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across Firms**

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ABSTRACT

Differences in On-the-Job Learning across Firms*

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” using a clustering methodology which groups together firms with similar distributions of unexplained earnings growth. Equipped with this categorization of firms—which our conceptual framework interprets as skill-learning classes—we document three main results. First, Mincerian returns to experience vary substantially across experiences acquired in different firm classes, and the magnitude of this heterogeneity is associated with significant shifts across the distribution of early-career wage growth. Second, past experience at firms with better on-the-job learning is associated with subsequent jobs featuring greater non-routine task content. Third, firms’ observable characteristics only mildly predict on-the-job learning opportunities. Our findings hold among involuntarily displaced workers who have no seniority at their new jobs, which is consistent with a portable skills interpretation.

JEL Classification: J24, J31

Keywords: human capital, firms, on-the-job learning

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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. We believe our parallel analysis in two very different economies is valuable: the broadly consistent findings we uncover in both countries speak to the generality of firm heterogeneity in on-the-job learning as a labor market phenomenon.

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 estimates 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 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), 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 (Dustmann and Meghir, 2005), and we exploit a “clean” separation between workers' current 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 categorization capturing differences in the learning of portable skills, but hard to reconcile

¹In 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.

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. Moreover, these results hold in the sample of displaced workers, further highlighting how changes in task contents remain when workers change employers.

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 are also consistent with skill generality.

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 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 around 24% 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-

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

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

the-job learning. First, we find no meaningful relationship between firms' learning classes and their pay premia. Second, in both Rio and Veneto, larger firms are somewhat less likely to belong to the lowest-learning class. Lastly, 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.

Lastly, we quantify the importance of heterogeneous experiences in shaping workers' early career outcomes in two additional ways. First, we compute the growth rates associated with counterfactual trajectories across firm classes, and place them on the empirical distribution of annualized total growth between ages 18–mid-30s. Being exclusively employed in the lowest-learning firm class is associated with the 16th and 18th percentile of early-career growth in Rio de Janeiro and Veneto, respectively, whereas being exclusively employed in the top-learning class throughout the early career is associated with reaching the 78th and 66th percentiles. Second, we measure how much of the variance of realized earnings is accounted for by differential access to heterogeneous experiences. By the mid-30s, heterogeneous experiences account for over 6% and 4% of the earnings variance in Rio de Janeiro and Veneto, respectively. Crucially, we would reach a very different conclusion if we assumed all experiences were homogeneous, as the corresponding shares for the variance of earnings accounted for by homogeneous experience equal 3.5% and 1%, respectively.

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, previous work has explored how learning-by-doing varies depending on workplace characteristics such as exporter status ([Macis and Schivardi, 2016](#)), the quality of coworkers ([Jarosch et al., 2021](#); [Nix, 2020](#)), 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](#)). 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. \(1999, 2006\)](#) estimate firm-varying returns to tenure,

⁴By 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](#)).

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

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 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.

A contemporaneous paper that tackles a similar question to this one but following a different methodological approach is Gregory (2021). She 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 (Rio de Janeiro 1994-2010 and Veneto 1984-2001).

The rest of this paper is organized as follows. Section 2 describes our administrative datasets from Brazil and Italy. Section 3 lays out our conceptual and empirical frameworks regarding heterogeneity across firm classes in learning opportunities, and the classification of firms using a clustering algorithm. Section 4 presents our main results on heterogeneous returns to experiences acquired in different firm classes, including results for the sample of displaced workers. Section 5 documents the link between heterogeneous experiences and tasks. Section 6 investigates how well can firm observables predict firms' learning class. Section 7 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.

⁶By 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).

⁷In 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 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

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, namely, 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.

levels, we focus on one state as our unit of analysis.

⁸Given the distribution of educational attainment in Brazil, we classify workers as high school dropouts, high school graduates, or having gone beyond high school.

⁹Following [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.

¹⁰Previous 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 4,196,508 unique workers in Rio de Janeiro and 1,163,473 workers in Veneto. Our main sample covers young workers who are ever employed in Rio de Janeiro or Veneto, yet in both cases we also observe their employment spells in other parts of the country and include 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 6.35 full-year equivalents employed in the formal sector and holds 3.5 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 (1)	Veneto (2)
Share Male	0.582	0.540
Age at Entry	20.76	20.49
Cumulative Experience	6.35	8.15
Cumulative Number of Jobs	3.51	3.30
Annualized Wage Growth (Average)	0.068	0.031
Annualized Wage Growth (Median)	0.055	0.023
Number of Workers	4,196,508	1,163,473
Observations	20,768,019	7,866,390

Notes: 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 299,249 and 94,031 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 3,075 involuntary displacement events during our period of interest, which affect 242,718 workers in our sample of young workers. In Veneto, meanwhile, 2,844 firms either shut down or undergo a mass layoff, affecting 70,149 young workers. Across Rio and Veneto, 85.3% and 74.2% of displaced workers eventually re-enter the sample, whereas 60.2% and 64.4% 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:

$$\ln H_{it} = \alpha_i + h_{it}, \quad (1)$$

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

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:

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

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

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

¹¹This 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:

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

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

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 ψ_j :

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

Log earnings are thus given by:

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

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

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

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:

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

where ψ_j are firm fixed effects, α_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 η_{it} is a mean zero error term.

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

¹²The $\text{Exp}(m)_{it}$ 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 $\gamma_1 = \dots = \gamma_K$). 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 α_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 ψ_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 γ_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 η_{it} —that is, components not already captured by person fixed effects α_i nor contemporaneous employer fixed effects ψ_j —must be uncorrelated with experience stocks across firm classes. That is, we assume that η_{it} satisfies the strict exogeneity assumption:

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

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

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

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 ε_{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., $\gamma_1 = \dots = \gamma_K$), 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 $\{\gamma_m\}_{m=1}^K$,

¹³We 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 α_i . That is, we include the term $\sum_{m=1}^K \delta_{m,i} \cdot \text{Exp}(m)_{it}$ in our estimating equation, where we parametrize $\delta_{m,i} = \alpha_i \cdot \delta_m$. Second, we estimate equation (8) allowing for heterogeneous returns across workers' characteristics which may be related to their learning ability, 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, ψ_j , and baseline human capital, α_i . Earnings growth for worker i who stays at firm j between $t - 1$ and t , g_{ijt} , amounts to:

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

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:

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

where $k(1), \dots, k(J)$ is the classification of firms into classes, F_k are distribution functions, n_j is the number of worker-years in firm j , and λ is a measure supported on a discrete grid. Note that classifying firms based on earnings *growth* according to equation (12), is a modi-

fication 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:

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

where $g_{ijt} \equiv \ln y_{i,t} - \ln y_{i,t-1}$ (y is hourly wage in Brazil and daily wage in Veneto), δ_t are year fixed effects, and Z_{it} includes a quadratic polynomial in age and a gender dummy in Veneto; in Brazil, additionally, Z_{it} includes a quadratic polynomial of years of education and an interaction term between years of education and age.¹⁵ The residual $\tilde{g}_{ijt} \equiv g_{ijt} - Z'_{it}\hat{\theta} - \hat{\delta}_t$ 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

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

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

¹⁶Before 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.

¹⁷For 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.

¹⁸The 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: $\frac{Var_k[E_g(g|\text{firm-class}=k)]}{Var_j[E_g(g|\text{firm}=j)]}$.

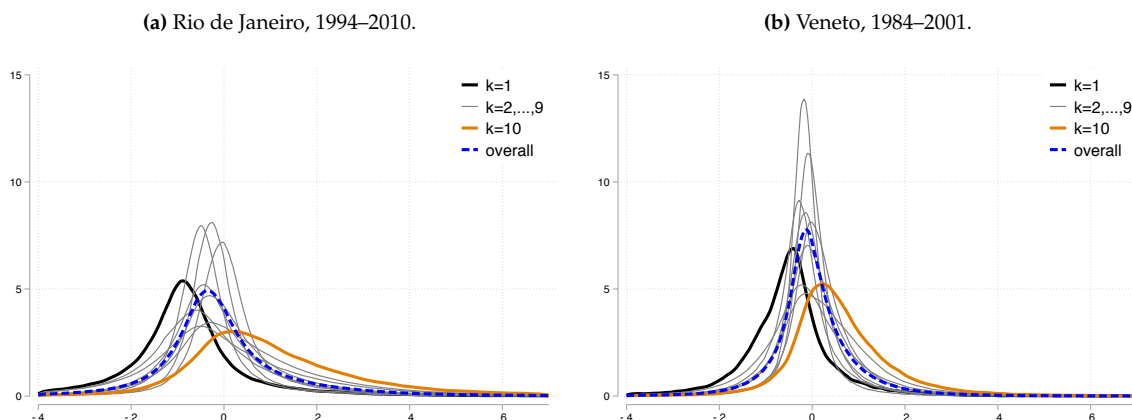
around 60% for $K = 10$. The gains in this ratio from increasing the number of firm classes past $K = 10$ are not large: the relationship asymptotes at about 65% for Rio de Janeiro and 70% for Veneto.

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.

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 -0.095 and 0.053, while the equivalent moments in firm-class 10 are 0.128 and 0.080 (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 (1.7-2.1%), along with a far larger share to class 7 (17.7-19.9%) 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 about 4% of all person-year observations in both Rio de Janeiro and Veneto.

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



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.

¹⁹Figures 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
	<u>Rio de Janeiro, 1994–2010</u>										
% person-years	2.13	8.92	7.52	20.13	10.21	9.69	17.73	7.31	9.40	2.86	4.10
% firms	3.10	3.32	6.87	4.30	8.29	3.09	5.01	7.28	4.22	2.79	51.74
	<u>Veneto, 1984–2001</u>										
% person-years	1.66	7.44	6.69	9.33	17.67	10.50	19.85	10.07	9.73	3.17	3.88
% firms	2.61	5.22	4.49	5.10	4.70	5.21	4.35	5.63	5.05	4.88	52.74

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 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 0.6%, whereas a year of experience at a class-9 or class-10 firm yields returns of 7.3% 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 -0.75%, while returns to class-10 firm experience reach 3.5%.²¹

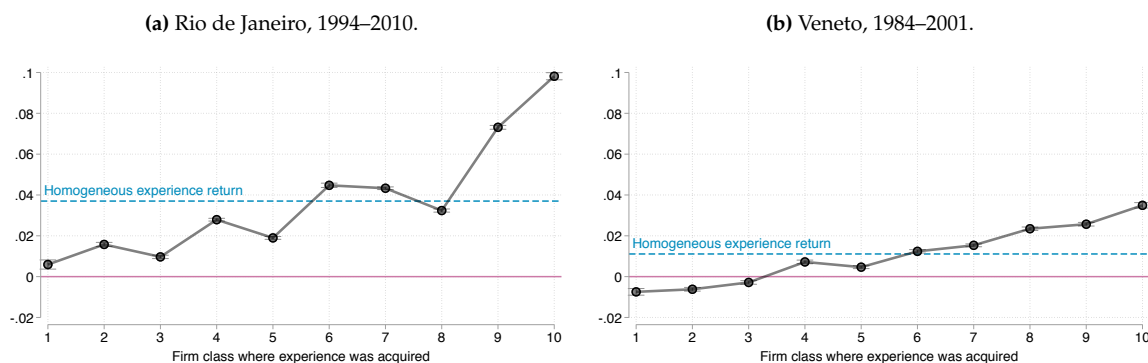
In both Rio de Janeiro and Veneto, the returns to experiences acquired in intermediate firm classes lie between class 1 (i.e., “lowest-learning” firms) and class 10 (i.e., “top learning” firms), with a gradient between returns and firm class which is generally increasing.²² In Rio de Janeiro, returns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

²⁰Understanding 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.

²¹Tables 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.

²²The returns-firm class gradient is not exactly 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; $N=8,754,064$; number of persons = 1,510,168. Veneto: outcome is log daily wage; sample composed of private sector observations, workers born in 1966 or later while aged 18–35; $N=3,614,154$; number of persons = 484,953. Corresponding Appendix regression tables: Tables A2 and A3.

erogeneity 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. All baseline results are robust to different 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) (see Tables A4 and A5), or 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 observations, 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 learning of 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

²³A 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.

²⁴The 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.

²⁵Figure 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 comparable to the approach in Veneto.

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.

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

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

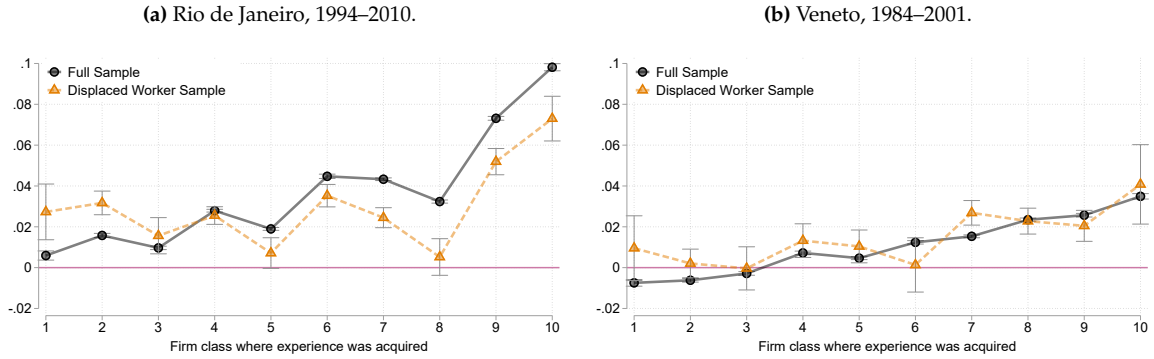
where i indexes displaced workers, y_i is the first post-displacement wage, $\psi_{j(i)}$ are fixed effects for the firm where worker i re-enters employment, X_i are workers’ observed characteristics and time to re-entry, $\text{Exp}(m)_i$ is the amount of experience worker i had acquired in firms of 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 $\{\gamma_1^D \dots \gamma_K^D\}$ 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 5.2% and 7.3%, 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% and 4%, 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 evidence that our firm classification captures differences in on-the-job learning of portable skills.

Tenure. The analysis on displaced workers allays potential concerns of tenure effects confounding our estimates of heterogeneous experience returns (Topel, 1991; Altonji and Williams, 2005; Dustmann and Meghir, 2005), as displaced workers’ tenure is exogenously set to zero. To 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 in both countries. As such, our key result—heterogeneous returns to experiences acquired across firm classes—remains unchanged when explicitly controlling for tenure in the full sample.

²⁶In 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).

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



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; $N=102,459$. Veneto: outcome is log daily wage; $N=26,236$. Corresponding Appendix regression table: Table A7.

4.3 Heterogeneous returns by unobserved skills, education, and occupation

We now estimate 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:

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

where α_i represents worker fixed effects, and δ_m captures whether higher-skilled workers enjoy larger returns to experience acquired at firm class m .²⁷ We present the results in the

²⁷We estimate equation (15) following the recursive algorithm proposed by De La Roca and Puga (2017). The

first two panels of Figure 4, comparing the estimated returns for individuals at the 25th and 75th 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.

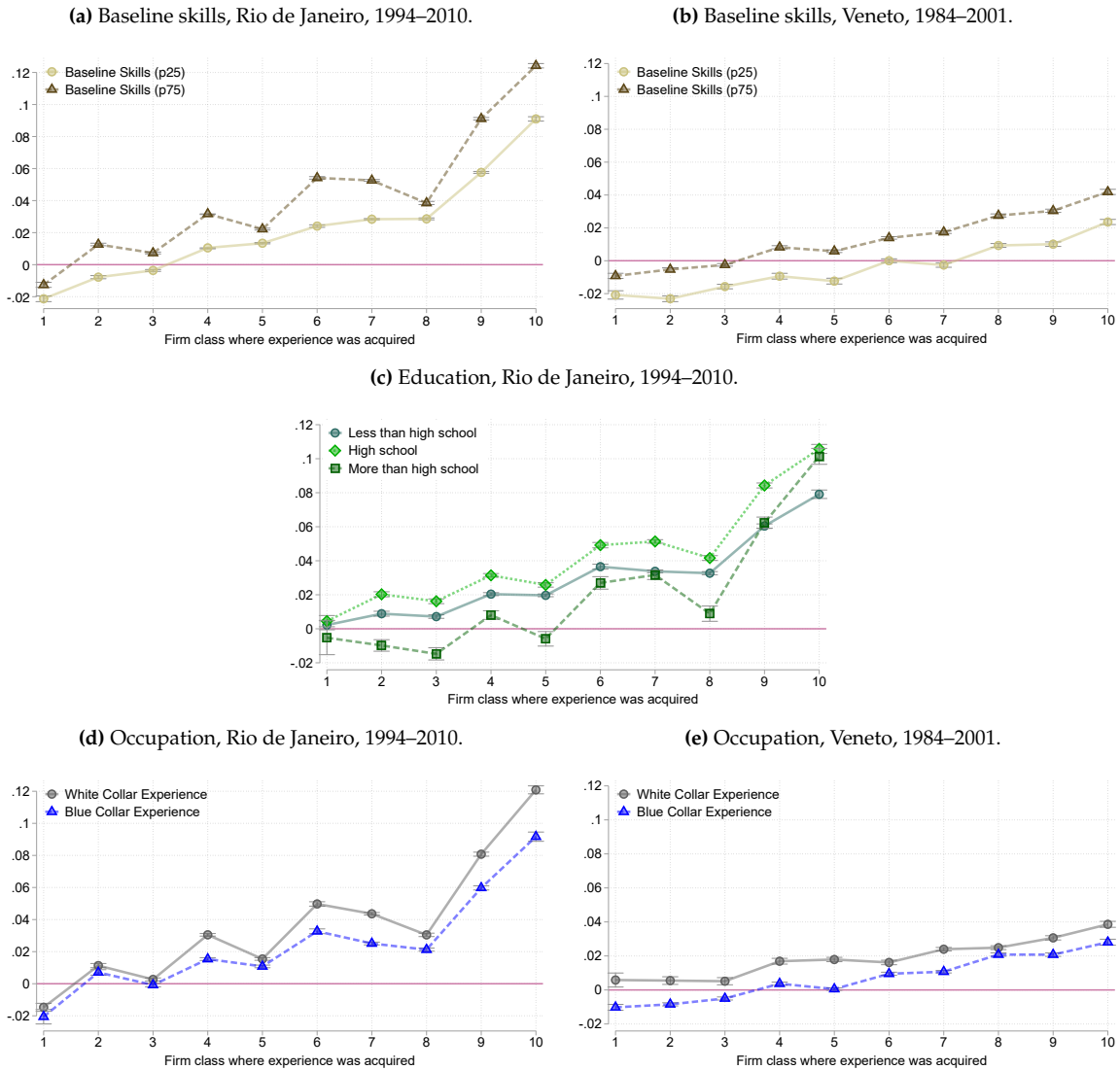
We estimate returns to heterogeneous experiences separately for high school dropouts, high school graduates, and those with more than a high school education and present the results in the third panel of Figure 4. Returns to experiences acquired across firm classes largely follow the same structure across the three groups: an additional year of experience at the “top-learning” firms results in higher hourly wages by close to 7% for high school dropouts, reaching close to 10% for their more educated peers. Although the pattern of heterogeneous returns is broadly similar for the three groups of workers, interestingly, there are some differences in how the education groups disproportionately benefit from different firm classes. The most educated disproportionately benefit from experience acquired at classes 9 and 10, but relatively very little from classes 3, 5, or 8. Compared to more educated individuals, high school dropouts enjoy large relative benefits from classes 5 and 8.

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. We define occupations as either white- or blue-collar following a standard classification using occupational information at the one-digit ISCO level in Brazil.²⁸ In Veneto, we classify managers and white-collar workers into white-collar occupations and apprentices along

first value of α_i in the interaction term follows from the estimated results of equation (8). We then estimate equation (15) and replace the interacted $\hat{\alpha}_i$ with the fixed effect recovered in the previous iteration. We repeat this procedure until the estimated $\hat{\alpha}_i$ parameters converge.

²⁸We 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.

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



Notes: Panels (a) and (b): estimates and 95% confidence intervals of returns to experiences acquired in different firm classes, separately for workers in the 25th and 75th 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 three different education levels (HS dropouts, HS graduates and more than HS) 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 A9. Corresponding Appendix regression table for panel C: Table A10. Corresponding Appendix regression tables for panels (d) and (e): Tables A11 and A12.

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, respectively. In both countries, one year of white-collar experience yields higher returns than one year of blue-collar experience, across all types of firms. 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 ex-

perience. 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.²⁹ 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.

4.4 Comparison to heterogeneous returns by firms’ observable characteristics

We now 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 across experiences acquired in firms of different sizes, in different sized cities, and by coworkers’ education.

In the first two panels of Figure 5, 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 5 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 signifi-

²⁹In Figure A7, we additionally show the returns to experiences acquired in different firm classes are very similar for both genders in both countries.

Figure 5: Returns to experiences acquired in different firm classes: comparison to firm categorization based on firm size, city size and coworkers' education.



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 A13.

cantly more homogeneous than those based on our proposed firm classification.

Lastly, the bottom panel of Figure 5 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.

4.5 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 by extending equation (8) in two ways. First, we include 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.³⁰ We present the results in the first two panels of Figure 6. 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.³¹

In a second extension, we assess whether current employment at “top learning” class-10 firms increases the relative returns to experiences acquired in *any* firm type. We re-estimate equation (8) adding an interaction term for being presently employed at a class-10 firm to all experience types. We show the results in the last two panels of Figure 6. In both countries, we find that working at class-10 firms does not result in higher returns to experiences acquired at lower ranked firms, while returns to experience acquired at class-10 firms are somewhat higher. We thus conclude that returns to experiences at different firm classes remain quite similar, independently of the firm that workers are currently employed at.³²

4.6 Quantifying early-career impacts of heterogeneous experiences

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 quantify the extent to which heterogeneous experiences shape early career outcomes, we carry out two additional complementary analyses. First, we quantify how much of the variance of young workers’ earnings is accounted for by differential access to heterogeneous experiences, and second, we examine the extent to which different counterfactual employment trajectories are associated with heterogeneous long-term wage growth. Both exercises focus on the birth cohort we observe for the longest since age 18.³³

Analysis of variance. In spite of the large differences in heterogeneous returns, if expe-

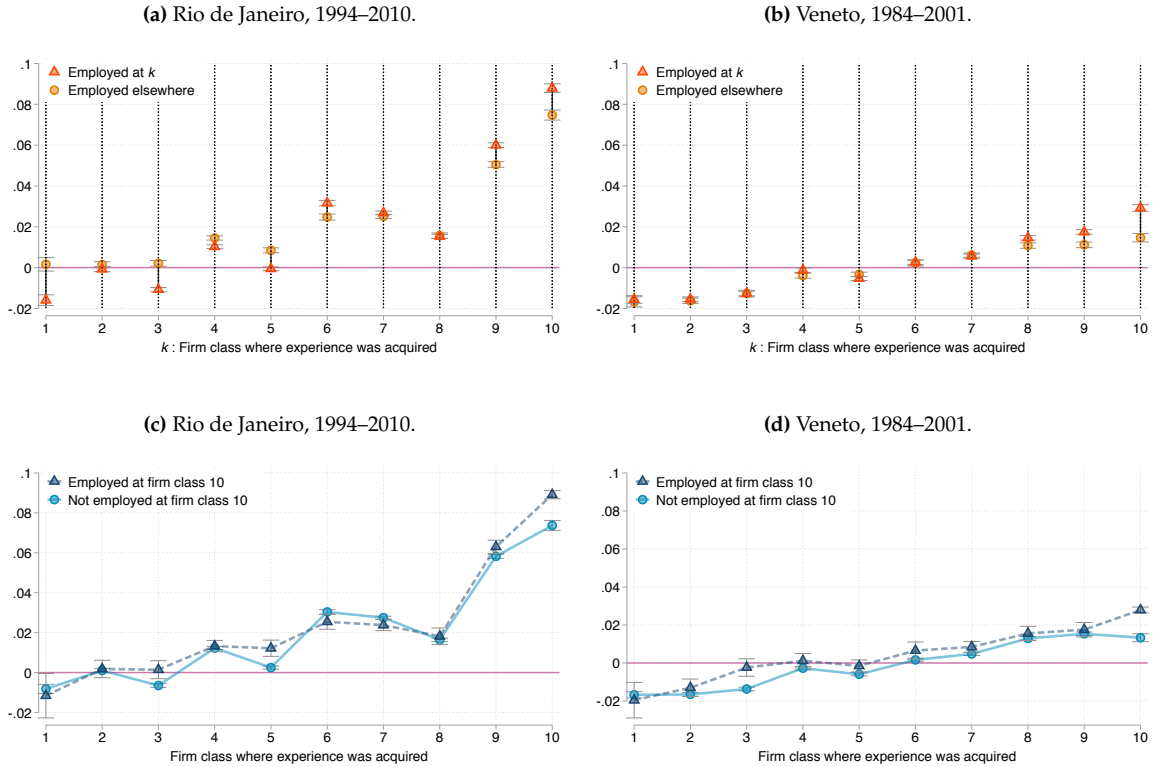
³⁰Note that we are able to study such complementarities in a transparent and tractable way thanks to our empirical approach which discretizes the firm-type space.

³¹Interestingly, these results indicate that the returns to experience at low-class firms are lower if workers are currently employed at such firms (in Rio de Janeiro), with the opposite pattern emerging for high-class firms in both Rio and Veneto.

³²In both specifications, to account for firm-specific returns when studying firm class-times firm class interactions, we additionally control for firm tenure.

³³These are the 1976 birth cohort in Rio de Janeiro who we observe from age 18 through 34, and the 1966 birth cohort in Veneto who we observe between 18–35.

Figure 6: Returns to experiences acquired in different firm classes: allowing richer returns patterns.



Notes: Panels (a) and (b): 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. Rio de Janeiro: outcome is log hourly wage. Veneto: outcome is log daily wage. Panels (c) and (d): 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. 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.

periences in firms with better and worse learning opportunities were similarly distributed across young workers, the returns to experiences would not account for much of the variance in realized earnings. On the other hand, if many workers spent the bulk of their careers at, e.g., type-10 firms and many others at type-1 firms instead, then the returns to experiences could potentially account for a substantial fraction of the variance in realized earnings. Following the notation from equation (8), we consider the following statistic:

$$\rho = \frac{\text{Var} \left(\sum_{m=1}^K \hat{\gamma}_m \cdot \text{Exp}(m)_{it} \right)}{\text{Var} (\ln y_{it})}, \quad (16)$$

where ρ captures the share of the variance of earnings that is explained by the heterogeneity in workers' experiences. We note that we are only able to compute (16) among our sample of young workers—those used to estimate $\{\gamma_m\}_{m=1}^K$ —for whom we observe actual experiences since labor market entry. As a result, ρ is likely lower among young workers vis-à-vis the full workforce since they have limited amounts of experiences which, by construction, cannot be largely different from each other. To illustrate this point and to assess how large

ρ may be in the full population, we compute the following age-varying ρ :

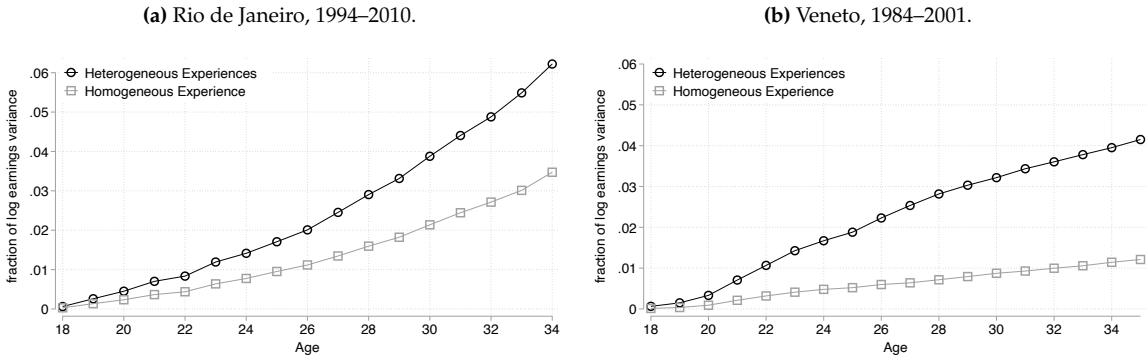
$$\rho_a = \frac{\text{Var} \left(\sum_{m=1}^K \hat{\gamma}_m \cdot \text{Exp}(m)_{it} \mid \text{age}_{it} = a \right)}{\text{Var} \left(\ln y_{it} \mid \text{age}_{it} = a \right)}. \quad (17)$$

Lastly, for comparison purposes, we also compute the version of ρ_a that arises when one imposes an “homogeneous experience” restriction in equation (8):

$$\rho_a^H = \frac{\text{Var} \left(\hat{\gamma} \cdot \text{Exp}_{it} \mid \text{age}_{it} = a \right)}{\text{Var} \left(\ln y_{it} \mid \text{age}_{it} = a \right)}. \quad (18)$$

ρ_a^H captures the share of the variance of earnings which would be explained by experience if one assumed that different experience types were in fact homogeneous, which is an implicit assumption in the classical Mincerian framework.

Figure 7: Variance of returns-to-experiences component over variance of log earnings, by age.



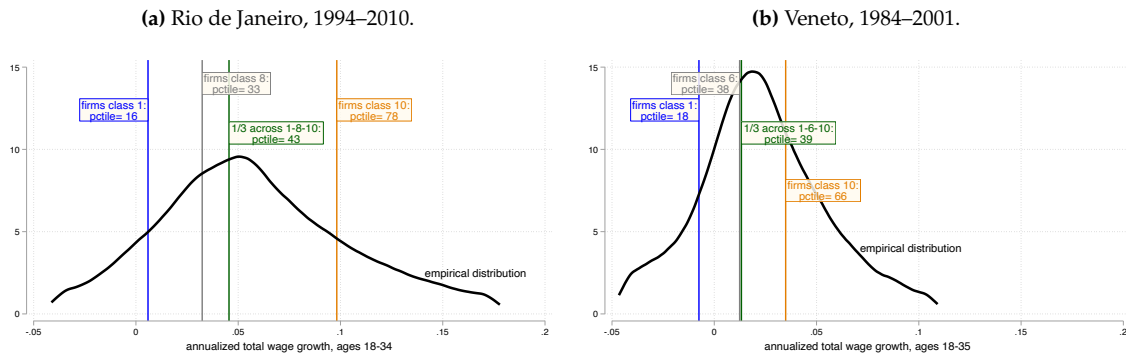
Notes: This figure shows the ratio between the variance of the returns-to-experience component of earnings over the variance of log earnings. The ratio is computed by age, for the birth cohorts of 1976 in Rio de Janeiro and 1966 in Veneto. Black circles represent the ratio when allowing for heterogeneous experiences (defined in the text as ρ_a). Gray squares represent the ratio when imposing homogeneous experience (defined in the text as ρ_a^H).

Figure 7 shows ρ_a (black circles) and ρ_a^H (gray squares), estimated in each of the two datasets using the cohort discussed above. The share of earnings variance accounted for by heterogeneous experiences steadily grows in the early career, reaching 6% and 4% by age 34 in Rio de Janeiro and Veneto, respectively. Heterogeneity across different types of experience plays an important role over and above the accumulation of total experience. This is evidenced by the comparison between ρ_a and ρ_a^H : by age 34, the share of the variance of earnings accounted for by heterogeneous experiences compared to homogeneous experience is roughly double in Rio de Janeiro and roughly four times as large in Veneto.³⁴ We thus emphasize that the conventional approach of assuming all experience to be homogeneous substantially underestimates the fraction of earnings variance that is accounted for by varying experience profiles across workers.

³⁴While the increasing gradient with respect to age in ρ_a and ρ_a^H is important for interpretation, we should not extrapolate beyond the mid-thirties: this would represent an out-of-sample extrapolation since heterogeneous returns are estimated in a sample of 18–35-year old workers.

Counterfactual trajectories and early career wage growth. In the second exercise, we highlight how heterogeneous employment trajectories across firm classes can meaningfully shape individual workers’ early career wage growth outcomes. To do this, we first compute the person-level distribution of annualized total wage growth between age 18 and the mid-30s as follows: for each worker, we take the difference in log earnings between the last time and first time we observe them, and divide over the number of years between such observations.³⁵ Figure 8 shows the empirical distributions of this measure of wage growth.

Figure 8: Annualized earnings growth distribution (age 18–mid 30s): Trajectories across firm classes



Notes: This figure shows where the wage growth resulting from different counterfactual trajectories across firm classes falls in the person-level distribution of annualized total wage growth between ages 18–34 in Rio de Janeiro and 18–35 in Veneto. The distribution of annualized total wage growth is computed for the birth cohort we fully observe the longest since age 18, using the difference in log earnings between the last and first time we observe each worker, divided over the number of years between such observations. See Table A15 for more details. Kernel densities in this figure are truncated at the 5th and 95th percentiles.

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

The results from this exercise, shown in Figure 8 and Table A15, indicate that different trajectories are associated with sizable shifts across the distribution of total wage growth. Workers who are exclusively employed in class 1 firms experience wage growth outcomes at the 16th and 18th percentiles of the wage growth distribution in Rio and Veneto, respectively. Instead, being exclusively employed at the top-learning class-10 firms is associated with reaching the 78th and 66th percentiles of the wage growth distribution in Rio and Veneto, respectively. Meanwhile, workers who are employed exclusively at firms delivering “homogeneous” returns to experience, as well as those with combined experience across firm classes experience early wage growth lying between the 33rd and 43rd per-

³⁵We restrict attention to workers who we observe for the first time before age 30, and for whom there are at least 5 years between their first and last earnings observation.

centiles of the wage growth distribution. We interpret these results as further evidence on the quantitative importance of firm heterogeneity in skill-development and its implications for early-career wage growth.

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.³⁶ 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 9, 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 0.027 and 0.030 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.

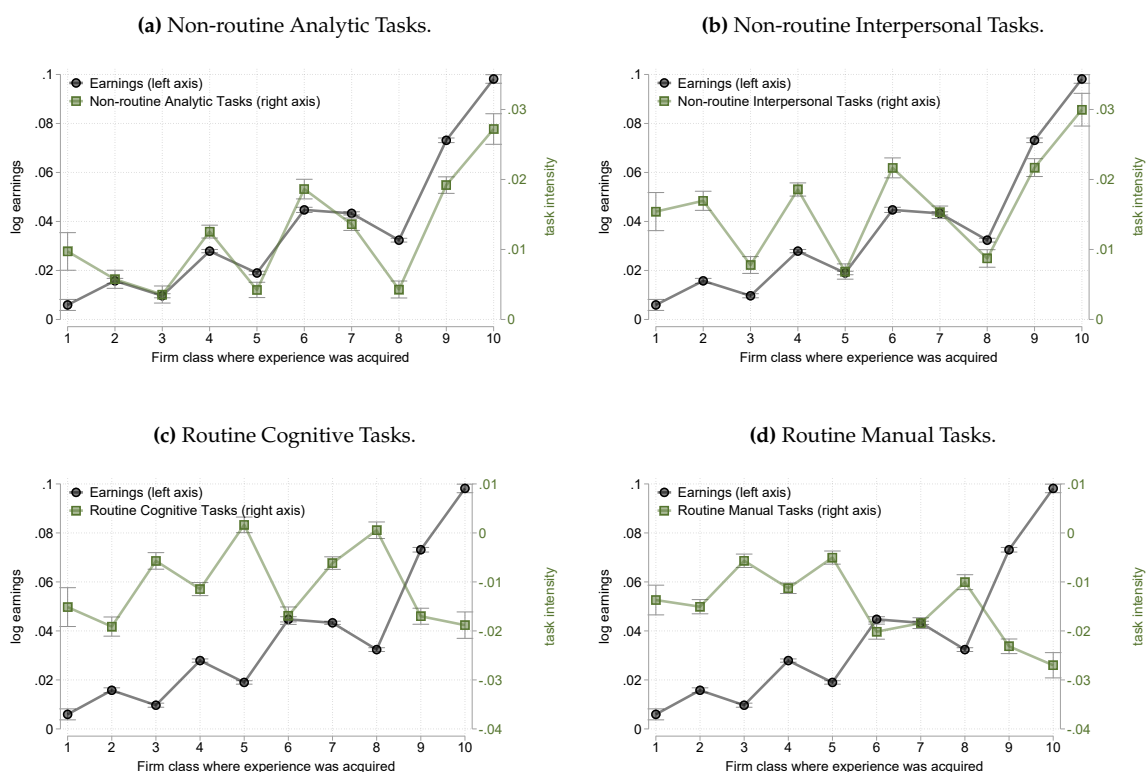
The bottom two panels of Figure 9 show that our heterogeneous experience classification—which is positively correlated with non-routine task intensity—is negatively correlated with routine task intensity.³⁷ All types of experience have associated negative returns in terms of routine tasks intensity—indicating 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.

Following our approach in Section 4, we re-estimate our task-based results using the sample of involuntarily displaced workers. This exercise allows us to ensure that the impacts of heterogeneous experiences on workers' task contents are portable and also present when workers move across firms for exogenous reasons. The results, presented in Figure A8 are quite similar to the results for the full sample described above. Overall, we take results

³⁶Previous 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).

³⁷Measures 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.

Figure 9: 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=8,602,938. Corresponding Appendix regression table: Table A16.

on tasks as providing further evidence of the existence of differential learning opportunities across our firm-class categorization in Rio de Janeiro.³⁸

6 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 ta-

³⁸We have also examined heterogeneity in task returns across workers' education and gender. The estimated task returns are very similar for all three education groups as well as for men and women.

³⁹Using 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 $k = 1, \dots, 10$ are firm classes.

bles with unconditional workforce and firm mean characteristics across firm classes in the Appendix (see Tables A18–A21).

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

Using the data at the firm level (firm is the unit of observation, with characteristics averaged across years), we use half of the sample to train and validate a random forest classification algorithm (Athey and Imbens, 2019). In the other half of the data, we use the algorithm to predict firm class and compare it against its actual classification. We feed the random forest a variety of firm characteristics, but no variables related to employees’ wage growth as this is the input our clustering methodology in Section 3.2 uses to classify firms.⁴⁰

Table 3 shows results from the random forest prediction exercise. In both Rio de Janeiro and Veneto, the algorithm correctly classifies between 24–25% of firms. If we do the same exercise focusing only on large firms (50 employees or more), the algorithm correctly classifies 26% of large firms in Rio and 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.

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	106,168	67,290
Correctly classified by algorithm	24.72%	24.19%
	(b) Firms with ≥ 50 employees	
	Rio de Janeiro, 1994–2010	Veneto, 1984–2001
Number of firms to classify	4,212	1,385
Correctly classified by algorithm	26.12%	32.47%

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.

⁴⁰The 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.

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

Figures 10 and 11 show the estimated multinomial logit probabilities of a firm belonging to each class for Rio de Janeiro and Veneto, respectively (see Figures A9 and A10 for additional variables in Rio de Janeiro, including workforce education). Each characteristic of interest is evaluated at the 25th and at the 75th 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, high- and low-paying firms in Rio de Janeiro—as measured by firm effects $\hat{\psi}_j$ from equation (8)—are equally likely to belong to class 1. Higher-paying firms are somewhat more likely than low-paying firms to belong to class 10, yet the difference is not statistically significant (see Figure 10). In Veneto, high- and low-paying firms are equally likely to belong to class 1, and high-paying firms are only slightly more likely than low-paying firms to belong to class 10 (see Figure 11).

Firms' pay premia are thus not strongly associated with firms' learning opportunities, as captured by our firm classification. If anything, higher-paying firms are slightly more likely to present good learning opportunities (see the unconditional means in Tables A18 and A19). In any case, we find no evidence of a *negative* relationship between learning opportunities and pay premia. Such a negative relationship would have been consistent with models of costly on-the-job training where workers bear at least some of these costs (Becker, 1964; Acemoglu and Pischke, 1999) or compensating differentials more generally (Rosen, 1972).

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 A18). In Veneto, while there is no clear relationship between firm classes and firm size, we find that workers in both classes 1 and 10 have the smallest employers (Table A19). 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 10), and less likely to belong to class 1 and to class 10 in Veneto (Figure 11). 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.

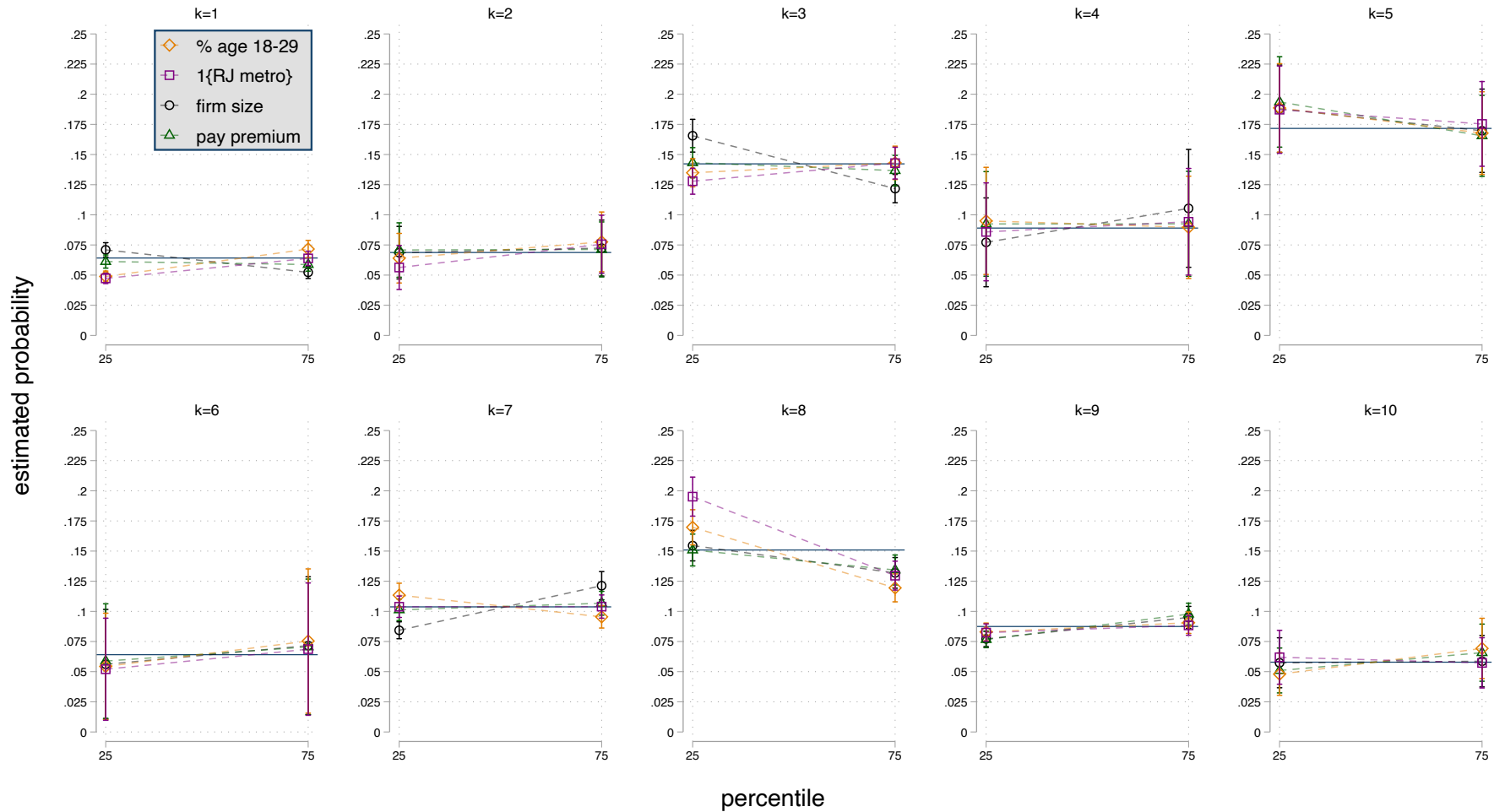
Geographic location. In Brazil, we classify firms with a dummy variable equal to one if located in the metropolitan area of Rio de Janeiro, and zero if elsewhere in the state. In Veneto, we construct a dummy equal to one if a firm is located in one of the five largest

cities: Venezia, Verona, Padova, Vicenza, and Treviso. The share of the workforce employed in the Rio de Janeiro metro area is between 75–86 percent across firm classes (Table A18). 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 number for class 10 is 38 percent (Table A19). 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 10). In Veneto, large-city firms are less likely to belong to class 1 and more likely to belong to class 10 (Figure 11). 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 7, which disproportionately employ lower-education workers (Table A18). In spite of this moderate variation, the workforce at class 10 has the second largest share of workers with more than a high school degree, reaching 18 percent (class 4 has 20 percent). The fact that class 10 has a relatively high share of highly educated workers aligns with existing evidence on learning from highly educated (Nix, 2020) or highly paid (Jarosch et al., 2021) coworkers. We find a similar pattern at the firm level, keeping constant other covariates: Figure A9 shows that a large share of low-educated workers is negatively associated with belonging to class 10 (but also negatively associated with class 1).

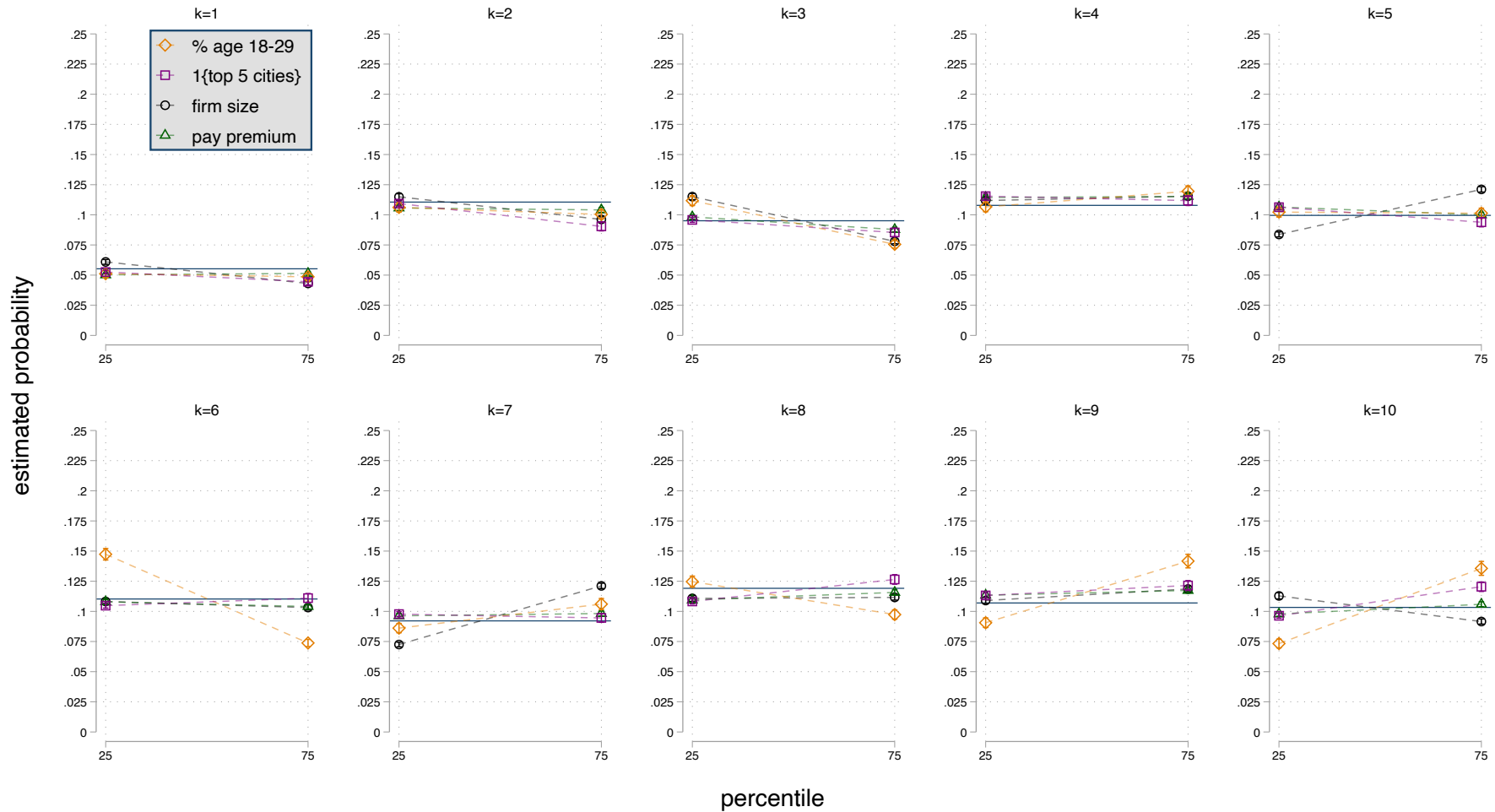
All in all, observed characteristics account for a relatively small share of the difference in firms' on-the-job learning opportunities. In Appendix B, we additionally show that—at least among a small fraction of our sample—firms' management practices are not strongly correlated with the learning opportunities 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 10: 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 ψ_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 11: 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.

7 Conclusion

In this paper, we have documented evidence on earnings and job task contents 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. Our findings are notably consistent across two rather different economies in Brazil and Italy.

We further consider whether firms' learning opportunities can be predicted using their observed characteristics. We find, however, that firm observables are only mildly helpful in predicting learning opportunities. We reach this conclusion after considering a wide range of firm attributes, yet our analysis is limited to observables typically available in matched employer-employee datasets. Further research could investigate whether important firm attributes previously considered in the literature, yet unobserved to us—such as firm-level productivity, technological adoption, exporter status, and multinational status—might improve the identification of firms with good learning opportunities.

In this context, it would be important to better understand the extent to which young workers and policymakers can recognize firms with good or bad learning opportunities. Young workers' ability to identify firms with good learning opportunities could be critical for their long-run outcomes. For policy purposes, identifying such employers would be especially relevant if firms that embody better learning opportunities do not internalize this fact and, on the contrary, create positive externalities for young workers and the economy as a whole.

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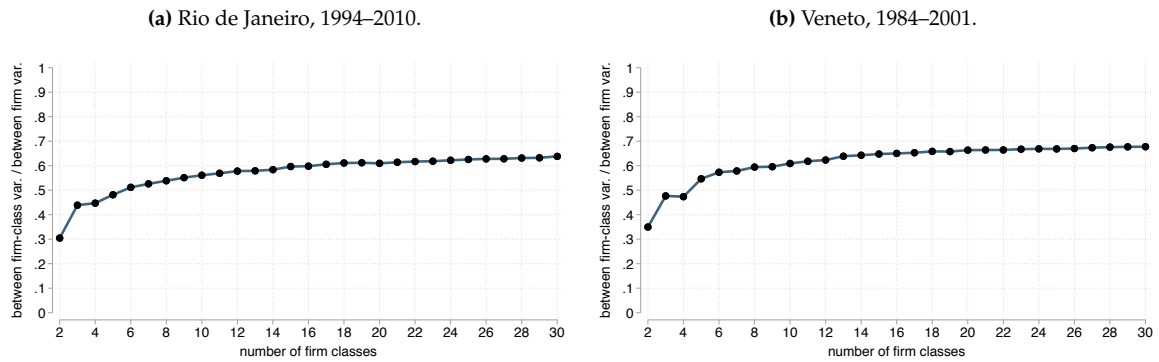
- SUPPLEMENTARY APPENDICES -

- **Appendix A:** Additional Figures and Tables p. **A2**
- **Appendix B:** Firms' Management Practices p. **A30**

A Additional Figures and Tables

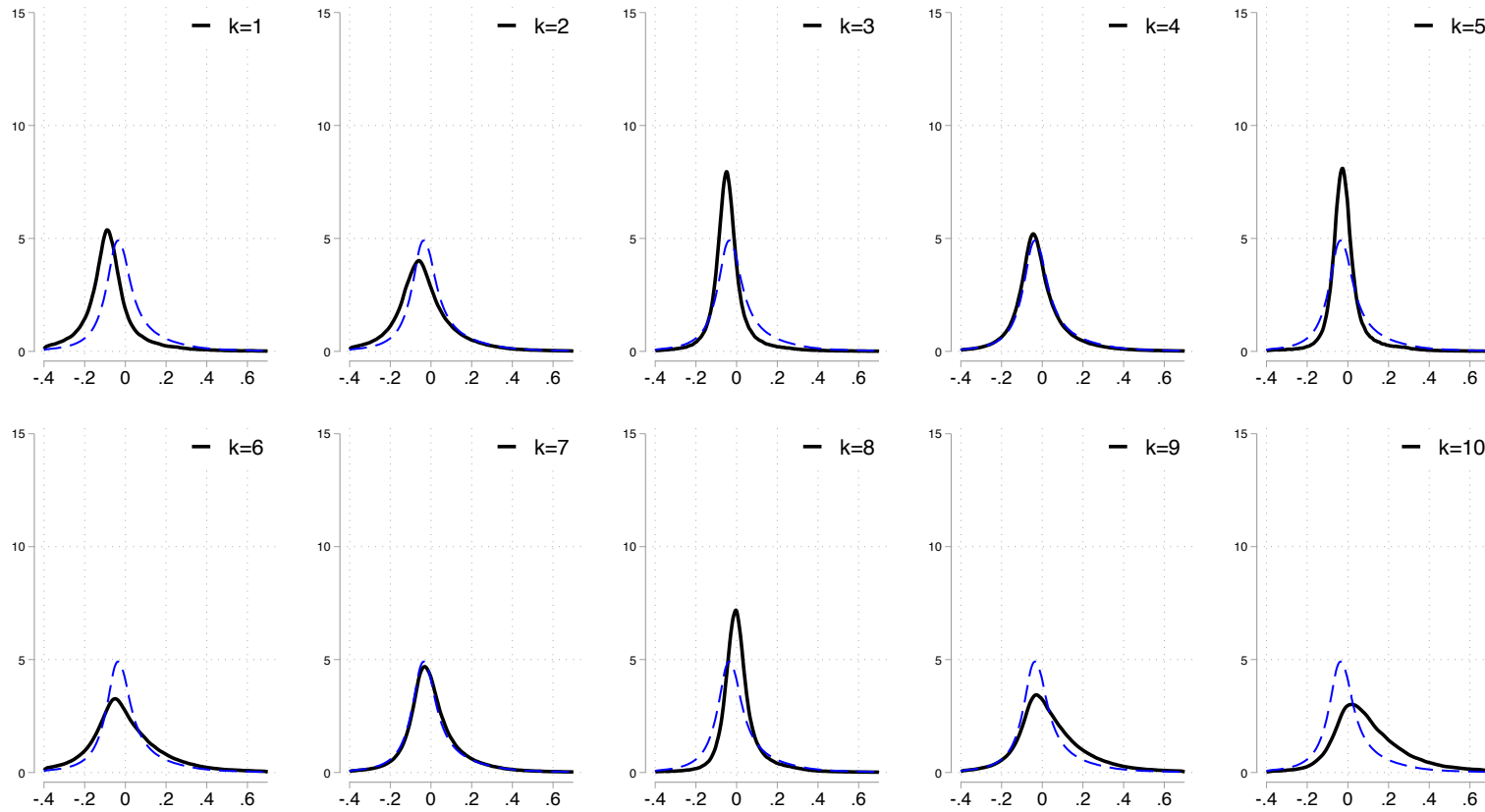
A.1 Figures

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



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).

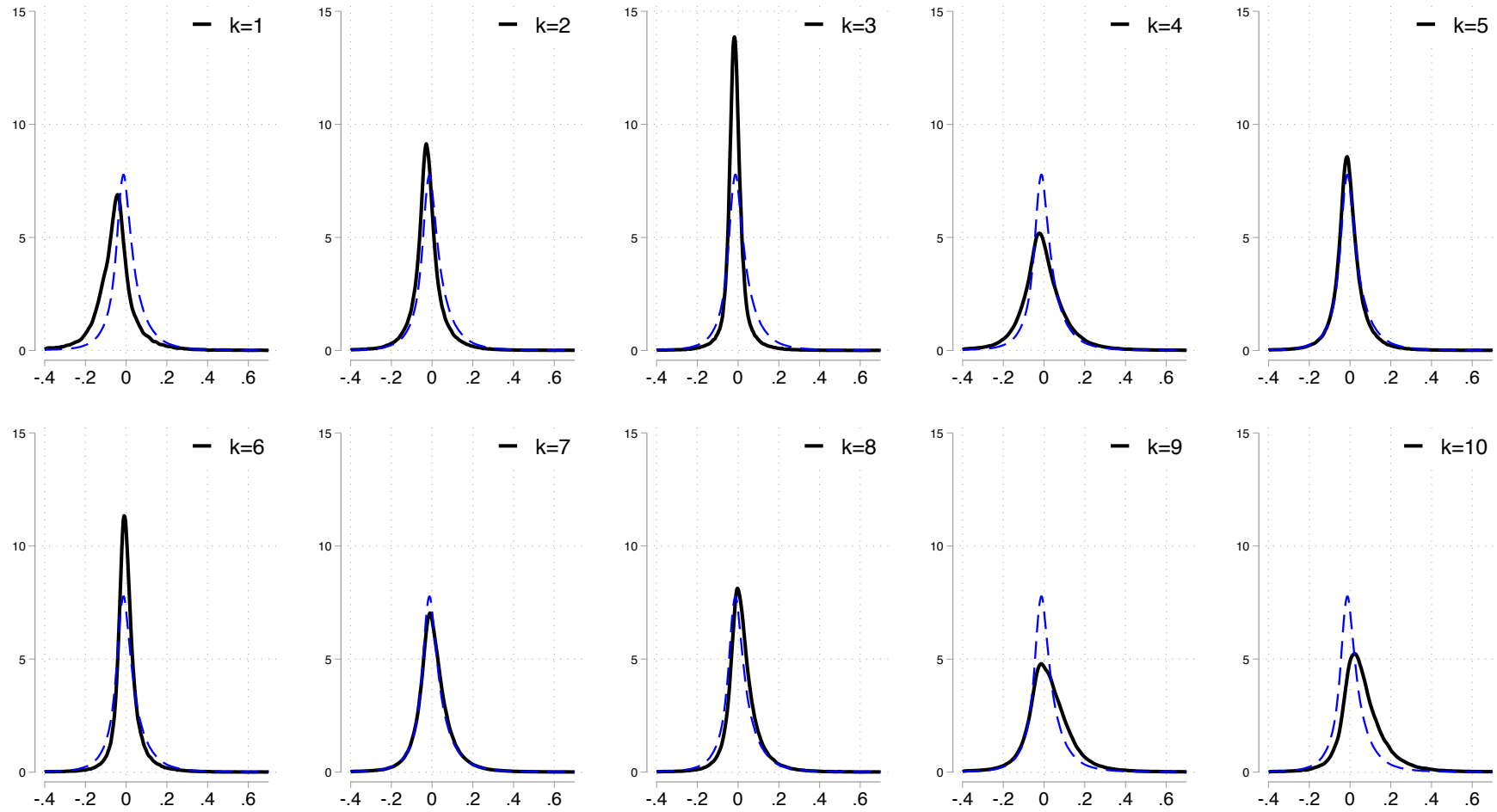
Figure A2: Density of unexplained earnings growth in each firm class. Rio de Janeiro, 1994–2010.



A3

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.

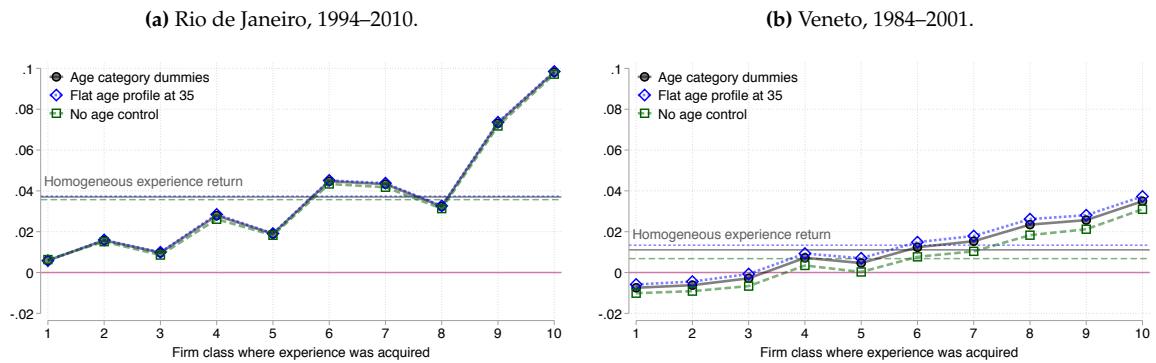
Figure A3: Density of unexplained earnings growth in each firm class. Veneto, 1984–2001.



A4

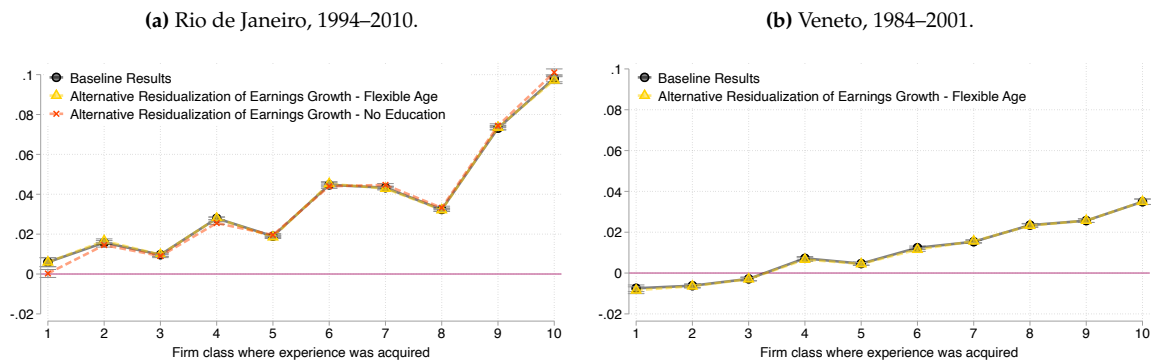
Notes: Densities of unexplained earnings growth across firm classes. Classes ordered according to mean unexplained earnings growth. Dashed line marks the density of the overall distribution.

Figure A4: Robustness by alternative age controls: returns to experiences acquired in different firm classes.



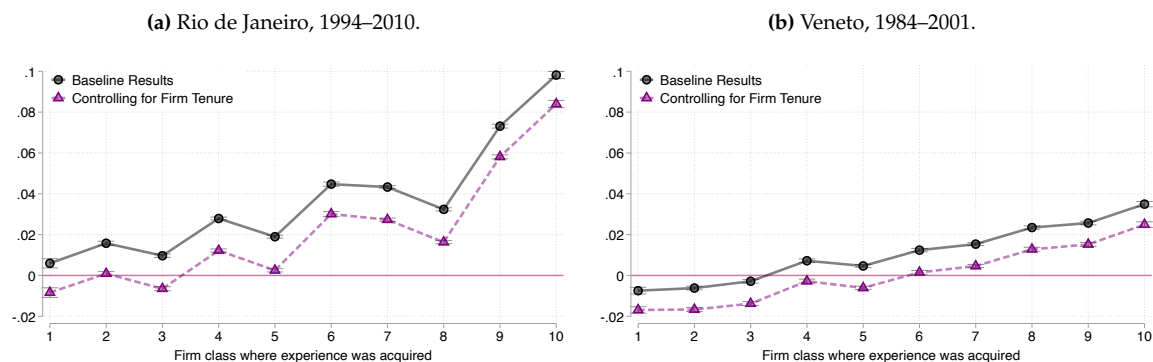
Notes: Estimates of returns to experiences acquired in different firm classes, using different ways of controlling for age effects. Black dots: baseline estimates from Figure 2, controlling for six age-category fixed effects. Blue diamonds: control for an age polynomial restricting the age profile to 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.



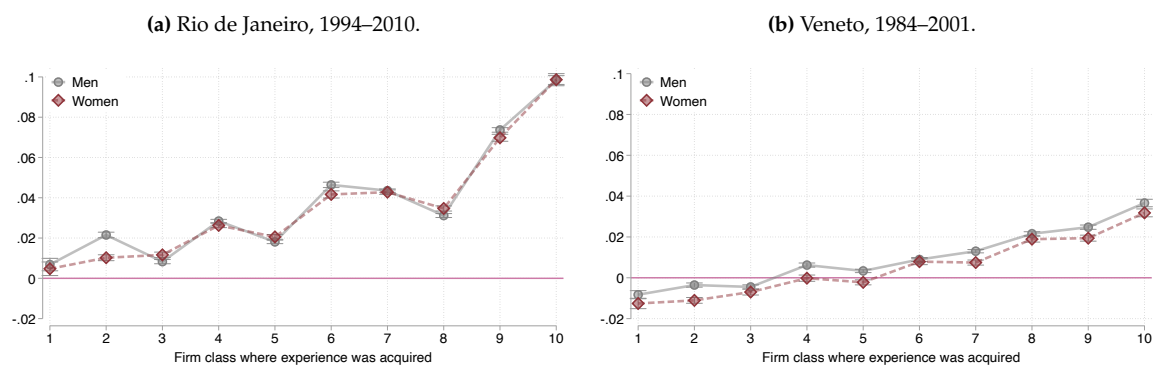
Notes: Estimates of returns to experiences acquired in different firm classes, using different ways of residualizing unexplained earnings growth. Black dots: baseline estimates from Figure 2. Yellow diamonds: fully flexible specification of age effects (interacted with education in Rio de Janeiro). Orange 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.



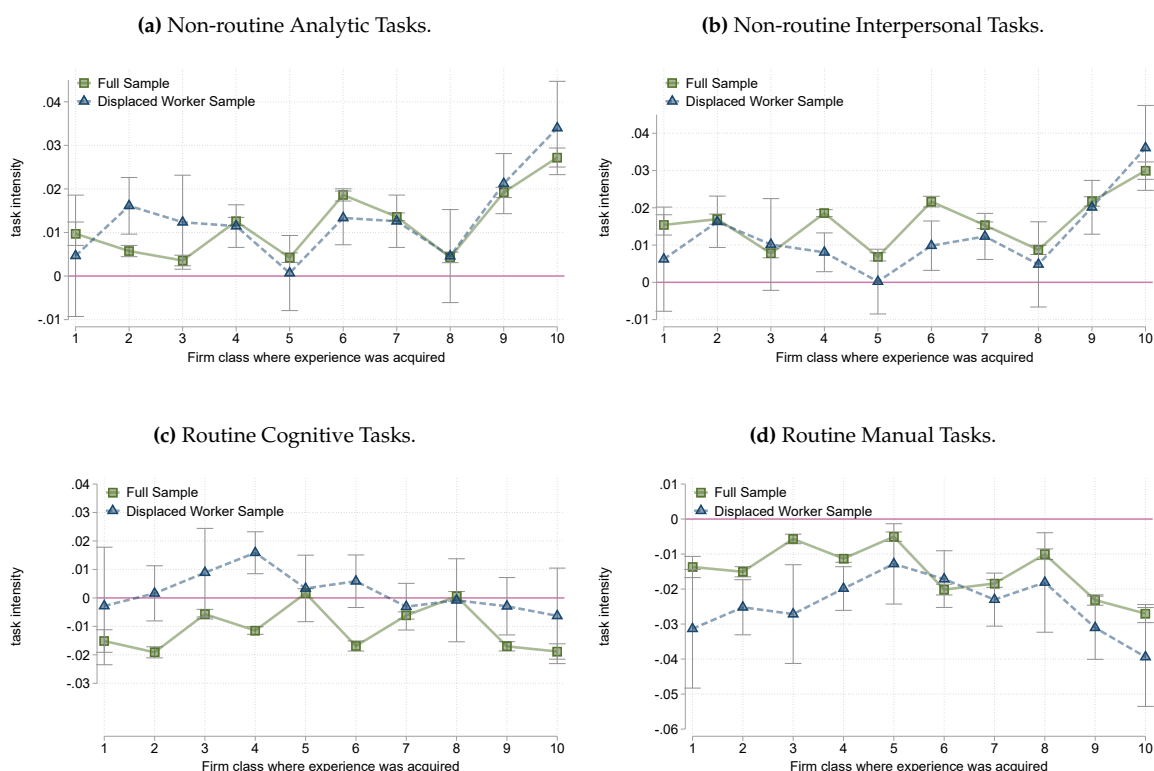
Notes: Estimates of returns to experiences acquired in different firm classes. Baseline estimates (black dots, described in Figure 2), and estimates which further control for tenure at the current employer (purple triangles).

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



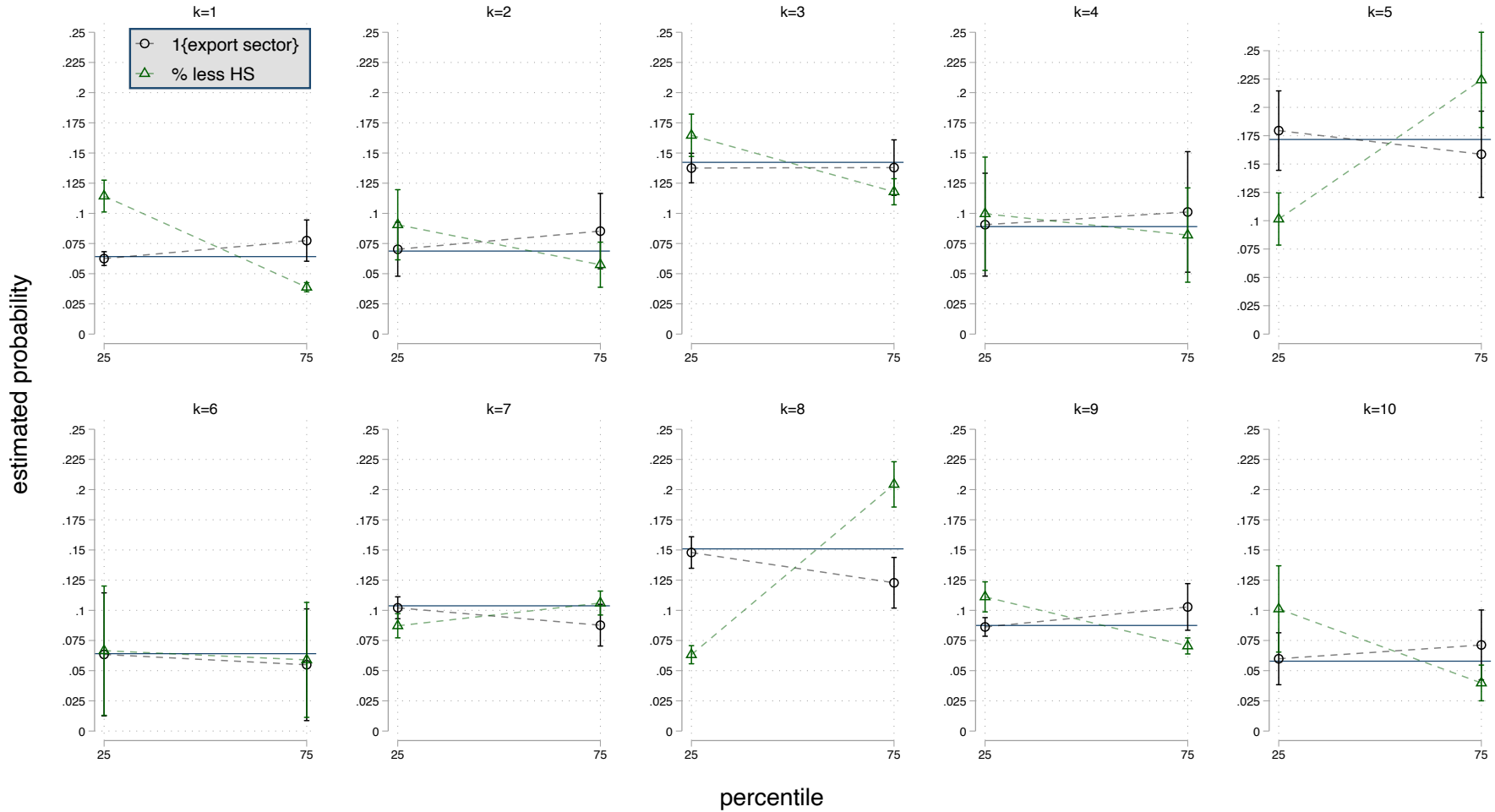
Notes: Point estimates of returns to experiences acquired in different firm classes, estimated separately for men and for women.

Figure A8: Task content returns to experiences acquired in different firm classes, Rio de Janeiro: sample of displaced workers



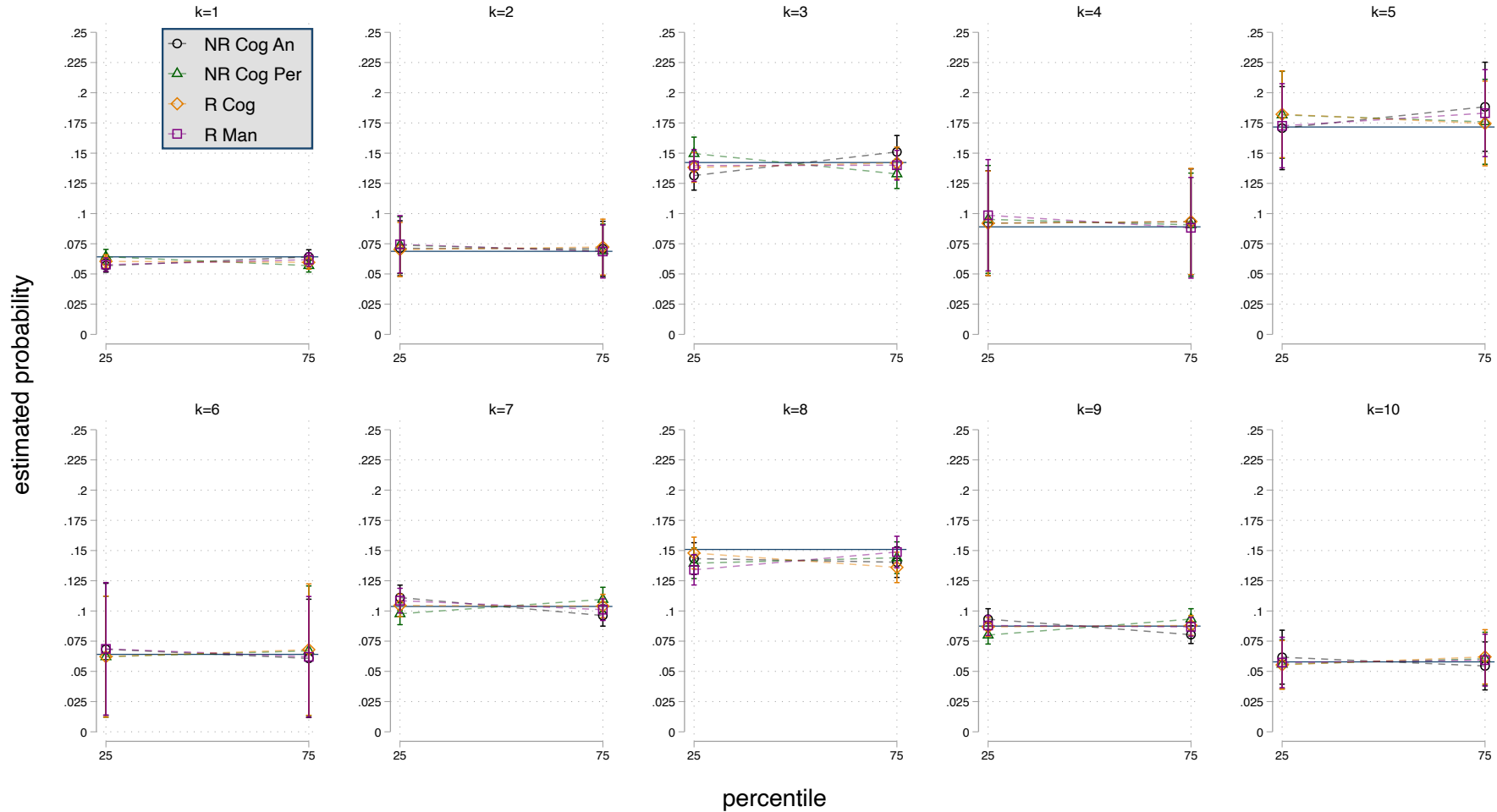
Notes: Green plots: Estimates of task content returns to experiences acquired in different firm classes, described in Figure 9. Blue plots: Estimates and 95% confidence intervals of task content returns to experiences acquired in different firm classes, estimated using the first post-displacement observation of workers experiencing a mass layoff or firm closure. Robust standard errors. Regressions control for time to re-entry after displacement, worker demographics—including gender in both countries, education in Brazil and nationality in Italy—and post-displacement firm fixed effects. 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. Regression results presented in Table A17.

Figure A9: Multinomial Logit Estimated Probabilities: $Pr(\text{class} = k|X)$. Rio de Janeiro, 1994–2010.



Notes: Estimated probabilities and 95% confidence intervals from firm-level multinomial logit with the following explanatory variables: workforce age distribution, workforce gender distribution, workforce education distribution, log firm size, firm effects ψ_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 A10: Multinomial Logit Estimated Probabilities: $Pr(\text{class} = k|X)$. Rio de Janeiro, 1994–2010.



A9

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 ψ_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.

Veneto, 1984–2001.

Class	Mean	Median	Variance	Skewness	Class	Mean	Median	Variance	Skewness
1	-0.094	-0.089	0.050	-1.442	1	-0.058	-0.050	0.020	-0.488
2	-0.040	-0.052	0.050	0.146	2	-0.026	-0.026	0.014	-0.916
3	-0.036	-0.046	0.021	1.151	3	-0.016	-0.016	0.008	-1.367
4	-0.016	-0.033	0.037	0.891	4	-0.012	-0.014	0.023	-0.489
5	-0.010	-0.023	0.019	2.861	5	-0.009	-0.011	0.013	-0.745
6	0.004	-0.023	0.081	0.466	6	0.002	-0.003	0.009	-0.459
7	0.010	-0.012	0.043	1.277	7	0.003	-0.002	0.015	-0.562
8	0.017	0.001	0.023	3.065	8	0.018	0.010	0.011	-0.052
9	0.052	0.014	0.071	1.106	9	0.019	0.012	0.021	-0.282
10	0.122	0.074	0.078	1.438	10	0.058	0.044	0.019	0.246
overall	-0.000	-0.022	0.046	1.049	overall	-0.000	-0.006	0.015	-0.481

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

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

Notes: Outcome is log daily wage. Workers born 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	0.004	0.022	0.012	0.035	0.016	0.059	0.050	0.030	0.086	0.114
3	0.017	0.061	0.035	0.101	0.052	0.165	0.145	0.093	0.247	0.324
5	0.035	0.094	0.058	0.160	0.094	0.255	0.235	0.163	0.392	0.507
10	0.105	0.153	0.112	0.278	0.222	0.406	0.434	0.362	0.688	0.852

Notes: Experience profiles evaluated at one, three, five, and ten years of experience using estimates of heterogeneous returns to different classes of experience featuring a quadratic functional form. 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 $k \in \{1, 2, \dots, 10\}$.

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	-0.016	-0.000	0.000	0.012	0.011	0.019	0.024	0.035	0.039	0.058
3	-0.045	-0.004	0.000	0.034	0.029	0.054	0.069	0.099	0.109	0.161
5	-0.070	-0.012	-0.001	0.051	0.044	0.085	0.108	0.156	0.170	0.246
10	-0.117	-0.052	-0.007	0.075	0.065	0.144	0.181	0.264	0.282	0.382

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 $k \in \{1, 2, \dots, 10\}$.

Table A6: Robustness: including tenure. Returns to experiences acquired in different firm classes.

Rio de Janeiro, 1994–2010.			Veneto, 1984–2001.		
	(1)	(2)		(1)	(2)
Experience	0.0233*** (0.0003)		Experience	0.0007* (0.0004)	
Experience: class 1		-0.0084*** (0.0012)	Experience: class 1		-0.0169*** (0.0008)
Experience: class 2		0.0009* (0.0005)	Experience: class 2		-0.0167*** (0.0005)
Experience: class 3		-0.0065*** (0.0005)	Experience: class 3		-0.0138*** (0.0005)
Experience: class 4		0.0122*** (0.0004)	Experience: class 4		-0.0028*** (0.0005)
Experience: class 5		0.0025*** (0.0004)	Experience: class 5		-0.0061*** (0.0004)
Experience: class 6		0.0301*** (0.0006)	Experience: class 6		0.0015*** (0.0005)
Experience: class 7		0.0273*** (0.0004)	Experience: class 7		0.0046*** (0.0004)
Experience: class 8		0.0163*** (0.0004)	Experience: class 8		0.0128*** (0.0005)
Experience: class 9		0.0581*** (0.0005)	Experience: class 9		0.0152*** (0.0005)
Experience: class 10		0.0840*** (0.0009)	Experience: class 10		0.0249*** (0.0007)
Experience: NC		0.0108*** (0.0005)	Experience: NC		0.0017*** (0.0005)
Experience: PS		0.0430*** (0.0029)	Experience: PS		-0.0076 (0.0053)
Experience: non-RJ		0.0419*** (0.0005)	Experience: non-Veneto		0.0060*** (0.0005)
Tenure	0.0165*** (0.0002)	0.0186*** (0.0002)	Tenure	0.0110*** (0.0002)	0.0112*** (0.0002)
Adj. R^2	0.760	0.763	Adj. R^2	0.602	0.605
Within adj. R^2	0.014	0.025	Within adj. R^2	0.014	0.023
Person FE	yes	yes	Person FE	yes	yes
Firm FE	yes	yes	Firm FE	yes	yes
SE clusters (persons)	1,510,168	1,510,168	SE clusters (persons)	484,953	484,953
N	8,754,064	8,754,064	N	3,614,154	3,614,154

Notes: Left panel: Same specification as that reported for Rio de Janeiro in Table A2, columns (5) and (6), adding a linear term of tenure at the current employer. Right panel: Same specification as that reported for Veneto in Table A3, columns (5) 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	0.0458*** (0.0056)	0.0273*** (0.0070)	-0.0017 (0.0035)	0.0095 (0.0081)
Experience: class 2	0.0552*** (0.0026)	0.0317*** (0.0030)	-0.0049*** (0.0019)	0.0020 (0.0036)
Experience: class 3	-0.0045 (0.0039)	0.0156*** (0.0045)	-0.0371*** (0.0040)	-0.0004 (0.0054)
Experience: class 4	0.0302*** (0.0019)	0.0255*** (0.0022)	0.0059*** (0.0021)	0.0132*** (0.0042)
Experience: class 5	-0.0338*** (0.0032)	0.0071* (0.0038)	0.0105*** (0.0022)	0.0104** (0.0041)
Experience: class 6	0.0513*** (0.0023)	0.0353*** (0.0028)	0.0060* (0.0031)	0.0013 (0.0068)
Experience: class 7	0.0362*** (0.0022)	0.0245*** (0.0025)	0.0221*** (0.0017)	0.0268*** (0.0031)
Experience: class 8	-0.0305*** (0.0037)	0.0052 (0.0046)	0.0421*** (0.0021)	0.0228*** (0.0032)
Experience: class 9	0.1056*** (0.0030)	0.0519*** (0.0033)	0.0290*** (0.0024)	0.0205*** (0.0039)
Experience: class 10	0.1390*** (0.0046)	0.0730*** (0.0056)	0.0401*** (0.0044)	0.0408*** (0.0099)
Experience: NC	-0.0092** (0.0046)	0.0115** (0.0053)	-0.0342*** (0.0041)	-0.0015 (0.0063)
Experience: PS	0.1898*** (0.0114)	0.0734*** (0.0133)	0.0408*** (0.0044)	0.0015 (0.0073)
Experience: Other	0.0826*** (0.0032)	0.0413*** (0.0037)	0.0234*** (0.0019)	0.0214*** (0.0034)
Adjusted R^2	0.197	0.540	0.136	0.414
Year FE	yes	yes	yes	yes
Time to Reentry	yes	yes	yes	yes
Observables	yes	yes	yes	yes
Post-ML Firm FE	no	yes	no	yes
Observations	102459	102459	26236	26236

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	0.0490*** (0.0056)	0.0274*** (0.0070)	0.0015 (0.0035)	0.0101 (0.0081)
Experience: class 2	0.0596*** (0.0026)	0.0319*** (0.0029)	-0.0012 (0.0019)	0.0037 (0.0035)
Experience: class 3	0.0005 (0.0039)	0.0158*** (0.0045)	-0.0327*** (0.0040)	0.0013 (0.0054)
Experience: class 4	0.0346*** (0.0019)	0.0257*** (0.0022)	0.0100*** (0.0021)	0.0149*** (0.0042)
Experience: class 5	-0.0283*** (0.0032)	0.0074* (0.0038)	0.0147*** (0.0022)	0.0117*** (0.0041)
Experience: class 6	0.0551*** (0.0023)	0.0354*** (0.0028)	0.0100*** (0.0031)	0.0027 (0.0067)
Experience: class 7	0.0414*** (0.0022)	0.0247*** (0.0025)	0.0267*** (0.0016)	0.0284*** (0.0030)
Experience: class 8	-0.0238*** (0.0036)	0.0055 (0.0045)	0.0469*** (0.0021)	0.0241*** (0.0032)
Experience: class 9	0.1105*** (0.0029)	0.0521*** (0.0033)	0.0337*** (0.0024)	0.0221*** (0.0039)
Experience: class 10	0.1437*** (0.0046)	0.0732*** (0.0056)	0.0447*** (0.0044)	0.0428*** (0.0099)
Experience: NC	-0.0041 (0.0045)	0.0118** (0.0053)	-0.0298*** (0.0041)	0.0007 (0.0063)
Experience: PS	0.1919*** (0.0113)	0.0736*** (0.0133)	0.0482*** (0.0044)	0.0044 (0.0073)
Experience: Other	0.0876*** (0.0032)	0.0415*** (0.0037)	0.0289*** (0.0019)	0.0232*** (0.0034)
Adjusted R^2	0.196	0.540	0.130	0.412
Year FE	yes	yes	yes	yes
Time to Reentry	no	no	no	no
Observables	yes	yes	yes	yes
Post-ML Firm FE	no	yes	no	yes
Observations	102459	102459	26236	26236

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: 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} (1)	p_{75} (2)	p_{25} (3)	p_{75} (4)
Experience: class 1	-0.0213*** (0.0013)	-0.0131*** (0.0011)	-0.0208*** (0.0013)	-0.0092*** (0.0008)
Experience: class 2	-0.0105*** (0.0007)	0.0106*** (0.0005)	-0.0231*** (0.0009)	-0.0053*** (0.0005)
Experience: class 3	-0.0048*** (0.0005)	0.0066*** (0.0004)	-0.0157*** (0.0007)	-0.0025*** (0.0004)
Experience: class 4	0.0080*** (0.0004)	0.0301*** (0.0003)	-0.0094*** (0.0009)	0.0082*** (0.0005)
Experience: class 5	0.0124*** (0.0003)	0.0212*** (0.0005)	-0.0124*** (0.0009)	0.0058*** (0.0004)
Experience: class 6	0.0215*** (0.0006)	0.0516*** (0.0006)	0.0000 (0.0006)	0.0139*** (0.0004)
Experience: class 7	0.0260*** (0.0003)	0.0497*** (0.0004)	-0.0026*** (0.0007)	0.0174*** (0.0004)
Experience: class 8	0.0274*** (0.0004)	0.0381*** (0.0006)	0.0093*** (0.0006)	0.0275*** (0.0005)
Experience: class 9	0.0553*** (0.0005)	0.0883*** (0.0005)	0.0101*** (0.0007)	0.0304*** (0.0005)
Experience: class 10	0.0919*** (0.0010)	0.1229*** (0.0010)	0.0236*** (0.0008)	0.0419*** (0.0008)
Experience: NC	0.0213*** (0.0010)	0.0454*** (0.0010)	0.0080*** (0.0006)	0.0124*** (0.0005)
Experience: PS	0.0258*** (0.0032)	0.0416*** (0.0026)	-0.0203** (0.0086)	-0.0008 (0.0046)
Experience: Other	0.0244*** (0.0005)	0.0514*** (0.0004)	-0.0004 (0.0007)	0.0176*** (0.0004)
Observations	8,787,079		3,606,266	

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 25th and 75th 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. We present the estimates in different columns for expositional convenience. Standard errors clustered at the person level. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table A10: Returns to experiences acquired in different firm classes by education: Rio de Janeiro.

	HS Dropouts (1)	HS Graduates (2)	More than HS (3)
Experience: class 1	0.002 (0.001)	0.004*** (0.002)	-0.005 (0.005)
Experience: class 2	0.009*** (0.001)	0.020*** (0.001)	-0.010*** (0.002)
Experience: class 3	0.007*** (0.001)	0.016*** (0.001)	-0.015*** (0.002)
Experience: class 4	0.020*** (0.000)	0.031*** (0.001)	0.008*** (0.001)
Experience: class 5	0.020*** (0.000)	0.026*** (0.001)	-0.006*** (0.002)
Experience: class 6	0.037*** (0.001)	0.049*** (0.001)	0.027*** (0.002)
Experience: class 7	0.034*** (0.000)	0.051*** (0.001)	0.032*** (0.001)
Experience: class 8	0.033*** (0.000)	0.042*** (0.001)	0.009*** (0.002)
Experience: class 9	0.060*** (0.001)	0.084*** (0.001)	0.062*** (0.002)
Experience: class 10	0.079*** (0.001)	0.106*** (0.001)	0.101*** (0.002)
Experience: NC	0.022*** (0.001)	0.034*** (0.001)	0.031*** (0.002)
Experience: PS	0.023*** (0.005)	0.036*** (0.004)	0.034*** (0.008)
Experience: non-RJ	0.046*** (0.001)	0.057*** (0.001)	0.037*** (0.001)
R^2	0.729	0.770	0.871
Observations	3,683,190	3,908,269	1,076,871

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, high school graduates and those beyond high school. 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 occupation at the time experience was acquired: Rio de Janeiro.

	(1)	White Collar (2)	Blue Collar (3)
Experience: White Collar	0.0365*** (0.0003)		
Experience: Blue Collar	0.0230*** (0.0003)		
Heterogeneous Experience: class 1		-0.0147*** (0.0013)	-0.0206*** (0.0023)
Heterogeneous Experience: class 2		0.0113*** (0.0007)	0.0071*** (0.0009)
Heterogeneous Experience: class 3		0.0027*** (0.0005)	-0.0008 (0.0006)
Heterogeneous Experience: class 4		0.0305*** (0.0004)	0.0154*** (0.0004)
Heterogeneous Experience: class 5		0.0154*** (0.0004)	0.0108*** (0.0004)
Heterogeneous Experience: class 6		0.0497*** (0.0007)	0.0327*** (0.0008)
Heterogeneous Experience: class 7		0.0436*** (0.0004)	0.0251*** (0.0004)
Heterogeneous Experience: class 8		0.0305*** (0.0005)	0.0212*** (0.0005)
Heterogeneous Experience: class 9		0.0808*** (0.0006)	0.0597*** (0.0007)
Heterogeneous Experience: class 10		0.1209*** (0.0013)	0.0917*** (0.0015)
Heterogeneous Experience: NC		0.0456*** (0.0013)	0.0090*** (0.0017)
Heterogeneous Experience: PS		0.0483*** (0.0034)	-0.0042 (0.0058)
Heterogeneous Experience: non-RJ		0.0564*** (0.0005)	0.0358*** (0.0006)
Adj. R^2	0.760	0.762	
Within adj. R^2	0.154	0.162	
Person FE	yes	yes	
Firm FE	yes	yes	
SE clusters (persons)	1,524,582	1,524,582	
N	8,787,302	8,787,302	

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. We present the estimates in different columns for expositional convenience. 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: Veneto.

	(1)	White Collar (2)	Blue Collar (3)
Experience: White Collar	0.0220*** (0.0003)		
Experience: Blue Collar	0.0055*** (0.0003)		
Heterogeneous Experience: class 1		0.0058*** (0.0021)	-0.0102*** (0.0009)
Heterogeneous Experience: class 2		0.0055*** (0.0011)	-0.0085*** (0.0005)
Heterogeneous Experience: class 3		0.0051*** (0.0011)	-0.0050*** (0.0005)
Heterogeneous Experience: class 4		0.0169*** (0.0009)	0.0037*** (0.0005)
Heterogeneous Experience: class 5		0.0179*** (0.0006)	0.0005 (0.0004)
Heterogeneous Experience: class 6		0.0162*** (0.0007)	0.0095*** (0.0005)
Heterogeneous Experience: class 7		0.0240*** (0.0005)	0.0107*** (0.0004)
Heterogeneous Experience: class 8		0.0249*** (0.0006)	0.0208*** (0.0005)
Heterogeneous Experience: class 9		0.0306*** (0.0006)	0.0208*** (0.0005)
Heterogeneous Experience: class 10		0.0386*** (0.0009)	0.0281*** (0.0009)
Heterogeneous Experience: NC		0.0118*** (0.0007)	0.0119*** (0.0006)
Heterogeneous Experience: PS		0.0086 (0.0070)	-0.0105 (0.0073)
Heterogeneous Experience: non-Veneto		0.0300*** (0.0006)	0.0041*** (0.0005)
Adj. R^2	0.603		0.606
Within adj. R^2	0.088		0.094
Person FE	yes		yes
Firm FE	yes		yes
SE clusters (persons)	484,977		484,977
N	3,614,280		3,614,280

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. We present the estimates in different columns for expositional convenience. Standard errors clustered at the person level. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table A13: Returns to experiences acquired in different firms, categorizing firms based on observables: firm size, city size, and workforce education.

	(1) Firm Size, Rio de Janeiro	(2) Firm Size, Veneto	(3) City Size, Rio de Janeiro	(4) City Size, Veneto	(5) Education, Rio de Janeiro
Experience: firm observable, group 1	0.0233*** (0.0003)	0.0127*** (0.0003)	0.0328*** (0.0022)	0.0068*** (0.0004)	0.0181*** (0.0004)
Experience: firm observable, group 2	0.0268*** (0.0004)	0.0082*** (0.0004)	0.0353*** (0.0018)	0.0092*** (0.0004)	0.0189*** (0.0005)
Experience: firm observable, group 3	0.0305*** (0.0005)	0.0119*** (0.0005)	0.0278*** (0.0008)	0.0102*** (0.0004)	0.0203*** (0.0005)
Experience: firm observable, group 4	0.0358*** (0.0005)	0.0110*** (0.0004)	0.0346*** (0.0008)	0.0117*** (0.0004)	0.0238*** (0.0004)
Experience: firm observable, group 5	0.0400*** (0.0005)	0.0098*** (0.0004)	0.0330*** (0.0005)	0.0139*** (0.0005)	0.0279*** (0.0004)
Experience: firm observable, group 6	0.0463*** (0.0007)	0.0087*** (0.0006)	0.0477*** (0.0007)	0.0121*** (0.0013)	0.0339*** (0.0004)
Experience: firm observable, group 7	0.0459*** (0.0006)	0.0070*** (0.0007)	0.0281*** (0.0005)	0.0160*** (0.0008)	0.0378*** (0.0004)
Experience: firm observable, group 8	0.0417*** (0.0005)	0.0130*** (0.0006)	0.0280*** (0.0004)	0.0135*** (0.0007)	0.0431*** (0.0004)
Experience: firm observable, group 9	0.0424*** (0.0005)	0.0130*** (0.0006)	0.0340*** (0.0005)	0.0169*** (0.0005)	0.0475*** (0.0005)
Experience: firm observable, group 10	0.0381*** (0.0004)	0.0152*** (0.0006)	0.0368*** (0.0003)	0.0151*** (0.0005)	0.0515*** (0.0005)
Adj. R^2	0.760	0.601	0.760	0.601	0.760
Within adj. R^2	0.014	0.012	0.013	0.013	0.016
Person FE	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes
SE clusters (persons)	1,509,799	484,976	1,510,168	484,977	1,510,168
N	8,751,381	3,614,266	8,754,064	3,614,280	8,754,064

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. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

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

	Firm class $k \times$ currently employed at class k .		Firm class $k \times$ currently employed at class 10.	
	(1) Rio de Janeiro	(2) Veneto	(1) Rio de Janeiro	(2) Veneto
Experience: class 1	0.0016 (0.0017)	-0.0168*** (0.0013)	-0.0082*** (0.0012)	-0.0167*** (0.0008)
Experience: class 1 \times employed in class 1	-0.0175*** (0.0019)	0.0012 (0.0013)	-0.0034 (0.0057)	-0.0028 (0.0047)
Experience: class 2	0.0014* (0.0007)	-0.0163*** (0.0007)	0.0010* (0.0005)	-0.0165*** (0.0005)
Experience: class 2 \times employed in class 2	-0.0022*** (0.0008)	0.0008 (0.0007)	0.0008 (0.0022)	0.0035 (0.0023)
Experience: class 3	0.0021*** (0.0007)	-0.0127*** (0.0008)	-0.0065*** (0.0005)	-0.0137*** (0.0005)
Experience: class 3 \times employed in class 3	-0.0129*** (0.0007)	0.0000 (0.0008)	0.0079*** (0.0023)	0.0113*** (0.0023)
Experience: class 4	0.0145*** (0.0005)	-0.0039*** (0.0006)	0.0123*** (0.0004)	-0.0027*** (0.0005)
Experience: class 4 \times employed in class 4	-0.0043*** (0.0005)	0.0026*** (0.0006)	0.0010 (0.0014)	0.0039** (0.0019)
Experience: class 5	0.0085*** (0.0006)	-0.0033*** (0.0005)	0.0025*** (0.0004)	-0.0059*** (0.0004)
Experience: class 5 \times employed in class 5	-0.0090*** (0.0006)	-0.0020*** (0.0005)	0.0097*** (0.0021)	0.0044*** (0.0016)
Experience: class 6	0.0248*** (0.0008)	0.0023*** (0.0008)	0.0304*** (0.0006)	0.0016*** (0.0005)
Experience: class 6 \times employed in class 6	0.0068*** (0.0008)	0.0004 (0.0008)	-0.0049*** (0.0019)	0.0048** (0.0023)
Experience: class 7	0.0251*** (0.0005)	0.0061*** (0.0005)	0.0275*** (0.0004)	0.0048*** (0.0004)
Experience: class 7 \times employed in class 7	0.0017*** (0.0005)	-0.0005 (0.0005)	-0.0037*** (0.0014)	0.0037*** (0.0014)
Experience: class 8	0.0156*** (0.0007)	0.0108*** (0.0007)	0.0164*** (0.0004)	0.0130*** (0.0005)
Experience: class 8 \times employed in class 8	-0.0003 (0.0007)	0.0038*** (0.0007)	0.0018 (0.0021)	0.0026 (0.0019)
Experience: class 9	0.0505*** (0.0007)	0.0112*** (0.0007)	0.0582*** (0.0005)	0.0154*** (0.0005)
Experience: class 9 \times employed in class 9	0.0095*** (0.0007)	0.0063*** (0.0007)	0.0048*** (0.0016)	0.0022 (0.0019)
Experience: class 10	0.0747*** (0.0013)	0.0147*** (0.0010)	0.0737*** (0.0013)	0.0133*** (0.0011)
Experience: class 10 \times employed in class 10	0.0132*** (0.0013)	0.0146*** (0.0011)	0.0154*** (0.0013)	0.0146*** (0.0011)
Experience: NC	0.0121*** (0.0009)	-0.0077*** (0.0008)	0.0109*** (0.0005)	0.0019*** (0.0005)
Experience: NC \times employed in NC	-0.0030*** (0.0009)	0.0122*** (0.0008)	0.0003 (0.0024)	0.0017 (0.0018)
Experience: PS	0.0433*** (0.0029)	-0.0080 (0.0053)	0.0433*** (0.0029)	-0.0080 (0.0053)
Experience: Other	0.0516*** (0.0006)	0.0093*** (0.0007)	-0.0042 (0.0073)	0.0115 (0.0164)
Experience: Other \times employed in Other	-0.0127*** (0.0004)	-0.0029*** (0.0006)	0.0418*** (0.0005)	0.0060*** (0.0005)
Tenure	0.0200*** (0.0003)	0.0098*** (0.0003)	0.0107*** (0.0012)	0.0165*** (0.0019)
Adj. R^2	0.763	0.606	0.0184*** (0.0002)	0.0110*** (0.0002)
Within adj. R^2	0.026	0.023	0.763	0.605
Person FE	yes	yes	0.025	0.023
Firm FE	yes	yes	yes	yes
SE clusters (persons)	1,510,168	484,977	1,510,168	484,977
N	8,754,064	3,614,280	8,754,064	3,614,280

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: Trajectories across firm classes and the annualized total wage growth distribution (age 18–mid 30s)

Trajectory	Percentile in total wage growth distribution	
	<u>Rio de Janeiro</u>	<u>Veneto</u>
<i>Employed always in same firm class</i>		
Firm class 10	78	66
Firm class 1	16	18
Firm class closest to homogeneous returns (class 8 for Rio, class 6 for Veneto)	33	38
<i>Mixed trajectory: moves across firm classes</i>		
1/3rd of the time across the three classes above	43	39

Notes: This table shows where the wage growth resulting from different counterfactual trajectories across firm classes falls in the person-level distribution of annualized total wage growth between ages 18–34 in Rio de Janeiro and 18–35 in Veneto. The distribution of annualized total wage growth is computed for the birth cohort we observe the longest since age 18, using the difference in log earnings between the last (up to age 35) and first time we observe each worker, divided over the number of years between such observations. In the third counterfactual trajectory, class 8 is chosen for Rio de Janeiro and class 6 is chosen for Veneto because these are the classes whose returns we find are closest to the homogeneous experience benchmark (see Figure 2).

Table A16: Task content returns to experiences acquired in different firm classes: Rio de Janeiro

	Non-Routine Analytic (1)	Non-Routine Interpersonal (2)	Routine Cognitive (3)	Routine Manual (4)
Experience: class 1	0.0097*** (0.0014)	0.0154*** (0.0014)	-0.0151*** (0.0020)	-0.0137*** (0.0015)
Experience: class 2	0.0057*** (0.0007)	0.0170*** (0.0007)	-0.0191*** (0.0010)	-0.0151*** (0.0007)
Experience: class 3	0.0036*** (0.0006)	0.0078*** (0.0006)	-0.0057*** (0.0009)	-0.0057*** (0.0007)
Experience: class 4	0.0126*** (0.0005)	0.0186*** (0.0005)	-0.0115*** (0.0007)	-0.0113*** (0.0005)
Experience: class 5	0.0042*** (0.0006)	0.0068*** (0.0006)	0.0016** (0.0008)	-0.0050*** (0.0007)
Experience: class 6	0.0186*** (0.0007)	0.0217*** (0.0007)	-0.0169*** (0.0009)	-0.0202*** (0.0008)
Experience: class 7	0.0136*** (0.0005)	0.0153*** (0.0005)	-0.0062*** (0.0007)	-0.0184*** (0.0006)
Experience: class 8	0.0043*** (0.0006)	0.0087*** (0.0006)	0.0005 (0.0009)	-0.0101*** (0.0008)
Experience: class 9	0.0192*** (0.0006)	0.0217*** (0.0007)	-0.0170*** (0.0008)	-0.0231*** (0.0008)
Experience: class 10	0.0272*** (0.0011)	0.0300*** (0.0012)	-0.0188*** (0.0014)	-0.0270*** (0.0013)
Experience: NC	0.0050*** (0.0006)	0.0101*** (0.0007)	-0.0057*** (0.0009)	-0.0086*** (0.0008)
Experience: PS	0.0402*** (0.0031)	0.0495*** (0.0032)	-0.0379*** (0.0042)	-0.0269*** (0.0032)
Experience: non-RJ	0.0177*** (0.0005)	0.0216*** (0.0005)	-0.0163*** (0.0007)	-0.0196*** (0.0006)
adj. R^2	0.672	0.628	0.644	0.729
Year FE	yes	yes	yes	yes
Person FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
N	8602938	8602938	8602938	8602938

Notes: Outcome variables capture non-routine analytic, non-routine interpersonal, routine cognitive and routine manual task content. Task content is as defined in the text. Workers born in 1976 or later. 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. 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 A17: Task content returns to experiences acquired in different firm classes in first post-displacement observation: Rio de Janeiro.

	Non-Routine Analytic		Non-Routine Interpersonal		Routine Cognitive		Routine Manual	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Experience: class 1	0.0193*** (0.0056)	0.0046 (0.0071)	0.0086 (0.0059)	0.0062 (0.0071)	0.0681*** (0.0090)	-0.0028 (0.0105)	-0.1016*** (0.0079)	-0.0313*** (0.0086)
Experience: class 2	-0.0064** (0.0026)	0.0161*** (0.0033)	-0.0127*** (0.0027)	0.0162*** (0.0035)	0.0468*** (0.0041)	0.0016 (0.0049)	-0.0347*** (0.0037)	-0.0252*** (0.0040)
Experience: class 3	0.0244*** (0.0045)	0.0124** (0.0055)	0.0086* (0.0052)	0.0102 (0.0063)	0.0121* (0.0068)	0.0089 (0.0079)	-0.0738*** (0.0066)	-0.0272*** (0.0072)
Experience: class 4	0.0044** (0.0019)	0.0115*** (0.0025)	-0.0064*** (0.0020)	0.0081*** (0.0027)	0.0624*** (0.0030)	0.0159*** (0.0038)	-0.0645*** (0.0025)	-0.0199*** (0.0032)
Experience: class 5	0.0108*** (0.0035)	0.0007 (0.0044)	0.0123*** (0.0037)	0.0002 (0.0044)	-0.0212*** (0.0051)	0.0033 (0.0060)	-0.0325*** (0.0049)	-0.0128** (0.0059)
Experience: class 6	0.0187*** (0.0023)	0.0134*** (0.0031)	0.0033 (0.0024)	0.0098*** (0.0034)	0.0240*** (0.0036)	0.0059 (0.0047)	-0.0159*** (0.0034)	-0.0172*** (0.0041)
Experience: class 7	0.0099*** (0.0024)	0.0126*** (0.0031)	0.0026 (0.0024)	0.0123*** (0.0032)	0.0016 (0.0032)	-0.0031 (0.0042)	-0.0311*** (0.0030)	-0.0230*** (0.0039)
Experience: class 8	-0.0078* (0.0041)	0.0046 (0.0054)	0.0089** (0.0044)	0.0048 (0.0058)	-0.0655*** (0.0060)	-0.0008 (0.0074)	-0.0066 (0.0059)	-0.0181** (0.0073)
Experience: class 9	0.0380*** (0.0027)	0.0212*** (0.0035)	0.0243*** (0.0027)	0.0201*** (0.0037)	0.0019 (0.0040)	-0.0029 (0.0051)	-0.0079** (0.0036)	-0.0311*** (0.0046)
Experience: class 10	0.0415*** (0.0040)	0.0340*** (0.0055)	0.0373*** (0.0042)	0.0361*** (0.0058)	-0.0322*** (0.0064)	-0.0063 (0.0086)	-0.0004 (0.0058)	-0.0394*** (0.0072)
Experience: NC	0.0304*** (0.0049)	0.0008 (0.0059)	0.0304*** (0.0051)	0.0076 (0.0061)	0.0209*** (0.0076)	0.0140 (0.0092)	-0.0611*** (0.0064)	-0.0181** (0.0074)
Experience: PS	0.0945*** (0.0099)	0.0293** (0.0149)	0.0645*** (0.0126)	0.0368* (0.0201)	-0.0946*** (0.0131)	-0.0043 (0.0164)	-0.2413*** (0.0127)	-0.0466*** (0.0154)
Experience: non-RJ	0.0371*** (0.0031)	0.0123*** (0.0040)	0.0183*** (0.0031)	0.0105** (0.0043)	0.0006 (0.0040)	-0.0015 (0.0052)	-0.0155*** (0.0040)	-0.0218*** (0.0047)
Education	0.0482*** (0.0007)	0.0284*** (0.0009)	0.0268*** (0.0006)	0.0198*** (0.0009)	0.0468*** (0.0009)	0.0185*** (0.0013)	-0.0888*** (0.0008)	-0.0509*** (0.0012)
Male	0.0261*** (0.0040)	0.0288*** (0.0053)	0.0073* (0.0040)	0.0403*** (0.0054)	-0.2893*** (0.0065)	-0.2634*** (0.0086)	0.2992*** (0.0051)	0.1321*** (0.0064)
adj. R^2	0.088	0.437	0.034	0.371	0.105	0.458	0.197	0.544
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Time to Reentry	yes	yes	yes	yes	yes	yes	yes	yes
Observables	yes	yes	yes	yes	yes	yes	yes	yes
Post-ML Firm FE	no	yes	no	yes	no	yes	no	yes
N	98860	98860	98860	98860	98860	98860	98860	98860

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

Table A18: Workforce characteristics in each class of firms. Rio de Janeiro, 1994–2010.

Class	1	2	3	4	5	6	7	8	9	10	NC
Number of Worker-Years	841,309	3,528,349	2,973,921	7,964,829	4,039,786	3,834,176	7,016,132	2,893,551	3,718,893	1,131,109	1,620,207
Number of Firms	13,623	14,598	30,200	18,897	36,441	13,609	22,020	32,040	18,570	12,287	227,552
Firm Size: Mean	1184.56	2151.91	311.76	2585.48	271.05	755.65	1043.38	708.67	662.91	926.28	595.59
Firm Size: Median	34.17	458.67	24.17	459.42	24.42	260.17	155.58	25.58	123.08	79.25	4.25
% Firm > 50 Employees	0.455	0.730	0.395	0.756	0.353	0.756	0.667	0.378	0.645	0.567	0.229
% Men	0.632	0.657	0.638	0.656	0.615	0.686	0.629	0.596	0.741	0.699	0.579
% HS Dropouts	0.542	0.546	0.594	0.505	0.658	0.563	0.578	0.727	0.564	0.518	0.524
% HS Graduates	0.298	0.281	0.280	0.296	0.240	0.285	0.279	0.212	0.295	0.299	0.302
% More than HS	0.159	0.173	0.125	0.199	0.101	0.151	0.143	0.060	0.141	0.183	0.172
% Age 18-29	0.396	0.325	0.377	0.313	0.356	0.372	0.337	0.323	0.372	0.381	0.384
% Age 30-39	0.279	0.295	0.302	0.317	0.303	0.315	0.304	0.299	0.303	0.296	0.258
% Age 40-49	0.202	0.246	0.203	0.240	0.212	0.204	0.223	0.232	0.206	0.200	0.205
% Age 50+	0.122	0.133	0.119	0.129	0.129	0.109	0.136	0.146	0.119	0.123	0.153
% Export-Oriented Sectors	0.015	0.020	0.006	0.041	0.024	0.015	0.018	0.020	0.037	0.034	0.007
% Rio de Janeiro Metro Region	0.843	0.863	0.819	0.843	0.780	0.859	0.825	0.746	0.785	0.793	0.788
Non-routine Cognitive Analytical	0.040	0.011	0.013	0.074	-0.039	0.026	-0.020	-0.118	0.037	0.060	0.034
Non-routine Cognitive Interpersonal	-0.037	-0.116	-0.089	-0.027	-0.026	-0.031	-0.039	-0.070	-0.012	0.017	0.013
Routine Cognitive	0.121	0.218	0.154	0.116	-0.017	0.096	0.042	-0.104	0.059	0.055	0.072
Routine Manual	0.038	0.066	0.012	0.017	0.092	0.104	0.094	0.190	0.145	0.089	-0.040
% Agriculture, Livestock	0.008	0.010	0.003	0.003	0.036	0.007	0.010	0.027	0.002	0.003	0.009
% Extractive Industries	0.003	0.004	0.002	0.024	0.001	0.002	0.004	0.003	0.024	0.027	0.005
% Manufacturing	0.151	0.159	0.089	0.145	0.125	0.198	0.150	0.090	0.181	0.103	0.070
% Construction	0.054	0.028	0.016	0.019	0.043	0.102	0.058	0.057	0.133	0.162	0.059
% Retail, Trade	0.246	0.153	0.322	0.201	0.300	0.226	0.200	0.230	0.190	0.191	0.312
% Accommodation, Meals	0.039	0.025	0.034	0.039	0.097	0.060	0.075	0.107	0.052	0.046	0.063
% Transportation, Storage, Communications	0.127	0.173	0.212	0.136	0.038	0.060	0.069	0.020	0.072	0.065	0.031
% Finance, Insurance	0.025	0.044	0.037	0.043	0.031	0.023	0.020	0.005	0.015	0.026	0.145
% Business Services, Real Estate	0.165	0.194	0.123	0.136	0.160	0.168	0.217	0.314	0.221	0.235	0.149
% Education	0.038	0.056	0.062	0.073	0.069	0.030	0.036	0.038	0.018	0.068	0.029
% Health, Social Services	0.026	0.025	0.035	0.078	0.031	0.064	0.083	0.032	0.022	0.015	0.049
% Other Services (e.g. Leisure, Personal)	0.080	0.045	0.061	0.092	0.063	0.056	0.069	0.072	0.061	0.034	0.058
Wages: Mean	13.03	17.59	10.87	21.35	9.40	15.22	12.93	7.29	15.95	17.77	15.31
Wages: Median	6.26	8.17	6.11	8.12	5.09	8.07	6.62	4.99	8.28	8.62	5.48
Wages: Variance	555	945	739	2,690	703	790	971	203	867	805	1,261
Firm Pay Premium: Mean	0.026	0.160	-0.051	0.152	-0.126	0.142	0.027	-0.153	0.168	0.186	-0.007

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 A19: Workforce characteristics in each class of firms. Veneto, 1984–2001.

Class	1	2	3	4	5	6	7	8	9	10	NC
Number of Worker-Years	235,652	1,058,180	952,189	1,328,251	2,514,360	1,494,459	2,824,792	1,433,046	1,384,893	451,043	552,031
Number of Firms	7,416	14,842	12,767	14,480	13,368	14,808	12,370	15,998	14,362	13,868	149,859
Firm Size: Mean	32.46	40.80	42.96	191.56	320.79	109.80	425.78	255.39	586.23	53.00	6.24
Firm Size: Median	8.40	11.88	14.56	20.54	44.44	23.74	71.74	24.08	26.80	7.09	1.35
% Firm > 50 Employees	0.149	0.173	0.223	0.341	0.480	0.346	0.569	0.387	0.417	0.151	0.017
% Men	0.589	0.572	0.616	0.638	0.656	0.616	0.677	0.593	0.633	0.499	0.529
% Age 18-29	0.547	0.506	0.402	0.442	0.365	0.314	0.359	0.348	0.416	0.523	0.551
% Age 30-39	0.220	0.247	0.299	0.270	0.295	0.317	0.310	0.327	0.299	0.289	0.202
% Age 40-49	0.138	0.150	0.192	0.177	0.219	0.239	0.216	0.215	0.186	0.127	0.120
% Age 50+	0.095	0.097	0.106	0.111	0.122	0.131	0.115	0.110	0.099	0.061	0.126
% 5 Largest Cities	0.138	0.125	0.128	0.246	0.161	0.242	0.232	0.379	0.444	0.381	0.223
% Extractive and Chemical Industries	0.032	0.044	0.058	0.045	0.087	0.074	0.070	0.069	0.054	0.025	0.018
% Manufacturing: Metal	0.145	0.121	0.104	0.236	0.247	0.185	0.340	0.175	0.200	0.197	0.099
% Manufacturing: Other	0.450	0.531	0.525	0.266	0.444	0.281	0.217	0.141	0.122	0.118	0.166
% Construction	0.170	0.163	0.049	0.156	0.059	0.023	0.037	0.022	0.049	0.039	0.141
% Trade, Retail, Hospitality	0.088	0.066	0.136	0.090	0.092	0.294	0.194	0.325	0.178	0.314	0.369
% Transportation, Communications	0.033	0.012	0.031	0.026	0.019	0.052	0.020	0.044	0.086	0.040	0.032
% Finance, Insurance, Business Services	0.031	0.026	0.021	0.091	0.013	0.032	0.057	0.128	0.224	0.154	0.076
% Other Services	0.044	0.026	0.023	0.084	0.031	0.044	0.051	0.078	0.071	0.106	0.091
Daily Wages: Mean	112.77	108.73	97.61	118.09	122.21	116.37	134.86	137.99	144.80	126.34	98.47
Daily Wages: Median	97.83	96.94	94.76	106.42	108.87	108.45	117.53	117.37	117.45	105.16	93.94
Daily Wages: Variance	398,546	411,850	12,776	25,286	215,117	8,629	33,953	62,153	85,192	230,160	58,961
Firm Pay Premium: Mean	-0.015	-0.020	-0.096	0.015	0.035	0.005	0.063	0.062	0.071	0.004	-0.064

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 A20: Firm-level characteristics, by firm class. Rio de Janeiro, 1994–2010.

Class	1	2	3	4	5	6	7	8	9	10
Firm Size: Mean	10.10	22.30	8.89	30.21	9.37	26.44	25.90	9.10	19.56	16.42
Firm Size: Median	3.71	4.57	3.76	5.89	4.11	5.27	5.94	3.76	5.33	4.92
% Firms > 50 Employees	0.021	0.050	0.016	0.068	0.020	0.083	0.068	0.019	0.064	0.043
% Men Employees	0.602	0.607	0.607	0.616	0.610	0.627	0.647	0.600	0.651	0.610
% HS Dropouts	0.598	0.642	0.603	0.637	0.671	0.642	0.670	0.698	0.629	0.585
% HS Graduates	0.308	0.269	0.322	0.273	0.275	0.268	0.251	0.255	0.271	0.304
% More than HS	0.092	0.088	0.074	0.089	0.053	0.090	0.078	0.046	0.099	0.111
% Age 18-29	0.528	0.472	0.491	0.424	0.410	0.453	0.388	0.347	0.413	0.437
% Age 30-39	0.263	0.280	0.279	0.293	0.303	0.289	0.299	0.313	0.293	0.290
% Age 40-49	0.137	0.162	0.151	0.185	0.194	0.172	0.203	0.235	0.193	0.189
% Age 50+	0.072	0.086	0.079	0.098	0.092	0.087	0.109	0.104	0.100	0.084
% Export-Oriented Sectors	0.007	0.007	0.006	0.007	0.005	0.006	0.006	0.006	0.008	0.009
% Rio de Janeiro Metro Region	0.808	0.824	0.780	0.808	0.759	0.836	0.806	0.709	0.822	0.789
% Agriculture, Livestock	0.003	0.003	0.003	0.003	0.005	0.002	0.004	0.009	0.002	0.003
% Extractive Industries	0.003	0.004	0.002	0.003	0.002	0.003	0.003	0.003	0.005	0.006
% Manufacturing	0.108	0.098	0.091	0.106	0.096	0.101	0.095	0.076	0.095	0.099
% Construction	0.033	0.028	0.019	0.027	0.023	0.040	0.031	0.025	0.037	0.046
% Retail, Trade	0.461	0.436	0.531	0.397	0.478	0.384	0.325	0.388	0.319	0.355
% Accommodation, Meals	0.067	0.083	0.054	0.083	0.083	0.086	0.096	0.109	0.076	0.077
% Transportation, Storage, Communications	0.033	0.036	0.034	0.036	0.026	0.038	0.031	0.021	0.042	0.042
% Finance, Insurance	0.016	0.018	0.010	0.018	0.006	0.018	0.013	0.005	0.014	0.019
% Business Services, Real Estate	0.136	0.147	0.130	0.178	0.170	0.204	0.273	0.230	0.295	0.239
% Education	0.037	0.039	0.034	0.036	0.024	0.030	0.025	0.019	0.020	0.018
% Health, Social Services	0.026	0.031	0.029	0.046	0.025	0.034	0.042	0.036	0.032	0.031
% Other Services (e.g. Leisure, Personal)	0.077	0.076	0.060	0.067	0.062	0.058	0.061	0.076	0.060	0.060
Firm Pay Premium	-0.196	-0.164	-0.205	-0.143	-0.223	-0.100	-0.117	-0.214	-0.063	-0.077
N	13,623	14,598	30,200	18,897	36,441	13,609	22,020	32,040	18,570	12,287

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

Table A21: Firm-level characteristics, by firm class. Veneto, 1984–2001.

Class	1	2	3	4	5	6	7	8	9	10
Firm Size: Mean	5.86	6.58	6.22	8.06	13.94	7.72	16.28	7.54	8.40	4.45
Firm Size: Median	2.75	3.20	2.58	3.28	4.87	2.91	4.84	2.76	3.02	2.35
% Firms > 50 Employees	0.011	0.011	0.013	0.019	0.044	0.019	0.054	0.018	0.013	0.005
% Men Employees	0.597	0.622	0.628	0.564	0.604	0.511	0.576	0.430	0.489	0.418
% Age 18-29	0.614	0.575	0.450	0.589	0.498	0.399	0.507	0.454	0.598	0.597
% Age 30-39	0.200	0.230	0.300	0.226	0.271	0.323	0.276	0.314	0.240	0.249
% Age 40-49	0.114	0.121	0.172	0.118	0.153	0.194	0.146	0.165	0.109	0.110
% Age 50+	0.072	0.073	0.077	0.068	0.078	0.083	0.071	0.067	0.053	0.044
% 5 Largest Cities	0.153	0.144	0.179	0.190	0.168	0.257	0.210	0.302	0.243	0.303
% Primary Sector	0.006	0.006	0.013	0.007	0.007	0.010	0.007	0.009	0.008	0.006
% Utilities	0.001	0.001	0.000	0.000	0.001	0.001	0.001	0.002	0.001	0.000
% Extractive and Chemical Industries	0.028	0.035	0.040	0.033	0.054	0.033	0.045	0.023	0.025	0.019
% Manufacturing: Metal	0.135	0.137	0.117	0.177	0.189	0.113	0.219	0.117	0.176	0.120
% Manufacturing: Other	0.348	0.383	0.341	0.263	0.313	0.176	0.205	0.113	0.179	0.132
% Construction	0.207	0.193	0.093	0.162	0.119	0.048	0.084	0.042	0.081	0.057
% Trade, Retail, Hospitality	0.140	0.145	0.282	0.172	0.200	0.423	0.249	0.405	0.259	0.343
% Transportation, Communications	0.021	0.013	0.016	0.027	0.020	0.028	0.030	0.034	0.034	0.035
% Finance, Insurance, Business Services	0.039	0.031	0.034	0.069	0.038	0.083	0.083	0.160	0.129	0.174
% Other Services	0.075	0.056	0.064	0.091	0.060	0.085	0.078	0.097	0.108	0.115
Firm Pay Premium	-0.071	-0.071	-0.104	-0.068	-0.060	-0.084	-0.044	-0.065	-0.068	-0.067
<i>N</i>	7,416	14,842	12,767	14,480	13,368	14,808	12,370	15,998	14,362	13,868

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

B Firms' Management Practices

The empirical evidence presented in Section 6 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 strongly correlated with productivity (Bloom et al., 2019) and the retention of good workers (Cornwell et al., 2019).

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. (2019) 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 B1 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 B1, we further show the lack of correlation between firms' management practices and our their learning opportunities.

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

Table B1: Management Practices and Firm Classes: Evidence from WMS in Brazil

	Rio de Janeiro (1)	Brazil (2)
Firm class 2	0.672 (0.530)	-0.012 (0.162)
Firm class 3	0.367 (0.529)	0.244 (0.149)
Firm class 4	-0.300 (0.502)	0.269* (0.154)
Firm class 5	0.181 (0.508)	0.198 (0.148)
Firm class 6	0.694 (0.646)	-0.246 (0.178)
Firm class 7	0.631 (0.533)	-0.365* (0.213)
Firm class 8	0.191 (0.529)	1.730*** (0.138)
Firm class 9	0.501 (0.526)	0.146 (0.148)
Firm class 10	0.978* (0.502)	0.181 (0.179)
Constant	2.467*** (0.502)	2.492*** (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. \(2019\)](#) 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. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.