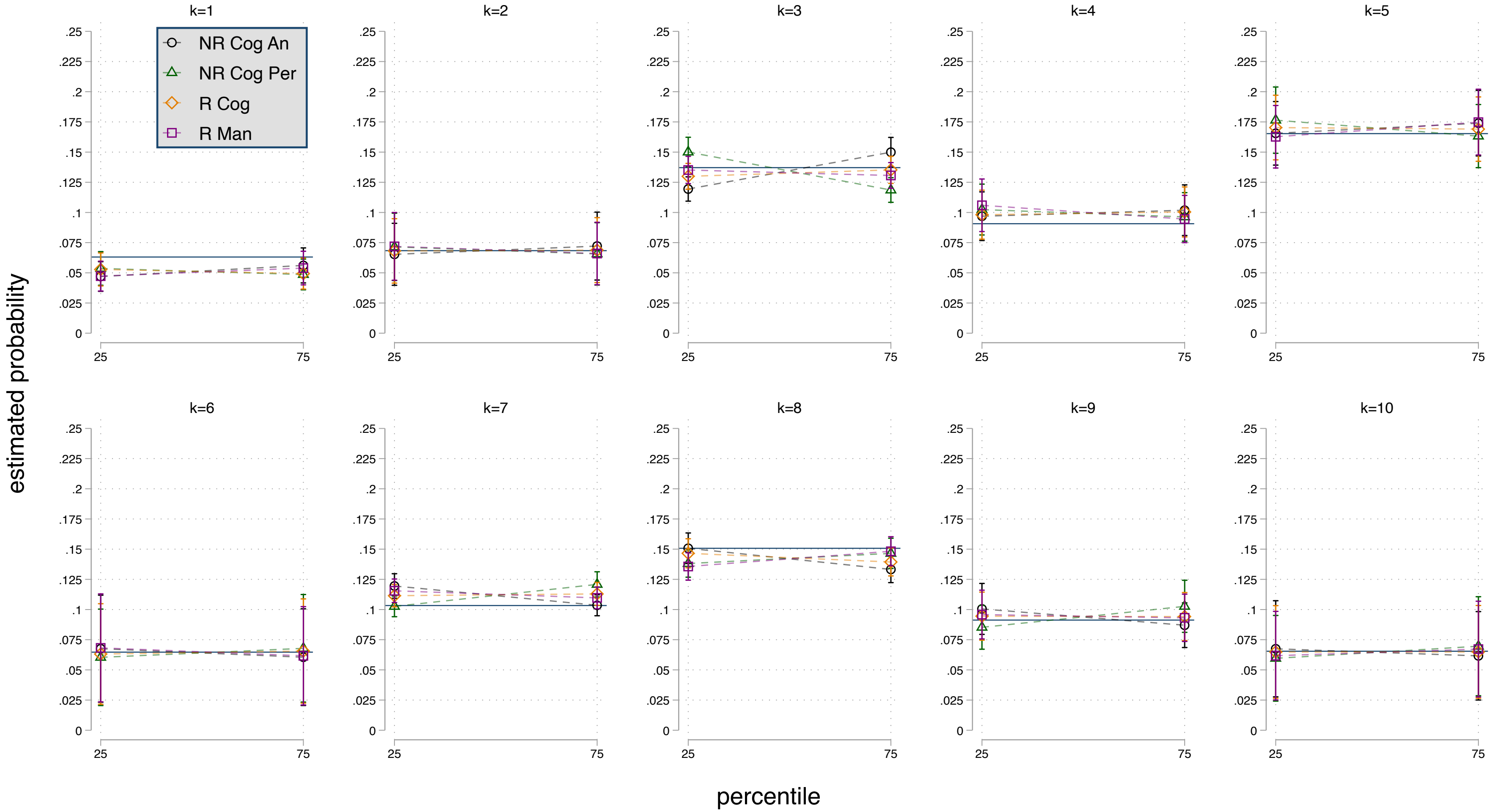

*Notes:* Summary of the results of the random forest classification exercise described in Section 8, Table 3. Each firm $j$ in the prediction data set is associated with its actual firm class, $k(j)$, and the one predicted by the random forest algorithm, $\hat{k}(j)$. This figure represents the firm-level distribution of $k(j)$, separately for each value of $\hat{k}(j)$. For example, the first subfigure in panel (a) shows the distribution of *actual* firm class, among firms in Rio de Janeiro that the random forest algorithm *predicted* to be of class 1.

**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, firm effects $\hat{\psi}_j$ from equation (8), 1-digit sector indicators, indicator for export-intensive 3-digit sector, indicator for being in Rio de Janeiro metropolitan area, and firm's task composition. For each firm class and each of four variables of interest, figure plots the estimated probability when said variable is evaluated at the 25th and 75th percentiles of the firm-level distribution (evaluated at 0 and 1 for the dummy variable 1{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 A11:** Multinomial Logit Estimated Probabilities: $Pr(\text{class} = k|X)$. Rio de Janeiro, 1994–2010.




*Notes:* Estimated probabilities and 95% confidence intervals from firm-level multinomial logit with the following explanatory variables: workforce age distribution, workforce gender distribution, workforce education distribution, log firm size, firm effects $\hat{\psi}_j$ from equation (8), 1-digit sector indicators, indicator for export-intensive 3-digit sector, indicator for being in Rio de Janeiro metropolitan area, and firm's task composition. For each firm class and each of four variables of interest, figure plots the estimated probability when said variable is evaluated at the 25th and 75th percentiles of the firm-level distribution, 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.

## A.2 Tables

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

Rio de Janeiro, 1994–2010.

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

Veneto, 1984–2001.

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

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

**Table A2:** Returns to experiences acquired in different firm classes: Rio de Janeiro, 1994–2010.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Experience | 0.0429*** | 0.0447*** | 0.0369*** | | | |
| | (0.0002) | (0.0003) | (0.0002) | | | |
| Experience: class 1 | | | | 0.0017 | 0.0050*** | 0.0022** |
| | | | | (0.0012) | (0.0012) | (0.0011) |
| Experience: class 2 | | | | 0.0472*** | 0.0332*** | 0.0182*** |
| | | | | (0.0006) | (0.0006) | (0.0005) |
| Experience: class 3 | | | | -0.0018*** | 0.0078*** | 0.0106*** |
| | | | | (0.0005) | (0.0005) | (0.0004) |
| Experience: class 4 | | | | 0.0541*** | 0.0450*** | 0.0305*** |
| | | | | (0.0004) | (0.0004) | (0.0003) |
| Experience: class 5 | | | | -0.0177*** | 0.0091*** | 0.0183*** |
| | | | | (0.0004) | (0.0004) | (0.0004) |
| Experience: class 6 | | | | 0.0676*** | 0.0629*** | 0.0465*** |
| | | | | (0.0006) | (0.0006) | (0.0005) |
| Experience: class 7 | | | | 0.0358*** | 0.0468*** | 0.0422*** |
| | | | | (0.0004) | (0.0004) | (0.0003) |
| Experience: class 8 | | | | -0.0119*** | 0.0198*** | 0.0302*** |
| | | | | (0.0005) | (0.0004) | (0.0004) |
| Experience: class 9 | | | | 0.0969*** | 0.0939*** | 0.0739*** |
| | | | | (0.0006) | (0.0006) | (0.0005) |
| Experience: class 10 | | | | 0.1251*** | 0.1283*** | 0.0978*** |
| | | | | (0.0013) | (0.0011) | (0.0009) |
| Experience: NC | | | | -0.0173*** | 0.0219*** | 0.0275*** |
| | | | | (0.0006) | (0.0006) | (0.0005) |
| Experience: PS | | | | 0.0787*** | 0.0968*** | 0.0457*** |
| | | | | (0.0022) | (0.0032) | (0.0028) |
| Experience: non-RJ | | | | 0.0727*** | 0.0631*** | 0.0516*** |
| | | | | (0.0004) | (0.0004) | (0.0004) |
| Adj. $R^2$ | 0.257 | 0.661 | 0.759 | 0.292 | 0.666 | 0.761 |
| Within adj. $R^2$ | | 0.016 | 0.012 | | 0.032 | 0.021 |
| Person FE | no | yes | yes | no | yes | yes |
| Firm FE | no | no | yes | no | no | yes |
| SE clusters (persons) | 1,928,968 | 1,580,092 | 1,568,990 | 1,928,968 | 1,580,092 | 1,568,990 |
| $N$ | 9,673,897 | 9,326,951 | 9,168,318 | 9,673,897 | 9,326,951 | 9,168,318 |

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

**Table A3:** Returns to experiences acquired in different firm classes: Veneto, 1984–2001.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Experience | 0.0166*** | 0.0241*** | 0.0114*** | | | |
| | (0.0001) | (0.0003) | (0.0003) | | | |
| Experience: class 1 | | | | -0.0029*** | -0.0004 | -0.0087*** |
| | | | | (0.0006) | (0.0009) | (0.0009) |
| Experience: class 2 | | | | 0.0009*** | 0.0045*** | -0.0051*** |
| | | | | (0.0003) | (0.0005) | (0.0005) |
| Experience: class 3 | | | | -0.0074*** | 0.0043*** | -0.0036*** |
| | | | | (0.0004) | (0.0005) | (0.0005) |
| Experience: class 4 | | | | 0.0162*** | 0.0225*** | 0.0092*** |
| | | | | (0.0003) | (0.0005) | (0.0004) |
| Experience: class 5 | | | | 0.0159*** | 0.0193*** | 0.0051*** |
| | | | | (0.0002) | (0.0004) | (0.0004) |
| Experience: class 6 | | | | 0.0158*** | 0.0241*** | 0.0117*** |
| | | | | (0.0003) | (0.0004) | (0.0004) |
| Experience: class 7 | | | | 0.0306*** | 0.0325*** | 0.0165*** |
| | | | | (0.0002) | (0.0004) | (0.0004) |
| Experience: class 8 | | | | 0.0342*** | 0.0374*** | 0.0228*** |
| | | | | (0.0004) | (0.0004) | (0.0004) |
| Experience: class 9 | | | | 0.0377*** | 0.0406*** | 0.0254*** |
| | | | | (0.0004) | (0.0005) | (0.0004) |
| Experience: class 10 | | | | 0.0356*** | 0.0475*** | 0.0352*** |
| | | | | (0.0006) | (0.0007) | (0.0007) |
| Experience: NC | | | | -0.0061*** | 0.0180*** | 0.0137*** |
| | | | | (0.0003) | (0.0005) | (0.0005) |
| Experience: PS | | | | 0.0265*** | 0.0276*** | 0.0034 |
| | | | | (0.0031) | (0.0058) | (0.0052) |
| Experience: non-Veneto | | | | 0.0307*** | 0.0313*** | 0.0158*** |
| | | | | (0.0003) | (0.0004) | (0.0004) |
| Adj. $R^2$ | 0.146 | 0.460 | 0.600 | 0.175 | 0.466 | 0.603 |
| 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) | 564,332 | 490,376 | 483,799 | 564,332 | 490,376 | 483,799 |
| $N$ | 3,767,051 | 3,693,095 | 3,608,754 | 3,767,051 | 3,693,095 | 3,608,754 |

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

**Table A4:** Returns to experiences 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 | 0.002 | 0.026 | 0.014 | 0.041 | 0.016 | 0.063 | 0.048 | 0.028 | 0.088 | 0.117 |
| 3 | 0.009 | 0.072 | 0.041 | 0.115 | 0.051 | 0.174 | 0.141 | 0.088 | 0.252 | 0.328 |
| 5 | 0.019 | 0.111 | 0.066 | 0.180 | 0.092 | 0.267 | 0.229 | 0.154 | 0.398 | 0.509 |
| 10 | 0.059 | 0.174 | 0.120 | 0.301 | 0.219 | 0.418 | 0.427 | 0.341 | 0.691 | 0.826 |

*Notes*: Experience profiles evaluated at one, three, five, and ten years of experience using estimates of heterogeneous returns to different classes of experience featuring a quadratic functional form. That is, an extension of equation (8) (specification of columns (6) in Tables A2 and A3) where heterogeneous experiences, instead of entering linearly, enter as $\gamma_{1k}Exp(k) + \gamma_{2k}Exp(k)^2$. This table shows $\hat{\gamma}_{1k}e + \hat{\gamma}_{2k}e^2$ for $e \in \{1, 3, 5, 10\}$, and $k \in \{1, 2, \ldots, 10\}$.

**Table A5:** Returns to experiences 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 | -0.006 | 0.003 | 0.001 | 0.015 | 0.011 | 0.018 | 0.025 | 0.033 | 0.037 | 0.050 |
| 3 | -0.019 | 0.004 | 0.002 | 0.043 | 0.030 | 0.050 | 0.072 | 0.094 | 0.104 | 0.139 |
| 5 | -0.032 | 0.001 | 0.001 | 0.067 | 0.046 | 0.079 | 0.111 | 0.146 | 0.161 | 0.215 |
| 10 | -0.066 | -0.029 | -0.014 | 0.108 | 0.072 | 0.135 | 0.184 | 0.241 | 0.262 | 0.340 |

*Notes*: Experience profiles evaluated at one, three, five, and ten years of experience using estimates of heterogeneous returns to different classes of experience featuring a quadratic functional form. That is, an extension of equation (8) (specification of columns (6) in Tables A2 and A3) 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 A6:** Robustness: including tenure. Returns to experiences acquired in different firm classes.

Rio de Janeiro, 1994–2010.

| | (1) | (2) |
|---|---|---|
| Experience | 0.0228*** | |
| | (0.0003) | |
| Experience: class 1 | | -0.0123*** |
| | | (0.0011) |
| Experience: class 2 | | 0.0028*** |
| | | (0.0006) |
| Experience: class 3 | | -0.0060*** |
| | | (0.0005) |
| Experience: class 4 | | 0.0143*** |
| | | (0.0004) |
| Experience: class 5 | | 0.0013*** |
| | | (0.0004) |
| Experience: class 6 | | 0.0315*** |
| | | (0.0006) |
| Experience: class 7 | | 0.0258*** |
| | | (0.0004) |
| Experience: class 8 | | 0.0135*** |
| | | (0.0004) |
| Experience: class 9 | | 0.0583*** |
| | | (0.0005) |
| Experience: class 10 | | 0.0831*** |
| | | (0.0009) |
| Experience: NC | | 0.0098*** |
| | | (0.0005) |
| Experience: PS | | 0.0411*** |
| | | (0.0028) |
| Experience: non-RJ | | 0.0378*** |
| | | (0.0004) |
| Tenure | 0.0170*** | 0.0190*** |
| | (0.0002) | (0.0002) |
| Adj. $R^2$ | 0.759 | 0.762 |
| Within adj. $R^2$ | 0.014 | 0.024 |
| Person FE | yes | yes |
| Firm FE | yes | yes |
| SE clusters (persons) | 1,568,990 | 1,568,990 |
| $N$ | 9,168,318 | 9,168,318 |

Veneto, 1984–2001.

| | (1) | (2) |
|---|---|---|
| Experience | 0.0011*** | |
| | (0.0004) | |
| Experience: class 1 | | -0.0182*** |
| | | (0.0009) |
| Experience: class 2 | | -0.0154*** |
| | | (0.0005) |
| Experience: class 3 | | -0.0145*** |
| | | (0.0005) |
| Experience: class 4 | | -0.0007 |
| | | (0.0005) |
| Experience: class 5 | | -0.0054*** |
| | | (0.0004) |
| Experience: class 6 | | 0.0010** |
| | | (0.0005) |
| Experience: class 7 | | 0.0060*** |
| | | (0.0004) |
| Experience: class 8 | | 0.0122*** |
| | | (0.0005) |
| Experience: class 9 | | 0.0151*** |
| | | (0.0005) |
| Experience: class 10 | | 0.0253*** |
| | | (0.0007) |
| Experience: NC | | 0.0029*** |
| | | (0.0005) |
| Experience: PS | | -0.0031 |
| | | (0.0051) |
| Experience: non-Veneto | | 0.0061*** |
| | | (0.0005) |
| Tenure | 0.0109*** | 0.0110*** |
| | (0.0002) | (0.0002) |
| Adj. $R^2$ | 0.601 | 0.604 |
| Within adj. $R^2$ | 0.014 | 0.023 |
| Person FE | yes | yes |
| Firm FE | yes | yes |
| SE clusters (persons) | 483,799 | 483,799 |
| $N$ | 3,608,754 | 3,608,754 |

*Notes*: Left panel: Same specification as that reported for Rio de Janeiro in Table A2, columns (3) and (6), adding a linear term of tenure at the current employer. Right panel: Same specification as that reported for Veneto in Table A3, columns (3) and (6), adding a linear term of tenure at the current employer.

**Table A7:** Returns to experiences 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 | 0.0689*** | 0.0328*** | 0.0060* | -0.0011 |
| | (0.0058) | (0.0069) | (0.0034) | (0.0099) |
| Experience: class 2 | 0.0600*** | 0.0347*** | 0.0026 | 0.0053 |
| | (0.0025) | (0.0028) | (0.0021) | (0.0043) |
| Experience: class 3 | 0.0080** | 0.0186*** | -0.0242*** | -0.0031 |
| | (0.0038) | (0.0042) | (0.0038) | (0.0061) |
| Experience: class 4 | 0.0412*** | 0.0329*** | 0.0154*** | 0.0173*** |
| | (0.0019) | (0.0021) | (0.0021) | (0.0045) |
| Experience: class 5 | -0.0272*** | 0.0139*** | 0.0131*** | 0.0092*** |
| | (0.0032) | (0.0037) | (0.0019) | (0.0036) |
| Experience: class 6 | 0.0532*** | 0.0343*** | 0.0169*** | 0.0078* |
| | (0.0024) | (0.0029) | (0.0026) | (0.0047) |
| Experience: class 7 | 0.0413*** | 0.0293*** | 0.0281*** | 0.0252*** |
| | (0.0022) | (0.0024) | (0.0018) | (0.0034) |
| Experience: class 8 | -0.0337*** | 0.0114** | 0.0367*** | 0.0211*** |
| | (0.0039) | (0.0048) | (0.0025) | (0.0044) |
| Experience: class 9 | 0.1159*** | 0.0577*** | 0.0503*** | 0.0289*** |
| | (0.0029) | (0.0035) | (0.0023) | (0.0039) |
| Experience: class 10 | 0.1431*** | 0.0696*** | 0.0536*** | 0.0388*** |
| | (0.0044) | (0.0052) | (0.0045) | (0.0082) |
| Experience: NC | -0.0101** | 0.0124** | -0.0295*** | -0.0041 |
| | (0.0048) | (0.0056) | (0.0048) | (0.0078) |
| Experience: PS | 0.0741*** | 0.0167 | -0.0217 | -0.0248 |
| | (0.0241) | (0.0197) | (0.0406) | (0.0625) |
| Experience: Other | 0.0937*** | 0.0448*** | 0.0043 | 0.0105* |
| | (0.0026) | (0.0029) | (0.0034) | (0.0062) |
| Adjusted $R^2$ | 0.189 | 0.548 | 0.175 | 0.487 |
| 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 | 109995 | 109995 | 18601 | 18601 |

*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 represent our firm categorization based on unexplained earnings growth distributions. NC are small firms not categorized by the clustering algorithm. PS is the public sector in each data set. Other is experience acquired outside the state of Rio de Janeiro or outside the region of Veneto. All specifications include year fixed effects and control for age with six age-category indicators. Robust standard errors in parentheses. *p<0.10; **p<0.05; ***p<0.01.

**Table A8:** Returns to experiences acquired in different firm classes in first post-displacement observation, no control for time to re-entry: Rio de Janeiro and Veneto.

| | Rio de Janeiro | | Veneto | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Experience: class 1 | 0.0731*** | 0.0336*** | 0.0078** | -0.0008 |
| | (0.0058) | (0.0069) | (0.0034) | (0.0099) |
| Experience: class 2 | 0.0663*** | 0.0364*** | 0.0051** | 0.0064 |
| | (0.0025) | (0.0028) | (0.0021) | (0.0042) |
| Experience: class 3 | 0.0151*** | 0.0206*** | -0.0215*** | -0.0022 |
| | (0.0038) | (0.0041) | (0.0038) | (0.0061) |
| Experience: class 4 | 0.0477*** | 0.0344*** | 0.0181*** | 0.0183*** |
| | (0.0018) | (0.0021) | (0.0021) | (0.0045) |
| Experience: class 5 | -0.0192*** | 0.0161*** | 0.0159*** | 0.0101*** |
| | (0.0032) | (0.0037) | (0.0019) | (0.0035) |
| Experience: class 6 | 0.0590*** | 0.0357*** | 0.0197*** | 0.0087* |
| | (0.0023) | (0.0029) | (0.0026) | (0.0047) |
| Experience: class 7 | 0.0491*** | 0.0314*** | 0.0311*** | 0.0260*** |
| | (0.0022) | (0.0024) | (0.0017) | (0.0034) |
| Experience: class 8 | -0.0239*** | 0.0144*** | 0.0399*** | 0.0220*** |
| | (0.0038) | (0.0047) | (0.0024) | (0.0043) |
| Experience: class 9 | 0.1236*** | 0.0595*** | 0.0535*** | 0.0297*** |
| | (0.0029) | (0.0034) | (0.0022) | (0.0039) |
| Experience: class 10 | 0.1504*** | 0.0712*** | 0.0569*** | 0.0399*** |
| | (0.0044) | (0.0052) | (0.0044) | (0.0082) |
| Experience: NC | -0.0030 | 0.0145*** | -0.0265*** | -0.0030 |
| | (0.0048) | (0.0056) | (0.0048) | (0.0078) |
| Experience: PS | 0.0842*** | 0.0194 | -0.0074 | -0.0207 |
| | (0.0241) | (0.0196) | (0.0411) | (0.0626) |
| Experience: Other | 0.1016*** | 0.0468*** | 0.0078** | 0.0115* |
| | (0.0025) | (0.0029) | (0.0034) | (0.0062) |
| Adjusted $R^2$ | 0.186 | 0.548 | 0.173 | 0.486 |
| 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 | 109995 | 109995 | 18601 | 18601 |

*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 represent our firm categorization based on unexplained earnings growth distributions. NC are small firms not categorized by the clustering algorithm. PS is the public sector in each data set. Other is experience acquired outside the state of Rio de Janeiro or outside the region of Veneto. All specifications include year fixed effects and control for age with six age-category indicators. Robust standard errors in parentheses. *p<0.10; **p<0.05; ***p<0.01.

**Table A9:** Percent of observations belonging to each firm class in the displaced sample.

| Firm class | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Rio de Janeiro, 1994–2010 | | | | | |
| % workers | 8.17 | 12.40 | 2.37 | 14.12 | 3.86 | 16.51 | 11.32 | 3.85 | 16.63 | 10.77 |
| % firms | 4.82 | 13.18 | 3.71 | 11.61 | 4.92 | 20.17 | 11.81 | 3.88 | 17.10 | 8.80 |
| | | | | | Veneto, 1984–2001 | | | | | |
| % workers | 4.65 | 8.05 | 4.09 | 14.83 | 10.87 | 5.49 | 19.69 | 12.09 | 15.02 | 5.20 |
| % firms | 5.73 | 10.73 | 5.34 | 15.27 | 14.14 | 8.26 | 13.35 | 9.64 | 12.11 | 5.44 |

*Notes*: Table A9 presents the share of workers and percent of firms belonging to each of the ten firm classes in both Rio de Janeiro (1994-2010) and Veneto (1984-2001) for the sample of displaced workers discussed in Section 4.2.

**Table A10:** Returns to experiences acquired in different firm classes by workers' unobserved skills ($p_{25}$ and $p_{75}$): Rio de Janeiro and Veneto.

| | Rio de Janeiro | | Veneto | |
|---|---|---|---|---|
| | $p_{25}$ | $p_{75}$ | $p_{25}$ | $p_{75}$ |
| | (1) | (2) | (3) | (4) |
| Experience: class 1 | -0.0120*** | -0.0009 | -0.0264*** | -0.0090*** |
| | (0.0013) | (0.0011) | (0.0015) | (0.0008) |
| Experience: class 2 | -0.0093*** | 0.0139*** | -0.0219*** | -0.0044*** |
| | (0.0007) | (0.0005) | (0.0009) | (0.0004) |
| Experience: class 3 | -0.0015*** | 0.0104*** | -0.0169*** | -0.0034*** |
| | (0.0005) | (0.0005) | (0.0008) | (0.0004) |
| Experience: class 4 | 0.0076*** | 0.0291*** | -0.0084*** | 0.0107*** |
| | (0.0004) | (0.0003) | (0.0009) | (0.0005) |
| Experience: class 5 | 0.0108*** | 0.0212*** | -0.0124*** | 0.0063*** |
| | (0.0004) | (0.0005) | (0.0008) | (0.0004) |
| Experience: class 6 | 0.0211*** | 0.0477*** | -0.0013** | 0.0135*** |
| | (0.0006) | (0.0006) | (0.0007) | (0.0004) |
| Experience: class 7 | 0.0236*** | 0.0500*** | -0.0018*** | 0.0186*** |
| | (0.0003) | (0.0004) | (0.0006) | (0.0004) |
| Experience: class 8 | 0.0243*** | 0.0359*** | 0.0095*** | 0.0263*** |
| | (0.0004) | (0.0006) | (0.0006) | (0.0005) |
| Experience: class 9 | 0.0479*** | 0.0831*** | 0.0103*** | 0.0297*** |
| | (0.0005) | (0.0005) | (0.0008) | (0.0006) |
| Experience: class 10 | 0.0680*** | 0.1073*** | 0.0230*** | 0.0426*** |
| | (0.0011) | (0.0010) | (0.0008) | (0.0008) |
| Experience: NC | 0.0182*** | 0.0321*** | 0.0089*** | 0.0135*** |
| | (0.0005) | (0.0006) | (0.0006) | (0.0005) |
| Experience: PS | 0.0197*** | 0.0396*** | -0.0155** | 0.0028 |
| | (0.0031) | (0.0027) | (0.0076) | (0.0047) |
| Experience: Other | 0.0200*** | 0.0483*** | -0.0005 | 0.0174*** |
| | (0.0004) | (0.0004) | (0.0007) | (0.0004) |
| Observations | 9,168,080 | | 3,599,428 | |

*Notes*: Outcome is hourly wage in Rio de Janeiro and daily wage in Veneto. Full sample of workers in Rio de Janeiro. Firm classes 1–10 represent our firm categorization based on unexplained earnings growth distributions. NC are small firms not categorized by the clustering algorithm. PS is the public sector in each data set. Other is experience acquired outside the state of Rio de Janeiro or outside the region of Veneto. All specifications include year fixed effects and control for age with six age-category indicators. We allow for returns to experiences acquired in different firm classes to differ across workers' unobserved skills recovered through the iterative method proposed by De La Roca and Puga (2017), as documented in Section 4.3. We present the marginal effects of the main specification evaluated at the $25^{th}$ and $75^{th}$ percentiles of the distribution of workers' unobserved skills in each country. The first and second columns present evidence from the same regression in Rio de Janeiro, whereas the last two columns do the same in Veneto. Standard errors clustered at the person level. *p<0.10; **p<0.05; ***p<0.01.

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

| | Less than HS<br>(1) | HS or more<br>(2) |
|---|---|---|
| Experience: class 1 | -0.0008 | 0.0004 |
| | (0.0015) | (0.0015) |
| Experience: class 2 | 0.0101*** | 0.0197*** |
| | (0.0007) | (0.0007) |
| Experience: class 3 | 0.0075*** | 0.0129*** |
| | (0.0005) | (0.0007) |
| Experience: class 4 | 0.0202*** | 0.0351*** |
| | (0.0005) | (0.0005) |
| Experience: class 5 | 0.0184*** | 0.0193*** |
| | (0.0004) | (0.0006) |
| Experience: class 6 | 0.0392*** | 0.0497*** |
| | (0.0008) | (0.0008) |
| Experience: class 7 | 0.0342*** | 0.0485*** |
| | (0.0004) | (0.0005) |
| Experience: class 8 | 0.0302*** | 0.0331*** |
| | (0.0005) | (0.0007) |
| Experience: class 9 | 0.0598*** | 0.0840*** |
| | (0.0006) | (0.0007) |
| Experience: class 10 | 0.0790*** | 0.1107*** |
| | (0.0013) | (0.0012) |
| Experience: NC | 0.0221*** | 0.0325*** |
| | (0.0006) | (0.0008) |
| Experience: PS | 0.0227*** | 0.0467*** |
| | (0.0055) | (0.0035) |
| Experience: non-RJ | 0.0429*** | 0.0542*** |
| | (0.0006) | (0.0005) |
| Adj. $R^2$ | 0.648 | 0.784 |
| Within adj. $R^2$ | 0.018 | 0.022 |
| Person FE | yes | yes |
| Firm FE | yes | yes |
| SE clusters (persons) | 652,767 | 911,050 |
| $N$ | 3,810,655 | 5,297,096 |

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

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

| | | White Collar | Blue Collar |
|---|---|---|---|
| | (1) | (2) | (3) |
| Experience: White Collar | 0.0366*** | | |
| | (0.0002) | | |
| Experience: Blue Collar | 0.0229*** | | |
| | (0.0003) | | |
| Heterogeneous Experience: class 1 | | -0.0029*** | -0.0106*** |
| | | (0.0013) | (0.0020) |
| Heterogeneous Experience: class 2 | | 0.0164*** | 0.0070*** |
| | | (0.0007) | (0.0008) |
| Heterogeneous Experience: class 3 | | 0.0071*** | 0.0019*** |
| | | (0.0005) | (0.0006) |
| Heterogeneous Experience: class 4 | | 0.0308*** | 0.0146*** |
| | | (0.0004) | (0.0004) |
| Heterogeneous Experience: class 5 | | 0.0144*** | 0.0106*** |
| | | (0.0005) | (0.0005) |
| Heterogeneous Experience: class 6 | | 0.0452*** | 0.0313*** |
| | | (0.0007) | (0.0008) |
| Heterogeneous Experience: class 7 | | 0.0434*** | 0.0244*** |
| | | (0.0004) | (0.0004) |
| Heterogeneous Experience: class 8 | | 0.0283*** | 0.0193*** |
| | | (0.0005) | (0.0005) |
| Heterogeneous Experience: class 9 | | 0.0755*** | 0.0552*** |
| | | (0.0006) | (0.0006) |
| Heterogeneous Experience: class 10 | | 0.0970*** | 0.0779*** |
| | | (0.0012) | (0.0013) |
| Heterogeneous Experience: NC | | 0.0238*** | 0.0128*** |
| | | (0.0006) | (0.0008) |
| Heterogeneous Experience: PS | | 0.0459*** | -0.0069 |
| | | (0.0034) | (0.0058) |
| Heterogeneous Experience: non-RJ | | 0.0522*** | 0.0329*** |
| | | (0.0005) | (0.0005) |
| Adj. $R^2$ | 0.759 | 0.761 | |
| Within adj. $R^2$ | 0.152 | 0.160 | |
| Person FE | yes | yes | |
| Firm FE | yes | yes | |
| SE clusters (persons) | 1,568,990 | 1,568,990 | |
| $N$ | 9,168,318 | 9,168,318 | |

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

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

| | (1) | White Collar (2) | Blue Collar (3) |
|---|---|---|---|
| Experience: White Collar | 0.0222*** | | |
| | (0.0003) | | |
| Experience: Blue Collar | 0.0059*** | | |
| | (0.0003) | | |
| Heterogeneous Experience: class 1 | | 0.0081*** | -0.0119*** |
| | | (0.0023) | (0.0009) |
| Heterogeneous Experience: class 2 | | 0.0061*** | -0.0073*** |
| | | (0.0011) | (0.0005) |
| Heterogeneous Experience: class 3 | | 0.0033*** | -0.0055*** |
| | | (0.0011) | (0.0005) |
| Heterogeneous Experience: class 4 | | 0.0200*** | 0.0052*** |
| | | (0.0009) | (0.0005) |
| Heterogeneous Experience: class 5 | | 0.0182*** | 0.0011*** |
| | | (0.0006) | (0.0004) |
| Heterogeneous Experience: class 6 | | 0.0167*** | 0.0085*** |
| | | (0.0007) | (0.0005) |
| Heterogeneous Experience: class 7 | | 0.0250*** | 0.0119*** |
| | | (0.0005) | (0.0004) |
| Heterogeneous Experience: class 8 | | 0.0239*** | 0.0205*** |
| | | (0.0006) | (0.0005) |
| Heterogeneous Experience: class 9 | | 0.0290*** | 0.0214*** |
| | | (0.0006) | (0.0005) |
| Heterogeneous Experience: class 10 | | 0.0396*** | 0.0279*** |
| | | (0.0009) | (0.0009) |
| Heterogeneous Experience: NC | | 0.0134*** | 0.0127*** |
| | | (0.0007) | (0.0006) |
| Heterogeneous Experience: PS | | 0.0097 | -0.0033 |
| | | (0.0066) | (0.0070) |
| Heterogeneous Experience: non-Veneto | | 0.0293*** | 0.0047*** |
| | | (0.0006) | (0.0005) |
| Adj. $R^2$ | 0.602 | 0.605 | |
| Within adj. $R^2$ | 0.088 | 0.094 | |
| Person FE | yes | yes | |
| Firm FE | yes | yes | |
| SE clusters (persons) | 483,799 | 483,799 | |
| $N$ | 3,608,754 | 3,608,754 | |

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

**Table A14:** Returns to experiences acquired in different firm classes: allowing richer returns patterns

Firm class $k$ × currently employed at class $k$.

| | (1) Rio de Janeiro | (2) Veneto |
|---|---|---|
| Experience: class 1 | -0.0013 | -0.0168*** |
| | (0.0016) | (0.0012) |
| Experience: class 1 × employed in class 1 | -0.0189*** | 0.0001 |
| | (0.0017) | (0.0013) |
| Experience: class 2 | 0.0047*** | -0.0147*** |
| | (0.0008) | (0.0007) |
| Experience: class 2 × employed in class 2 | -0.0038*** | 0.0011 |
| | (0.0008) | (0.0007) |
| Experience: class 3 | 0.0030*** | -0.0138*** |
| | (0.0007) | (0.0008) |
| Experience: class 3 × employed in class 3 | -0.0130*** | 0.0011 |
| | (0.0007) | (0.0008) |
| Experience: class 4 | 0.0162*** | -0.0019*** |
| | (0.0005) | (0.0006) |
| Experience: class 4 × employed in class 4 | -0.0032*** | 0.0034*** |
| | (0.0005) | (0.0006) |
| Experience: class 5 | 0.0070*** | -0.0035*** |
| | (0.0006) | (0.0005) |
| Experience: class 5 × employed in class 5 | -0.0081*** | -0.0004 |
| | (0.0006) | (0.0005) |
| Experience: class 6 | 0.0231*** | 0.0016** |
| | (0.0008) | (0.0008) |
| Experience: class 6 × employed in class 6 | 0.0121*** | 0.0012 |
| | (0.0008) | (0.0008) |
| Experience: class 7 | 0.0246*** | 0.0074*** |
| | (0.0005) | (0.0005) |
| Experience: class 7 × employed in class 7 | 0.0009* | 0.0002 |
| | (0.0005) | (0.0005) |
| Experience: class 8 | 0.0133*** | 0.0097*** |
| | (0.0007) | (0.0007) |
| Experience: class 8 × employed in class 8 | -0.0006 | 0.0050*** |
| | (0.0007) | (0.0007) |
| Experience: class 9 | 0.0506*** | 0.0115*** |
| | (0.0007) | (0.0007) |
| Experience: class 9 × employed in class 9 | 0.0100*** | 0.0063*** |
| | (0.0007) | (0.0007) |
| Experience: class 10 | 0.0732*** | 0.0148*** |
| | (0.0013) | (0.0010) |
| Experience: class 10 × employed in class 10 | 0.0149*** | 0.0154*** |
| | (0.0014) | (0.0011) |
| Experience: NC | 0.0121*** | -0.0058*** |
| | (0.0009) | (0.0008) |
| Experience: NC × employed in NC | -0.0037*** | 0.0120*** |
| | (0.0009) | (0.0008) |
| Experience: PS | 0.0414*** | -0.0035 |
| | (0.0028) | (0.0051) |
| Experience: Other | 0.0439*** | 0.0088*** |
| | (0.0006) | (0.0007) |
| Experience: Other × employed in Other | -0.0079*** | -0.0016*** |
| | (0.0004) | (0.0006) |
| Tenure | 0.0200*** | 0.0090*** |
| | (0.0003) | (0.0003) |
| Adj. $R^2$ | 0.762 | 0.605 |
| Within adj. $R^2$ | 0.025 | 0.023 |
| Person FE | yes | yes |
| Firm FE | yes | yes |
| SE clusters (persons) | 1,568,990 | 483,799 |
| $N$ | 9,168,318 | 3,608,754 |

Firm class $k$ × currently employed at class 10.

| | (1) Rio de Janeiro | (2) Veneto |
|---|---|---|
| Experience: class 1 | -0.0123*** | -0.0181*** |
| | (0.0011) | (0.0009) |
| Experience: class 1 × employed in class 10 | 0.0060 | 0.0107** |
| | (0.0046) | (0.0046) |
| Experience: class 2 | 0.0029*** | -0.0152*** |
| | (0.0006) | (0.0005) |
| Experience: class 2 × employed in class 10 | 0.0011 | 0.0026 |
| | (0.0022) | (0.0021) |
| Experience: class 3 | -0.0060*** | -0.0143*** |
| | (0.0005) | (0.0005) |
| Experience: class 3 × employed in class 10 | 0.0068*** | 0.0045* |
| | (0.0021) | (0.0026) |
| Experience: class 4 | 0.0144*** | -0.0006 |
| | (0.0004) | (0.0005) |
| Experience: class 4 × employed in class 10 | 0.0000 | 0.0029 |
| | (0.0015) | (0.0020) |
| Experience: class 5 | 0.0014*** | -0.0052*** |
| | (0.0004) | (0.0004) |
| Experience: class 5 × employed in class 10 | 0.0085*** | 0.0032** |
| | (0.0020) | (0.0016) |
| Experience: class 6 | 0.0317*** | 0.0011** |
| | (0.0006) | (0.0005) |
| Experience: class 6 × employed in class 10 | -0.0036** | 0.0026 |
| | (0.0018) | (0.0022) |
| Experience: class 7 | 0.0260*** | 0.0061*** |
| | (0.0004) | (0.0004) |
| Experience: class 7 × employed in class 10 | -0.0018 | 0.0048*** |
| | (0.0013) | (0.0015) |
| Experience: class 8 | 0.0136*** | 0.0124*** |
| | (0.0004) | (0.0005) |
| Experience: class 8 × employed in class 10 | 0.0042** | 0.0055*** |
| | (0.0020) | (0.0019) |
| Experience: class 9 | 0.0584*** | 0.0153*** |
| | (0.0005) | (0.0005) |
| Experience: class 9 × employed in class 10 | 0.0036** | 0.0008 |
| | (0.0016) | (0.0019) |
| Experience: class 10 | 0.0721*** | 0.0137*** |
| | (0.0013) | (0.0011) |
| Experience: class 10 × employed in class 10 | 0.0166*** | 0.0147*** |
| | (0.0014) | (0.0011) |
| Experience: NC | 0.0099*** | 0.0030*** |
| | (0.0005) | (0.0005) |
| Experience: NC × employed in class 10 | 0.0029 | 0.0026 |
| | (0.0023) | (0.0017) |
| Experience: PS | 0.0413*** | -0.0030 |
| | (0.0029) | (0.0052) |
| Experience: PS × employed in class 10 | -0.0030 | -0.0046 |
| | (0.0067) | (0.0140) |
| Experience: Other | 0.0378*** | 0.0062*** |
| | (0.0004) | (0.0005) |
| Experience: Other × employed in class 10 | 0.0076*** | 0.0111*** |
| | (0.0011) | (0.0019) |
| Tenure | 0.0188*** | 0.0108*** |
| | (0.0002) | (0.0002) |
| Adj. $R^2$ | 0.762 | 0.604 |
| Within adj. $R^2$ | 0.024 | 0.023 |
| Person FE | yes | yes |
| Firm FE | yes | yes |
| SE clusters (persons) | 1,568,990 | 483,799 |
| $N$ | 9,168,318 | 3,608,754 |

*Notes*: Left panel: returns to experiences acquired in different firm classes, with returns to each class of experience allowed to vary between those currently employed at that same firm class and those employed elsewhere. Right panel: returns to experiences acquired in different firm classes, with returns allowed to vary between those currently employed at a class 10 firm and those employed elsewhere. NC are small firms not categorized by clustering algorithm. PS is the public sector. Other is experience acquired outside the state of Rio de Janeiro or outside the region of Veneto. All specifications include year fixed effects and control for age with six age-category indicators. Rio de Janeiro: outcome is log hourly wage. Veneto: outcome is log daily wage. Standard errors clustered at the person level. *p<0.10; **p<0.05; ***p<0.01.

**Table A15:** Task content returns to experiences acquired in different firm classes, main and displaced samples: Rio de Janeiro

| | Non-Routine Analytic | | Non-Routine Interpersonal | | Routine Cognitive | | Routine Manual | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Experience: class 1 | 0.0079*** | 0.0111* | 0.0108*** | 0.0192*** | -0.0117*** | -0.0230** | -0.0108*** | -0.0545*** |
| | (0.0013) | (0.0067) | (0.0013) | (0.0066) | (0.0020) | (0.0098) | (0.0016) | (0.0084) |
| Experience: class 2 | 0.0044*** | 0.0133*** | 0.0152*** | 0.0166*** | -0.0130*** | 0.0017 | -0.0121*** | -0.0210*** |
| | (0.0007) | (0.0032) | (0.0007) | (0.0034) | (0.0010) | (0.0048) | (0.0007) | (0.0041) |
| Experience: class 3 | 0.0035*** | 0.0079 | 0.0084*** | 0.0126** | -0.0049*** | 0.0084 | -0.0060*** | -0.0201*** |
| | (0.0006) | (0.0050) | (0.0006) | (0.0054) | (0.0009) | (0.0071) | (0.0007) | (0.0065) |
| Experience: class 4 | 0.0125*** | 0.0115*** | 0.0194*** | 0.0092*** | -0.0151*** | 0.0102*** | -0.0125*** | -0.0217*** |
| | (0.0005) | (0.0024) | (0.0005) | (0.0025) | (0.0007) | (0.0037) | (0.0005) | (0.0031) |
| Experience: class 5 | 0.0042*** | 0.0015 | 0.0075*** | 0.0038 | -0.0004 | 0.0144** | -0.0053*** | -0.0238*** |
| | (0.0005) | (0.0045) | (0.0005) | (0.0045) | (0.0008) | (0.0057) | (0.0007) | (0.0059) |
| Experience: class 6 | 0.0197*** | 0.0146*** | 0.0242*** | 0.0102*** | -0.0183*** | 0.0173*** | -0.0202*** | -0.0168*** |
| | (0.0007) | (0.0029) | (0.0007) | (0.0030) | (0.0009) | (0.0044) | (0.0008) | (0.0039) |
| Experience: class 7 | 0.0130*** | 0.0136*** | 0.0148*** | 0.0137*** | -0.0049*** | 0.0012 | -0.0174*** | -0.0282*** |
| | (0.0005) | (0.0030) | (0.0005) | (0.0030) | (0.0007) | (0.0041) | (0.0006) | (0.0036) |
| Experience: class 8 | 0.0051*** | 0.0073 | 0.0098*** | 0.0152*** | -0.0005 | -0.0153** | -0.0108*** | -0.0223*** |
| | (0.0006) | (0.0054) | (0.0006) | (0.0058) | (0.0008) | (0.0066) | (0.0007) | (0.0073) |
| Experience: class 9 | 0.0198*** | 0.0242*** | 0.0226*** | 0.0191*** | -0.0162*** | 0.0130** | -0.0239*** | -0.0320*** |
| | (0.0006) | (0.0035) | (0.0006) | (0.0036) | (0.0008) | (0.0052) | (0.0008) | (0.0045) |
| Experience: class 10 | 0.0234*** | 0.0256*** | 0.0284*** | 0.0224*** | -0.0197*** | -0.0014 | -0.0237*** | -0.0401*** |
| | (0.0011) | (0.0051) | (0.0012) | (0.0052) | (0.0014) | (0.0083) | (0.0013) | (0.0067) |
| Experience: NC | 0.0048*** | -0.0052 | 0.0106*** | 0.0009 | -0.0057*** | 0.0215** | -0.0084*** | 0.0016 |
| | (0.0006) | (0.0056) | (0.0007) | (0.0056) | (0.0009) | (0.0086) | (0.0008) | (0.0074) |
| Experience: PS | 0.0419*** | 0.0472* | 0.0513*** | 0.0368 | -0.0390*** | 0.0165 | -0.0314*** | -0.0824*** |
| | (0.0031) | (0.0258) | (0.0032) | (0.0247) | (0.0041) | (0.0313) | (0.0033) | (0.0277) |
| Experience: non-RJ | 0.0184*** | 0.0120*** | 0.0223*** | 0.0058* | -0.0156*** | 0.0211*** | -0.0184*** | -0.0169*** |
| | (0.0005) | (0.0032) | (0.0005) | (0.0031) | (0.0007) | (0.0046) | (0.0006) | (0.0038) |
| adj. $R^2$ | 0.668 | 0.435 | 0.624 | 0.370 | 0.641 | 0.458 | 0.729 | 0.540 |
| Sample | main | displaced | main | displaced | main | displaced | main | displaced |
| Year FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Person FE | yes | no | yes | no | yes | no | yes | no |
| Observables | no | yes | no | yes | no | yes | no | yes |
| Firm FE | yes | yes | yes | yes | yes | yes | yes | yes |
| $N$ | 8971906 | 106754 | 8971906 | 106754 | 8971906 | 106754 | 8971906 | 106754 |

*Notes*: Outcome variables capture non-routine analytic, non-routine interpersonal, routine cognitive and routine manual task content. Task content is as defined in the text. Workers born in 1976 or later. Firm classes 1–10 represent our firm categorization based on unexplained earnings growth distributions. NC are small firms not categorized by the clustering algorithm. PS is the public sector in each data set. Specifications with the main sample are estimated following equation (8). Specifications with the displaced sample are estimated following equation (14). 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 A16:** Wage variance decomposition, Rio de Janeiro and Veneto

| | Rio de Janeiro | | Veneto | |
|---|---|---|---|---|
| | Heterogeneous | Homogeneous | Heterogeneous | Homogeneous |
| | (1) | (2) | (3) | (4) |
| $Var(y_{it})$ | 0.45247 [100.0] | 0.45247 [100.0] | 0.14116 [100.0] | 0.14116 [100.0] |
| $Var(\alpha_i)$ | 0.14349 [31.7] | 0.14614 [32.3] | 0.05216 [37.0] | 0.05278 [37.4] |
| $Var(\psi_j)$ | 0.11390 [25.2] | 0.11692 [25.8] | 0.05328 [37.7] | 0.05423 [38.4] |
| $Var(\gamma Exp)$ | 0.01506 [3.3] | 0.00988 [2.2] | 0.00338 [2.4] | 0.00149 [1.1] |
| $Var(_{it}\beta)$ | 0.01336 [3.0] | 0.01412 [3.1] | 0.00742 [5.3] | 0.00741 [5.2] |
| | | | | |
| $2 \times Cov(\alpha_i, \psi_j)$ | 0.04896 [10.8] | 0.05517 [12.2] | -0.01770 [-12.5] | -0.01690 [-12.0] |
| $2 \times Cov(\alpha_i, \gamma Exp)$ | 0.00655 [1.4] | 0.00641 [1.4] | 0.00195 [1.4] | 0.00249 [1.8] |
| $2 \times Cov(\alpha_i, X_{it}\beta)$ | -0.00821 [-1.8] | -0.00910 [-2.0] | -0.00910 [-6.4] | -0.00887 [-6.3] |
| $2 \times Cov(\psi_j, \gamma Exp)$ | 0.01668 [3.7] | 0.00898 [2.0] | 0.00222 [1.6] | 0.00076 [0.5] |
| $2 \times Cov(\psi_j, X_{it}\beta)$ | 0.00344 [0.8] | 0.00403 [0.9] | -0.00082 [-0.6] | -0.00069 [-0.5] |
| $2 \times Cov(\gamma Exp, X_{it}\beta)$ | 0.00429 [0.9] | 0.00441 [1.0] | 0.00148 [1.0] | 0.00122 [0.9] |
| | | | | |
| $Var(\eta_{it})$ | 0.08504 [18.8] | 0.08586 [19.0] | 0.04409 [31.2] | 0.04447 [31.5] |

*Notes*: Shares of the (log) wage variance explained by the various components of equation (16). The first row denotes the overall wage variance. The numbers in brackets indicate the percent of the overall variance accounted for by each of the components in equation (16). Columns (1) and (3) show results using our approach with heterogeneous experiences. Columns (2) and (4) show corresponding results when making an "homogeneous experience" assumption.

**Table A17:** Workforce characteristics in each class of firms. Rio de Janeiro, 1994–2010.

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

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

**Table A18:** Workforce characteristics in each class of firms. Veneto, 1984–2001.

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

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

**Table A19:** Firm-level characteristics, by firm class. Rio de Janeiro, 1994–2010.

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

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

**Table A20:** Firm-level characteristics, by firm class. Veneto, 1984–2001.

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

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

**Table A21:** Firm-level correlations between actual and predicted $\gamma_k$.

**(a) All firms**

| | Rio de Janeiro, 1994–2010 | Veneto, 1984–2001 |
|---|---|---|
| $Corr_j\left(\hat{\gamma}_{k(j)}, \hat{\gamma}_{\hat{k}(j)}\right)$ | 0.245 | 0.361 |
| $Corr_j\left(\hat{\gamma}_{k(j)}, \hat{\gamma}_{\hat{k}(j)} \vert k(j) \neq \hat{k}(j)\right)$ | 0.080 | 0.162 |

**(b) Firms with $\geq$ 50 employees**

| | Rio de Janeiro, 1994–2010 | Veneto, 1984–2001 |
|---|---|---|
| $Corr_j\left(\hat{\gamma}_{k(j)}, \hat{\gamma}_{\hat{k}(j)}\right)$ | 0.306 | 0.382 |
| $Corr_j\left(\hat{\gamma}_{k(j)}, \hat{\gamma}_{\hat{k}(j)} \vert k(j) \neq \hat{k}(j)\right)$ | 0.111 | 0.186 |

*Notes*: Summary of the results of the random forest classification exercise described in Section 8, Table 3. Each firm $j$ in the prediction data set is associated with its actual firm class, $k(j)$, and the one predicted by the random forest algorithm, $\hat{k}(j)$. The prediction for firm $j$ is correct if $k(j) = \hat{k}(j)$. Let $\gamma_m$ be the on-the-job learning parameter corresponding to firm class $m$, and $\hat{\gamma}_m$ its baseline estimate from Figure 2. This Table shows the firm-level correlation between $\hat{\gamma}_{k(j)}$ and $\hat{\gamma}_{\hat{k}(j)}$; for all firms (first and third rows), and for firms that the algorithm classifies incorrectly (second and fourth rows).

## B Comparison to heterogeneous returns by firms' observable characteristics

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

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

In the first two panels of Figure B1, we compare the heterogeneity in returns arising from our proposed firm classification to one arising from classifying firms based on their size—also using ten discrete categories ranging from firms with fewer than 10 workers to those with more than 1,000. Experiences acquired in firms of different sizes are differentially valuable. In Rio de Janeiro, the value of experience is initially increasing in the size of the firm where it was acquired, and then flattens for the largest size categories. Veneto presents evidence of a U-shaped relationship, with somewhat greater returns to experiences acquired in the smallest and the largest firms. All in all, our firm categorization captures heterogeneity in returns that is much richer than that captured by size in both countries (i.e., the slope of heterogeneous returns based on our proposed classification is steeper than that based on firm size).

The middle panels of Figure B1 show that a similar conclusion arises when comparing our proposed classification to one based on the size of the municipality where a firm is located. The relationship between returns to experience and size of the municipality where such experience was acquired is essentially flat in Rio de Janeiro, and increasing in Veneto. However, even in Veneto, returns based on a municipality size classification are significantly more homogeneous than those based on our proposed firm classification.

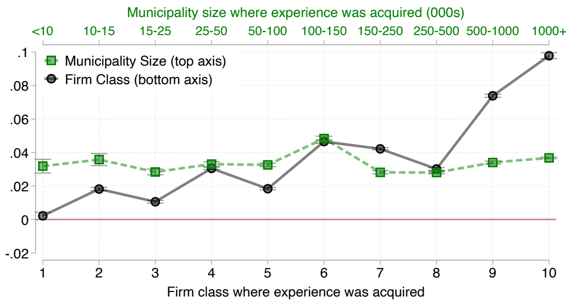
Lastly, the bottom panel of Figure B1 shows that, in Rio de Janeiro, our firm classification also captures richer heterogeneity than a classification based on level of education of the firm's workforce. Returns to experience are increasing in coworkers' education level at the firm where experience was acquired but, yet again, the slope of this gradient is flatter than the one arising from our proposed firm classification.

**Figure B1:** Returns to experiences acquired in different firm classes: comparison to firm categorization based on firm size, city size and coworkers' education.

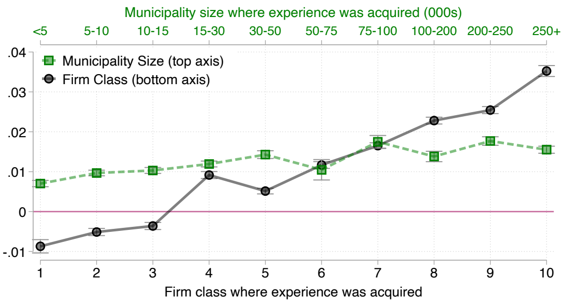
**(a)** Firm Size, Rio de Janeiro, 1994–2010.


**(b)** Firm Size, Veneto, 1984–2001.

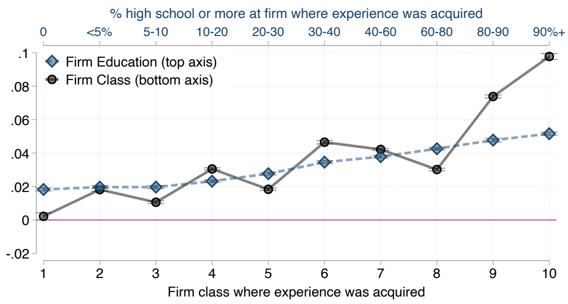

**(c)** City Size, Rio de Janeiro, 1994–2010.




**(d)** City Size, Veneto, 1984–2001.




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




*Notes:* Across all panels, the black plot presents our baseline estimates of returns to experiences acquired in different firm classes, described in Figure 2. In panels (a) and (b), the orange plot presents the estimated coefficients and 95% confidence intervals of the returns to experiences acquired in firms of different sizes. The green lines in panels (c) and (d) present corresponding evidence for experiences acquired in firms located in municipalities of different sizes. The blue plot in the panel (e) presents evidence on the returns to experiences acquired across firms categorized by the fraction of coworkers with a high school degree or more. In all panels, the outcome variable for Rio de Janeiro is log hourly wages and log daily wages for Veneto. Standard errors are clustered at the person level. Corresponding Appendix regression table: Table B1.

**Table B1:** Returns to experiences acquired in different firms, categorizing firms based on observables: firm size, city size, and workforce education.

| | (1)<br>Firm Size,<br>Rio de Janeiro | (2)<br>Firm Size,<br>Veneto | (3)<br>City Size,<br>Rio de Janeiro | (4)<br>City Size,<br>Veneto | (5)<br>Education,<br>Rio de Janeiro |
|---|---|---|---|---|---|
| Experience: firm observable, group 1 | 0.0230*** | 0.0129*** | 0.0319*** | 0.0070*** | 0.0182*** |
| | (0.0003) | (0.0003) | (0.0021) | (0.0004) | (0.0004) |
| Experience: firm observable, group 2 | 0.0270*** | 0.0088*** | 0.0358*** | 0.0097*** | 0.0197*** |
| | (0.0004) | (0.0004) | (0.0018) | (0.0004) | (0.0005) |
| Experience: firm observable, group 3 | 0.0306*** | 0.0126*** | 0.0284*** | 0.0103*** | 0.0197*** |
| | (0.0005) | (0.0005) | (0.0009) | (0.0004) | (0.0005) |
| Experience: firm observable, group 4 | 0.0354*** | 0.0111*** | 0.0330*** | 0.0119*** | 0.0232*** |
| | (0.0005) | (0.0005) | (0.0007) | (0.0004) | (0.0004) |
| Experience: firm observable, group 5 | 0.0395*** | 0.0099*** | 0.0326*** | 0.0143*** | 0.0277*** |
| | (0.0005) | (0.0004) | (0.0005) | (0.0005) | (0.0004) |
| Experience: firm observable, group 6 | 0.0459*** | 0.0090*** | 0.0483*** | 0.0105*** | 0.0346*** |
| | (0.0007) | (0.0006) | (0.0007) | (0.0013) | (0.0004) |
| Experience: firm observable, group 7 | 0.0468*** | 0.0071*** | 0.0282*** | 0.0175*** | 0.0379*** |
| | (0.0006) | (0.0007) | (0.0005) | (0.0008) | (0.0004) |
| Experience: firm observable, group 8 | 0.0422*** | 0.0139*** | 0.0280*** | 0.0138*** | 0.0426*** |
| | (0.0005) | (0.0006) | (0.0004) | (0.0007) | (0.0004) |
| Experience: firm observable, group 9 | 0.0424*** | 0.0130*** | 0.0340*** | 0.0177*** | 0.0477*** |
| | (0.0005) | (0.0006) | (0.0005) | (0.0005) | (0.0005) |
| Experience: firm observable, group 10 | 0.0383*** | 0.0151*** | 0.0368*** | 0.0155*** | 0.0516*** |
| | (0.0004) | (0.0006) | (0.0003) | (0.0005) | (0.0005) |
| Adj. $R^2$ | 0.759 | 0.600 | 0.759 | 0.600 | 0.759 |
| Within adj. $R^2$ | 0.014 | 0.012 | 0.013 | 0.013 | 0.015 |
| Person FE | yes | yes | yes | yes | yes |
| Firm FE | yes | yes | yes | yes | yes |
| SE clusters (persons) | 1,568,606 | 483,799 | 1,568,990 | 483,799 | 1,568,990 |
| $N$ | 9,165,554 | 3,608,754 | 9,168,318 | 3,608,754 | 9,168,318 |

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

# C Firms' Management Practices

The empirical evidence presented in Section 8 indicates that observed characteristics explain a limited share of heterogeneous learning opportunities across firms. A natural question is whether learning opportunities are hard to predict using firm-level characteristics, or only so when limited to the ones that we observe in our data. In this context, we analyze—for a restricted number of firms in our sample—the explanatory power of another dimension of firm heterogeneity, namely, firms' management practices. These measures have been found to be are strongly correlated with productivity (Bloom et al., 2019) and the retention of good workers (Cornwell et al., 2021).

We employ the World Management Survey (WMS) data, which surveys manufacturing firms with 50–5,000 workers on their management practices. We follow Cornwell et al. (2021) and consider a measure of firms' structured management practices, which capture the extent to which firms have formal management processes in place. We use data from the 2008 and 2013 survey waves carried out in Brazil, which covered 585 and 560 firms, respectively, with 331 firms being surveyed in both rounds. We match these firms to RAIS data in Rio de Janeiro from 1994 through 2010 using their unique identifier (CNPJ), yielding a sample of 76 firms.

We estimate an OLS regression to examine the relationship between management scores and our firm classification.[1] The first column of Table C1 shows no systematic relationship between management scores and our firm classification, indicating that differential opportunities across firms are not accounted for by their management practices. As a robustness check, we re-estimate the empirical approach outlined in Section 3.2 for the entire country, allowing us to match 602 firms across RAIS and WMS. In the second column of Table C1, we further show the lack of correlation between firms' management practices and our their learning opportunities.

[1] We use the average score for firms surveyed in both waves. Results are similar when using other definitions.

**Table C1:** Management Practices and Firm Classes: Evidence from WMS in Brazil

| | Rio de Janeiro<br>(1) | Brazil<br>(2) |
|---|---|---|
| Firm class 2 | 0.672 | -0.012 |
| | (0.530) | (0.162) |
| Firm class 3 | 0.367 | 0.244 |
| | (0.529) | (0.149) |
| Firm class 4 | -0.300 | 0.269* |
| | (0.502) | (0.154) |
| Firm class 5 | 0.181 | 0.198 |
| | (0.508) | (0.148) |
| Firm class 6 | 0.694 | -0.246 |
| | (0.646) | (0.178) |
| Firm class 7 | 0.631 | -0.365* |
| | (0.533) | (0.213) |
| Firm class 8 | 0.191 | 1.730*** |
| | (0.529) | (0.138) |
| Firm class 9 | 0.501 | 0.146 |
| | (0.526) | (0.148) |
| Firm class 10 | 0.978* | 0.181 |
| | (0.502) | (0.179) |
| Constant | 2.467*** | 2.492*** |
| | (0.502) | (0.138) |
| $R^2$ | 0.121 | 0.063 |
| $N$ | 76 | 602 |

*Notes*: This table shows the relationship between firm-level management techniques and our classification of firms' learning opportunities. We use the World Management Survey data and follow Cornwell et al. (2021) by considering firms' 'structured management practices,' which are rated on a scale from 1 to 5. The first column includes results for the matched RAIS-WMS sample in Rio de Janeiro where the explanatory variables (firm classes 1–10) represent our firm categorization based on unexplained earnings growth distribution in Rio. In the second column, we categorize all firms in Brazil into ten firm classes and examine their relationship to management scores in the entire country. Firms in class 1 are the omitted category. Robust standard errors are presented in parenthesis. *p<0.10; **p<0.05; ***p<0.01.