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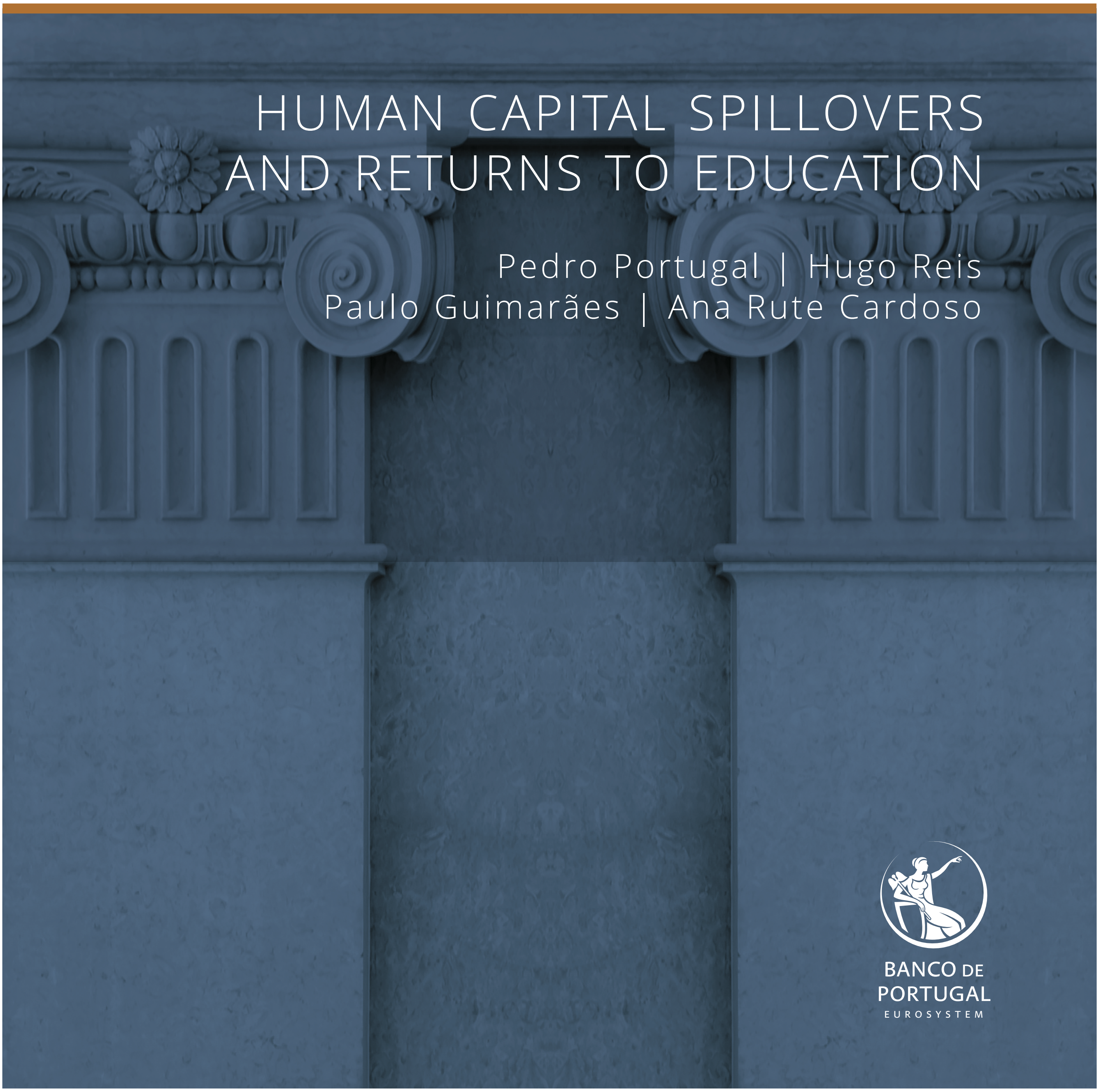

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Human Capital Spillovers and Returns to Education

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Abstract
In this paper, we quantify the impact of co-workers' human capital on a worker's productivity and, more specifically, the spillovers of co-workers' education within the workplace. We identify the impact of peer quality and provide an unambiguous decomposition of the impact of unobserved heterogeneity on the estimated returns to education. We find that peer effects are quite sizeable. A one standard deviation increase in the measure of peer quality leads to a wage increase of 2.1 percent. We also unveil that an additional year of average education of co-workers yields a 0.5 percent increase in the individual own wage.

JEL: J31; J24; I26

Keywords: wage distribution; human capital spillovers; returns to education; peer effects; linked employer-employee data; high-dimensional fixed effects; workplace; job and occupation.

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1. Introduction

Work within a firm is not undertaken in isolation. Rather, individuals collaborate with co-workers and they can benefit especially from interactions with colleagues in the same job. We study the impact of co-workers on a worker's productivity. We base our approach on the framework devised by Arcidiacono *et al.* (2012) to quantify spillovers within the classroom. They exploit longitudinal data to overcome well-known challenges in the identification of peer effects (Manski 1993; Angrist 2014). The cornerstone of their procedure is the inclusion of the average fixed effects of peers as a regressor, whose coefficient quantifies the magnitude of the spillovers within the group. Their procedure tackles the problems of selection into peer groups and spillovers from peers' unobserved quality.

The first step of our analysis estimates a wage regression in which the peers' average unobserved quality is the key variable of interest. Our model also includes the individual's own education, along with a set of controls. This step in our analysis bears resemblance to the analyses of the contemporaneous influence of peers' quality on a worker's wage by Cornelissen *et al.* (2017) and Battisti (2017). Results are unsettled. Cornelissen and co-authors found a small effect of peers' quality on a worker's wage, based on data from the Munich region in Germany, from 1989 to 2005. Differently, Battisti found larger effects of peer quality on a worker's wage, relying on data from the Veneto region in Italy, from 1982 to 2001. There is also no consensus on the definition of peer groups. In the first study, peers are workers in the same establishment and detailed occupation, whereas in the latter they are all coworkers in the firm.

In the second step of our analysis, we aim at understanding the mechanisms that generate the observed returns to a worker's education. Workers with different levels of education are not randomly allocated to firms and firms' pay standards are known to be heterogeneous. Likewise, workers are not randomly allocated to jobs or peer groups, and some jobs pay better than others. To the extent that education can grant a "passport" to better paying firms or jobs or access to better peers, part of the overall return on education would operate through a firm, job, or peer channel. Therefore, we measure the contribution of peer quality, as well as the non-random allocation of workers to firms and jobs, to the observed returns to a worker's education. To do so, we adapt Gelbach (2016) decomposition method to our setting. His approach is based on the OLS formula for omitted variable bias and allows for a decomposition that unequivocally quantifies the portion of the variation in a coefficient of interest attributed to each variable added to a regression.

In the third step of the analysis we explicitly account for co-workers' education, adding that regressor to go beyond the co-workers' fixed effect or time-invariant unobserved characteristics. Given that education is time-variant, both own schooling and peers' average schooling can be included in the peer effects regression. Using a procedure similar to the one described above, our subsequent decomposition exercise enables quantifying the impact of different channels that shape the returns to peers' education.

We rely on extremely rich data to build on the previous literature. First of all, we control for very fine combinations of establishment, job title, and year, a unit that coincides with our preferred definition of peer groups. Also, we rely on the observation of every worker and firm in the private sector of the Portuguese economy for over two decades, allowing us to include worker fixed effects in our model. Furthermore, we can track workers changing jobs and exploit time-series variation in the composition and size of the peer groups. We also observe the entire distribution of characteristics and outcomes of both the individual and all of his co-workers. In addition, our dataset reports the schooling of the worker, the number of hours worked, and a control variable on whether the worker's earnings refer to full schedule and full earnings during the month. The combination of full coverage of the economy with data on schooling has never before been used for research on the returns to education and peer effects. Also, unlike earlier studies on peer effects at the firm level, we can undertake an analysis of hourly wages, which are less contaminated by measurement error than labor earnings. Finally, our earnings data are not subject to any type of censoring. Crucially, our results on the impact of peers are not restricted to a narrow set of occupations or industries and are likely to be representative of the economy at large.

We present several robustness checks. We rely on alternative definitions of peers within the establishment in the same year – either workers in the same occupation or those in the same job title, which is a finer classification that takes into account the complexity of tasks performed and the degree of responsibility. We also consider alternative definitions of education: the number of years of education required for the highest degree completed or whether the worker holds a university degree.

Several studies on the impact of peers at work adopt a dynamic perspective, which diverges from our approach. Jarosch *et al.* (2021) and Hong and Lattanzio (2022) measure the impact of peers' unobserved quality on a worker's future wage, whereas Nix (2020) defines peers' knowledge as their level of education. They all find a sizable impact of peers on a worker's wage. Earlier less ambitious empirical exercises on the impact of co-workers' education have been undertaken by Battu *et al.* (2003) and Wirz (2008), who relied on cross-section data; and Martins and Jin (2010), who considered the firm as the unit of analysis, rather than the individual.

We find that peer effects are quite sizeable: a one standard deviation increase in the measure of peer quality leads to a wage increase of 2.1 percent. We also find that an additional year of average education of co-workers yields a 0.5 percent increase in individual own wage.

Section 2 provides an overview of the literature on wage heterogeneity across employers and education spillovers. Section 3 describes the institutional setting in the Portuguese labor market, followed by the data section. Section 5 presents the results on the benchmark wage equation. Section 6 presents the methodology and our estimation results on the returns to peers' quality. Section 7, in turn, explicitly considers peers' education, accounting for worker, peers', establishment, and job-title heterogeneity. Section 8 concludes.

2. Returns to Education: Current Evidence on the Role of the Peers

The literature on the spillovers of education is characterized by an unsettled debate. From a microeconomic perspective there are mainly two broad branches explaining how and why positive external returns to education may arise. They are highlighted by Acemoglu and Angrist (2000) and summarized by Moretti (2004a). The first is a theory of non-pecuniary external returns (technological spillovers), according to which the external returns arise from technological linkages across agents or firms. The second is a pecuniary model of external returns, in which spillovers arise from market interactions and changes in market prices resulting from the average education level of the workers. Furthermore, firms may deliberately cultivate a "team dynamic", with information-sharing, co-training, monitoring, and support, in order to exploit these spillovers.

The key idea in technological spillovers is that the exchange of ideas among workers raises productivity. Marshall (1890) was the first to argue that social interactions among workers in the same industry and location create learning opportunities that enhance productivity. Building on Marshall's insight, an influential paper by Lucas (1988) suggests that human capital spillovers may help explain differences in long-run economic performance of countries. The knowledge diffusion through formal and informal interaction is viewed as the channel that generates positive spillovers across workers.[1]

In turn, the key idea in pecuniary spillovers is that human capital encourages more investment by firms and raises other workers' wages. In particular, human capital spillovers may arise if human and physical capital are complements even in the absence of learning or technological spillovers. The best example is provided by Acemoglu (1996), as job search is costly and education spillovers are present due to the complementarity between physical and human capital. This complementary is discussed under labor market imperfections, innovation investment by firms, and training by workers. Human capital externalities arise here because firms choose their physical capital in anticipation of the average human capital of the workers they will employ in the future.

In contrast, in theoretical terms, co-worker education may also have negative spillovers. First, in signaling or screening models of education, education may be associated with negative externalities (Spence 1973), as it enables some workers to access higher paying firms, while excluding others, who are thus left unemployed or engaged in lower paying firms (Moen 1999). Furthermore, co-workers' education may also have negative spillovers if high and low-skill workers are imperfect substitutes (e.g., Moretti 2004a; Ciccone and Peri 2006), or if workers compete for promotions and do not share their human capital. If co-workers have different amounts of human capital, there may be as well a "skills incompatibility" problem

1. This notion of human capital externalities is also present in the works of Jovanovic and Rob (1989) and Glaeser (1999).

(see Kremer 1993). In this case, within an O-ring type of model, a firm with a uniform standard of education may have higher productivity than one where both the average education level and its dispersion are high.

In the empirical literature there is no consensus on the presence of education spillovers. Most of the existing evidence for human capital externalities relies on US estimates of the effects of regionally aggregated human capital on individual wages. For example, Rauch (1993), Acemoglu and Angrist (2000), Moretti (2004b), Moretti (2004c), and Ciccone and Peri (2006) have taken the city or region as the main unit of analysis where education spillovers could operate. Acemoglu and Angrist (2000) do not find significant external returns, Ciccone and Peri (2006) find negative spillovers, while Moretti (2004b) and Moretti (2004c) report significant positive impacts of graduates on the wages of workers in the same city. Rauch (1993) points to positive but small effects on wages.[2]

At the firm level, the empirical evidence on spillovers of education is relatively scarce. There are, nevertheless, noteworthy exceptions. Battu *et al.* (2003) find significantly positive effects in a cross-section study of British establishments, proxying firm average education from the distribution of workers across occupations.[3] Martins and Jin (2010) estimate social (firm-wide) returns to education and find implausibly large effects using Portuguese data. Wirz (2008) studies the Swiss economy relying on a cross-section of sample data and a two-stage estimation process to identify the returns to own and peers' education, while accounting for firm effects. She also finds positive and significant external returns on peers' education.

Some studies adopt a dynamic perspective on the impact of peers' knowledge on future earnings. Jarosch *et al.* (2021) rely on a sample of German establishments' entire workforce, from 1999 to 2009. They show that a worker's future wage growth is an increasing function of the current peers' knowledge. Hong and Lattanzio (2022) similarly analyze the impact of peer quality on future wage growth, finding a sizable impact that fades over time. Relying on data from the Veneto region, Italy, from 1975 to 2001, they also document an immediate impact of joining high-quality groups. Nix (2020) analysis is grounded on a theoretical model on the dynamics of learning within the firm. Differently from the previous authors, though, she defines peers' knowledge as their level of education. She shows that a worker's wage is an increasing function of the past peers' education, relying on the male workforce of a 5% sample of establishments in Sweden, from 1985 to 2012.[4]

2. Rauch (1993) does not take into account the endogeneity of location choices, arguably leading to an upward bias in the estimates.

3. Kirby and Riley (2008) look at this problem but at the more aggregated level of the industry.

4. A different strand of literature analyzes the contemporaneous impact of co-workers' behavior on an individual's productivity. These studies focus mainly on two specific channels (effort and team dynamics), based on small datasets and very specific sectors and tasks or laboratory experiments. For example, Falk and Ichino (2006) report on an experiment over a task putting letters into envelopes, Mas and Moretti (2009) study workers in one large supermarket chain, and Bandiera *et al.* (2010)

More recently, she showed that a worker's wage is an increasing function of the past peers' education. Her work is closest to ours, even though with notable differences. She defines peers as co-workers in the same firm, rather than an occupation within the firm. She quantifies the impact of the education level of past peers on a worker's current wage. Instead, we quantify the impact of the education of current peers on a worker's wage, controlling for spillovers of peers' time-invariant unobserved quality. Her outcome variable is monthly wages and the analysis is restricted to males, due to lack of information on hours of work, the estimation is performed on a 5% sample of the overall population. Our outcome of interest is hourly wages and the model is estimated on the population of workers and employers in the private sector of the economy. Nix's empirical analysis is backed-up by an ingenious theoretical model.

3. Institutional Setting on Wages

A national minimum wage is enforced in Portugal, defined as a monthly rate for full-time work. Currently, sub-minimum wages apply only to physically disabled workers and trainees, after the abolition in 1999 of all reductions based on age.

Collective bargaining plays a central role in the Portuguese labor market, as in several other continental European economies. Massive collective agreements, often covering an industry, are common in the economy. Firm level collective bargaining traditionally covers a low share of the workforce, less than 10%. Extension mechanisms are common, either by mandatory government regulation or on a voluntary basis, as employers automatically apply the contents of collective agreements to their non-unionized workforce.

Collective agreements set wage floors for very disaggregated job titles (see Carneiro *et al.* 2012; Card and Cardoso 2022). To take an example in the ship building industry there is a distinction between painters of the starboard and the port side of the ship.[5] Furthermore, note that under this definition of job title, two workers with the same job description (i.e. performing the same tasks and having the same responsibilities) covered by different bargaining agreements will have different job titles. Commonly, that results from the job being performed in different industries. This level of detail is much more granular than the conventional occupation classification. We take advantage of such an unusually fine accounting of the tasks to fill a job to determine the boundaries of highly homogeneous peer groups, under one of our alternative procedures to define peer groups within the firm.

look at soft-fruit pickers in one large U.K. farm. For an interesting summary of the empirical results in the more general literature on the impact of peer effects on worker output, see Herbst and Mas (2015). However, these works do not examine the returns to education.

5. It seems that the reasoning for the distinction relies upon the risk of falling in the water or on the ground.

It should be noted that despite the relevance of collective bargaining, firms have always enjoyed some degree of freedom in wage setting. Wage cushion (the difference between the actual wage level and the bargained wage level) promotes an alignment of wages with industry- and firm-level conditions, as documented in detail by Cardoso and Portugal (2005), Card and Cardoso (2022), and Addison *et al.* (2022). It follows from such an institutional setting that it is of key interest to quantify the impact of the firm when estimating the returns to education.

4. Data Source and Concepts Used

Quadros de Pessoal (QP) is an unusually rich and comprehensive linked employer-employee data set, gathered annually by the Ministry of Employment. It covers all establishments having at least one wage earner. The wage information is collected with reference to the month of October. Civil servants, self-employed, and household employees are not covered; the share of wage-earners in agriculture is low and therefore the coverage of this sector is low. Instead, for manufacturing and the services private sector of the economy, the survey covers virtually the entire population of workers and firms.

The following variables are reported on each worker: gender, date of birth (year and month), schooling, occupation, date of hire into the firm, monthly earnings, hours of work, the collective bargaining agreement, and the worker's job title ("*categoria profissional*") in that agreement. The schooling information refers to the highest completed level of education. Information on the employer includes the industry and location. In the current exercise we use information stretching from 1994 to 2013.[6]

We have restricted the analysis to workers aged 16 to 64, reported working full-time in the non-agricultural sectors, with at least 120 monthly hours of work, whose base wage does not fall below the national minimum wage, with non-missing schooling, and reported job duration between 0 and 600 months. To assure that our job title definition is meaningful, we dropped observations that are not assigned to any collective agreement and job titles that are defined as residual categories. Furthermore, to assure that co-workers share the same workplace we dropped workers in industries that provide services to other firms mainly through outsourcing (e.g., cleaning and security industries;).

Given the purpose of our analysis, we employ a rather strict definition of peers. The aim is to guarantee that workers share the same workplace and the same task. Hence, workers belong to a given peer group if, in a given year, they have a common job title and establishment. To quantify the human capital spillovers, we of course restrict the analysis to peer groups with at least two workers. Moreover, to separately identify establishment/job-title/year and worker fixed

6. Notice that no worker data are available for 2001.

effects, the analysis must be restricted to the set of peer groups (establishment/job-title/year) that are connected by worker mobility (see the discussion in Abowd *et al.* 2002). We therefore limit our analysis to the largest connected set of observations defined as connected for two fixed effects. The largest dataset under analysis comprises 19,051,268 observations on 3,663,524 million workers, 1,699,290 establishments/year, and 310,305 job-titles/year in collective bargaining. In total, we consider 3,912,653 peer groups with an average of 4.9 workers per peer group (see Table A.2.1 in Appendix).

Hourly wages are computed as the actual overall monthly earnings (including base wage, tenure-related and other regularly paid components) over the number of regular hours of work. Wages were deflated using the consumer price index (base 2013), but this correction is inconsequential since we always include year dummies in the regression analysis. Table A.2.2 in the Appendix presents the descriptive statistics for the variables used in the estimation.

The education variable is defined as the number of years needed to achieve the highest schooling degree. This variable is time-varying but the reader should have in mind that only a tiny proportion of workers actually change their schooling degree once they enter the labor market.

5. The Benchmark Wage Equation

We start by estimating a conventional OLS human capital wage regression including as covariates a quadratic term on age of the worker, a quadratic term on her job tenure, a measure of firm size (log of number of employees), the worker gender and schooling, together with year fixed effects. Table 1 reports the results of the OLS specification.

As expected, wages increase with age and tenure at a decreasing rate, reaching the maximum at 60 and 31 years, respectively. Also, not surprisingly, larger firms pay higher wages and the gender wage gap in Portugal over this period is estimated to be larger than 20 percent. In Portugal, each additional year of education increases wages, on average, by 8.3 percent (8.0 log points). This return is in line with international evidence, even though it places Portugal among the countries with relatively high returns to schooling (see Harmon *et al.* 2003; Card 1999; the cross-country survey of estimates by Ashenfelter *et al.* 1999; Trostel *et al.* 2002; and Montenegro and Patrinos 2014).

Age	0.0362
	(0.0006)
Age squared	-0.0003
	(0.0000)
Tenure	0.0184
	(0.0005)
Tenure squared	-0.0003
	(0.0000)
Firm size (log)	0.0602
	(0.0048)
Gender (Female=1)	-0.2713
	(0.0043)
Schooling	0.0796
	(0.0009)
Year effects	✓
N	19,051,268
R Squared	0.5517

Table 1. Wage Equation

Notes: The dependent variable is the logarithm of real hourly wages. The table reports the results of the benchmark specification including as covariates age, age squared, tenure, tenure squared, size of the firm, gender, worker schooling, and year fixed effects. Standard errors are clustered at the firm level.

6. Human Capital Spillovers

6.1. Estimation of Arcidiacono's et al. (2000) regression model

In this section we extend the basic OLS specification of Section 5 to account for the presence of human capital spillovers. We do so by adopting and extending the framework proposed by Arcidiacono *et al.* (2012). The nature of our extension is the inclusion of covariates in the wage regression equation, which will later be instrumental to decompose the return to education. Thus, our wage regression is now specified as follows:

$$y_{it} = \mathbf{x}_{it}\gamma + \alpha_i + \eta_0 \overline{\alpha}_{-it} + \theta_{\mathbf{E}\times\mathbf{J}\times\mathbf{t}} + \varepsilon_{it} \quad , \tag{1}$$

where y_{it} is the logarithm of the hourly wage for each worker i $(i = 1, ..., N)$ at year t $(t = 1, ..., T)$; $\mathbf{x}_{it}$ is a vector of observed time-varying regressors; α_i is the time-invariant fixed effect for worker i; $\overline{\alpha}_{-it}$ is the average of the fixed effects for the peers of worker i (the human capital spillovers); $\theta_{\mathbf{E}\times\mathbf{J}\times\mathbf{t}}$ is an establishment/job-title/year fixed effect; and ε_{it} is the disturbance term of the regression. We assume strict exogeneity, $E(\varepsilon_{it}|\mathbf{x}_{it}, \alpha_i, \theta_{\mathbf{E}\times\mathbf{J}\times\mathbf{t}})$, to ensure unbiasedness of all regression coefficients.

Estimation of this model is better discussed if we resort to matrix algebra. To simplify notation we let $\mathbf{X}$ be a matrix that contains all but the variables involving the worker-fixed effects. These include worker and firm observable characteristics, as well as other control variables such as additional sets of fixed effects. The number of linearly independent columns of $\mathbf{X}$ is given by k and the coefficients associated with the columns of $\mathbf{X}$ are represented by $\boldsymbol{\beta}$. The total number of observations is M (N stands for the total number of workers) and P is the number of mutually exclusive peer groups. In matrix terms worker fixed effects are given by the product of the worker design matrix $\mathbf{D}$ by the vector $\boldsymbol{\alpha}$ containing coefficients on worker fixed effects. Thus, $\mathbf{X}$ is $(M \times k)$, $\boldsymbol{\beta}$ is $(k \times 1)$, $\mathbf{D}$ is $(M \times N)$ and $\boldsymbol{\alpha}$ is $(N \times 1)$. The variable containing the peer average of the worker fixed effects can be represented by the vector $\mathbf{WD}\boldsymbol{\alpha}$ where $\mathbf{W}$ is an $M \times M$ mean computing matrix. Note that $\mathbf{W}$ is symmetric and block diagonal:

$$\mathbf{W} = diag(\mathbf{w}_1, \mathbf{w}_2, ..., \mathbf{w}_P) \quad .$$

Each generic submatrix $\mathbf{w}_j$ identifies a peer group and is given by

$$\mathbf{w_j} = (n_j - 1)^{-1}[\mathbf{ii}' - \mathbf{I}]) \tag{2}$$

where n_j stands for the number of elements in peer group j and $\mathbf{i}$ is a column vector of 1s with size n_j. Multiplication of $\mathbf{w}_j$ by any vector $[\alpha_1, \alpha_2, ..., \alpha_{n_j}]'$ will result in a vector with the same dimension, $[\overline{\alpha}_{-1}, \overline{\alpha}_{-2}, ..., \overline{\alpha}_{-n_j}]'$, containing the mean of all elements excluding the self. This means that we can write (1) as

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{D}\boldsymbol{\alpha} + \eta_0\mathbf{WD}\boldsymbol{\alpha} + \varepsilon = \mathbf{X}\boldsymbol{\beta} + [\mathbf{I} + \eta_0\mathbf{W}]\mathbf{D}\boldsymbol{\alpha} + \varepsilon \quad . \tag{3}$$

The equation in (3) is nonlinear on the αs. However, as suggested by Arcidiacono *et al.* (2012), this equation can be estimated using nonlinear least squares. To estimate $(\boldsymbol{\beta}, \eta_0, \boldsymbol{\alpha})$ using least squares define the vector of residuals

$$\mathbf{e} = \mathbf{Y} - \mathbf{X}\widehat{\boldsymbol{\beta}} - \mathbf{D}\widehat{\boldsymbol{\alpha}} - \widehat{\eta}_0\mathbf{WD}\widehat{\boldsymbol{\alpha}}$$

and let $S(\widehat{\boldsymbol{\beta}}, \widehat{\eta}_0, \widehat{\boldsymbol{\alpha}}) = \mathbf{e}'\mathbf{e}$. Thus,

$$S(\widehat{\boldsymbol{\beta}}, \widehat{\eta}_0, \widehat{\boldsymbol{\alpha}}) = \left[\mathbf{Y}' - \widehat{\boldsymbol{\beta}}'\mathbf{X}' - \widehat{\boldsymbol{\alpha}}'\mathbf{D}' - \widehat{\eta}_0\widehat{\boldsymbol{\alpha}}'\mathbf{D}'\mathbf{W}\right]\left[\mathbf{Y} - \mathbf{X}\widehat{\boldsymbol{\beta}} - \mathbf{D}\widehat{\boldsymbol{\alpha}} - \widehat{\eta}_0\mathbf{WD}\widehat{\boldsymbol{\alpha}}\right]$$

and from the first order conditions for minimization of $S(.)$ we obtain:

$$\frac{\partial S(.)}{\partial \widehat{\boldsymbol{\beta}}} = \mathbf{X}'\mathbf{e} = \mathbf{0} \tag{4}$$

$$\frac{\partial S(.)}{\partial \widehat{\eta}_0} = \widehat{\boldsymbol{\alpha}}'\mathbf{D}'\mathbf{W}\mathbf{e} = \mathbf{0} \tag{5}$$

$$\frac{\partial S(.)}{\partial \widehat{\boldsymbol{\alpha}}} = \left[\mathbf{D}' + \widehat{\eta}_0\mathbf{D}'\mathbf{W}\right]\mathbf{e} = \mathbf{0} \quad . \tag{6}$$

The above set of conditions makes it clear that in Arcidiacono *et al.*'s peer effects model there is no requirement that $\mathbf{D}'\mathbf{e} = \mathbf{0}$ the practical implication being that the coefficients of time-invariant variables associated with the worker may be identified.[7] These f.o.cs can be solved iteratively by alternating between the solution of each condition. But this approach is complicated by the high-dimensionality of $\mathbf{D}$ (and possibly that of other fixed effects included in $\mathbf{X}$). The main obstacle is solving the condition $[\mathbf{D}' + \widehat{\eta}_0 \mathbf{D}'\mathbf{W}]\,\mathbf{e} = \mathbf{0}$. Conditional on $\widehat{\eta}_0$ we can solve this f.o.c iteratively. Rewriting

$$\left[\mathbf{D}' + \widehat{\eta}_0 \mathbf{D}'\mathbf{W}\right] \left[\mathbf{Y} - \mathbf{X}\widehat{\boldsymbol{\beta}} - \mathbf{D}\widehat{\boldsymbol{\alpha}} - \widehat{\eta}_0 \mathbf{W}\mathbf{D}\widehat{\boldsymbol{\alpha}}\right] = \mathbf{0} \quad ,$$

and rearranging and solving for $\mathbf{D}'\mathbf{D}\widehat{\boldsymbol{\alpha}}$

$$\mathbf{D}'\mathbf{D}\widehat{\boldsymbol{\alpha}} = \mathbf{D}'\left[\mathbf{I} + \widehat{\eta}_0 \mathbf{W}\right]\mathbf{Y} - \mathbf{D}'\left[\mathbf{I} + \widehat{\eta}_0 \mathbf{W}\right]\mathbf{X}\widehat{\boldsymbol{\beta}} - \mathbf{D}'\widehat{\eta}_0\left[2\mathbf{I} + \widehat{\eta}_0 \mathbf{W}\right]\mathbf{W}\mathbf{D}\widehat{\boldsymbol{\alpha}} \quad ,$$

and now premultiplying by $\left[\mathbf{D}'\mathbf{D}\right]^{-1}$ and letting $\mathbf{M}_{\mathbf{D}} \equiv \left[\mathbf{D}'\mathbf{D}\right]^{-1}\mathbf{D}'$ we obtain

$$\widehat{\boldsymbol{\alpha}} = \mathbf{M}_{\mathbf{D}}\left[\mathbf{I} + \widehat{\eta}_0 \mathbf{W}\right]\left[\mathbf{Y} - \mathbf{X}\widehat{\boldsymbol{\beta}}\right] - \widehat{\eta}_0 \mathbf{M}_{\mathbf{D}}\left[2\mathbf{I} + \widehat{\eta}_0 \mathbf{W}\right]\mathbf{W}\mathbf{D}\widehat{\boldsymbol{\alpha}} \quad .$$

The above expression provides a natural way to solve recursively for $\widehat{\boldsymbol{\alpha}}$ and this is basically the suggestion in Arcidiacono *et al.* (2012), plug in values for $\widehat{\boldsymbol{\alpha}}$ on the right hand side and solve for the $\widehat{\boldsymbol{\alpha}}$ on the left hand side. More specifically, letting h index iteration the updating equation becomes

$$\widehat{\boldsymbol{\alpha}}_{[h]} = \mathbf{M}_{\mathbf{D}}\left[\mathbf{I} + \widehat{\eta}_0 \mathbf{W}\right]\left[\mathbf{Y} - \mathbf{X}\widehat{\boldsymbol{\beta}}\right] - \widehat{\eta}_0 \mathbf{M}_{\mathbf{D}}\left[2\mathbf{I} + \widehat{\eta}_0 \mathbf{W}\right]\mathbf{W}\mathbf{D}\widehat{\boldsymbol{\alpha}}_{[h-1]} \quad . \tag{7}$$

There is, however, a faster approach to solve the f.o.c. $[\mathbf{D}' + \widehat{\eta}_0 \mathbf{D}'\mathbf{W}]\,\mathbf{e} = \mathbf{0}$. Rewrite the condition as

$$\mathbf{D}'\widetilde{\mathbf{W}}\left[\mathbf{Y} - \mathbf{X}\widehat{\boldsymbol{\beta}} - \widetilde{\mathbf{W}}\mathbf{D}\widehat{\boldsymbol{\alpha}}\right] = \mathbf{0}$$

where $\widetilde{\mathbf{W}} = \mathbf{I} + \widehat{\eta}_0 \mathbf{W}$. We can then rewrite the equation as

$$\mathbf{D}'\widetilde{\mathbf{W}}\widetilde{\mathbf{W}}\mathbf{D}\widehat{\boldsymbol{\alpha}} = \mathbf{D}'\widetilde{\mathbf{W}}\left[\mathbf{Y} - \mathbf{X}\widehat{\boldsymbol{\beta}}\right]$$

and since this is now expressed as a system of linear equations it is possible to apply the conjugate gradient method to obtain a solution for $\widehat{\boldsymbol{\alpha}}$ (conditional on $\widehat{\eta}_0$). This is the solution that we implement in our estimations.[8]

7. In a conventional linear regression with worker fixed-effects, $\mathbf{Y} = \mathbf{X}\beta + \mathbf{D}\alpha + \varepsilon$, the first order conditions are $\mathbf{X}'\mathbf{e} = \mathbf{0}$ and $\mathbf{D}'\mathbf{e} = \mathbf{0}$. Since any time-invariant characteristic of the worker can be expressed as $\mathbf{D}\mathbf{z}$ (where $\mathbf{z}$ is a vector of length N with worker-level characteristics) the associated f.o.c. becomes redundant because $\mathbf{z}'\mathbf{D}'\mathbf{e} = \mathbf{0}$.

8. We have developed a Stata command, *regpeer*, which implements this estimation procedure.

6.2. Empirical results on human capital spillovers

We now present the results of a model that includes a measure of human capital spillovers according to equation (1). As discussed above, we rely on an iterative estimation procedure to estimate the model. In this specification we include establishment/job-title/year fixed effects, a definition of fixed effect that overlaps with that of the peer group. Proceeding in this way, we are adding the role of time-varying changes in the wage policies of the firms (and within firms across establishments), the influence of the secular trends in the remuneration of job titles, and the interplay between establishment, job title, and year effects. Table 2 reports the results.

There is clear empirical support for the notion that peer quality has a strong impact on individual wages. The key parameter of interest (η_0) is estimated to be 0.2, meaning that if the quality of the peers as measured by $\overline{\alpha}_{-it}$ increases by 10 percent wages will increase by 2.0 percent. Put differently, a one standard deviation increase in the measure of human capital spillover (0.1029) leads to a wage increase of about 2.1 percent (0.2044 $\times$ 0.1029).[9] This figure is significantly higher than those provided by Cornelissen *et al.* (2017) for Munich, but closer to the figures presented by Battisti (2017) for the Italian region, when using the closest definition of the peer group.[10]

The identification of the effects of human capital spillovers arises strictly from changes in the size of the peer groups, eliminating any endogenous contamination from sorting into establishments and job titles, over time (this point is also discussed in Cornelissen *et al.* 2017). Note that $\overline{\alpha}_{-it}$ in peer group p can be expressed as $(\alpha_{\bullet p} - \alpha_i)/(n_p - 1) = \alpha_{\bullet p}/(n_p - 1) - \alpha_i/(n_p - 1)$ where $\alpha_{\bullet p}$ is the sum of the fixed effects for all workers in group p. The first term, $\alpha_{\bullet p}/(n_p - 1)$, is completely absorbed by the peer group fixed effect while the second term, $\alpha_i/(n_p - 1)$, is absorbed by the worker fixed effect unless n_p changes with i. In sum, with the inclusion of establishment/job-title/year fixed effects, identification of η_0 is only possible if workers are participating in peer groups of different sizes.

There is no obvious optimal level of disaggregation in the use of high-dimensional fixed effects. However, this seems to be a reasonable identification strategy. Furthermore, with this identification strategy, we isolate the occurrence of firm specific shocks, which may influence both the level of wages and co-worker composition. A similar argument can be advanced for the case of job-title specific shocks. A remaining concern could be that the overlapping of the

9. The standard deviation estimate (0.1029) corresponds to the average of the standard deviations of the measure of peer quality (as measured by the fixed effects of each peer). This and other statistical moments from the wage distribution corresponding to this specification are given in Table A.2.3 in the Appendix.

10. Our specification is identical to that given in equation (6) by Cornelissen *et al.* (2017), where the fixed effect definition corresponds to the definition of the peer group. Whereas in their case the human capital spillover parameter estimate is 0.01 (given in their Online Appendix B), in our case is 0.20.

	Base	Full
Age	0.0362	0.0147
	(0.0006)	(0.0001)
Age squared	-0.0003	-0.0002
	(0.0000)	(0.00001)
Tenure	0.0184	0.0066
	(0.0005)	(0.00003)
Tenure squared	-0.0003	-0.0001
	(0.0000)	(0.00001)
Firm size (log)	0.0602	-
	(0.0048)	-
Gender (Female=1)	-0.2713	-0.0310
	(0.0043)	(0.0029)
Schooling	0.0796	0.0020
	(0.0009)	(0.0001)
HC spillovers ($\overline{\alpha}_{-it}$)	-	0.2044
	-	(0.0012)
Year effects	✓	
Worker effects		✓
Establishment/Job-title/Year effects		✓
N	19,051,268	19,051,268
R Squared	0.5517	0.9766

Table 2. Wage Equation with Human Capital Spillovers

Notes: The dependent variable is the logarithm of real hourly wages. Column (1) reports the results of the benchmark specification including as covariates age, age squared, tenure, tenure squared, size of the firm, gender, worker schooling, and year fixed effects. Column (2) shows the full specification, including worker, establishment/job-title/year fixed effects, and human capital spillovers effect (peer group fixed effects). The conditional decomposition of the return to education is based on Gelbach (2016). Standard errors are clustered at the firm level in column (1). Standard errors in Columns (2) are obtained as explained in Appendix A.1.

establishment/job-title/year fixed effect with the definition of peer group may not leave enough sources of variation to identify the human capital spillovers. Arguably, this is strictly an empirical question that can be answered after the estimation of the model.

6.3. Gelbach's decomposition

To understand the contribution that human capital spillovers along with the allocation of workers to establishments and jobs to the observed education pay differential we adapt Gelbach's (2016) decomposition method to this particular setting. His approach is based on the OLS formula for omitted variable bias and allows for a decomposition that unequivocally quantifies the portion of the variation attributed to a set of variables added to a regression. In our particular case, we want to understand the individual contribution of the returns to education when we move from the base to the full model in Table 2. Gelbach's decomposition is easier to present if we resort to matrix notation. Consider the Mincerian equation underlying the specification in the base equation. For convenience, we collect all variables but worker schooling, into the matrix $\mathbf{Z}$. Our variable of interest, schooling, is introduced separately and represented by the variable $\mathbf{S}$. Thus, we have

$$\mathbf{Y} = \mathbf{Z}\boldsymbol{\gamma_0} + \delta_0 \mathbf{S} + \boldsymbol{\varepsilon} \quad . \tag{8}$$

By the Frisch-Waugh-Lovell theorem we know that the same OLS estimate of δ_0 may be obtained by running a simple regression of $\mathbf{Y}$ on $\mathbf{S}$ after partialing out the effect of $\mathbf{Z}$ from both variables. More specifically,

$$\widehat{\delta}_0 = \left(\mathbf{S}'\mathbf{M_Z}\mathbf{S}\right)^{-1}\mathbf{S}'\mathbf{M_Z}\mathbf{Y} = \mathbf{P_Z}\mathbf{Y} \quad , \tag{9}$$

where $\mathbf{M_Z} \equiv \mathbf{I} - \mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'$ is the well-known symmetric and idempotent residual-maker matrix. Here $\widehat{\delta}_0$ is the OLS estimator that produced the estimates for the returns to education in the base model. To show how Gelbach's decomposition can be used to tease out the contribution of the added variables to the returns to education, consider now the full regression to which we added the human capital spillovers as well as two sets of fixed effects: worker ($\boldsymbol{\alpha}$) and establishment/job-title/year fixed effects ($\boldsymbol{\theta}$). This regression, written in terms of its fitted least squares expression, is:

$$\mathbf{Y} = \mathbf{Z}\widehat{\gamma} + \widehat{\delta}\mathbf{S} + \mathbf{D}\widehat{\boldsymbol{\alpha}} + \widehat{\eta}_0\mathbf{W}\mathbf{D}\widehat{\boldsymbol{\alpha}} + \mathbf{L}\widehat{\boldsymbol{\theta}} + \mathbf{e} \quad . \tag{10}$$

To obtain a decomposition of $\widehat{\delta}_0$ we multiply both terms of equation (10) by $\mathbf{P_Z}$. On the left-hand side we obtain $\widehat{\delta}_0$ directly and from the f.o.c in (4) we know that $\mathbf{P_Z}\mathbf{Z}\widehat{\gamma} = \mathbf{0}$ and $\mathbf{P_Z}\mathbf{e} = \mathbf{0}$. Thus, the right-hand side becomes:

$$\widehat{\delta}_0 = \widehat{\delta} + \mathbf{P_Z}\mathbf{D}\widehat{\boldsymbol{\alpha}} + \mathbf{P_Z}(\widehat{\eta}_0\mathbf{W}\mathbf{D}\widehat{\boldsymbol{\alpha}}) + \mathbf{P_Z}\mathbf{L}\widehat{\boldsymbol{\theta}} = \widehat{\delta} + \widehat{\delta}_{\boldsymbol{HC}} + \widehat{\delta}_{\boldsymbol{\alpha}} + \widehat{\delta}_{\boldsymbol{\theta}} \quad . \tag{11}$$

Note that $\widehat{\delta}$ is the estimate of the coefficient associated with education from the full model and $\mathbf{D}\widehat{\boldsymbol{\alpha}}$, $\mathbf{W}\mathbf{D}\widehat{\boldsymbol{\alpha}}$, and $\mathbf{L}\widehat{\boldsymbol{\theta}}$ are column vectors containing the estimates for the worker fixed effects, the average of the peers, and the establishment/job-title/year fixed effects, respectively. Thus, to obtain Gelbach's decomposition we need only regress these components on education while controlling for the remaining observable variables ($\mathbf{Z}$).

This means that the conventional return on education, $\widehat{\delta}_0$, can be decomposed into three terms that reflect the impact of the workers, their peers, and the workplace/job-title channel. If, conditional on all $\mathbf{Z}$ covariates, workers were randomly allocated to workplace/job-title combinations, then the estimate for

$\widehat{\delta}_{\boldsymbol{\theta}}$ would be zero. In this case the distribution of schooling levels within each workplace/job-title cell would replicate the distribution of schooling levels in the economy, such that the matching of schooling levels to firm/job-titles with different pay standard would not be a source of returns to education. On the other hand, a positive value for $\widehat{\delta}_{\boldsymbol{\theta}}$ would be a clear indication that better educated workers are sorted to higher-paying workplaces and/or job titles. From the equation above we see that the estimate of $\widehat{\delta}_{\boldsymbol{\theta}}$ may be interpreted as the log point reduction/increase that occurs in the returns to schooling due to the allocation of workers to firms and job titles.

It is possible to go further and decompose $\widehat{\delta}_{\boldsymbol{\theta}}$ on the contribution due to (time-varying) establishments and job effects. To do this we need to separate $\mathbf{L}\widehat{\boldsymbol{\theta}}$ into three components, say:

$$\mathbf{L}\widehat{\boldsymbol{\theta}} = \widehat{\boldsymbol{\Phi}} + \widehat{\boldsymbol{\Lambda}} + \widehat{\boldsymbol{\zeta}} \tag{12}$$

where $\widehat{\boldsymbol{\Phi}}$ would reflect the contribution of establishments over time, $\widehat{\boldsymbol{\Lambda}}$ that of jobs over time, and $\widehat{\boldsymbol{\zeta}}$ would pick the remaining interactions. If we multiply the above expression by $\mathbf{P}_{\mathbf{Z}}$ we obtain

$$\widehat{\delta}_{\boldsymbol{\theta}} = \widehat{\delta}_{\boldsymbol{\Phi}} + \widehat{\delta}_{\boldsymbol{\Lambda}} + \widehat{\delta}_{\boldsymbol{\zeta}} \quad . \tag{13}$$

Unfortunately there is no unique way to implement the decomposition in equation (12). However, we can follow the approach of Woodcock (2015) and assume that the (time-varying) establishments and job effects are orthogonal to the interactions between establishment, job, and time. In practical terms this amounts to running a linear regression of the fitted values $\mathbf{L}\widehat{\boldsymbol{\theta}}$ on a fixed effect given by the establishment time interaction, and another fixed effect for the job title and time interaction. The estimates of these fixed effects give us the separate contribution of estimates and job titles while the residual can only be attributed to interactions between establishments, jobs, and time. With this approach we are ascribing as much as possible of the variation on $\mathbf{L}\widehat{\boldsymbol{\theta}}$ to the additive effects of temporal establishment and job effects. Thus, the estimate we obtain for the establishment/job-title/time interaction ($\widehat{\delta}_{\boldsymbol{\zeta}}$) should be seen as a lower bound.

6.4. Decomposing the returns to education with human capital spillovers

Table 3 exhibits the decomposition of the returns to education in the presence of human capital spillovers.[11] The first panel shows that the difference between the returns to education in the base model (0.0796) and in the full model (0.0020) can be exactly decomposed in three components: the contribution of worker

11. We consider the possibility of employing a two-step IV procedure (using changes in compulsory education as an instrument). We are not reporting those results because the statistical properties of this estimator in this framework are not well known. Be that as it may, the decomposition exercise from the IV procedure produces similar results.

Gelbach Decomposition of the Return to Education

Benchmark Regression	Full Specification	Decomposition into: Worker FE	Establishment/Job-title/Year	Human Capital spillovers
(1)	(2)	(3)	(4)	(5)
0.0796				
(0.0009)				
	0.0020	0.0298	0.0420	0.0058
	(0.0001)	(0.0004)	(0.0006)	(0.0001)

Panel B - Decomposition of the Establishment/Job-title/Time FE

Establishment/Job-title/Year FE	Establishment/Year	Job Title/Year	Interaction
(1)	(2)	(3)	(4)
0.0420	0.0215	0.0197	0.0008
(0.0006)	(0.0007)	(0.0003)	(0.0001)

Table 3. Conditional Decomposition of the Return to Education, with Human Capital Spillovers

Notes: The conditional decomposition of the return to education is based on Gelbach (2016). Column (1) reports the coefficient of the benchmark result on return to education. Column (2) reports the coefficient of the full specification after including worker and establishment/job-title/Year fixed effects, and human capital spillovers (peer group fixed effects). The results of the decomposition are reported in Columns (3), (4), and (5). Adding up the results of Columns (3) to (5) we obtain the benchmark coefficient in Column (1). Standard errors are clustered at the firm level in columns (1), (3), (4), and (5). Standard errors in Column (2) are obtained as explained in Appendix A.1.

component, the contribution of sorting across establishment/job-title over time, and the contribution of human capital spillovers.

The worker component (0.0298) can be interpreted as the returns to education for the case in which workers are randomly assigned into establishment and job-titles, and co-workers.

The contribution of the establishment/job-title/year component (0.0420) means that more educated workers are assigned into better paying establishments and better paid job-titles. We can further decompose the effect of this sorting mechanism into three parts (see equation 13): sorting into better paying establishments accounts for 0.0215 of the returns to education, and sorting into better paid job-title accounts for 0.0197 of the returns to education. The remaining component (interaction between establishment and job-title fixed effects) plays a minor role (0.0008).

The key innovation of this exercise is the estimation of the contribution of the peer quality to the individual return to education (0.0058). The indication that more educated workers tend to match with higher quality peers leads to a boost in the returns to education of 0.6 percentage points. Put differently, 7.3 percent of the returns to education arrive from the spillover channel.

6.5. Robustness checks

We now undertake three exercises of robustness checks. First, we control for alternative levels of heterogeneity instead of the baseline control for establishment/job title/year effects. Second, we consider peers as workers in the same occupation instead of establishment. Finally, we use an alternative definition of education, classifying workers depending on whether they hold a university degree.

6.5.1. Control for different levels of heterogeneity (FE). In Table 4 we explore the sensitivity of the human capital spillovers to different definitions of the establishment, job-title, and year fixed effects. Furthermore, we compare specifications with and without covariates.

	HC spillovers ($\overline{\alpha}_{-it}$)			
	(1)	(2)	(3)	(4)
Full Specification	0.2044 (0.0012)	0.4892 (0.0006)	0.3583 (0.0005)	0.1525 (0.0008)
Excluding Covariates	0.1984 (0.0012)	0.4394 (0.0006)	0.3417 (0.0005)	0.1457 (0.0008)
Year effects (μ_t)		✓		
Worker effects (α_i)	✓	✓	✓	✓
Establishment/Job-title effects		✓		✓
Establishment/year effects			✓	✓
Job-title/year effects			✓	✓
Establishment/job-title/year effects	✓			
N	19,051,268	19,051,268	19,051,268	19,051,268

Table 4. Sensitivity of the Human Capital Spillovers

Notes: The covariates used in the full specification are the same as in column (2) in Table 2. Standard errors are obtained as explained in Appendix A.1.

The first column corresponds to the specification present in the last column of Table 2, where the definition of the fixed effects corresponds to the definition of the peer group. In general, more aggregate definitions of the fixed effects seems to generate higher values for the human capital spillover parameter. There is however, a notable exception for the case in which we use four high-dimensional fixed effects (column 4).

As hinted at before, the absence of covariates in the specifications does not affect significantly the estimate of the human capital spillovers, in particular for the case of more disaggregated fixed effects. In all cases the omission of variables seems to lead to an attenuation bias.

More importantly, it is clear that using a specification with the highest possible level of disagregation, whereby the source of identification arises solely from the size of the peer group, does not wash away in our data the impact of human capital spillovers, as feared for example by Cornelissen *et al.* (2017).

6.5.2. Peers defined as workers in the same occupation. In Table 5 we present the regression results using a broader definition of peer group using the more conventional occupation classification. We rely on the 4 digit ISCO classification of occupations, including 4164 categories. The estimate of the elasticity of wages with respect to the peers' human capital is now 0.31. This means that when the human capital of the co-workers increases by 1 standard deviation (0.1234), wages increase by 3.8 percent.

	Base	Full
Age	0.0351	0.0168
	(0.0006)	(0.0001)
Age squared	-0.0003	-0.0002
	(0.0000)	(0.0000)
Tenure	0.0180	0.0086
	(0.0006)	(0.0000)
Tenure squared	-0.0002	-0.0002
	(0.00002)	(0.0000)
Firm size (log)	0.0604	-
	(0.0049)	-
Gender (Female=1)	-0.2709	-0.0355
	(0.0044)	(0.0022)
Schooling	0.0782	0.0024
	(0.0010)	(0.0001)
HC spillovers ($\overline{\alpha}_{-it}$)	-	0.3087
	-	(0.0012)
Year effects	✓	
Worker effects		✓
Establishment/Occupation/Year effects		✓
N	17,978,306	17,978,306
R Squared	0.5423	0.9726

Table 5. Wage Equation with Human Capital Spillovers - Occupation

Notes: The dependent variable is the logarithm of real hourly wages. Standard errors are clustered at the firm level in Column (1). Standard errors in Column (2) are obtained as explained in Appendix A.1.

The decomposition of the returns to education now points to a contribution of human capital spillovers on the order of 13 percent (Table 6). Those values suggest that a broader definition of the peer group, which also increases the average size of the peer group, leads to a greater impact of the human capital spillovers. In the same vein, it is no surprise that the importance of sorting into an occupation is less when compared to the sorting into the job-title.

Panel A - Gelbach Decomposition of the Return to Education

Benchmark Regression	Full Specification	Decomposition into: Worker FE	Establishment/Occupation/Year	Human Capital spillovers
(1)	(2)	(3)	(4)	(5)
0.0782				
(0.0010)				
	0.0024	0.0365	0.0289	0.0105
	(0.0000)	(0.0006)	(0.0006)	(0.0002)

Panel B - Decomposition of the Establishment/Occupation/Time FE

Establishment/Job-title/Year FE	Establishment/Year	Occupation/Year	Interaction
(1)	(2)	(3)	(4)
0.0289	0.0190	0.0097	0.0002
(0.0006)	(0.0007)	(0.0002)	(0.0001)

Table 6. Conditional Decomposition of the Returns to Education with Human Capital Spillovers

Notes: The conditional decomposition of the return to education is based on Gelbach (2016). Standard errors are clustered at firm level in columns (1), (3), (4), and (5). Standard errors in Column (2) are obtained as explained in Appendix A.1.

6.5.3. College premium. We now present the wage regression results considering an alternative definition of education, classifying workers depending on whether they hold a university degree. Results are reported in Table 7.

In Portugal, the college premium is estimated to be quite large implying that the wages of college graduates are, on average, 135 percent higher than those without a college degree. One should have in mind that education level among non-graduates is historically very low and encompasses a non-negligible percentage of workers without primary school.

It can be shown that changing the measure of schooling does not materially change the estimate of the human capital spillovers, which remains at 0.2. This result is a first indication that choice of covariates does not significantly affect the estimate of the effect of peer quality.

Table 8 gives the decomposition of the college premium in the presence of human capital spillovers. The estimate suggests that the most influential channel driving the college premium is the indication that individuals with a college degree tend to sort themselves into better paying establishment and job-titles (accounting for two thirds of college premium). The worker component accounts for 37.4 percent.

In line with our previous decomposition exercise, working with higher quality (more productive) co-workers leads to a higher college premium. In other words, 7.5 percent of the college premium arrives from the human capital spillovers effect.

	Base	Full
Age	0.0331	0.0146
	(0.0007)	(0.0001)
Age squared	-0.0004	-0.00015
	(0.0000)	(0.00000)
Tenure	0.0178	0.0065
	(0.0007)	(0.0000)
Tenure squared	-0.0003	-0.00015
	(0.00002)	(0.00000)
Firm size (log)	0.0795	-
	(0.0060)	-
Gender (Female=1)	-0.2623	-0.0319
	(0.0055)	(0.0029)
College	0.8555	0.0349
	(0.0143)	(0.0006)
HC spillovers ($\overline{\alpha}_{-it}$)	-	0.2025
	-	(0.0012)
Year effects	✓	
Worker effects		✓
Establishment/Job-title/Year effects		✓
N	19,051,268	19,051,268
R Squared	0.4424	0.9766

Table 7. Wage Equation with Human Capital Spillovers - College premium

Notes: The dependent variable is the logarithm of real hourly wages. Standard errors are clustered at the firm level in Column (1). Standard errors in Column (2) are obtained as explained in Appendix A.1.

Panel A - Gelbach Decomposition of the Return to Education

Benchmark Regression	Full Specification	Decomposition into: Worker FE	Establishment/Job-title/Year	Human Capital spillovers
(1)	(2)	(3)	(4)	(5)
0.8555 (0.0143)				
	0.0350 (0.0001)	0.3201 (0.0063)	0.4367 (0.0091)	0.0638 (0.0011)

Panel B - Decomposition of the Establishment/Job-title/Time FE

Establishment/Job-title/Year FE	Establishment/Year	Job Title/Year	Interaction
(1)	(2)	(3)	(4)
0.4367 (0.0091)	0.1979 (0.0087)	0.2276 (0.0056)	0.0112 (0.0001)

Table 8. Conditional Decomposition of the College premium with Human Capital Spillovers

Notes: The conditional decomposition of the return to education is based on Gelbach (2016). Standard errors are clustered at firm level in columns (1), (3), (4), and (5). Standard errors in Column (2) are obtained as explained in Appendix A.1.

7. The Role of Co-worker Education

To capture educational spillovers we now explicitly account for the average education of the co-workers. Consistent with the previous analysis, co-workers of an individual worker are defined as all individuals that, in a given year, share the same establishment and job title.

Adding the average education of the co-worker to our benchmark specification raises a number of identification problems and specification pitfalls that have been exposed in the literature, in particular by Manski (1993) and more recently by Angrist (2014). Indeed, even in the absence of social interactions, individuals in the same firm and job title category will tend to have similar wages, which in general will lead to an upward bias in the estimation of the co-worker education effect. Even without causal “peer" effects there are mechanical and statistical issues that may lead to similar outcomes between peers. We can distinguish three main problems in the estimation of these effects: homophily, selection, and “mechanical" measurement error. The homophily problem states that it is very hard to disentangle whether or not the average behavior in one group is actually influencing that same behavior at the individual level of the members of that group. The selection problem arises if the group is formed endogenously, making it hard to distinguish peer effects from selection effects. The “mechanical" measurement error problem, discussed by Angrist (2014), states that even in settings where peers are assigned randomly there is a mechanical relationship between own and peer attributes that may bias the estimation of the peer effect.[12]

12. Feld and Zölitz (2017) build on Angrist (2014) and study the role of measurement error in the estimation of peer effects.

We are confident that our methodological approach can address the three above mentioned estimation hurdles. First of all, we explore a very rich and exhaustive longitudinal database that allows us to overcome the issue of homophily via the presence of individual fixed effects. Second, by controlling for highly disaggregated establishment/job-title/year combinations, we circumvent the issues raised by sorting and peer group formation. Third, measurement error problems are attenuated in our administrative dataset because both wages and hours of work are obtained with unusual accuracy.

7.1. Empirical results on the returns to education and its spillover effects

Table 9 Column (1) reports the results of the extended regression. This specification suggests that the return to own education is reduced in a non-negligible way to 4.1 log points for an extra year of own education. More striking, an additional year of the co-workers' schooling with the same job title in a firm raises wages by 5.8 log points. This outcome should be interpreted with great caution, as it indicates that one additional year of co-workers' schooling would be more influential driving workers' wages than one additional year of their own education.[13]

In column (2) we present the full model specification. Reassuringly, the human capital spillover coefficient estimate remains at 0.2. Not surprisingly, the regression coefficient estimate for individual and co-worker schooling are close to zero.

We now proceed to a twofold generalization of the decomposition exercise (Gelbach) discussed at length in the previous section. The results are reported in Table 10.

For a given distribution of co-worker schooling, the effect of one additional year of own schooling is 1.6 log points, after discounting the role of sorting among establishment/job-title/year cells and the role of peers' quality. That is to say that if workers were randomly allocated into establishment/job-title/year cells the return to education would be reduced by 2.0 log points.

The remaining component of the returns to education emerges because more educated workers tend to be matched with higher quality co-workers. This indication of positive assortative matching (in the spirit of Lopes de Melo 2018) suggests that own education and peer quality are complements, generating a human capital spillover in the returns to education (of 0.3 log points). Put differently, if co-workers were allocated through a randomized experiment (holding constant the co-worker education distribution) the returns to education would be reduced by 0.3 log points.

In sum, the estimated return to education (4.1 log points) can be decomposed into the individual return to education (contributing 40 percent), a sorting component corresponding to 49 percent (among establishment/job-title/year), and

13. This result has some parallel with the studies on social returns to education at the firm level (Battu *et al.* 2003; Wirz 2008; and Martins and Jin 2010).

	Base	Full
Age	0.0351	0.0147
	(0.0005)	(0.0001)
Age squared	-0.0003	-0.0002
	(0.00001)	(0.000001)
Tenure	0.0194	0.0066
	(0.0005)	(0.00003)
Tenure squared	-0.0003	-0.0001
	(0.00002)	(0.000001)
Firm size (log)	0.0533	-
	(0.0044)	-
Gender (Female=1)	-0.2778	-0.0310
	(0.0039)	(0.0029)
Schooling	0.0410	0.0018
	(0.0004)	(0.0001)
Co-worker schooling	0.0579	-0.0005
	(0.0007)	(0.0005)
HC spillovers ($\overline{\alpha}_{-it}$)	-	0.2049
	-	(0.0012)
Year effects (μ_t)	✓	
Worker effects (α_i)		✓
Establishment/Job-title/Year effects		✓
N	19,051,268	19,051,268
R Squared	0.6057	0.9766

Table 9. Wage Equation, with Human Capital Spillovers and Co-worker Education

Notes: In column (1) standard errors are clustered at the firm level and standard errors in Column (2) are obtained as explained in Appendix A.1.

a peer quality term responsible for 7 percent. The remaining return to education in the full model accounts for 4 percent.

The naive regression coefficient estimate of the effect of co-worker schooling on wages (5.8 log points) can also be decomposed into different channels. The first component (2.0 log points) arises from the correlation between co-workers' education and the worker individual fixed effect. This component is engendered by homophily or the resemblance between the worker and his co-worker counterparts. More specifically, the return to co-worker education is reduced by 2.0 log points when worker fixed effects are included in the regression (in the spirit of Arcidiacono *et al.* (2012). The second component (3.3 log points) arises from the allocation of more educated co-workers into higher paying establishment/job-title/year cells.

	Benchmark Regression	Decomposition into: Full	Worker	Establishment/Job-title/Year	Human Capital Spillovers
	(1)	(2)	(3)	(4)	(5)
Own Schooling	0.0410				
	(0.0004)	0.0018	0.0164	0.0201	0.0027
		(0.0001)	(0.0002)	(0.0003)	(0.0001)
Co-worker Schooling	0.0579				
	(0.0007)	-0.0005	0.0202	0.0334	0.0047
		(0.0005)	(0.0003)	(0.0005)	(0.0001)

Table 10. Decomposing Returns to Own and Co-workers' Education

Notes: The conditional decomposition of the return to education is based on Gelbach (2016). Standard errors are clustered at the firm level in columns (1), (3), (4), and (5). Standard errors in Column (2) are obtained as explained in Appendix A.1.

Finally, the impact of one additional year of co-workers' education is estimated to be 0.5 log points. This is the return to co-workers' education that would remain after dismissing the bias arising from homophily and the selection of more educated co-workers into better paying establishment/job-title/year combinations.

Our results compare to those of Nix (2020), who also accounts for worker and employer fixed effects and several controls to tackle worker sorting and firm heterogeneity. She finds a 0.3 percent increase in a worker's wage as the share of college educated colleagues increases by 10 percentage points.[14]

A key point to retain from our analysis is therefore the quantification of the impact of co-workers' schooling on wages, net of homophily and sorting effects. Indeed, the naive model specification reported in the literature, which simply adds co-worker education to a traditional wage regression, has led to implausibly large estimates. We show that sorting of education levels across firms and job titles can account for as much as 58 percent of that apparent return on co-worker education; homophily can additionally account for 35 percent. We identify the remaining 0.5 log points as the direct impact of co-worker schooling on a worker's wage. In other words, our best guess of the effect of an additional year of co-workers' education, a measure of the so called social returns, is to increase individual wages by 0.5 percent.

14. The overall share of college-educated colleagues in her sample of Swedish males is 31 percent.

7.2. Robustness checks

7.2.1. Peers defined as workers in the same occupation. Table 11 reports the results on wage regressions with own and co-workers' education using a peer definition at the occupation level as discussed before. Table 12 reports the Gelbach decomposition of both own and co-workers' education for this specification.

The coefficient estimates on own and co-worker schooling are not significantly disturbed by the different definition of the peer group. Not surprisingly, the elasticity of wages with respect to the peers' human capital is estimated to be, again 0.3.

In this specification, the effect of one additional year of co-workers' education is higher, reaching 0.9 percent (Table 12)

	(1)	(2)
Age	0.0330	0.0168
	(0.0005)	(0.0001)
Age squared	-0.0003	-0.0002
	(0.0000)	(0.0000)
Tenure	0.0185	0.0086
	(0.0005)	(0.0001)
Tenure squared	-0.0003	-0.0002
	(0.00002)	(0.0000)
Firm size (log)	0.0530	-
	(0.0045)	-
Gender (Female=1)	-0.2801	-0.0352
	(0.0041)	(0.0001)
Own Schooling	0.0378	0.0025
	(0.0065)	(0.00001)
Co-worker Schooling	0.0618	0.0003
	(0.0009)	(0.00002)
HC spillovers ($\overline{\alpha}_{-it}$)	-	0.3086
	-	(0.0005)
Year effects (μ_t)	✓	
Worker effects (α_i)		✓
Establishment/Occupation/Year effects		✓
N	17,978,306	17,978,306
R Squared	0.6014	0.9726

Table 11. Wage Equation with Human Capital Spillovers and Co-worker Education - Occupation

Notes: Standard errors are clustered at the firm level in column (1). Standard errors in Column (2) are obtained as explained in Appendix A.1.

Gelbach Decomposition of the returns to schooling (Own and Co-worker)					
	Benchmark Regression	Decomposition into: Full	Worker	Establishment/Occupation/Year	Human Capital spillovers
	(1)	(2)	(3)	(4)	(5)
Own Schooling	0.0378				
	(0.0005)	0.0025	0.0190	0.0117	0.0047
		(0.00001)	(0.0003)	(0.0003)	(0.0001)
Co-worker Schooling	0.0618				
	(0.0009)	0.0003	0.0268	0.0259	0.0089
		(0.00002)	(0.0005)	(0.0005)	(0.0001)

Table 12. Decomposing Returns to Own and Co-workers' Education - Occupation

Notes: The conditional decomposition of the return to education is based on Gelbach (2016). Standard errors are clustered at the firm level in columns (1), (3), (4), and (5). Standard errors in Column (2) are obtained as explained in Appendix A.1.

7.2.2. College premium. Table 13 reports the results on wage regressions with own and co-workers' education coded as a dummy variable on whether the worker holds a university diploma. This specification suggests that the college premium is estimated to be 46 percent. As before, we obtain the spurious result that the regression coefficient estimate on the fraction of graduates is greater than the regression coefficient estimate of the college degree dummy variable.

In line with our previous results, the full model result points to a human capital spillover estimate of 0.2, reinforcing the notion that this parameter is not sensitive to the choice of covariates.

Table 14 reports the Gelbach decomposition of the effect of being a college graduate and the impact of the fraction of college graduates in the peer group. Overall, the results are consistent with the previous decomposition (Table 8). It is worth mentioning that the presence of college graduate in the co-workers group increases wages by 6.2 log points. In other words, if all the co-workers are college graduates, wages will increase by 6.4 percent in comparison to a peer group without any college graduate.

	(1)	(2)
Age	0.0338	0.0146
	(0.0006)	(0.00003)
Age squared	-0.0004	-0.0001
	(0.0000)	(0.0000)
Tenure	0.0163	0.0065
	(0.0006)	(0.00002)
Tenure squared	-0.0002	-0.0001
	(0.00002)	(0.0000)
Firm size (log)	0.0725	-
	(0.0050)	-
Gender (Female=1)	-0.2579	-0.0322
	(0.0049)	(0.00004)
College graduate	0.3812	0.0383
	(0.0065)	(0.0002)
Fraction of college graduates	0.8492	0.0022
	(0.0101)	(0.0002)
HC spillovers ($\overline{\alpha}_{-it}$)	-	0.2036
	-	(0.0005)
Year effects (μ_t)	✓	
Worker effects (α_i)		✓
Establishment/Job-title/Year effects		✓
N	19,051,268	19,051,268
R Squared	0.4933	0.9766

Table 13. Wage Equation with Human Capital Spillovers and Co-worker Education - College

Notes: Standard errors are clustered at the firm level in column (1). Standard errors in Column (2) are obtained as explained in Appendix A.1.

Gelbach Decomposition of the effects of college graduation (Own and Co-worker)					
	Benchmark Regression	Decomposition into: Full	Worker	Establishment/Job-title/Year	Human Capital spillovers
	(1)	(2)	(3)	(4)	(5)
College graduate	0.3812				
	(0.0065)	0.0383	0.1267	0.1914	0.0248
		(0.0025)	(0.0041)	(0.0038)	(0.0005)
Fraction of college graduates	0.8492				
	(0.0101)	0.0022	0.3041	0.4810	0.0620
		(0.0023)	(0.0049)	(0.0075)	(0.0012)

Table 14. Decomposing Returns to Own and Co-workers' Education - College

Notes: The conditional decomposition of the return to education is based on Gelbach (2016). Standard errors are clustered at the firm level in columns (1), (3), (4), and (5). Standard errors in Column (2) are obtained as explained in Appendix A.1.

8. Conclusion

We combine longitudinal linked employer-employee data of remarkable quality with tailor-made empirical methods to address common problems in the estimation of the returns to peer attributes, namely: the homophily problem, selection issues, common measurement errors, and confounding factors.

We start our analysis with the canonical Mincer wage equation. The estimate of the returns to education is 8.3 percent, in line with the international evidence. In the second part of the analysis we show that peer quality has a sizeable impact driving wages. In our preferred specification, a 10 percent increase in the measure of peer quality – defined as the mean of the co-worker fixed effects – leads to a wage increase of 2 percent. A direct implication of this result leads to another key contribution of this paper, in which we estimate the impact of the peer quality to the individual return to education. We conclude that more educated workers tend to sort with higher quality peers, leading to an increase of 0.6 percentage points in the individual returns to education.

Extending the analysis to the effect of co-workers' education, we arrive to our third key contribution. We show that increasing by one year the average education of the co-workers, a measure of social returns to education, leads to a half percent increase in a worker's wage, after netting out the presence of homophily (similarity of own and peers' characteristics), and the role of sorting into workplaces and jobs. Our results show a discernible effect of co-workers' education on a worker's wage, consistent with the operation of spillover effects.

The evidence provided in this study of the importance of human capital spillovers has direct implications regarding the widespread debate on the public financing of the education policies.

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Appendix A.1 - Calculation of Standard Errors

As shown in Davidson *et al.* (2004), once we obtain the NLS estimates for the parameters $(\boldsymbol{\beta}^o, \eta_0^o, \boldsymbol{\alpha}^o)$, we can easily estimate the corresponding variance-covariance matrix. The idea consists of using the associated Gauss-Newton regression (GNR). The estimated variance-covariance matrix of this linear regression provides a valid estimate of the covariance matrix of the NLS estimates.Thus, for our case and after some simplication, the GNR becomes,

$$\mathbf{y} + \eta_0^o \mathbf{W}\mathbf{D}\boldsymbol{\alpha}^o = \mathbf{X}\boldsymbol{\beta} + [\mathbf{I} + \eta_0^o \mathbf{W}]\mathbf{D}\boldsymbol{\alpha} + \eta_0 \mathbf{W}\mathbf{D}\boldsymbol{\alpha}^o + \varepsilon \tag{14}$$

Unfortunately, estimation of this linear regression is complicated by the inclusion of the regressors $[\mathbf{I} + \eta_0^o \mathbf{W}]\mathbf{D}$ as well as other high-dimensional fixed effects that may be present in $\mathbf{X}$. But since this is a linear regression we can take advantage of the Frisch-Waugh-Lovell theorem and partial out the effects of all high dimensional variables including the set of variables $[\mathbf{I} + \eta_0^o \mathbf{W}]\mathbf{D}$ and calculate a matrix that contains only the estimates of the variance-covariances associated with the set of parameters we are interested in. To clarify let $\mathbf{X} = [\mathbf{X}_1\, \mathbf{X}_2]$ where $\mathbf{X}_1$ represents the regressors of interest and $\boldsymbol{\beta}_1$ the corresponding coefficients. Thus, to estimate the variance-covariance matrix of the estimators of $\boldsymbol{\beta}_1$ we have to regress each element of $\mathbf{X_1}$ on $\mathbf{X_2}$ and $[\mathbf{I} + \eta_0^o \mathbf{W}]\mathbf{D}$ and calculate the residuals, which we collect into a matrix denoted by $\mathbf{X_1^*}$. We do the same for the dependent variable $\mathbf{y} + \eta_0^o \mathbf{W}\mathbf{D}\boldsymbol{\alpha}^o$ and call the residual $\mathbf{y}^*$. Finally, we calculate the residual associated with the variable $\mathbf{W}\mathbf{D}\boldsymbol{\alpha}^o$ which we denote by $\mathbf{w}^*$. To implement these non-trivial regressions we use a similar strategy as detailed above for the calculation of the NLS estimates. The estimated variance-covariance matrix of the linear regression shown below provides estimates for the NLS model:

$$\mathbf{y}^* = \mathbf{X_1^*}\boldsymbol{\beta_1} + \eta_0 \mathbf{w}^* + \varepsilon$$

With proper correction for degrees of freedom the (cluster) robust covariance matrix estimator implied by the above regression can also be used for the NLS regression. The *Stata* ado file *regpeer* coded by one of the authors implements the approach discussed above. This file relies heavily on Sergio Correia's *reghdfe* command for efficient estimation of linear regressions with high-dimensional fixed effects (Correia 2016).

Appendix A.2 - Tables and Figures

	(1)
Number of Observations	19,051,268
Number of Workers	3,663,524
Number of peer groups	3,912,653
Number of establishments/year	1,699,290
Number of Job-titles/year	310,305

Table A.2.1. Sample Definition and Statistics

	(1)
Log wages	0.3583
	(0.5482)
Age	37.4539
	(10.5645)
Tenure	8.6320
	(8.7512)
Firm size (log)	4.7032
	(2.0502)
Gender (Female=1)	0.4265
	-
Schooling	8.0003
	(3.9987)
Fraction of college graduates	0.0730
	-
N	19,051,268

This table reports the summary statistics from *Quadros de Pessoal* (1994-2013).

Table A.2.2. Summary Statistics

Panel A - Variance Decomposition	
α_i - worker	0.3109
$\eta_0 \overline{\alpha}_{-it}$ - co-worker	0.0513
$\theta_{\mathbf{P}(i,t)}$ - peer group fixed effect	0.5706
$Z_{it}\widehat{\gamma}$	0.0438
Residual	0.0234
Panel B - Correlations	
$\rho(\alpha_i, \overline{\alpha}_{-it})$	0.7645
$\rho(\alpha_i, \theta_{\mathbf{P}(i,t)})$	0.1864
$\rho(\overline{\alpha}_{-it}, \theta_{\mathbf{P}(i,t)})$	0.0262
Panel C - Fixed Effect Heterogeneity	
σ_{α_i}	0.2519
$\sigma_{\overline{\alpha}_{-it}}$	0.2777
$\overline{\sigma}_{\alpha_{i\mathbf{P}(i,t)}}$	0.1029
$\sigma_{\theta_{\mathbf{P}(i,t)}}$	0.3791

Note: The statistics are computed from the estimates given in Column (4) from Table 10. Panel A gives the variance decomposition according to the covariances between wages and the components of the wage equation (worker, co-worker, peer group(establishment/job-title/year) and time variant covariates). Panel B shows the correlations between the worker, co-worker, and peer group fixed effects. Panel C provides the standard deviations of worker, co-worker, peer group fixed effects, and the average of the standard deviations of the measure of peer quality (as measured by the fixed effect of the peers).

Table A.2.3. Statistical Moments from Wage Distribution

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