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DISCUSSION PAPER SERIES

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ABSTRACT

Human Capital Spillovers and the External Returns to Education*

We employ a regression model with spillover effects to show that the impact of peer quality on wages is quite large. We estimate that a 10 percent increase in peer quality implies a 2.1 percent increase in an individual's wage. In addition, we estimate the external returns to education using a novel identification strategy, which is strictly based on the peer effect channel, netting out the role of homophily and labor market sorting. We show that a one-year increase in the co-workers' education leads to a 0.58 percent increase in wages. We also show that both effects fade smoothly over time.

JEL Classification: J31, J24, I26

Keywords: wage distribution, human capital spillovers, external 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, as individuals collaborate with co-workers and can benefit from interactions with colleagues, especially those in the same job. We study the impact of co-workers on a worker's wage, contributing to a long line of literature with unsettled results. Marshall (1890) argued that social interactions among workers in the same industry and location create learning opportunities that enhance productivity. Lucas (1988) suggested that human capital spillovers may explain differences in the long-run economic performance of countries. Human capital spillovers may also arise in the absence of an exchange of knowledge. Firms choose their physical capital in anticipation of the average human capital of the workers they will employ. Given the complementarity between physical and human capital, working with more schooled colleagues can raise a worker's wage (see the model by Acemoglu (1996) and the discussions in Acemoglu and Angrist (2000) and Moretti (2004a)). However, the empirical literature on the impact of the schooling of co-workers on individual wages remains unsettled. Acemoglu and Angrist (2000) and Rauch (1993) find small or non-significant external returns and Ciccone and Peri (2006) find negative spillovers. On the contrary, Moretti (2004b) and Moretti (2004c) report significant positive impacts of graduates on the wages of workers in the same city.

Recent empirical studies have progressed to analyze the impact of co-workers within the firm. Cornelissen et al. (2017) and Battisti (2017) analyzed the contemporaneous impact of peers' unobserved quality on a worker's wage, while Nix (2020), Jarosch et al. (2021), Hong and Lattanzio (2022), and Herkenhoff et al. (2024) introduced a dynamic perspective of peer effects. Nix (2020), in particular, focused on the dynamic impact of peers' education. Jarosch et al. (2021) find that the returns to current peers' knowledge rise over time, whereas Hong and Lattanzio (2022), instead, find that the sizeable impact fades over time. Herkenhoff et al. (2024) show that learning from co-workers accounts for a large fraction of the stock of human capital accumulated on the job. This literature has been influenced by the seminal contribution of Arcidiacono et al. (2012) quantifying spillovers within the classroom and by the attempt to overcome the multiple challenges that may threaten the identification of peer effects (Manski, 1993; Angrist, 2014).

We contribute to the empirical literature in four important ways. First, we employ a regression model with spillover effects to show that the impact of peer quality on individual wages is quite large. The identification of this effect comes solely from the variation in the size of the peer groups, meaning that endogenous changes in the peer group composition are adequately controlled through the presence of a peer group fixed effect. We estimate that a 10 percent increase in peer quality implies a 2.1 percent increase in the individual wages.

Second, building on Portugal et al. (2024) we show that the private returns to education also incorporate spillovers from their peers. The decomposition of the returns to education is based on the OLS formula for omitted variable bias, which unambiguously quantifies the portion of the variation attributed to each variable of interest (Gelbach, 2016). The exercise unveils the complementarity between a worker's own education and the quality of the peers. The estimated component of the return to own education arising from the spillover of co-workers' human capital corresponds to 9 percent of the private returns to education.

Third, and most importantly, a critical finding emerges as we progress to account for the peer's education explicitly. We add the average education of peers as a regressor to estimate the external returns to education using a novel identification strategy that is strictly based on the operation of the spillover effect mechanism. For estimating the external returns to education we isolate the bias arising from homophily, showing that the education of co-workers captures the unobserved characteristics of the individual. We also show that another important source of the overestimation of the impact of co-workers' education is the failure to account for the sorting of workers into high-paying firms and job-titles. Relying again on the Gelbach (2016) decomposition, we provide evidence that a one-year increase in the co-workers' education leads to a 0.58 percent increase in individual wages, the return to co-worker education net of sorting and homophily. Keeping in mind the methodological differences, our findings are comparable to those of Acemoglu and Angrist (2000).

Fourth, considering the dynamic spillover effects, we show that the impact of peers' education fade smoothly over time. In particular, the spillovers from peers' education decline from the contemporaneous 0.58 percent, to 0.55 percent one year later, and 0.20 percent 10 years later.

Our analysis also provides a number of methodological contributions. We build on the framework devised by Arcidiacono et al. (2012) to quantify spillovers, introducing less restrictive assumptions that allow for the inclusion of time-invariant covariates. Our efficient estimation strategy, which incorporates peers' average unobserved quality alongside other high-dimensional fixed effects, is a variant of the zigzag algorithm of Guimarães and Portugal (2010). Additionally, we provide a method to correctly estimate standard errors for the regression parameters in this context.[1]

Section 2 describes the institutional setting in the Portuguese labor market, followed by Section 3 with a discussion of the data. Section 4 presents the methodology and our estimation results on the returns to peers' unobserved quality. Section 5, in turn, explicitly considers peers' education, accounting for worker, peers', establishment, and job-title heterogeneity. Section 6 concludes.

2 Institutional Setting on Wages

National minimum wages and collective bargaining influence the wage distribution in general and the returns to schooling in particular. In Portugal the national minimum wage is defined as the monthly level for full-time work, paid 14 times a year. For part-time workers, a pro-rata level is enforced. Sub-minimum wages can only be applied to physically disabled workers or trainees, as all wage reductions based on age were abolished in 1999.

Collective bargaining institutions in Portugal bear resemblance to those of other Continental European countries. Sector-wide agreements predominate and the most decentralized bargaining, at the firm level, covers a small share of the working population, less than 10%. Collective agreements signed by employers' and workers' representatives are often extended to non-signatory parties, either by government mandatory regulation or voluntarily by employers. This results in a very high rate of coverage by collective bargaining, above 80% of the workforce in the private sector, despite the low unionization rate in the country.

Collective agreements set wage floors for very disaggregated job titles that are finer than occupations (see Carneiro et al., 2012; Card and Cardoso, 2022). For example, the ship-building industry distinguishes between painters of the starboard and the port side of the ship.[2] Relevantly, the same job title (i.e. workers performing the same tasks and having the same responsibilities) in different bargaining agreements (such as different industries) will have a different wage floor. We take advantage of such an unusually

[1]These contributions are incorporated into our stata *regpeerw* command.

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

granular definition of the tasks to determine the boundaries of highly homogeneous peer groups. In the robustness exercises we consider an alternative definition of peers, as workers in the same occupation within the establishment.

Actual wages may deviate considerably from the collective bargaining wage floor for the respective job category. Wage cushion (the difference between the actual wage level and the bargained wage level) facilitates the adjustment of wages to industry – and firm-level conditions, granting employers some degree of flexibility, as documented by Cardoso and Portugal (2005), Card and Cardoso (2022), and Addison et al. (2022). In this respect, European countries such as Portugal differ from the more familiar US collective bargaining setting. Therefore, it is of major interest to quantify the role of the firm when estimating the returns to education.

3 Data Source and Concepts Used

Quadros de Pessoal (QP) is a rich longitudinal linked employer-employee dataset gathered annually by the Ministry of Employment at a reference week during the month of October. It covers all establishments having at least one wage earner and excludes civil servants, self-employed, and household employees. For the private sector in manufacturing and the services, QP covers virtually the entire population of workers and firms in Portugal.

Worker information includes: gender, date of birth, 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 education variable is defined as the number of years required to achieve the highest schooling degree. This variable may vary over time. Information on the employer includes the industry and location. We rely on information from 1995 to 2021.[3]

The analysis is restricted to workers aged 16 to 64, 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 ensure 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 (missing) categories. Furthermore, to ensure that co-workers share the same workplace we dropped workers in industries that provide services to other

[3] No worker data are available for 2001.

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 tasks. 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 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 worker and peer fixed effects. For the study of peer effects, the largest dataset under analysis comprises 22.6 million observations on 4.1 million workers, 2.5 million establishments/year, and 424,721 job-titles/year in collective bargaining. In total, we consider 5.5 million peer groups with an average of 4.1 workers per peer group (see Table D.1 in Appendix).[4]

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 D.2 in the Appendix presents the descriptive statistics for the variables used in the estimation.

4 Human Capital Spillovers

4.1 The benchmark wage equation

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

As expected, wages increase with age and tenure at a decreasing rate, reaching the maximum at age 58. Also, the gender wage gap in Portugal over this period is estimated to be 29 log points. Each additional year of education increases wages, on average, by 8.5 percent (8.2 log points). This return is in line with international evidence, even though it

[4]We truncate the peer groups at the 99 percentile of the peer size, ranging from 2 to 32. The size of the peer group ranges from 2 to 42 when the peer is defined at the occupation level.

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).

4.2 Estimation of Arcidiacono's et al. (2012) regression model

In this section we extend the basic OLS specification of Section 4.1 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 in decomposing the return to education. Thus, our wage regression is now specified as follows:

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

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 worker level regressors listed earlier; 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, assumed to follow standard assumptions such as strict exogeneity, $E(\varepsilon_{it}|\mathbf{x}_{it}, \alpha_i, \theta_{\mathbf{E}\times\mathbf{J}\times\mathbf{t}}) = 0$.[5] 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 observable characteristics and 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:

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

[5]See Arcidiacono et al. (2012) for a discussion of additional assumptions required for consistency of the least squares solution of this model.

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

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

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

$$\mathbf{e} = \mathbf{Y} - \mathbf{X}\widehat{\boldsymbol{\beta}} - \mathbf{D}\widehat{\boldsymbol{\alpha}} - \widehat{\eta_0}\mathbf{W}\mathbf{D}\widehat{\boldsymbol{\alpha}}$$

and let $S(\widehat{\boldsymbol{\beta}}, \widehat{\eta_0}, \widehat{\boldsymbol{\alpha}}) = \mathbf{e}'\mathbf{e}$. Thus,

$$S(\widehat{\boldsymbol{\beta}}, \widehat{\eta_0}, \widehat{\boldsymbol{\alpha}}) = \left[\mathbf{Y}' - \widehat{\boldsymbol{\beta}}'\mathbf{X}' - \widehat{\boldsymbol{\alpha}}'\mathbf{D}' - \widehat{\eta_0}\widehat{\boldsymbol{\alpha}}'\mathbf{D}'\mathbf{W}\right]\left[\mathbf{Y} - \mathbf{X}\widehat{\boldsymbol{\beta}} - \mathbf{D}\widehat{\boldsymbol{\alpha}} - \widehat{\eta_0}\mathbf{W}\mathbf{D}\widehat{\boldsymbol{\alpha}}\right]$$

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

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

$$\frac{\partial S(.)}{\partial \widehat{\eta_0}} = \widehat{\boldsymbol{\alpha}}'\mathbf{D}'\mathbf{W}\mathbf{e} = \mathbf{0} \tag{5}$$

$$\frac{\partial S(.)}{\partial \widehat{\boldsymbol{\alpha}}} = [\mathbf{D}' + \widehat{\eta_0}\mathbf{D}'\mathbf{W}]\,\mathbf{e} = \mathbf{0} \quad . \tag{6}$$

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 are not fully absorbed by the worker fixed effect.[6] These first-order conditions 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 condition iteratively. Rewriting

$$[\mathbf{D}' + \widehat{\eta_0}\mathbf{D}'\mathbf{W}]\left[\mathbf{Y} - \mathbf{X}\widehat{\boldsymbol{\beta}} - \mathbf{D}\widehat{\boldsymbol{\alpha}} - \widehat{\eta_0}\mathbf{W}\mathbf{D}\widehat{\boldsymbol{\alpha}}\right] = \mathbf{0} \quad ,$$

[6] In a conventional linear regression with worker fixed-effects, $\mathbf{Y} = \mathbf{X}\beta + \mathbf{D}\alpha + \epsilon$, 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 $\mathbf{Dz}$ (where $\mathbf{z}$ is a vector of length N with worker-level characteristics) the associated first-order condition becomes redundant because $\mathbf{z}'\mathbf{D}'\mathbf{e} = \mathbf{0}$.

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 $\mathbf{M_D} \equiv \left[\mathbf{D}'\mathbf{D}\right]^{-1}\mathbf{D}'$ we obtain

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

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

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

There is, however, a faster approach to solve the condition $\left[\mathbf{D}' + \widehat{\eta}_0\mathbf{D}'\mathbf{W}\right]\mathbf{e} = \mathbf{0}$. 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 an explicit solution for $\widehat{\boldsymbol{\alpha}}$ (conditional on $\widehat{\eta}_0$). This is the approach implemented in our estimations.

4.3 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 1, Column (2), reports the results.[7]

[7] Some key statistical moments of the wage distribution, including variance decomposition, correlations, and fixed effects heterogeneity, are provided in Table D.3 in the Appendix D.

Table 1: Wage Equation with Human Capital Spillovers

	Base	Full
	(1)	(2)
Age	0.0346	0.0173
	(0.0001)	(0.0002)
Age squared	-0.0003	-0.0002
	(0.0000)	(0.00001)
Tenure	0.0197	0.0078
	(0.0001)	(0.0001)
Tenure squared	-0.0002	-0.0002
	(0.0000)	(0.00001)
Gender (Male=1)	0.2923	0.0288
	(0.0005)	(0.0039)
Schooling	0.0816	0.0020
	(0.0001)	(0.0001)
HC spillovers ($\overline{\alpha}_{-it}$)	-	0.2137
	-	(0.0024)
Year effects	✓	
Worker effects		✓
Establishment/Job-title/Year effects		✓
N	22,550,063	22,550,063
R Squared	0.4438	0.9617

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, 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). Standard errors are clustered at the worker level in Column (1). Standard errors in Column (2) are obtained as explained in Appendix B and clustered at the peer group level.

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 0.21, meaning that if the quality of the peers as measured by $\overline{\alpha}_{-it}$ increases by 10 percent wages will increase by 2.1 percent. 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.[8]

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). One way to understand this is by noting 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 absorbed by the peer group fixed effect while the second term, $\alpha_i/(n_p - 1)$, is absorbed by the worker fixed effect if n_p is constant for all the peer groups in which i participates. In sum, with the inclusion of establishment/job-title/year fixed effects, identification of η_0 is possible only if over time workers belong to 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 built for the case of job-title specific shocks. A remaining concern could be that overlapping the 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 estimation of the model.

The reader may find it surprising that the individual fixed effect does not fully absorb the estimate for the gender dummy. This outcome comes from the OLS solution not implying that the individual fixed effects are orthogonal to the residual, as explained in the previous subsection. This makes the interpretation of this regression coefficient estimate more complex. With time-invariant covariates it is not possible to disentangle the individual and the average effects (see Appendix A). In this case, one possible interpretation is that, in the absence of spillover effects and gender sorting across establishments or job

[8]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 Appendix B), in our case it is 0.21.

titles, the gender wage gap would be equal to 0.0288.

4.4 Decomposing the returns to education with human capital spillovers

To understand the contribution of 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 1 (see Appendix C for details).

This means that the difference between the return to education in the benchmark and full models, $\widehat{\delta_0} - \widehat{\delta}$, can be decomposed into three terms that reflect the impact of the workers, their peers, and the workplace/job-title channel:

$$\widehat{\delta_0} - \widehat{\delta} = \widehat{\delta}_{\boldsymbol{\alpha}} + \widehat{\delta}_{\boldsymbol{HC}} + \widehat{\delta}_{\boldsymbol{\theta}} \quad . \tag{8}$$

Table 2: Conditional Decomposition of the Return to Education, with Human Capital Spillovers

Benchmark	Full	Decomposition into:		
Regression	Specification	Worker FE	Establishment/job-title/year	HC Spillovers
(1)	(2)	(3)	(4)	(5)
0.0816	0.0020	0.0371	0.0352	0.0073
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.00001)

Note: 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 difference between the coefficients in the benchmark and the full specifications, in Columns (1) and (2), respectively. Standard errors are clustered at the group level of the corresponding fixed effects.

Table 2 reports the decomposition of the returns to education in the presence of human capital spillovers. It shows that the difference between the returns to education in the base model (0.0816) and in the full model (0.0020) can be exactly decomposed in three components: the contribution of worker component, the contribution of sorting across establishment/job-title over time, and the contribution of human capital spillovers.

The worker component (0.0371) can be interpreted as the returns to education in case workers were randomly assigned into establishment and job titles, and co-workers. It is the portable part of a worker's human capital, which she will carry across firms, without regard to sorting into establishments or peer groups of a certain type. The contribution of the establishment/job-title/year component (0.0352) reflects sorting, as more educated workers are assigned into better-paying establishments and job titles.

The key innovation of this exercise is the estimation of the contribution of peer quality to the individual return to education (0.0073). The indication that more educated workers tend to match with higher quality peers leads to a boost in the returns to education of 0.7 percentage points.

It is worth mentioning that the identification of the spillover effect does not arise from the, possibly endogenous, change in the composition of the peer group (which is absorbed in the peer group fixed effect) but is identified from the notion that high-quality peers are more influential in small peer groups than in large peer groups (which is a mechanical implication of the use of a leave-one-out mean). More generally, the spillover effect is identified strictly due to workers being present in peer groups of varying sizes over time.

The reader may be concerned with the problem of endogeneity of the education variable and the need to use an IV method. In fact, if we use the changes in compulsory schooling age laws in Portugal as an instrumental variable, as we do in our companion paper Portugal et al. (2024), the impact of peer quality in the returns to education is materially indistinguishable from the OLS solution (0.0071) (see Table D.4 in Appendix). We are not reporting those results in the main text because the statistical properties of this estimator in this framework are not well known.

4.5 Alternative specifications

We now perform three 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 job title. Third, we use an alternative definition of education, classifying workers depending on whether they hold a university degree.

Different ways to account for heterogeneity

In Table 3 we explore the sensitivity of the human capital spillovers to different combinations of the workplace, job-title, and year fixed effects. Furthermore, we compare specifications with and without covariates. Columns (1) to (4) consider as peer a worker in the same job, whereas in Columns (5) to (8) peers are defined at the occupation level. Column (4) corresponds to the specification reported in the last column of Table 1, where the scope of the fixed effects corresponds exactly to the definition of the peer group. In general, finer controls generate lower values for the human capital spillover parameter.

As hinted at above, the absence of covariates in the specifications does not significantly affect the estimate of the human capital spillovers, in particular for the case of more disaggregated fixed effects controls.

More importantly, it is clear that using a specification with the finest possible level of controls, 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.

Table 3: Sensitivity of the Impact of Human Capital Spillovers ($\overline{\alpha}_{-it}$) on (log) Wages

	Peers defined at the job-title level				Peers defined at the occupation level			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Full Specification	0.4271 (0.0009)	0.4021 (0.0009)	0.2903 (0.0010)	0.2137 (0.0024)	0.3270 (0.0008)	0.3083 (0.0008)	0.2594 (0.0009)	0.1774 (0.0022)
Excluding Covariates	0.4306 (0.0009)	0.4109 (0.0009)	0.2816 (0.0010)	0.2155 (0.0022)	0.3035 (0.0007)	0.2926 (0.0008)	0.2349 (0.0009)	0.1843 (0.0020)
F/Y	✓				✓			
E/Y		✓				✓		
E/Y and J/Y			✓					
E/J/Y				✓				
E/Y and O/Y							✓	
E/O/Y								✓
N	22,550,063	22,550,063	22,550,063	22,550,063	24,903,854	24,903,854	24,903,854	24,903,854

Notes: The covariates used in the full specification are the same as in Column (2) in Table 1. Standard errors are obtained as explained in Appendix B and clustered at the peer group level. F/Y stands for firm/year fixed effects, E/Y for establishment/year fixed effects, J/Y for job-title/year fixed effects, E/J/Y for establishment/job-title/year fixed effects, O/Y for occupation/year fixed effects, and E/O/Y for establishment/occupation/year fixed effects.

Peers defined as workers in the same occupation

In Table D.5 we present the regression results using the broader definition of peer group, the more conventional occupation classification. We rely on the 4 digit ISCO classification, including 10,112 occupations/year. The estimate of the elasticity of wages with respect to the peers' human capital is now 0.18. This means that when the human capital of the co-workers increases by 10 percent, wages increase by 1.8 percent.

The decomposition of the returns to education now points to a contribution of human capital spillovers of 0.0060 (Table D.6), which compares to 0.0073 using job-title instead of occupation.

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 D.7. In Portugal the college premium is estimated to be quite large, implying that the wages of college graduates are, on average, 123 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 0.21. This result is a first indication that choice of covariates does not significantly affect the estimate of the effect of peer quality.

Table D.8 reports the decomposition of the college premium in the presence of human capital spillovers, corroborating the findings on the relative importance of each of the channels reported in Table 2 for the returns on years of education. The individual or portable component of human capital and the establishment-job sorting channel are the most influential channels driving the college premium, confirming that individuals with college degrees tend to sort themselves into better-paying establishments and job titles. The third component, the human capital spillover channel, accounts for approximately 9% of the college wage premium.

4.6 Dynamic perspective: The impact of peers' quality on workers' future wages

In this section we expand our analysis to consider the dynamic effects of peers spillovers. In Table D.9 we consider a model in which the dependent variable corresponds to one year wage lead. The key result of this exercise implies a modest reduction in the impact of co-workers' quality on future wages in comparison with the contemporaneous effect. In other words, the coefficient on human capital spillovers is now 0.1593, which implies that a 10 percent increase in peer quality leads to a wage increase of 1.6 percent in the next period (2.1 percent in the contemporaneous framework specifications). Our result is in line with the estimates in Hong and Lattanzio (2022).

Table 4 panel A summarizes the estimates for longer time horizons. The impact of peers' quality on a worker's wages fades smoothly over time. The spillover effect remains positive and statistically significant even after 10 years. In this case, a 10 percent increase in the peers' quality at time t will generate a 0.3 percent wage increase at $t+10$. This result is in sharp contrast to the increasing trend observed in the work by Jarosch et al. (2021). We speculate that their indication of increasing spillovers may spuriously arise in long-horizon predictive regressions whenever the covariates are strongly persistent (Demetrescu et al., 2023).

The decomposition of the returns to schooling given in Table 4 panel B exhibits a similar decreasing pattern of the contribution of the human capital spillover. After 10 years the contribution of the quality of the co-workers to the individual returns to education is around one third of the contemporaneous one.[9]

[9]For completeness, Table D.10 reports the contribution of the remaining components for the one year lag.

Table 4: Sensitivity of the Human Capital Spillovers - Peer Dynamics

Panel A - HC spillovers ($\overline{\alpha}_{-it}$)	y_{it}	y_{it+1}	y_{it+2}	y_{it+3}	y_{it+5}	y_{it+10}
	(1)	(2)	(3)	(4)	(5)	(6)
Full Specification	0.2137 (0.0024)	0.1593 (0.0036)	0.1233 (0.0041)	0.0986 (0.0045)	0.0525 (0.0051)	0.0267 (0.0064)
Excluding Covariates	0.2155 (0.0022)	0.1615 (0.0035)	0.1274 (0.0037)	0.1019 (0.0044)	0.0554 (0.0050)	0.0281 (0.0062)
Panel B - Contribution of HC spillovers to the individual returns to schooling						
Contribution of HC spilovers	0.0073	0.0072	0.0068	0.0063	0.0040	0.0025
Establishment/job-title/year effects	✓	✓	✓	✓	✓	✓
N	22,550,063	12,314,502	9,648,671	7,855,504	5,529,746	2,649,769

Notes: The covariates used in the full specification are the same as in Column (2) in Table 1. Standard errors are obtained as explained in Appendix B and clustered at the peer group level.

5 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 who, 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, notably 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 in which peers are assigned randomly there is a mechanical relationship between own and peer attributes that may bias the estimation of the peer effect.[10]

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 address 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.

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

5.1 Empirical results on the returns to co-workers' education

Table 5 Column (1) reports the results of the base regression extended to include co-workers' schooling. This specification suggests that the return to own education is reduced in a non-negligible way to 4.7 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 5.2 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 the worker's own education.[11]

Table 5: Wage Equation, with Human Capital Spillovers and Co-worker Education

	Base	Full
	(1)	(2)
Age	0.0352	0.0174
	(0.0001)	(0.0002)
Age squared	-0.0003	-0.0002
	(0.00001)	(0.000001)
Tenure	0.0195	0.0078
	(0.0001)	(0.00001)
Tenure squared	-0.0002	-0.0002
	(0.00002)	(0.000001)
Gender (Male=1)	0.3002	0.0289
	(0.0004)	(0.0039)
Schooling	0.0467	0.0020
	(0.0001)	(0.0001)
Co-worker schooling	0.0520	-0.00004
	(0.0001)	(0.0001)
HC spillovers ($\overline{\alpha}_{-it}$)	-	0.2138
	-	(0.0025)
Year effects (μ_t)	✓	
Worker effects (α_i)		✓
Establishment/Job-title/Year effects		✓
N	22,550,063	22,550,063
R Squared	0.4904	0.9617

Notes: Standard errors are clustered at the worker level in Column (1). Standard errors in Column (2) are obtained as explained in Appendix B and clustered at the peer group level.

[11] 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).

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 is close to zero, once we include worker fixed effects and establishment/job-tile/year fixed effects.

Table 6: Conditional Decomposition of the Returns to Co-workers' Education

	Benchmark Regression	Full Specification	Decomposition into: Worker FE	Establishment/Job-title/Year	HC Spillovers
	(1)	(2)	(3)	(4)	(5)
Co-worker Schooling	0.0520	-0.00004	0.0208	0.0254	0.0058
	(0.0001)	(0.0001)	(0.00001)	(0.00004)	(0.00001)

Notes: The conditional decomposition of the return to education is based on Gelbach (2016). Standard errors are clustered at the group level of the corresponding fixed effects.

We now proceed to the decomposition exercise of the effect of co-worker schooling on wages (Table 6). The naive regression coefficient estimate of the effect of co-worker schooling on wages (5.2 log points) can be decomposed into different channels. The first component (2.1 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 2.1 log points when worker fixed effects are included in the regression (in the spirit of Arcidiacono et al. (2012)). The second component (2.5 log points) arises from the allocation of more educated co-workers into higher paying establishment/job-title/year cells. Finally, the remaining impact of one additional year of co-workers' education is estimated to be 0.6 log points, a measure of the so called external returns. 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. In other words, this is the spillover channel. Our results are broadly consistent with the findings of Acemoglu and Angrist (2000) for the US, relying on data from 1960 to 1980. They argued that external returns of approximately 1%, their central estimate, could justify substantial public investment in education.

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. The 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 49 percent of that apparent return on co-worker education; homophily can additionally account for 40 percent. We identify the remaining 11 percent as the direct impact of co-worker schooling on a worker's wage, a measure of the so-called external returns to education. We remind the reader that the identification of the external returns to education is strictly dependent on differences in the individuals' peer group sizes. For example, if a more educated worker is added to a peer group, the identification arises purely because the impact on wages will be higher in a small group rather than a large one, bypassing the endogeneity that may arise from changes in the composition of peer groups.

5.2 Alternative specifications

Peers defined as workers in the same occupation

Table D.11 reports the results on wage regressions with own and co-workers' education using a peer definition at the occupation level as discussed above. Table D.12 reports the Gelbach decomposition of co-workers' education for this specification. The coefficient estimates on co-worker schooling is not significantly disturbed by the different definitions of the peer group. Not surprisingly, the elasticity of wages with respect to the peers' human capital is estimated to be close to 0.2. In this specification, the effect of one additional year of co-workers' education is 0.52 percent (Table D.12).

College premium

Table D.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 degree. The baseline specification suggests that the college premium is 52 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 D.14 reports the Gelbach decomposition of the impact of the fraction of college graduates in the peer group. Overall, the results are consistent with the previous decomposition (Table D.8). It is worth mentioning that the presence of college graduates in the group of co-workers increases wages by 0.0688 log points. In other words, if the fraction of college graduate co-workers increases by 10 percentage points, wages will increase by 0.7 percent in comparison to a peer group without any college graduates.

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.

Using data from cities and drawing on both Census and NLSY data, Moretti (2004a) estimates that a 10 percentage point increase in the share of college-educated individuals raises wages by 6% to 12%. This is substantially higher than our comparable estimate. The reader should bear in mind, however, that the level of aggregation of spillover effects is quite different in the two studies.

5.3 Co-worker education in a dynamic framework

In Table D.15 we added co-worker schooling to one year ahead wage regression. There are no surprises in either base or full specifications. As before, the large coefficient estimate for co-worker education contrasts with a smaller own individual returns to education in the base model. The regression coefficient for peer quality is indistinguishable from the one presented in Table D.9.

The key result in Table D.16 has to do with the contribution of an additional year of average education of co-workers on an individual's own wage in the following year, after controlling for homophily and labor market sorting. The estimate of 0.0055 means that an additional year of co-workers' education will lead to a 0.6 percent increase in future wages. This result is fairly close to that in the contemporaneous specification.

Finally, the effect of co-worker education at future time horizons is given in Table 7. The impact of the spillover effect of an additional year of average co-worker education on a worker's wages fades smoothly over time. The observed decaying trend results, of course, from the declining coefficient estimates for the human capital spillovers, as in Table 4. It is remarkable, nevertheless, that after 10 years the impact of the co-workers' education is still sizable and statistically significant.

Table 7: Sensitivity of the Contribution of Human Capital Spillovers on Co-worker Returns to Schooling - Peer Dynamics

	y_{it}	y_{it+1}	y_{it+2}	y_{it+3}	y_{it+5}	y_{it+10}
	(1)	(2)	(3)	(4)	(5)	(6)
Contribution of HC spillovers	0.0058	0.0055	0.0052	0.0047	0.0031	0.0020
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Establishment/job-title/year effects	✓	✓	✓	✓	✓	✓
N	22,550,063	12,314,502	9,648,671	7,855,504	5,529,746	2,649,769

Notes: The covariates used in the full specification are the same as in Column (2) in Table 1. Standard errors are obtained as explained in Appendix B and clustered at the peer group level.

6 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 8.5 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 2.1 percent.

A novel contribution of this paper is to unveil the impact of peer quality on the individual returns to education. We conclude that more educated workers tend to sort with higher quality peers, leading to an increase of 0.7 percentage points in the individual returns to education. In other words, 9 percent of the returns to education can be attributed to the spillover channel.

Extending the analysis to the effect of co-workers' education, we arrive at our key contribution. We show that increasing by one year the average education of the co-workers leads to a 0.6 percent increase in a worker's wage, a measure of external returns to education, 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 regarding the importance of human capital spillovers has direct implications pertaining to the widespread debate on the public financing of education policies.

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Appendix A - Interpretation of Coefficients of Time-invariant Variables in the Arcidiacono (2012) Model

To understand how to interpret coefficients for time-invariant variables in the Arcidiacono model consider the following reduced specification

$$y_{itn} = \beta_0 + \beta_1 z_i + u_i + \gamma_1 \overline{z}_{-i} + \gamma_2 \overline{u}_{-i} + \varepsilon_{itn}$$

where z_i is a time-invariant observed variable, u_i is a time-invariant unobserved variable, and $\overline{z}_{-i}$ and $\overline{u}_{-i}$ are the respective peer group averages for worker i. A worker fixed effect α_i can be defined as

$$\alpha_i = \theta z_i + u_i - k$$

where k and θ are unknown parameters. In this case,

$$\overline{\alpha}_{-i} = \theta \overline{z}_{-i} + \overline{u}_{-i} - k \ .$$

We can rewrite the equation for y_{itn} incorporating the worker fixed effects and their peer average. Adding the terms α_i and $\gamma_2 \overline{\alpha}_{-i}$ to the equation and rearranging we obtain

$$y_{itn} = \gamma_0 + \alpha_i + \gamma_2 \overline{\alpha}_{-i} + (\beta_1 - \theta) z_i + (\gamma_1 - \gamma_2 \theta) \overline{z}_{-i} + \varepsilon_{itn} \ ,$$

where γ_0 is a constant. The above equation suggests that if we include both z_i and $\overline{z}_{-i}$ as regressors their coefficients will be undetermined because θ can take any value. Excluding z_i from the regression is akin to setting $\theta = \beta_1$ and likewise, omitting $\overline{z}_{-i}$ is equivalent to setting $\theta = \gamma_1/\gamma_2$. On the other hand, omitting both z_i and $\overline{z}_{-i}$ from the equation requires the strong assumption that $\beta_1 = \gamma_1/\gamma_2$ (the assumption in Arcidiacono et al. (2012)). To avoid an omitted variable bias we can either add z_i or $\overline{z}_{-i}$ to the equation. If z_i is added by itself its coefficient will be $(\beta_1 - \gamma_1/\gamma_2)$ so its true effect will be underestimated. Only if there are no spillover effects from z_i, (i.e. $\gamma_1 = 0$), will the z_i coefficient be identical to the structural parameter β_1.

Appendix B - Calculation of Standard Errors

As shown in Davidson et al. (2004), once we obtain the non-linear least-squares (NLS) regression 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,

$$\mathbf{y} + \eta_0^o \mathbf{W}\mathbf{D}\boldsymbol{\alpha}^o = \mathbf{X}\boldsymbol{\beta} + [\mathbf{I} + \eta_0^o \mathbf{W}]\mathbf{D}\boldsymbol{\alpha} + \eta_0 \mathbf{W}\mathbf{D}\boldsymbol{\alpha}^o + \varepsilon \tag{9}$$

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:

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

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 *regpeerw* 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 C - Gelbach's Decomposition

To understand the contribution of 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 1. 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

$$\mathbf{Y} = \mathbf{Z}\boldsymbol{\gamma_0} + \delta_0\mathbf{S} + \boldsymbol{\varepsilon} \quad . \tag{10}$$

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,

$$\widehat{\delta_0} = (\mathbf{S}'\mathbf{M_Z}\mathbf{S})^{-1}\mathbf{S}'\mathbf{M_Z}\mathbf{Y} = \mathbf{P_Z}\mathbf{Y} \quad , \tag{11}$$

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:

$$\mathbf{Y} = \mathbf{Z}\widehat{\boldsymbol{\gamma}} + \widehat{\delta}\mathbf{S} + \mathbf{D}\widehat{\boldsymbol{\alpha}} + \widehat{\eta_0}\mathbf{W}\mathbf{D}\widehat{\boldsymbol{\alpha}} + \mathbf{L}\widehat{\boldsymbol{\theta}} + \mathbf{e} \quad . \tag{12}$$

To obtain a decomposition of $\widehat{\delta_0}$ we multiply both terms of equation (12) 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 $\mathbf{P_Z}\mathbf{Z}\widehat{\boldsymbol{\gamma}} = \mathbf{0}$ and $\mathbf{P_Z}\mathbf{e} = \mathbf{0}$. Thus, the right-hand side becomes:

$$\widehat{\delta_0} = \widehat{\delta} + \mathbf{P_Z}\mathbf{D}\widehat{\boldsymbol{\alpha}} + \mathbf{P_Z}(\widehat{\eta_0}\mathbf{W}\mathbf{D}\widehat{\boldsymbol{\alpha}}) + \mathbf{P_Z}\mathbf{L}\widehat{\boldsymbol{\theta}} = \widehat{\delta} + \widehat{\delta}_{\boldsymbol{HC}} + \widehat{\delta}_{\boldsymbol{\alpha}} + \widehat{\delta}_{\boldsymbol{\theta}} \quad . \tag{13}$$

Note that $\widehat{\delta}$ is the estimate of the coefficient associated with education from the full model and $\mathbf{D}\widehat{\boldsymbol{\alpha}}$, $\mathbf{WD}\widehat{\boldsymbol{\alpha}}$, 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 jobs.

Appendix D - Tables and Figures

Table D.1: Sample Definition and Statistics

	Peers defined as same: Job	Occupation
	(1)	(2)
Number of Observations	22,550,063	24,903,854
Number of workers	4,071,250	4,277,947
Number of peer groups	5,489,488	5,309,834
Number of firms	318,498	348,121
Number of establishments/year	2,452,699	2,842,765
Number of job-titles/year	424,721	-
Number of occupations/year	-	10,112

Source: *Quadros de Pessoal* (1995-2021). Notes: In Column (1) the average size of the peer group is 4.1 workers. In Column (2), it is 4.7 workers.

Table D.2: Summary Statistics

	Peers defined as same: Job	Occupation
	(1)	(2)
Log wages	1.6963	1.6782
	(0.5439)	(0.5596)
Age	38.7965	38.7140
	(10.8885)	(10.9509)
Tenure	8.762	8.6401
	(8.9742)	(8.8941)
Gender (Male=1)	0.5741	0.5691
	-	-
Schooling	8.6355	8.5957
	(4.0860)	(4.0332)
Fraction of college graduates	0.1104	0.1035
	-	-
N	22,550,063	24,903,854

Source: *Quadros de Pessoal* (1995-2021).

Table D.3: Statistical Moments from Wage distribution moments

	Peers defined as same:	
	Job	Occupation
Panel A - Variance Decomposition		
α_i - worker	0.3646	0.3845
$\eta_0\overline{\alpha}_{-it}$ - co-worker	0.0586	0.0479
$\theta_{\mathbf{P}(i,t)}$ - peer group fixed effect	0.4948	0.4660
$Z_{it}\widehat{\gamma}$	0.0438	0.0549
Residual	0.0383	0.0467
Panel B - Correlations		
$\rho(\alpha_i, \overline{\alpha}_{-it})$	0.7351	0.7048
$\rho(\alpha_i, \theta_{\mathbf{P}(i,t)})$	0.0483	0.0670
$\rho(\overline{\alpha}_{-it}, \theta_{\mathbf{P}(i,t)})$	0.0540	0.0777
Panel C - Fixed Effect Heterogeneity		
σ_{α_i}	0.3029	0.3038
$\sigma_{\overline{\alpha}_{-it}}$	0.2726	0.2646
$\overline{\sigma}_{\alpha_{i\mathbf{P}(i,t)}}$	0.1282	0.1495
$\sigma_{\theta_{\mathbf{P}(i,t)}}$	0.3779	0.3529

Note: The statistics are computed from the estimates given in Column (2) from Table 1. 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 D.4: Conditional Decomposition of the Return to Education, with Human Capital Spillovers - IV Method

Benchmark	Full	Decomposition into:		
Regression	Specification	Worker FE	Establishment/job-title/Year	HC Spillovers
(1)	(2)	(3)	(4)	(5)
0.0789	0.0028	0.0270	0.0419	0.0071
(0.0012)	(0.0001)	(0.0008)	(0.0005)	(0.0001)

Note: 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 using IV method. 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 difference between the coefficients in the benchmark and the full specifications, in Columns (1) and (2), respectively. Standard errors are clustered at the group level of the corresponding fixed effects.

Table D.5: Wage Equation with Human Capital Spillovers - Occupation

	Base	Full
	(1)	(2)
Age	0.0359	0.0234
	(0.0001)	(0.0002)
Age squared	-0.0003	-0.0002
	(0.00001)	(0.0000)
Tenure	0.0190	0.0099
	(0.0001)	(0.0000)
Tenure squared	-0.0002	-0.0002
	(0.00002)	(0.0000)
Gender (Male=1)	0.2800	0.0152
	(0.0005)	(0.0050)
Schooling	0.0786	0.0022
	(0.0001)	(0.0001)
HC spillovers ($\overline{\alpha}_{-it}$)	-	0.1774
	-	(0.0022)
Year effects	✓	
Worker effects		✓
Establishment/Occupation/Year effects		✓
N	24,903,854	24,903,854
R Squared	0.4272	0.9533

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

Table D.6: Conditional Decomposition of the Returns to Education with Human Capital Spillovers - Occupation

Benchmark	Full	Decomposition into:		
Regression	Specification	Worker FE	Establishment/job-title/Year	HC Spillovers
(1)	(2)	(3)	(4)	(5)
0.0786	0.0022	0.0378	0.0331	0.0060
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)

Notes: The conditional decomposition of the return to education is based on Gelbach (2016). Standard errors are clustered at the group level of the corresponding fixed effects.

Table D.7: Wage Equation with Human Capital Spillovers - College

	Base	Full
	(1)	(2)
Age	0.0317	0.0173
	(0.0001)	(0.0002)
Age squared	-0.0003	-0.0002
	(0.00001)	(0.00001)
Tenure	0.0203	0.0077
	(0.0001)	(0.0005)
Tenure squared	-0.0002	-0.0002
	(0.0005)	(0.000001)
Gender (Male=1)	0.2792	0.0297
	(0.0005)	(0.0039)
College	0.8035	0.0372
	(0.0011)	(0.0009)
HC spillovers ($\overline{\alpha}_{-it}$)	-	0.2130
	-	(0.0025)
Year effects	✓	
Worker effects		✓
Establishment/job-title/year effects		✓
N	22,550,063	22,550,063
R Squared	0.3513	09618

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

Table D.8: Conditional Decomposition of the Returns to Education with Human Capital Spillovers - College

Benchmark Regression	Full Specification	Decomposition into: Worker FE	Establishment/job-title/year	HC Spillovers
(1)	(2)	(3)	(4)	(5)
0.8035	0.0372	0.3663	0.3266	0.0734
(0.0010)	(0.0009)	(0.0008)	(0.0006)	(0.0001)

Notes: The conditional decomposition of the return to education is based on Gelbach (2016). Standard errors are clustered at the group level of the corresponding fixed effects.

Table D.9: Wage Equation with Human Capital Spillovers - One Year Wage Lead

	Base	Full
	(1)	(2)
Age	0.0352	0.0178
	(0.0002)	(0.0003)
Age squared	-0.0003	-0.0002
	(0.0000)	(0.00001)
Tenure	0.0177	0.0058
	(0.0001)	(0.0001)
Tenure squared	-0.0001	-0.0001
	(0.0000)	(0.00001)
Gender (Male=1)	0.3145	0.0388
	(0.0006)	(0.0078)
Schooling	0.0878	0.0015
	(0.0001)	(0.0001)
HC spillovers ($\overline{\alpha}_{-it}$)	-	0.1593
	-	(0.0036)
Year effects	✓	
Worker effects		✓
Establishment/job-title/year effects		✓
N	12,314,502	12,314,502
R Squared	0.4678	0.9670

Notes: The dependent variable is the logarithm of real hourly wages with a one-year lead. Column (1) reports the results of the benchmark specification including as covariates age, age squared, tenure, tenure squared, 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). Standard errors are clustered at the worker level in Column (1). Standard errors in Column (2) are obtained as explained in Appendix B and clustered at the peer group level.

Table D.10: Conditional Decomposition of the Return to Education, with Human Capital Spillovers - One Year Wage Lead

Benchmark Regression	Full Specification	Decomposition into: Worker FE	Establishment/job-title/year	HC Spillovers
(1)	(2)	(3)	(4)	(5)
0.0878	0.0015	0.0480	0.0311	0.0072
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.00001)

Note: 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 difference between the coefficients in the benchmark and the full specifications, in Columns (1) and (2), respectively. Standard errors are clustered at the group level of the corresponding fixed effects.

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

	Base	Full
	(1)	(2)
Age	0.0352	0.0237
	(0.0001)	(0.0002)
Age squared	-0.0003	-0.0002
	(0.000001)	(0.0000)
Tenure	0.0181	0.0099
	(0.0001)	(0.0001)
Tenure squared	-0.0002	-0.0002
	(0.00002)	(0.0000)
Gender (Male=1)	0.2923	0.0169
	(0.0004)	(0.0050)
Own Schooling	0.0435	0.0020
	(0.0001)	(0.00001)
Co-worker Schooling	0.0537	-0.0007
	(0.0001)	(0.0001)
HC spillovers ($\overline{\alpha}_{-it}$)	-	0.1785
	-	(0.0022)
Year effects (μ_t)	✓	
Worker effects (α_i)		✓
Establishment/occupation/year effects		✓
N	24,903,854	24,903,854
R Squared	0.4769	0.9533

Notes: Standard errors are clustered at the worker level in Column (1). Standard errors in Column (2) are obtained as explained in Appendix B and clustered at the peer group level.

Table D.12: Conditional Decomposition of the Returns to Co-workers' Education - Occupation

	Benchmark Regression	Full Specification	Decomposition into: Worker FE	Establishment/job-title/year	HC Spillovers
	(1)	(2)	(3)	(4)	(5)
Co-worker Schooling	0.0537	-0.0007	0.0222	0.0270	0.0052
	(0.0001)	(0.00001)	(0.0001)	(0.0001)	(0.0001)

Notes: The conditional decomposition of the return to education is based on Gelbach (2016). Standard errors are clustered at the group level of the corresponding fixed effects.

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

	(1)	(2)
Age	0.0310	0.0172
	(0.0001)	(0.0002)
Age squared	-0.0003	-0.0002
	(0.00001)	(0.0000)
Tenure	0.0191	0.0077
	(0.0001)	(0.00001)
Tenure squared	-0.0002	-0.0002
	(0.00002)	(0.0000)
Gender (Male=1)	0.2804	0.0273
	(0.0005)	(0.0040)
College graduate	0.4174	0.0409
	(0.0012)	(0.0011)
Fraction of college graduates	0.6509	0.0099
	(0.0014)	(0.0015)
HC spillovers ($\overline{\alpha}_{-it}$)	-	0.2122
	-	(0.0025)
Year effects (μ_t)	✓	
Worker effects (α_i)		✓
Establishment/job-title/year effects		✓
N	22,550,063	22,550,063
R Squared	0.4040	0.9618

Notes: Standard errors are clustered at the worker level in Column (1). Standard errors in Column (2) are obtained as explained in Appendix B and clustered at the peer group level.

Table D.14: Conditional Decomposition of the Returns to Co-workers' Education - College

	Benchmark Regression	Full Specification	Decomposition into: Worker FE	Establishment/job-title/year	HC Spillovers
	(1)	(2)	(3)	(4)	(5)
Fraction of college graduates	0.6509	0.0099	0.2892	0.2830	0.0687
	(0.0014)	(0.0025)	(0.0001)	(0.0006)	(0.0001)

Notes: The conditional decomposition of the return to education is based on Gelbach (2016). Standard errors are clustered at the group level of the corresponding fixed effects.

Table D.15: Wage Equation, with Human Capital Spillovers and Co-worker Education - One Year Wage Lead

	Base	Full
	(1)	(2)
Age	0.0354	0.0179
	(0.0002)	(0.00002)
Age squared	-0.0003	-0.0002
	(0.00001)	(0.000001)
Tenure	0.0173	0.0058
	(0.0001)	(0.00001)
Tenure squared	-0.0002	-0.0001
	(0.00002)	(0.000001)
Gender (Male=1)	0.3195	0.0389
	(0.0006)	(0.00002)
Schooling	0.0495	0.0015
	(0.0001)	(0.00001)
Co-worker schooling	0.0561	-0.0001
	(0.0001)	(0.0001)
HC spillovers ($\overline{\alpha}_{-it}$)	-	0.1594
	-	(0.0036)
Year effects (μ_t)	✓	
Worker effects (α_i)		✓
Establishment/job-title/year effects		✓
N	12,314,502	12,314,502
R Squared	0.5193	0.9670

Notes: Standard errors are clustered at the worker level in Column (1). Standard errors in Column (2) are obtained as explained in Appendix B and clustered at the peer group level.

Table D.16: Conditional Decomposition of the Returns to Co-workers' Education - One Year Wage Lead

	Benchmark Regression	Full Specification	Decomposition into: Worker FE	Establishment/job-title/year	HC Spillovers
	(1)	(2)	(3)	(4)	(5)
Co-worker Schooling	0.0561	-0.0001	0.0281	0.0226	0.0055
	(0.0001)	(0.00001)	(0.0001)	(0.0001)	(0.00001)

Notes: The conditional decomposition of the return to education is based on Gelbach (2016). Standard errors are clustered at the group level of the corresponding fixed effects.