The Peer Effect on Future Wages in the Workplace*

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April 12, 2023

Abstract

We study a critical driver of future wages: peers. Using linked employer-employee data for Italy, we explore peer effects in two directions. First, accounting for the endogenous sorting of workers into peer groups, we estimate that a 10 percent rise in peer quality increases one's wage in the next year by 1.8 percent. The effect decreases gradually over time and becomes about 0.7 percent after five years. Second, using an event study specification around mobility episodes, we show that hiring high-quality workers, separating from low-quality workers, and moving into high-quality peer groups, are significant drivers of wage growth.

Keywords: Peer effects, wage growth, linked employer-employee data

JEL codes: J24, J31, J41, L14, M52

1 Introduction

The literature has well documented that wages typically increase over the life cycle. However, significant heterogeneity exists in wage growth among workers. In line with the canonical models in Becker (1964) and Ben-Porath (1967), wage growth reflects workers' accumulation of knowledge and skills on the job. As interaction is essential in the workplace, it is natural that on-the-job learning is primarily the result of interaction with coworkers. Despite the importance, little is known about the link between coworkers and wage growth from both empirical and theoretical perspectives. If two workers have the same ability, does the worker with better coworkers have higher wages in the future? How persistent are such peer effects? How does the move of a high-quality worker in a firm contribute to the wage growth of his or her new coworkers, and how are past ones affected? This paper answers these questions.

There is a growing literature that investigates the relationship between coworkers and wages.[1] Earlier empirical evidence mainly focuses on the effect of coworkers on contemporaneous wage levels in a specific workplace (e.g., Mas and Moretti, 2009) or based on laboratory experiments (e.g., Falk and Ichino, 2006). For example, Mas and Moretti (2009) provide persuasive evidence in a supermarket chain that a cashier's productivity increases when they work alongside more productive coworkers. Nevertheless, it is unclear to what extent these findings, based on a specific firm or laboratory experiment, apply to more general settings and labor markets. Increased access to administrative data allowed researchers to investigate peer effects in one or more local labor markets. For example, Cornelissen et al. (2017) and Cardoso et al. (2018) use employer-employee matched administrative data in Germany and Portugal, respectively, to provide estimates of the peer effect in the workplace. Both focus on the overall impact of coworkers on contemporaneous wage levels, and find a positive effect, though much larger in the Portuguese labor market. However, if the peer effect is persistent over time, it would also be appropriate to consider dynamic effects. That is, the impact of coworkers could materialize on current *and* future wages. Despite the potential relevance, only a handful of papers have examined the link between coworkers and wage growth.

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[1]Throughout the paper we use the terms peer and coworkers interchangeably.

Two related papers, Jarosch et al. (2021) and Herkenhoff et al. (2018) employ different structural models, and both find substantial knowledge spillovers from coworkers that facilitate wage growth, using data from Germany and the United States, respectively.

We aim to explore the causal effect of coworkers on wages in several directions. To this end, we use a matched employer-employee administrative dataset – the Veneto Worker History panel –, which covers the universe of private-sector workers and firms in Veneto, one of the largest Italian regions, from 1975 to 2001. The availability of the full employment information for all firms in the dataset is crucial for our purposes as it allows us to track workers and coworkers over a long period of time. The dataset further records broad occupations (blue-collar, white-collar, and managers), which we use as proxies for teams within firms, and we define peer groups as workers in the same firm and occupation in a given year.[2]

With this data, we first explore the overall impact of peer quality on one's future wages. By incorporating a coworker component in the canonical AKM model (Abowd et al., 1999), our econometric strategy helps circumvent the common reflection problem (Manski, 1993) and accounts for workers' endogenous sorting into peer groups and firms. We estimate the model by the method of moments, leveraging sparse matrices and the conjugate gradient method, to overcome the computational challenge induced by the high-dimensional fixed effects and matrix inversion. When estimating peer effects, we exploit two sources of identifying variation: changes in peer quality for workers who switch peer groups and changes in peer quality for workers who remain with their peer group as other workers join or leave the peer group.

Our analysis reveals that peer effects are an important and persistent driver of future wages. Our baseline results show that a 10 percent increase in coworker quality, as measured by the average AKM worker effect of one's peers, implies an increase of contemporaneous weekly wages by 2.6 percent and next year's wages by 1.8 percent. The effect decays over time, but it is also substantial in the future, as we find that better coworkers increase one worker's wage by 0.7 percent after

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[2]This definition of peer groups has limitations, as broad occupations may comprise more than one work team in a firm. However, the structure of the Italian labor market helps us circumvent this problem, as the average firm size in Veneto (and Italy, in general) is small and allows us to work with peer groups of comparable size to that reported in the literature (e.g., Cornelissen et al., 2017; Cardoso et al., 2018).

five years. The effect is stronger for workers moving to a new job, and for young and low-tenure workers. We do not find differences between workers employed by peer groups of different sizes.

In the second part of the paper, we delve deeper into the mechanisms that identify the peer effect and study mobility of workers across firms and how it affects coworkers' wages in the origin and destination firms. Specifically, we exploit an event study analysis around the mobility of workers and investigate how the *entry* of a high-quality worker, who could potentially transmit knowledge to her peers, changes the trajectory of peer average wages in the destination firm. As the choice to hire a worker is not random, comparing outcomes in firms that hire to those that do not hire would likely bias our estimates upward: hiring choices are correlated with firm performance and, therefore, average wages. We overcome this problem by selecting a sample of firms that hire a worker in a given year and analyzing coworkers' wages in firms hiring a high- or low-quality worker relative to firms hiring similar-quality workers: we define high, similar, and low-quality workers by comparing the estimated AKM worker fixed effect of the mover, from the first part of our analysis, to that of coworkers in the firm. Besides focusing only on firms hiring or separating from a worker, we perform ex-ante propensity score matching before mobility and assess the absence of observable differences between treated and control firms. Moreover, we use data for a subset of firms to show that mobility decisions in the matched sample are not correlated with leads and lags of sales and value added per worker, reassuring on the validity of our empirical strategy. These analyses reveal that hiring a high-quality worker is associated with an increase of peer wages of 3.1 percent relative to firms hiring similar-quality workers three years after mobility. The effect is stronger for coworkers belonging to the same occupation of the new hire, as one would expect that more interaction occurs in the workplace among them. The effect is not statistically significant, instead, for firms hiring low-quality workers.[3]

We also examine how wages of coworkers in the origin firm are affected by the departure of high- and low-quality workers. We find opposite results to those outlined above, as the departure of a high-quality worker leads to a drop in wages of about 1.3 percent for coworkers in the origin firm

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[3]Herkenhoff et al. (2018) and Jarosch et al. (2021), using two different approaches, also find similar results, where workers catch up to more knowledgeable coworkers but are not dragged down by less knowledgeable ones.

relative to firms separating from a similar-quality worker. On the contrary, we find that separating from low-quality workers benefits coworkers in the firm, whose wages increase by 2.4 percent on average in the three years after the move.

Finally, we shift the focus to movers and examine how wages of workers who move into different peer groups evolve over time, by comparing the wage trajectories of workers moving into high- and low-quality peer groups to that of matched workers moving into similar-quality peer groups. We find that workers gain from moving into high-quality peer groups. On average, their wage increases by 3.9 percent relative to workers moving into similar peer groups. We find, instead, a null effect for workers moving into a low-quality peer group. Taken together, these findings highlight the importance and persistence of coworkers – and high-quality ones, especially – in shaping wage growth.

Our paper makes three contributions to the literature. First, we improve on the existing evidence on peer effects by studying how they evolve over time, allowing for dynamic effects that may not be captured by research focusing only on contemporaneous effects, either in a specific workplace (e.g., Mas and Moretti, 2009; Papay et al., 2020; Brune et al., 2020; Sandvik et al., 2020) or in a more general labor market (e.g., Lengermann, 2002; Battisti, 2017; Cornelissen et al., 2017; Cardoso et al., 2018). In particular, the closest papers to ours in this strand of the literature are Cornelissen et al. (2017) and Battisti (2017), who study the peer effect in the Munich and Veneto local labor markets, respectively. They both use an empirical model similar to ours and find a positive peer effect on wages, but the magnitude is larger in Veneto than in Munich. We innovate with respect to these papers, by providing evidence on how peers influence not only contemporaneous but also future wages.[4]

Our paper is also related to Jarosch et al. (2021), Herkenhoff et al. (2018), and Nix (2020), who study learning from coworkers as a driver of wage growth. Their empirical evidence adopts

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[4]Cornelissen et al. (2017) provide evidence on the dynamics of peer effects as an additional result, by estimating the effect of lagged peer quality on worker's wages fixing current peer composition. They find that in high-skill occupations, lagged peer quality matters only marginally. We depart from their approach by fixing current peer composition and examining its effect on worker's future wages. We find larger effects than in their paper, which we discuss below, both when examining contemporaneous and dynamic effects.

a similar econometric specification to ours, where a worker's quality is measured by observed wages and college education, respectively. We instead follow Arcidiacono et al. (2012) and use the average of coworkers' long-term productivity (proxied by the individual fixed effect) to measure peer quality, allowing us to overcome the aforementioned reflection problem, and we control for a rich set of fixed effects, allowing us to reduce concerns for the endogeneity of peer quality.

We further depart from these papers by adding evidence on which mechanism plays a more prominent role in determining the peer effect, by separating job stayers who change their peer group as workers join or leave the firm and job switchers who change their peer group by moving to a new firm. This leads to our second contribution to the literature, as we exploit the richness of our data to explore the impact of mobility of workers across firms on the wage growth of movers and peers. Researchers in the past proved the importance of hiring "good" workers for firm performance (e.g., Serafinelli, 2019). However, little is known about the trickle-down effects on coworkers. We fill this gap in the literature by providing comprehensive evidence on the effect of hiring high-quality workers or moving into high-quality peers on the wages of movers and peers.

Lastly, we contribute to a growing literature that studies the firm-specific environment as a driver of wage growth (e.g., Arellano-Bover and Saltiel, 2021; Gregory, 2019). We focus on one of the most important components of the firm, coworkers, and explore how they impact wages.

2 Data and Descriptive Statistics

Data   We use social security administrative data that contain the entire working population and private firms in the region of Veneto in Northern Italy[5] – the Veneto Worker History (VWH) dataset – from 1975 to 2001. We can observe every coworker of each worker over their working life. The database contains three types of administrative datasets: (1) a worker-level demographic register, (2) a firm-level record, and (3) an annual firm-worker social security contribution register. A brief description of each follows.

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[5]Veneto is the fifth largest region in terms of population and the third most prosperous region in terms of GDP in Italy. As a comparison, its population size is similar to Wisconsin in the United States.

1. The worker register tracks over 3 million workers from 1975 to 2001. It records the entire working history of a worker in the private sector, as long as he/she worked one day in Veneto. It contains basic demographic information, including birth year and place, gender, nationality.

2. The firm register contains all private firms that employ each individual in the worker register.[6] It includes a firm's detailed information such as national tax code, address, start and closure dates, industry. This register also includes information on firms outside of Veneto if the worker has been employed in one such firm.

3. The last register links the firm and worker registers. A private firm has to report the payment to its workers and the corresponding labor contract to the National Institute of Social Security (INPS). Therefore, the register contains accurate information on annual earnings[7] (without top-coding), weeks worked, occupation (white-collar, blue-collar, manager, apprentice), type of contract (fixed-term or open-ended) and type of working schedule (full-time or part-time). Annual earnings have been inflation-adjusted to the price level of the year 2003.

Sample selection We use all workers and firms within the Veneto region only. We focus on the period from 1982 to 2001 because the information on working weeks before 1982 is not accurate (Battisti, 2017). Besides, we have a few minimal restrictions, mainly following the standard practice in the literature. First, we keep only a worker's primary job if he or she holds multiple job contracts in a year,[8] and we restrict the working ages from 16 to 65. Also, we exclude part-time jobs and apprentices because their wages cannot be compared to regular full-time employment (as we have no information on working hours). Since we are interested in coworkers, we drop single-worker

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[6]There are two important related points. First, the public sector is not included in this database. Second, the firm is not at the establishment level. It might be ideal to use establishment-level data for our analysis, but using firm-level data would not make a difference for two reasons. First, most firms, especially in our sample period where the franchise is not typical, are single-establishment firms. Second, the firm size is typically small, with a median size of six workers, and firms with fewer than 25 employees take up around 90 percent of the total number of firms.

[7]The annual earnings equal full net earnings, plus all kinds of pecuniary compensation, grossed up with labor income taxes and social security contributions on the employee.

[8]Specifically, if a worker has two or more employment contracts in a year, we keep the job with the highest annual earnings or the highest number of weeks worked. We break the very few ties (less than 1 percent of the data) by choosing randomly the primary job.

firms. Following the practice of Cornelissen et al. (2017) and Caldwell and Harmon (2019), we also restrict the firm size to be smaller than 5000.[9]

Peer group definition   We define the peer group as all the workers employed in the same firm with the same occupation in a given year, where the occupation is given by broad professional levels (blue-collar, white-collar and executive).[10]

Descriptive statistics   Table 1 presents descriptive statistics of the sample used in the analysis. We have 17.7 million person-year observations, 2.5 million workers and 168 thousand firms. Full-time workers earn annually on average 33.4 thousand euros (in 2003 prices) and the mean weekly wage is 744 Euros. The average number of weeks worked is 42 (and the median is 52, indicating that the median worker is a full-time and full-year one). Average age is 34.5 and average tenure is 2.5 years. As expected, firms are small, reflecting the structure of the Italian labor market, with a mean firm size of 17 employees and a median of 6. Similarly, the peer group size – that is, workers in the same occupation and firm – is on average 12 and 4 at the median. The mean number of movers per firm is 4, indicating that, on average, 4 workers move to other firms or to non-employment. Overall, 61 percent of workers change job at least once throughout the whole period of analysis. The share of women is 36 percent, reflecting the relative low female labor force participation. The majority of workers are employed in blue-collar occupations (70 percent) and are on open-ended contracts (97 percent). More than half of the workers are employed in manufacturing (53 percent).

There exists considerable heterogeneity in wage profiles for workers employed in peer groups of different quality. To see this point, we run a canonical two-way fixed effects AKM regression

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[9]Lastly, due to the identification requirement in the AKM analysis below, we need to restrict the sample to the largest connected set (Abowd et al., 1999), which takes up around 97 percent of the sample.

[10]Compared to Cornelissen et al. (2017), who use a similar peer group definition, we have a lower detail of occupational categories, as we do not have detailed occupation codes. However, given the small average size of firms in Veneto – especially in the period of time we focus on – we end up with peer groups that are comparable in size to those reported in Cornelissen et al. (2017): the average peer group size in our data is 12, whereas in their paper is 9.3.

(Abowd et al., 1999), i.e.,

$$w_{it} = \alpha_i + \psi_j + \mathbf{x}'_{it}\gamma + \varepsilon_{it}, \tag{1}$$

where w_{it} are log weekly wages of individual i at time t; α_i are worker fixed effects; ψ_j are firm fixed effects; $\mathbf{x}_{it}$ contains age squared, tenure, tenure squared, and a dummy for tenure larger than ten years; ε_{it} is an error term. Using the estimates of α_i from equation (1), we compute for each worker the leave-one out average peer quality as the average worker effect of his or her coworkers in a given firm and year.[11] We then show descriptively how wage growth varies for workers joining a firm with better or worse peers, by grouping workers into different quantiles of the peer quality distribution. The results are reported in Figure 1 for white-collar and blue-collar workers in panels A and B, respectively. The figure depicts the growth in log weekly wages (i.e., the difference relative to the entry log wage) for workers entering the firm at age 25 by tenure with the firm and by peer quality, grouped in six discrete groups based on percentiles of its distribution: below 10, 10-25, 25-50, 50-75, 75-90 and above 90. The figure shows that there is wide heterogeneity in wage growth for workers joining a firm in different parts of the peer quality distribution, for both blue- and white-collar employees. Six years after joining the firm, white-collar workers in the top decile experience $0.16 \, (= 0.36 - 0.20)$ log points larger wage growth than a worker in the bottom decile of peer quality, whereas for blue-collar workers the additional wage growth equals $0.12 \, (= 0.19 - 0.07)$ log points. The difference in wage growth between workers with better and worse peers signals the contribution of the workplace environment to wage growth. However, we can say little about the direct effect of peers on wage growth as this descriptive analysis does not rule out sorting on productivity between workers and firms. This evidence likely suggests that part of the differential in wage growth is attributable to peers and part to firm-time and occupation-time

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[11]In other terms, we compute for each worker i the following quantity:

$$\overline{\alpha}_{-i,j,t} = \frac{1}{|N_{-i,j,t}|} \sum_{k \in N_{-i,j,t}} \alpha_k$$

where $|N_{-i,j,t}|$ is the number of coworkers of i in firm j at time t.

specific shocks. In the next section, we adopt a more formal empirical strategy to measure the causal effect of peers on wages.

3 An AKM Approach to Identify Peer Effects

In this section, we explore the overall effect of coworkers on future wages. Specifically, we build our empirical strategy on the canonical AKM model (Abowd et al., 1999), by incorporating the average peer quality and additional fixed effects to better deal with the sorting of workers across firms and occupations. Moreover, we discuss in detail the identification of the model and our estimation method.

3.1 Empirical Strategy

Our regression specification builds on Cornelissen et al. (2017) and Nix (2020), that include the coworker component into the canonical AKM model, as expressed in equation (2):

$$w_{i,t+h} = \alpha_i + \beta \bar{\alpha}_{-i,t} + \mathbf{x}'_{it}\gamma + \psi_{jt} + \eta_{ot} + \theta_{oj} + \varepsilon_{it}, \tag{2}$$

where

$$\bar{\alpha}_{-i,t} = \frac{1}{|M_{-i,t}|} \sum_{k \in M_{-i,t}} \alpha_k, \text{ and } M_{-i,t} = \{k : oj(k,t) = oj(i,t), k \neq i\}. \tag{3}$$

In equation (2), $w_{i,t+h}$ is the log weekly wage at time $t+h$, where $h \geq 0$. α_i is the worker fixed effect, which measures the portable component of earnings and is a proxy for quality or innate ability of a worker. $\alpha_{-i,t}$ is the average coworker's quality at time t. Specifically, we define the peer group as all the workers in the same occupation o within the same firm j as described in equation (3), where $M_{-i,t}$ is the set of all workers in the same peer group, *excluding* worker i.[12] $\mathbf{x}_{i,t}$ is a set of individual time-varying characteristics, including age squared, tenure, tenure squared, and a dummy for tenure

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[12]$|.|$ defines the modulus of the coworker vector M_{-it}; hence, $|M_{-it}|$ represents the number of coworkers.

larger than ten years. ψ_{jt}, η_{ot}, θ_{oj} are firm-year, occupation-year, firm-occupation fixed effects. β is our parameter of interest. It describes how peer quality affects contemporaneous and future wages.

3.2 Identification Challenges

We face three challenges in the identification of peer effects: (*i*) the reflection problem; (*ii*) the non-random sorting of workers across peer groups; (*iii*) the presence of unobserved correlated shocks. The reflection problem was first introduced by Manski (1993) who referred to it when discussing the problem of identifying the peer effect from contemporaneous peer effort or productivity (e.g., wages). For example, in a firm, the effort of peers influences a worker's effort, which in turn affects his or her peers. In the presence of such "reflection," it is difficult to identify the peer effect. As explained by Cornelissen et al. (2017), using long-term predetermined characteristics of peers solves the reflection problem as it avoids contemporaneous productivity measures interacting with each other. For this reason, we measure peer quality with the leave-one-out average AKM worker fixed effect, which we interpret as a proxy of peers' long-term productivity.[13]

    We address the endogenous sorting of workers across peer groups and the presence of unobserved shocks by controlling for a rich set of fixed effects. Peer quality may be correlated with workers' wages if high-quality workers sort into high-quality peers. We therefore control for worker fixed effects α_i in equation (2), so to estimate the impact of within-individual changes in peer quality on wages. Moreover, peer quality can be correlated with worker's wages in the presence of sorting between high-quality workers into high-quality firms or occupations. For this reason, we include firm-time fixed effects ψ_{jt} that control for firm-level shocks, occupation-time fixed effects η_{ot} that control for different time trends in occupation-specific pay, and occupation-firm fixed effects θ_{oj} that control for the possibility that firms pay higher wages to specific occupations.[14]

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[13]Jarosch et al. (2021) use wages to measure peer quality and to provide reduced form evidence before focusing on a detailed structural model of knowledge flows within the workplace. Since we are interested in estimating a causal parameter, we do not follow their approach and measure, instead, peer quality with the average leave-out worker effect to circumvent the reflection problem.

[14]One concern with our empirical strategy is that we control for contemporaneous fixed effects even when estimating

Even in the presence of the rich set of fixed effects discussed above, the estimate of β can still be biased if there exist unobserved background characteristics that vary at the occupation-firm-time level (i.e., at the peer group-time level) that are correlated with changes in peer quality observed between consecutive periods. To see this point, observe that there are two sources of variations for the identification of β. For job switchers, peer quality changes when they move to another firm. For job stayers, peer quality changes when other workers join or leave the peer group.[15] Both these variations entail changes in the peer group that allow identification of β. If such changes are correlated with time-varying occupation-firm-specific shocks, then the estimates of β would be biased. For example, the firm may decide to invest in automation which complements white-collar workers and substitutes for blue-collar workers. Assuming that skills and occupations are correlated, and therefore white-collar workers are more skilled, this would raise peer quality and firm output (and therefore wages) simultaneously, leading to an upward bias in the estimate of β. The opposite would be true if a firm decides to divest in some occupation-specific technology which would decrease peer quality, and firm wages simultaneously, biasing downwards the estimate of β. One way to deal with time-varying occupation-firm shocks would be to include an occupation-firm-time effect and therefore exploit within peer group variation to estimate β. However, this would limit the identification to changes in peer group sizes of the job stayers only.[16] For this reason, we prefer our baseline specification, which exploits variation coming from both stayers and movers.

The discussion so far implicitly assumes that peer quality is an observed quantity, which in fact is not. The following section discusses how we estimate peer effects when both peer quality and other fixed effects are unobserved.

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equation (2) at time $t + h, h > 0$. As a matter of fact, using contemporaneous fixed effects has little impact on our findings.

[15]Note that our definition of the peer group allows us to take into account also within-firm mobility due to promotion, e.g., from blue-collar to white-collar or from blue- and white-collar to executive, since we define the peer group as workers in the same firm *and* occupation.

[16]See the discussion in Cornelissen et al. (2017).

3.3 Estimation

There are at least two main difficulties in the estimation of β in equation (2). First, the worker fixed effect is unobserved and needs to be estimated, but, at the same time, the average coworker quality is a function of the worker fixed effects. Second, the high dimensionality of the fixed effects makes it hard to solve the resulting system of equations. We employ a standard method of moments strategy, leveraging sparse matrices and the conjugate gradient method to overcome the computational burden of the estimation.

To facilitate the analysis, we rewrite equation (2) in matrix form:

$$w = A\alpha + F\psi + O\eta + V\theta + X\gamma + \beta \cdot \tilde{C}\alpha + \varepsilon, \tag{4}$$

where $w \in \mathbb{R}^n$ is the log weekly wage and n is the number of observations. A, F, O, V are the matrices containing all the corresponding dummies of the fixed effects $\alpha, \psi, \eta, \theta$, respectively. X is a matrix containing all the observables. $\tilde{C}$ is a coworker averaging matrix, where $\tilde{C}$ has the same dimension of A and $\tilde{C}\alpha = \bar{\alpha}_{-i,t}$.[17] $\beta \in B$ is our parameter of interest, where B is a compact parameter space. Rearranging terms of equation (4), we have

$$w = \begin{bmatrix} A & F & O & V & X \end{bmatrix} \begin{bmatrix} \alpha & \psi & \eta & \theta & \gamma \end{bmatrix}' + \beta \cdot \begin{bmatrix} \tilde{C} & \mathbf{0} \end{bmatrix} \begin{bmatrix} \alpha & \psi & \eta & \theta & \gamma \end{bmatrix}' + \varepsilon. \tag{5}$$

Defining $Z = \begin{bmatrix} A & F & O & V & X \end{bmatrix}, C = \begin{bmatrix} \tilde{C} & \mathbf{0} \end{bmatrix}$, where $\mathbf{0}$ is a matrix that has the same dimension of $\begin{bmatrix} F & O & V & X \end{bmatrix}$,[18] and $\delta = \begin{bmatrix} \alpha & \psi & \eta & \theta & \gamma \end{bmatrix}'$, equation (5) can be rewritten in a compact matrix form below:

$$w = Z\delta + \beta \cdot C\delta + \varepsilon, \tag{6}$$

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[17]The dimension of A is $n \times \ell$, where ℓ is the number of workers. Also, see Appendix A.1 for details on the construction of $\tilde{C}$.

[18]The dimension of $[F\ O\ V\ X]$ is $n \times r$, where r is the total number of coefficients except worker fixed effects in equation (2).

The peer effect β is estimated by solving a non-linear least squares problem in the following objective function Q_n:

$$\widehat{\beta} = \arg\min_{\beta \in B} Q_n(\beta) = \arg\min_{\beta \in B} \left\{ \min_{\delta \in \mathbb{R}^2} \|w - Z\delta - \beta \cdot C\delta\|^2/n \right\}. \tag{7}$$

We derive the moment condition for β by taking the first order conditions of β and δ in equation (7) and get:

$$S_n(\beta) = w'MC\left(R'R\right)^{-1}R'w/n = 0, \tag{8}$$

where $R = Z + C\beta$ and $M = I_n - R\left(R'R\right)^{-1}R'$. We propose the following theorem for the consistency of $\widehat{\beta}$.

Theorem 1 *Under assumptions A1-A3, the estimate $\widehat{\beta}$ in equation (7) is a consistent estimate of β_0, where β_0 is the unique minimizer of the population analog to Q_n, with $\mathbb{E}[S_n(\beta_0)] = 0$.*

A1. *Exogeneity.* $\mathbb{E}[\varepsilon|Z,C] = 0$;

A2. *Homoskedasticity.* $\mathbb{E}[\varepsilon\varepsilon'|Z,C] = \sigma^2 I_n$, where $\sigma^2 > 0$ is unknown;[19]

A3. *Full rank. The design matrix $X + C\beta$ has full rank k for any $\beta \in B$.*

Proof. See Appendix A.2.

Theorem 1 ensures that the solution to the moment condition (8) is consistent. However, the computation of the moment is still demanding. We exploit the feature that these matrices contain a large fraction of zeros by applying the sparse matrix operation to mitigate the computational burden. Moreover, the matrix inversion could be slow and infeasible due to the high dimensionality of the matrices. We solve this issue by employing the conjugate gradient method.

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[19] Although the homoskedasticity assumption is almost universal in the peer effect literature (see Arcidiacono et al., 2012), one could relax it to allow heteroskedasticity. Hong and Sølvsten (2021) propose a new estimator that shows non-negligible bias in estimating classroom peer effects. We have applied their method to the local labor market of Padua (due to computational barriers, we cannot use the whole Veneto region). We find that the heteroskedasticity estimator is somewhat larger than our estimate. We therefore maintain the homoskedasticity assumption in order to focus on the larger Veneto region rather than smaller local labor markets. Results are available upon request.

Our method is nevertheless a parallel yet more general development of Arcidiacono et al. (2012), which uses an iterative method.[20] The main idea of their method involves two steps. First, they start with a guess (or the estimates from the prior iteration) of α to construct $\bar{\alpha}_{-i,t}$ and estimate equation (2) by OLS. Second, conditional on the estimates, they update α, and thus $\bar{\alpha}_{-i,t}$. They repeat the two steps by solving a fixed-point problem until estimates converge.[21] We believe that there are virtues in adopting our method. Most importantly, instead of the black box of iteration, the standard method of moments approach will allow us to calculate and visually observe the behavior of the moment function $S(\beta)$, which provides guidance on whether β is well identified. Figure B.1 shows that our moment function is very smooth and monotonically increases in $\beta \in [-0.9, 0.9]$ and it crosses zero (i.e., $S(\beta) = 0$) at $\beta = \widehat{\beta}$.

4 Results on the Peer Effect on Future Wages

4.1 Baseline Results

Summary statistics after estimation   Table 2 reports summary statistics from the estimation of equation (2) for $h = 0$. The standard deviation of log weekly wages is 0.44. As typical in the literature that studies decompositions of the variance of wages, most of the variability in wages is accounted by variability in worker fixed effects (see Card et al., 2018, for a review). The standard deviation of the average peer fixed effect is 0.18 and, more importantly, the correlation between worker fixed effect and average peer fixed effect is 0.55, highlighting a positive assortative matching between workers and coworkers, documented as well, for example, in Lopes de Melo (2018). The table also reports the standard deviation of the change in peer effects between consecutive years. The identification of β in equation (2) rests on changes in peer quality between subsequent years. Hence, one needs sufficient variation in peer quality to identify β. The standard deviation of

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[20]Compared with Arcidiacono et al. (2012), our Theorem 1 provides a more general framework with covariates and is proved under a standard method of moments setting.

[21]The iterative method is a clever way to circumvent the computational burden from matrix inversion, which we solve by using the conjugate gradient method.

the change in the average peer fixed effect equals 0.09. We also distinguish between movers and stayers: for the former, changes in peer quality happen because they move into a new peer group; for the latter, changes in peer quality happen if peers join or leave the current peer group. Not surprisingly, there is larger variation in the change in peer quality for movers than for stayers (0.17 and 0.07, respectively), as for the latter peer quality may not change at all between consecutive years. We corroborate this finding by plotting the density of the change in peer quality for movers and stayers in Figure B.2, which shows the existence of a mass around 0 for stayers (i.e., when the peer group does not change) and more variability for movers. Even for stayers, the standard deviation of peer quality changes amounts to approximately 37 percent of the overall variability in peer quality, indicating substantial variation in the data to identify the peer effect.

Main estimates of the peer effect   Figure 2 shows our baseline results. Each dot in the graph represents the estimate β in equation (2) using current and future wages as the dependent variable in each year ahead (h), where $h \geq 0$.[22] The shaded area is a 95 percent confidence interval, retrieved from bootstrapped standard errors. The figure shows that the peer effect is large not only for the contemporaneous wage but also for the wages in the following years. A 10 percent increase in peer quality increases the contemporaneous wage by 2.58 percent[23] and next year's wage by 1.78 percent.[24] These are sizeable effects because the return to one year's experience during the same period was around 1.36 percent as shown in Table B.2. The effect gradually fades out to around 0.73 percent after five years. It is consistent with other papers that coworkers in the past three years play the most important role in wage growth (e.g., Caldwell and Harmon, 2019). The peer effect estimates are similar when we restrict to large local labor markets such as Padua and Venice, as

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[22]Different future wages are used as outcomes in separate estimations. In the cases when $h > 0$, workers who do not have wages in year $t + h$ are excluded. Therefore, each coefficient is estimated on different samples.

[23]This result is within the range of estimates reported in the literature adopting a similar identification strategy. In particular, a one standard deviation increase in peer quality increases contemporaneous wages by 4.6 percent (0.258*0.178). In Cornelissen et al. (2017) by 0.3 percent, in Cardoso et al. (2018) by 5.7 percent and in Battisti (2017) by 7.8 percent. Differences are likely due to the different labor markets being analyzed. Differences with Battisti (2017), who uses the same data source as ours, may be also a consequence of different sample selection – in particular, we use a narrower peer definition by occupations and use weekly instead of monthly earnings as the wage measure – and model specification – we include a richer set of fixed effects (i.e., firm-year, occupation-year, and firm-occupation fixed effects).

[24]See Table B.1 for detailed estimates and sample sizes.

Figure B.3 shows.

The peer effect can be a result of different factors. As highlighted in Cornelissen et al. (2017) peers may boost productivity and wages by a mechanism of either peer pressure, according to which a worker increases her own effort in response to increased effort by her coworkers, or production complementarity, for which a worker's productivity can be improved with the help of a good coworker (see, e.g., Moretti, 2004a, on production complementarities within geographic locations). At the same time, workplace interaction is crucial for human capital accumulation, as workers transmit knowledge among each other, which makes them more productive on the job (Jarosch et al., 2021).

One concern about our results is the effective ability of workers to bargain over their wages, which requires some degree of wage flexibility. Italy is characterized by a two-tier wage-setting scheme, with collective contracts defining wage floors at the sector level. At the firm level, workers can bargain, individually or through employees' organizations, top-up agreements that increase their compensation. Moreover, part of the pay that we observe is composed of bonuses and premiums that employees receive on top of the basic compensation established by either the collective or firm-level contract. These wage premia are sizeable: Bartolucci et al. (2018) document that in the Veneto sample, wage premia are about 24 percent above the basic pay at the median. Hence, wage setting in the Italian context should be flexible enough to incorporate peer effects.

4.2 Heterogeneous Effects

We explore heterogeneous effects across different groups of workers and firms. Figure 3A separates movers and stayers, where the former are workers that change employer in at least one year $t + h, h \geq 0$, whereas the latter are workers employed in the same firm throughout the whole time window. The figure shows that peer effects are more important for movers: after five years, the peer effect for them is 0.6 percent, whereas the effect for stayers is 0.1.[25] The difference between

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[25]The coefficients are smaller than those in the main analysis because the sample used in this case contains only continually observed workers.

movers and stayers can reflect differences in the ability to learn from peers for these two types of workers or the endogeneity of mobility to learning chances in the incumbent and poaching firm: the latter may offer better learning and, therefore, wage prospects that the incumbent firm cannot offer (e.g., Gregory, 2019). At the same time, we have highlighted that changes in peer quality are much more common for movers than for stayers (Figure B.2): hence, movers may have better chances of acquiring knowledge as they move into new peer groups.

Figure 3B shows that there are no evident differences among peer groups of different sizes. We divide peer groups among those with less than 10 workers, between 10 and 50, and more than 50. Peer effects are slightly larger in small peer groups, where interaction with coworkers is likely easier, but differences are small in magnitude between groups, indicating that peer effects are an important channel of wage growth irrespective of peer group size.

Figure 3C shows how the effects differ across different tenure years. Specifically, we assign workers at $h = 0$ to three discrete categories of tenure with the firm – 0-1 years, 2-3 years, and 4 or more years – and explore how peer effects change for each group of workers. The results illustrate a clear pattern that peers matter the most for low tenure workers, while the effect decreases as one experiences more years in the same firm. The finding is consistent with a learning process: there is more room for a new hire (a worker with low tenure) to learn from peers in a firm.

A similar pattern arises when we explore the heterogeneous impacts across different age groups, as shown in Figure 3D. The effects are larger for young workers (below age 30), but the decay over time is similar across age brackets.

5   Mobility, Workers' Quality and Wage Growth

Thus far, we have focused on the impact of past coworkers on future wages and have found a positive and long-lasting effect. In this section, we switch our focus and analyze the peer effect in a different, albeit connected, perspective. In particular, we ask how important is worker mobility in shaping peers and movers' wages. In doing so, we distinguish between workers of different quality

(or skill level) and separately analyze how the entry or leave of high- and low-quality workers affect coworkers in the origin or destination firms and how moving to peer groups with different average quality impacts movers' wages.

We move from the observation that, as mentioned before, the identification of β is achieved through the following channels:

1. for job stayers, the peer quality changes when a worker *enters* the peer group or when a worker *leaves* the peer group;

2. for job switchers, the peer quality changes as they move to another firm.

We separately study these channels, following the wage trajectories of workers and coworkers around mobility episodes in our data. We study channel 1 by setting up a coworker-level event study around the mobility of a worker and analyze the evolution of wages of coworkers of the mover in the destination and origin firms. We distinguish three types of movers: high-quality, low-quality, and similar-quality, where the quality of the mover is based on a comparison of her worker fixed effect with the average peer fixed effect of coworkers from equation (2). In particular, we classify firms as hiring a high-quality or low-quality worker if her worker fixed effect is at least 10 percent higher or lower, respectively, than the average peer fixed effect of coworkers in the destination firm. We classify, instead, firms as hiring a similar-quality worker if her worker fixed effect is between -10 and $+10$ percent of the average peer fixed effect in the destination firm. When we focus on coworkers in the origin firm, we use the same classification, based on the comparison between leavers and coworkers in the origin firm.

We study channel 2 in a similar fashion. We follow the wage trajectories of workers moving into peer groups of different quality, where, again, we define a peer group as high, average, or low-quality if the mean peer fixed effect is 10 percent higher, between -10 percent and $+10$ percent, or 10 percent lower than the worker fixed effect of the mover.

5.1 Empirical Strategy

We now turn to a more formal illustration of our empirical strategy.

5.1.1 Coworker-level Event Study

Empirical design Figure 4 illustrates the definition of treatment and control groups in the event study. Primarily, we define the event as a worker who moves to a firm and stays there for three years. We choose three years because we think that it takes time for the mover to have an effect on her coworkers' wages, especially because knowledge may need some time to be transmitted.[26] We then use as outcome wages of coworkers of the mover (thus excluding the mover from the sample) in either the destination or origin firm, when we study the impact of the move on the "new" or "old" coworkers, respectively: we define these two analyses the "hire" design and the "leave" design.

We restrict the sample firms to be observed for eight consecutive years, in which there is no worker mobility in the four years before and three years after the event. While we risk losing generalization by such a substantial restriction, we believe it is essential for our analysis. First, as shown in Section 4, the coworker's effect substantially decreases after three years. Second, we need the pre-event period to examine the parallel trend assumption from a methodological perspective. Finally, since learning and knowledge spillover take time to be reflected in wages, we need a few years after the event to show the wage trajectory after the new worker enters.

In order to measure the impact of mobility on coworkers' wages, we cannot simply compare outcomes in firms that choose to hire a worker to those in firms that choose not to hire any worker, as the worker flows are very likely endogenous to firm performance and, ultimately, workers' compensation. We overcome this issue by selecting only firms that hire a given worker in a specific year and comparing firms hiring high-quality or low-quality workers to firms hiring similar-quality workers. Similarly, when we look at the impact of mobility on coworkers' wages in the origin firm we select only firms that separate from a worker in a given year. In the first case, we define the treatment groups as the coworkers in the firms that hire a high- or low-quality worker in period

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[26]When the event year has multiple workers entering, we exclude the firm from the analysis.

$t = 0$, where high-quality and low-quality workers are defined as workers with worker fixed effect that is 10 percent higher or lower than the average peer effect at the firm, respectively. We denote the group that hires a high-quality worker as treatment 1 in Figure 4 and the group that hires a low-quality worker as treatment 2. We define the control group as the coworkers in the firms that hire a similar-quality worker, whose ability is similar (within 10 percent difference) to the workers in the firm.

Similarly, in the "leave" design, when we analyze the effect on "old" coworkers, we maintain the same definitions, but the reference for defining high-, similar- and low-quality workers are peers in the origin firm.

Propensity score matching   A critical issue that prevents us from identifying the effect is that worker mobility is not random. For example, the decision to hire a high-quality worker might be endogenous to firm performance, which also affects a worker's wage growth.[27] While there is no perfect remedy for this, we construct comparable firms between the treatment and control groups through ex-ante propensity score matching. The implicit assumption is that similar firms have similar hiring strategies, leading to a quasi-random hiring on average, such that the only difference between firms hiring a high- or low-quality worker rather than a similar-quality worker is precisely the worker quality.[28]

We estimate the propensity score using a wide range of firm-level variables and some industrial and geographic variables. We match on the following set of covariates at time $t = -3$: the AKM firm-time effects and AKM average worker effects estimated from section 3, the average age of employees, the share of female workers, the share of blue-collar workers, firm size, firm age, sales, value added,[29] industry dummies, and province dummies. We also match average weekly wages

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[27]Anecdotally, a firm may decide to hire a high-quality worker because he is complementary to some technology the firm decides to invest in. Such an investment could raise the productivity of the firm and eventually compensate all employees with wage raises.

[28]Our analysis will still be biased if the decision to hire is based on firms' unobservables which we cannot control for. We try to minimize the risk of the presence of such bias by including firm fixed effects in the regression analysis.

[29]Sales and value added variables are merged from the external balance-sheet firm-level database, AIDA. However, there is a good portion of firms that are not covered in AIDA. To utilize the information from balance-sheet data, we impute the missing value and create a dummy to indicate the missing observations.

at time $t = \{-4, -3, -2\}$.[30] We use the single nearest neighbor matching without replacement to match the treatment groups 1 and 2 with the control group, separately. Tables B.3 and B.4 in the Appendix report the means and the p-values of the differences in the covariates we have used for matching for the hire and leaver design, respectively, for both comparisons of high-quality vs similar-quality (columns 1-4) and low-quality vs similar-quality (columns 5-8). Both tables highlight the presence of significant differences in observables between treated and control firms before matching, which, apart from very few exceptions, become minimal and statistically insignificant in the matched samples. Moreover, we check the common support assumption by plotting the density of the propensity score in Figure B.4 and B.5 in the Appendix for the analysis on the entry and on the leave of a worker. In both cases, and for both treatments 1 and 2, there is a wide overlap in the propensity score densities.

Overall, when studying the entry of a worker in a firm, our sample consists of 2,164 firms hiring a high-quality worker, matched with the same number of firms from the control group. 1,848 firms have hired a low-quality worker, and they are matched with the same number of firms from the control group. The two matched samples consist of 285,350 and 238,046 person-year observations, respectively. When we focus on the leave of a worker from a firm, we have 2,905 firms where a high-quality worker leaves and 2,046 where a low-quality worker leaves, both matched with the same number of firms in the control group. The two matched samples consist of 390,135 and 234,016 person-year observations, respectively.

Event study   On the matched sample of firms, we use the following event study specification to analyze the impact of a high- or low-quality worker's entry or leave on past and current coworkers' wages.

$$w_{-i,j,t} = \eta_t + \psi_j + \sum_{k \neq -1} \beta_k (Treat_j \times \mathbf{1}\{t = k\}) + \varepsilon_{-i,j,t}, \tag{9}$$

where $w_{-i,j,t}$ is the log weekly wage of coworkers, excluding the mover i, in period $t \in \{-4, -3, ..., 3\}$ and firm j, where j is the firm the worker joins when in the hire design and it is the firm the worker

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[30]Hence, we are matching on a trend in weekly wages, but we leave wages at time -1 unmatched to allow for possible violations of the parallel trend assumption, which we graphically inspect.

leaves in the leave design. η_t and ψ_j are year and firm fixed effects, respectively. $\varepsilon_{-i,j,t}$ is an error term. $Treat_j$ is a dummy variable for treated firms. The coefficients of interest are the β_k's, which measure the differential impact of hiring a high- or low-quality worker relative to hiring a similar-quality worker on wages in each period k.[31]

5.1.2 Worker-level Event Study

Empirical design We study the impact on movers' wages of joining peer groups of different quality. In particular, we use an analogous empirical strategy to that outlined before: We follow movers between 4 years before the move and 5 years after. We focus on workers moving once and not changing employer in the 4 years before the move and in the 5 years after, as described by the scheme in Figure 5. We match on workers' characteristics measured 3 years before the move, such that, conditional on observables, the only difference between movers is the peer group they end up joining. As before, we compare movers into high-quality (treatment 1) and low-quality (treatment 2) peer groups with movers into similar-quality peer groups (control), where the comparison of own quality and peer quality is based on the worker and average peer fixed effect estimated in section 4.

Propensity score matching We perform ex-ante propensity score matching on the following set of worker and firm observables at time $t = -3$: the number of weeks worked, age, gender, tenure, occupation (blue-collar or white-collar), the decile of the AKM worker fixed effect, the AKM firm-time fixed effect, log firm size, sector dummies, and province dummies. Besides, we match workers on log weekly wages at time $t = \{-4, -3, -2\}$. As before, we use the single nearest neighbor matching without replacement. Table B.5 reports the mean difference and the p-values of the differences between treated and control workers, separately for treated workers that move into high-quality peer groups (columns 1-4) and treated workers that move into low-quality peer groups (columns 5-8) for both unmatched and matched samples. The differences between treated and control workers in the unmatched samples become statistically insignificant when we perform

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[31]Our unit of observation is the coworker-year pair. If we use average outcomes at the firm-year level, excluding the new hire or the leaver, we obtain very similar results.

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matching. Furthermore, we keep only workers in the common support of the propensity score, which, as shown in Figure B.6, displays a wide overlap for both groups of workers.

After matching, we are left with a sample of 31,102 workers (15,551 in the treatment and 15,551 in the control group) when studying movers into high-quality peer groups, for a total of 310,220 person-year observations. When we study movers into low-quality peer groups we have a sample of 25,556 workers (12,778 in the treatment and 12,778 in the control group), for a total of 255,560 person-year observations.

Event study   On the matched samples, we estimate the following event study regression:

$$
w_{i,t} = \eta_t + \alpha_i + \sum_{k \neq -1} \gamma_k (Treat_i \times \mathbf{1}\{t = k\}) + \varepsilon_{i,t}, \tag{10}
$$

where $w_{i,t}$ is the log weekly wage of worker i in period $t \in \{-4, -3, ..., 5\}$. η_t and α_i are year and individual fixed effects, respectively.[32] $\varepsilon_{i,t}$ is an error term. $Treat_i$ is a dummy variable for treated workers (either movers into high-quality peers or movers into low-quality peers). The coefficients of interest are the γ_k's, which measure the differential impact of moving into a high- or low-quality peer group relative to a similar-quality peer group on wages in each period k.

5.2   Results

5.2.1   Coworker-level Event Study

When a high- or low-quality worker *enters*   Figure 6 reports the event study coefficients β_k for each $k \in \{-4, ..., +3\}$, for both treatment groups (coworkers in firms hiring a high-quality worker and coworkers in firms hiring a low-quality worker), relative to the control group (coworkers in firms hiring a similar-quality worker). The parallel trend assumption holds as the effect before the

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[32]We do not include the destination firm fixed effects as in that case identification would only come from firms having more than one mobility event in the time period under analysis, hampering the external validity of our findings. Note, however, that we do match on ex-ante firm characteristics, such as the AKM firm-time effects, log firm size and the sector, which should ease concern that we are capturing wage changes related to firm characteristics besides the quality of the peer group.

event is small and statistically insignificant.

The post-event effects are quite different for the two treatments. Compared to firms hiring a similar-quality worker, peers in firms that hire a high-quality worker experience a positive and significant increase in wages. One year after the high-quality worker's entry, coworkers' wages are 1.9 percent higher than in control firms. The effect persists in the following years and reaches 3.1 percent after three years. In contrast, there is no effect in period 0. In other terms, the high-quality worker's entry does not affect the coworkers' wage on impact, but it takes some time for the peer effect to diffuse and be reflected in wages. On the other hand, when a firm hires a low-quality worker, the effect on her coworkers' future wages is slightly negative but statistically insignificant. The knowledge spillover may play a role in explaining our findings. A high-quality worker, when joining a new firm, would be able to transmit knowledge to her coworkers, and therefore eventually drive up their wages in the following years. On the contrary, when a low-quality worker enters, the amount of knowledge she can transmit is much more limited and, therefore, it is less relevant for coworkers' wages. This result is in line with the reduced form evidence provided in Jarosch et al. (2021), who show that the peer effect is stronger when coming from more knowledgeable (i.e., more productive) workers. As discussed already, learning from high-quality coworkers is not necessarily the only mechanism at play. The entry of a high-quality worker could affect coworkers' wages through alternative channels, e.g., peer pressure and production complementarity or better network (e.g., Moretti, 2004b; Mas and Moretti, 2009; Caldwell and Harmon, 2019).

To gather further insights into the mechanisms that determine our findings, we explore heterogeneous effects across different peer groups. Figure 7A shows the effect of a high-quality worker's entry on her peer and non-peer group, i.e., coworkers in the same and different occupation, respectively. For the peer group, the effect is almost identical to the one in Figure 6: on average, the effect in the post-event window is 1.8 percent. On the other hand, there is no significant effect for the non-peer group (the static difference-in-differences point estimate is 0.4 percent with a standard error of 0.7).

Figure 7B shows the same heterogeneous effects for coworkers of low-quality movers. We

find a small and statistically insignificant negative effect for coworkers in the same peer group and a positive (but still imprecise) effect for non-peers. The estimates are hardly significant, but the positive coefficient on non-peers could signal some within-firm organizational changes that follow the low-quality hire and allow the promotion of better-skilled workers to higher-paying occupations.

We separately study the effect for high-wage and low-wage workers in Figure 7C and 7D. We define high-wage workers as those having a wage higher than the median of the sector they belong to.[33] Figure 7C reports the estimates from the entry of a high-quality worker and shows that the benefit of working with such workers are equally shared between high-wage and low-wage workers. In contrast, Figure 7D seems to suggest different wage trajectories for high-wage and low-wage workers as they collaborate with the new low-quality hire. While high-wage workers do not experience any wage change, low-wage workers experience some wage loss, although the estimates are statistically insignificant.

When a high- or low-quality worker *leaves* We estimate equation (9) on the matched sample of coworkers in firms where high-quality and low-quality workers leave compared to coworkers in firms where a similar-quality worker leaves. The outcome variable is, in this case, the coworkers' wage in the origin firm. Figure 8 reports the event study coefficients β_k for each $k \in \{-4, ..., +3\}$.

Our findings are somewhat symmetric with respect to those we find for the entry of workers. When a low-quality worker leaves, coworkers' wages increase by 2.4 percent on average, whereas the departure of a high-quality worker depresses coworkers' wages by -1.3 percent. When a firm separates from a low-quality worker, the average peer quality in a firm increases: this likely makes knowledge spillover easier in the firm, which eventually increases future wages. On the other hand, when a high-quality worker leaves, there are potentially two (opposite) effects. First, the leave of a high-quality worker reduces overall peer quality, thus decreasing the intensity of knowledge spillover. Second, the high-quality worker's human capital "left" into the firm may still have a persistent effect over the next few years, which could help boost wage growth. Overall, results

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[33]We use sector groupings based on 1-digit Ateco 91.

suggest that the first channel exceeds the second, indicating an overall negative effect.[34]

We again explore heterogeneous effects distinguishing peers and non-peers in Figure 9A and 9B, respectively for high-quality and low-quality leaves. While the departure of a high-quality worker has similar effects on peers and non-peers, when a low-quality worker leaves the firm, peers seem to benefit more than non-peers, although the difference between groups is not statistically significant.

When we distinguish between high-wage and low-wage workers (defined as before, based on the median weekly wage in the sector), we do not find significant differences between the two groups of workers when a high-quality worker leaves the firm in Figure 9C. In contrast, low-wage coworkers gain more from the departure of low-quality workers than high-wage coworkers, especially in the first two years following mobility.

5.2.2 Worker-level Event Study

We report in Figure 10 the estimates from equation (10), comparing the wage trajectories of movers into high- and low-quality peer groups relative to movers into similar-quality peer groups for event period $k \in \{-4, ..., +5\}$. The event study analysis suggests that, before the move, there are no significant differences in wage trajectories of high- and low-quality peers relative to similar-quality peers. In the post-event window, estimates indicate that moving into high-quality peer groups represents an important and substantial driver of wage growth. On average, the weekly wages of such movers increase by 3.9 percent. The effect materializes on impact and then remains approximately constant throughout the five years after mobility. In contrast, moving into low-quality peer groups does not affect wages. This finding highlights the importance, in terms of wage progression, of working in a high-quality workplace.

We explore heterogeneous effects by workers' occupation in the year before the move. That is, we distinguish among blue-collar and white-collar movers in Figure 11A and 11B for movers into high-quality and low-quality peers, respectively. The positive effect of high-quality peers is

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[34]Moreover, a high-quality worker may have a hold-up power with the firm, which eases rent-sharing for coworkers. Losing such a worker would therefore represent a wage loss for incumbents (Bloesch et al., 2021).

larger for white-collar workers compared to blue-collar ones: the average difference-in-differences coefficient in the post-event window is 5.7 percent for the former vs. 3.6 percent for the latter, though we observe an increasing trend in wages before the move for white-collar workers (but a clear trend break, nonetheless). Interestingly, white-collar workers gain also when moving into low-quality peer groups (Figure 11B), as they earn 1.8 percent higher wages on average after mobility relative to white-collar movers into similar-quality peers.[35] Overall, the net gain for white-collar workers from moving into high-quality peers relative to low-quality peers is 3.9 percent $(5.7 - 1.8)$.

Figure 11C and 11D report heterogeneous effects for high-wage and low-wage movers (defined, as before, with respect to the median wage in the sector). High-quality peers benefit particularly low-wage workers, who experience instead a wage penalty when moving into low-quality peers.

Overall, this analysis helps us understand the mechanisms that identify the peer effect in section 4. We conclude that changes in peer quality for job stayers determined by the hire of a high-quality worker or the separation from a low-quality worker are the most important ones in determining wage growth for job stayers, with the positive effects being generally stronger for workers in the same peer group. For job switchers, moving into high-quality peer groups contribute to raising wages on impact, but moving to low-quality peers has a small and statistically insignificant negative effect, on average.

5.2.3 Discussion

How do the estimates of the event study analyses compare with the effects reported in Figure 2? The estimates from the two analyses cannot be quantitatively compared, but they have the same qualitative implications. Figure 2 reports the effects of a 10 percent increase in peer quality on workers' wages. The coworker-level event study analysis measure the wage changes stemming from hiring or separating from high- and low-quality workers with respect to similar-quality workers. The worker-level event study measures the effects on movers' wages of joining high- or low-quality

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[35]The positive effect for white-collar workers moving into the low-quality peer groups is consistent with the compensating differential mechanism: in order to accept the offer from the low-quality peer-group firm, the white-collar worker is compensated with a higher wage.

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peer groups with respect to similar-quality peer groups. The effect size we measure in the event study is therefore only approximately comparable to that in Figure 2, as high-quality (low-quality) mobility is defined as having a worker fixed effect that is *at least* 10 percent higher (lower) than the average of peers in the firm. With this caveat, we can still discuss whether the estimates for the two different analyses are broadly aligned. Specifically, when focusing on the hire of high-quality workers, the leave of low-quality workers and on movers into high-quality peer groups, we get average effects of 1.8, 2.4 and 3.9 percent, respectively. The contemporaneous effect from Figure 2 is 2.6 percent,[36] which lies within the boundaries of the event study estimates. When focusing on the hire of low-quality workers, the leave of high-quality workers and on movers into low-quality peer groups, we generally find either small negative or null effects. Therefore, we conclude that the two analyses provide broadly similar peer effects when focusing on *increases* in peer quality. The event study analysis further highlights that the peer effects are not necessarily symmetric, implying that working with high- or low-quality peers has different impacts on workers' current and future wages.

5.3 Robustness Checks

Firm-level shocks   One concern with our mobility design is that the entry or leave of a worker may be correlated with firm-level shocks, even after matching on a rich set of observables. On the one hand, the entry of a high-quality peer may be correlated with expectations of future sale growth. On the other hand, the departure of a high-quality peer may be correlated with expectations of negative shocks to firm sales. We attempt to address this concern by, first, comparing coworkers' wages in firms that hire (or separate from) workers of high- or low-quality relative to firms that hire (or separate from) workers of average quality and, second, by matching firms on observables before mobility happens. We also inspect the evolution of firms' sales around mobility episodes. Due to data limitations, we only have information on sales (and value added, as further robustness) for a

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[36]The comparison with the contemporaneous peer effect is the most appropriate as the event studies restrict to movers who are observed in the destination firm for the whole post-mobility window.

subset of our data over the period 1996-2001.[37] We re-estimate equation (9) in the matched sample using log sales (value added) per worker as a dependent variable and we weight regressions by firm size. Given the sample restrictions and the data limitations, we cannot have as many pre-periods as in the main analysis, hence we limit the period before mobility to two years. Figures B.7 and B.8 report the event study estimates for the hire and leave designs, respectively. Both figures show results for log sales per worker in panel A and log value added per worker in panel B and indicate that, in the subsample for which data is available, there is no significant correlation between the quality of workers who move between firms and firm sales or value added. Moreover, before the move, we do not observe different patterns in sales and value added evolution in different groups. This evidence, albeit descriptive and limited to a subset of data, indicates that, after matching, the different groups of firms are comparable in terms of their sale and value added growth. At the same time, this analysis does not really say whether workers' mobility is determined by *expectations* of sale growth, but only that it is not correlated with *realizations* of firm growth.

Continuous treatment   We replicate our analysis using a continuous treatment, rather than dividing firms into those hiring (separating from) high-, low- or similar-quality workers and movers into those joining high-, low- or similar-quality peer groups. Specifically, in the coworker-level event study, we replace the dummy $Treat_j$ in equation (9) with the AKM worker effect of the worker joining or leaving the firm, i.e., we estimate:

$$w_{-i,j,t} = \eta_t + \psi_j + \sum_{k \neq -1} \widetilde{\beta}_k(\widehat{\alpha}_i \times \mathbf{1}\{t = k\}) + \sum_{k \neq -1} \theta_k(X_j^{pre} \times \mathbf{1}\{t = k\}) + \varepsilon_{-i,j,t}, \qquad (11)$$

where $\widehat{\alpha}_i$ is the pre-estimated worker effect of the joiner or leaver and the other variables are defined as before. We include controls for pre-mobility firm characteristics in X_j^{pre}, interacted with time event dummies: average weekly wages in all pre-periods, the AKM firm effect, the average worker effect, the average age of employees, the share of female and blue-collar employees, firm size and

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[37]Specifically, in the matched sample, we have information on 325 firms in the hire design (13,029 person-year observations) and 338 firms (14,639 person-year observations) in the leave design.

age measured at time -3. The $\widehat{\beta}_k$'s measure in this case the dynamic effects on coworkers' wages of a one percent increase in the joiner/leaver quality.

In the worker-level event study, we replace $Treat_i$ in (10) with the average AKM peer effect of coworkers in the destination firm. In other terms, we estimate:

$$w_{i,t} = \eta_t + \alpha_i + \sum_{k \neq -1} \widetilde{\gamma}_k(\overline{\widehat{\alpha}}_{-i} \times \mathbf{1}\{t=k\}) + \sum_{k \neq -1} \kappa_k(X_i^{pre} \times \mathbf{1}\{t=k\}) + \varepsilon_{i,t}, \qquad (12)$$

where $\overline{\widehat{\alpha}}_{-i}$ is the average pre-estimated worker effect of coworkers in the destination firms and the other variables are defined as before. We include controls for pre-mobility worker characteristics in X_i^{pre}, interacted with time event dummies: weekly wage, number of weeks worked, decile of worker fixed effect distribution, age, gender, tenure, occupation, AKM firm effect and firm size, all measured at time -3. The $\widetilde{\gamma}_k$'s measure the dynamic effects on the mover's wage of a one percent increase in the peer quality of the destination firm.

Results are reported in Figure B.9, which shows a very similar pattern to that reported in the main analysis. A 10 percent increase in the quality of a new hire increases coworkers' wage by 0.9 percent on average in the period after mobility, whereas a 10 percent increase in the quality of separating workers does not affect coworkers' wages in the origin firm, although the dynamic effect shows some negative adjustment in the year following mobility. For a mover, a 10 percent increase in the quality of peers at the destination firm increases wages by 2 percent on average. These magnitudes are also broadly in line with those in Figure 2, as highlighted in Section 5.2.3. Overall, these results confirm the findings from the event study with discrete treatment groups.

6 Conclusion

This paper explores a critical driver of future wages: peer quality in the workplace. We find that the quality of coworkers plays an important role in increasing future wages. By incorporating a coworker component in the canonical AKM model, we show that a 10 percent increase in peer

quality raises the next year's wage by 1.8 percent, which is larger than the return to one year's experience during the same period. The peer effect gradually decreases in magnitude over time, but we find that after five years a 10 percent increase in past peer quality still determines 0.7 percent higher wages. When exploring heterogeneous effects, we find that the peer effect is larger for movers, workers with low tenure, young workers, and in small peer groups, although differences between peer groups of different sizes are small in magnitude.

Furthermore, the peer effect is estimated using the variations from both job stayers and job switchers. For job stayers, peer quality changes when a worker enters or leaves the firm. For job switchers, peer quality changes when they move into a new peer group. We separately analyze each of these channels by setting up a novel event study analysis around worker mobility, combined with propensity score matching in the pre-mobility period. We find that, in firms hiring a high-quality worker, coworkers' wages increase by 1.8 percent relative to coworkers' wages in firms hiring a similar-quality worker. We do not find, instead, significant effects in firms hiring a low-quality worker. The opposite effect is found in firms separating from a worker: coworkers' wages increase in firms separating from low-quality workers and moderately decrease in firms separating from high-quality workers. We also explore the wage trajectories of workers who move into peer groups of different quality and find that moving into high-quality peers is an important driver of wage growth, with wages being on average 3.9 percent higher than those of workers moving into similar-quality peer groups. In contrast, the wages of workers moving into low-quality peer groups remain unchanged. Overall, our findings suggest that hiring high-quality workers, separating from low-quality workers, and moving into high-quality peer groups generate higher wages than counterfactual scenarios where peer quality does not change.

Future research should focus on opening the black box of the mechanisms behind the contribution of peers to workers' future wages. Increased availability of administrative data, coupled with either structural or reduced-form models, or laboratory experiments, will help reach a more complete answer to this question.

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Tables and Figures

Table 1: Summary statistics

	(1) Mean	(2) S.D.	(3) Median
Annual earnings	33350.06	40250.33	31730
Weekly wage	744.38	1652.81	652
Weeks worked	42.41	15.24	52
Age	34.54	10.69	32
Tenure	2.45	2.58	2
Firm size	17	75	6
Movers per firm	4	26	1
Peer group size	12	54	4
Mover	0.61	0.49	
Woman	0.36	0.48	
Blue-collar	0.70	0.46	
White-collar	0.29	0.46	
Executive	0.01	0.10	
Open-ended contract	0.97	0.16	
Temporary contract	0.03	0.16	
Manufacturing	0.53	0.50	
Services	0.03	0.18	
Construction	0.06	0.23	
Domestic work	0.08	0.28	
Finance	0.04	0.18	
Health	0.03	0.16	
Transports	0.04	0.18	
Wholesale	0.10	0.29	
Accomodation	0.02	0.13	
Other	0.03	0.16	
Person-year observations		17,723,260	
Number of workers		2,531,411	
Number of firms		168,613	

Notes. The table reports means, standard deviations and medians of each variable in columns (1) to (3), based on the largest connected set of workers and firms from the Veneto Worker History Panel. See text for details about data and sample restrictions.
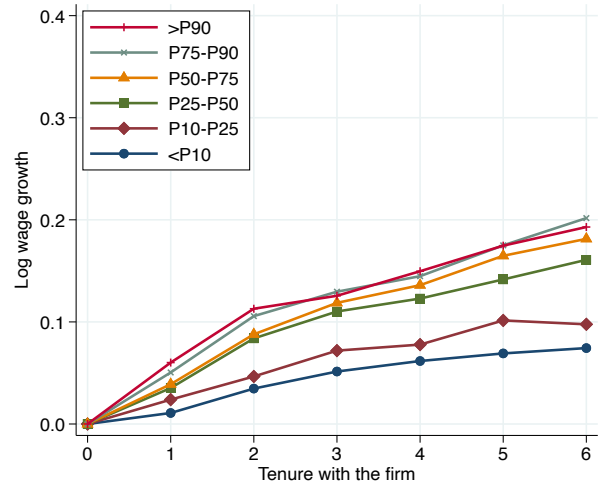
Table 2: Standard deviation of wages and fixed effects and correlation between fixed effects

Statistic	Value
Standard deviation log weekly wages	0.436
Standard deviation worker fixed effect	0.269
Standard deviation peer fixed effect	0.178
Standard deviation occupation-time fixed effect	0.065
Standard deviation firm-occupation fixed effect	0.103
Standard deviation firm-time fixed effect	0.137
Standard deviation change of peer fixed effect between t and $t-1$	0.090
Standard deviation change of peer fixed effect between t and $t-1$ for movers	0.173
Standard deviation change of peer fixed effect between t and $t-1$ for stayers	0.066
Correlation worker fixed effect/peer fixed effect	0.551

Notes. The table reports summary statistics from the estimation of equation (2) for $h = 0$, based on the largest connected set of workers and firms from the Veneto Worker History Panel. See text for details about data and sample restrictions.
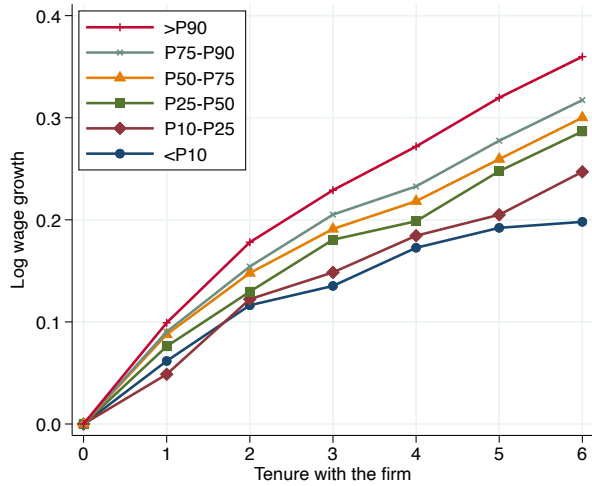
(A) White-collar, hired at age 25   (B) Blue-collar, hired at age 25

Figure 1: Log wage growth for workers entering the labor market in different quantiles of the peer quality distribution, by years of tenure and occupation

Notes. The figure reports the difference between average log weekly wages in tenure years 1 to 6 and baseline log weekly wage in tenure year 0 for workers entering the labor market in different quantiles of peer quality, defined as the average firm-level leave-one out worker effect estimated from equation (1). The sample includes workers hired at age 25. Panels A and B show results for white- and blue-collar workers, respectively.
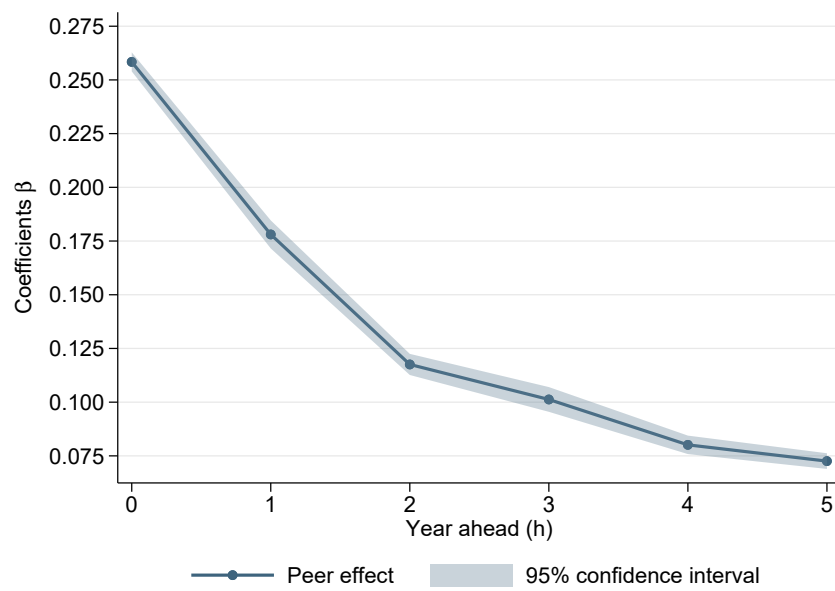
Figure 2: Peer effect on future wages (β)

Notes. The figure plots the estimates of β from equation (2) using the future wages as the dependent variable in each year ahead h, where $h = 0, 1, ..., 5$. Shaded areas are 95 percent confidence intervals, obtained from bootstrapped standard errors with clustering at the firm level. Detailed estimates and sample sizes are reported in Table B.1.
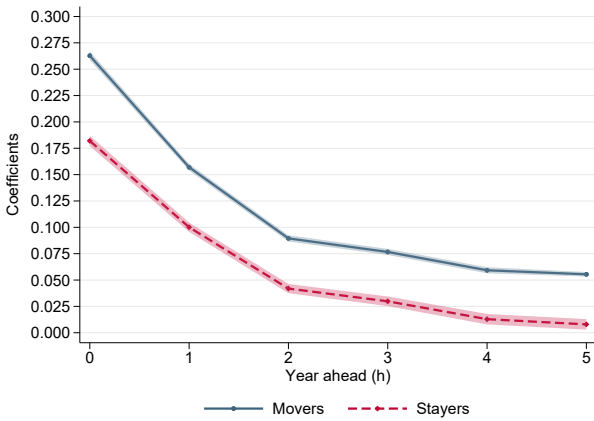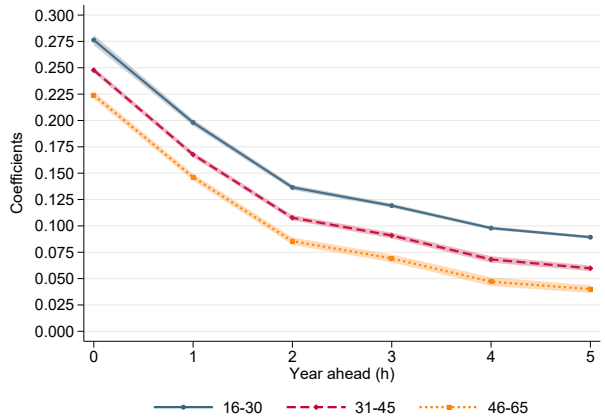
(A) Movers and stayers
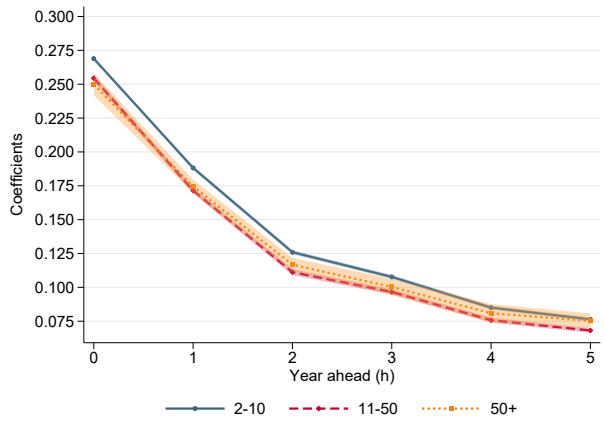
(B) Peer group sizes
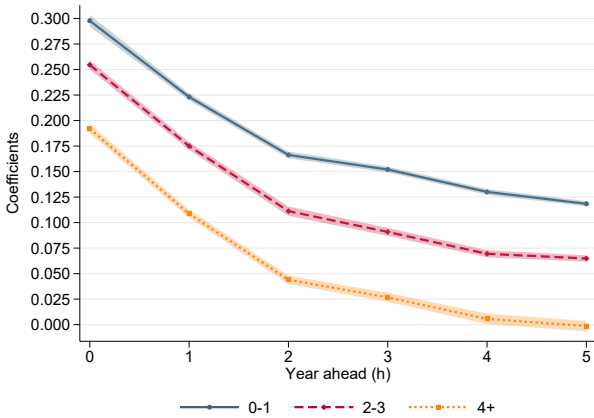
(C) Tenure brackets

(D) Age brackets

Figure 3: Heterogeneous peer effects across tenure and age brackets

Notes. The figure reports the estimates of β from equation (2) using current and future wages as the dependent variable in each year ahead h, where $h \geq 0$, focusing on different groups of workers. Panel A shows estimates for movers and stayers, panel B for workers in peer groups of different size (2-10, 11-50 and more than 50 employees), panel C for different tenure brackets (0-1, 2-3, 4 or more years) and panel D for different age brackets (16-30, 31-45, more than 45 years old). Detailed estimates and sample sizes are reported in Table B.1.
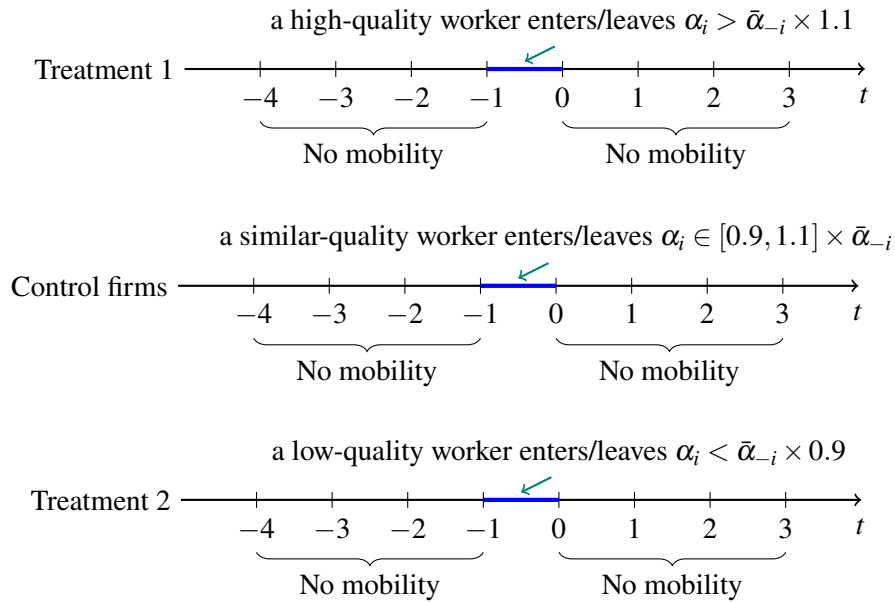
a high-quality worker enters/leaves $\alpha_i > \bar{\alpha}_{-i} \times 1.1$

Treatment 1

$$-4 \quad -3 \quad -2 \quad -1 \quad 0 \quad 1 \quad 2 \quad 3 \qquad t$$

No mobility   No mobility

a similar-quality worker enters/leaves $\alpha_i \in [0.9, 1.1] \times \bar{\alpha}_{-i}$

Control firms

$$-4 \quad -3 \quad -2 \quad -1 \quad 0 \quad 1 \quad 2 \quad 3 \qquad t$$

No mobility   No mobility

a low-quality worker enters/leaves $\alpha_i < \bar{\alpha}_{-i} \times 0.9$

Treatment 2

$$-4 \quad -3 \quad -2 \quad -1 \quad 0 \quad 1 \quad 2 \quad 3 \qquad t$$

No mobility   No mobility

Figure 4: Treatment and control groups in the event study analysis, hire and leaver design

Notes. The diagram shows the empirical design behind the coworker-level event study estimated in equation (9). *Treatment 1* refers to mobility of high-quality workers, whose worker effect is more than 10 percent larger than the average peer effect in the origin or destination firm. *Treatment 2* refers to mobility of low-quality workers, whose worker effect is more than 10 percent smaller than the average peer effect in the origin or destination firm. *Control firms* refer to mobility of similar-quality workers, whose worker effect is between -10 and $+10$ percent of the average peer effect in the origin or destination firm.
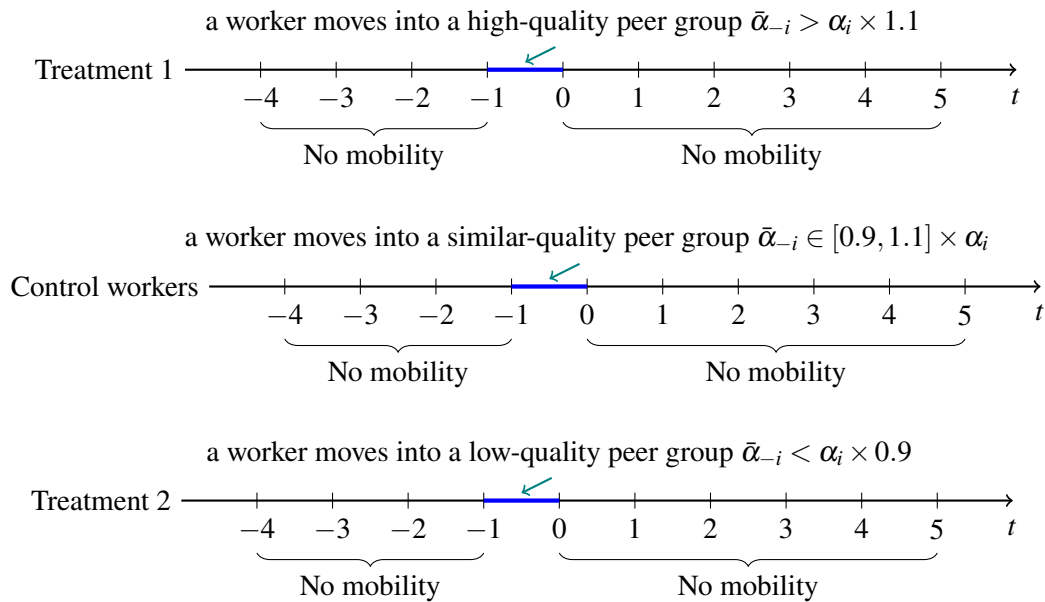
a worker moves into a high-quality peer group $\bar{\alpha}_{-i} > \alpha_i \times 1.1$

Treatment 1

$$-4 \quad -3 \quad -2 \quad -1 \quad 0 \quad 1 \quad 2 \quad 3 \quad 4 \quad 5 \quad t$$

No mobility $\qquad$ No mobility

a worker moves into a similar-quality peer group $\bar{\alpha}_{-i} \in [0.9, 1.1] \times \alpha_i$

Control workers

$$-4 \quad -3 \quad -2 \quad -1 \quad 0 \quad 1 \quad 2 \quad 3 \quad 4 \quad 5 \quad t$$

No mobility $\qquad$ No mobility

a worker moves into a low-quality peer group $\bar{\alpha}_{-i} < \alpha_i \times 0.9$

Treatment 2

$$-4 \quad -3 \quad -2 \quad -1 \quad 0 \quad 1 \quad 2 \quad 3 \quad 4 \quad 5 \quad t$$

No mobility $\qquad$ No mobility

Figure 5: Treatment and control groups in the event study analysis, mover design

Notes. The diagram shows the empirical design behind the worker-level event study estimated in equation (10). *Treatment 1* refers to mobility into high-quality peer groups, whose average peer effect is more than 10 percent larger than the worker effect of the mover. *Treatment 2* refers to mobility into low-quality peer groups, whose average peer effect is more than 10 percent smaller than the worker effect of the mover. *Control workers* refer to mobility of workers into similar-quality peer groups, whose average peer effect is between -10 and $+10$ percent of the worker effect of the mover.
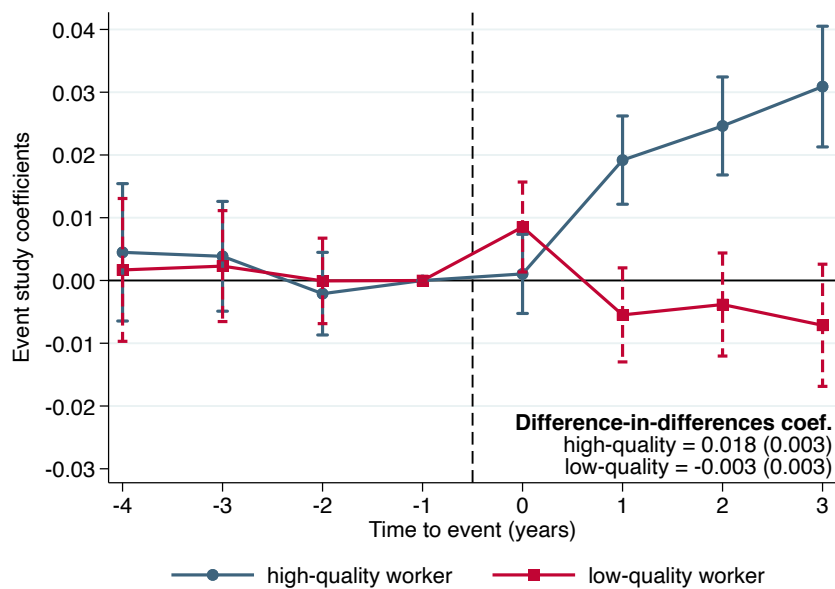
Figure 6: The effect of a high-/low- quality worker's entry on coworkers' future wages
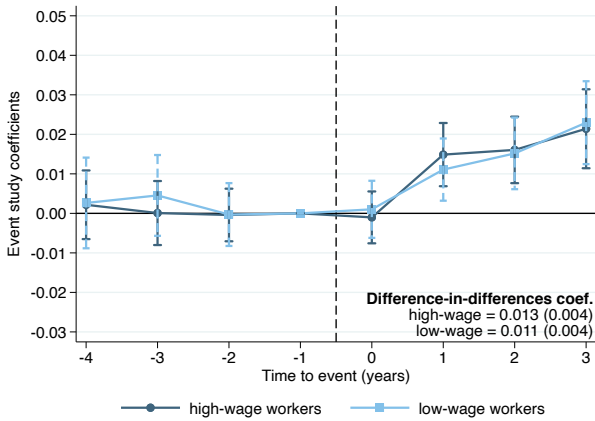
Notes. The figure reports estimates of β_k from equation (9), separately for firms hiring high-quality and low-quality workers relative to firms hiring similar-quality workers. The dependent variable is the log weekly wage of coworkers in the destination firm. Vertical bars are 95 percent confidence intervals, obtained from cluster-robust standard errors at the firm level.
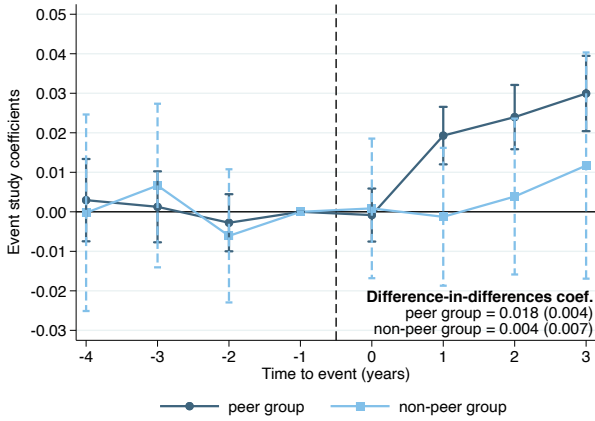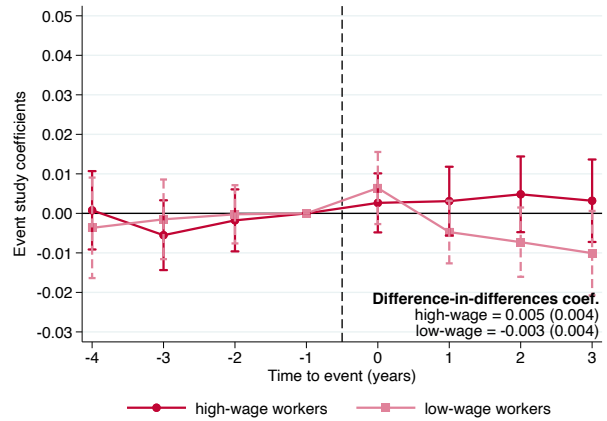
(A) High-quality entry, peers vs non-peers
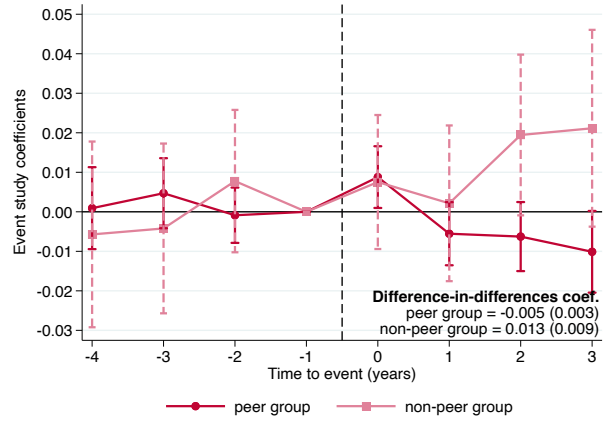
(B) Low-quality entry, peers vs non-peers

(C) High-quality entry, high- vs low-wage

(D) Low-quality entry, high- vs low-wage

Figure 7: Heterogeneous effects for peers and non-peers (top panels) and high-wage and low-wage coworkers (bottom panels), hire design

Notes. The figure reports estimates of β_k from equation (9) for different groups of workers. Panel A and B compare high- and low-quality hires, respectively, to similar-quality hires, distinguishing the effect for workers belonging to the same or different peer group (i.e., to the same occupation). Panel C and D compare high- and low-quality hires, respectively, to similar-quality hires, distinguishing the effect for high- and low-wage workers (i.e., above or below the median wage in the 1-digit sector they belong to). The dependent variable is the log weekly wage of coworkers in the destination firm. Vertical bars are 95 percent confidence intervals, obtained from cluster-robust standard errors at the firm level.
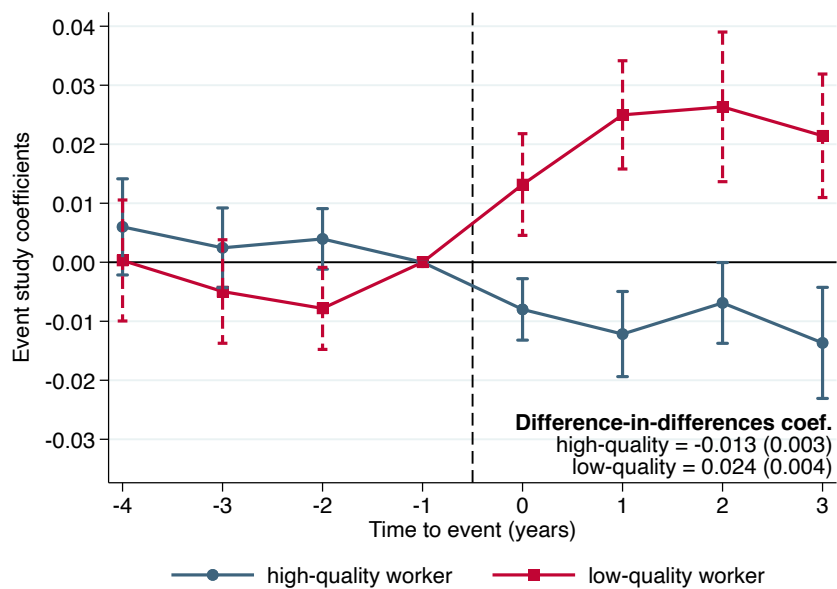
Figure 8: The effect of a high-/low-quality worker's leave on coworkers' future wages

Notes. The figure reports estimates of β_k from equation (9), separately for firms separating from high-quality and low-quality workers relative to firms separating from similiar-quality workers. The dependent variable is the log weekly wage of coworkers in the origin firm. Vertical bars are 95 percent confidence intervals, obtained from cluster-robust standard errors at the firm level.
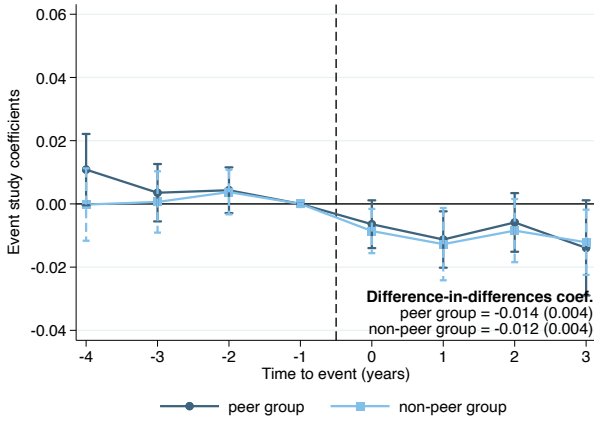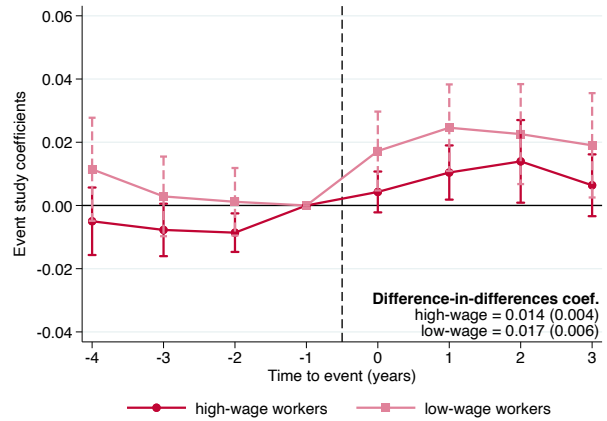
(A) High-quality leave, peers vs non-peers
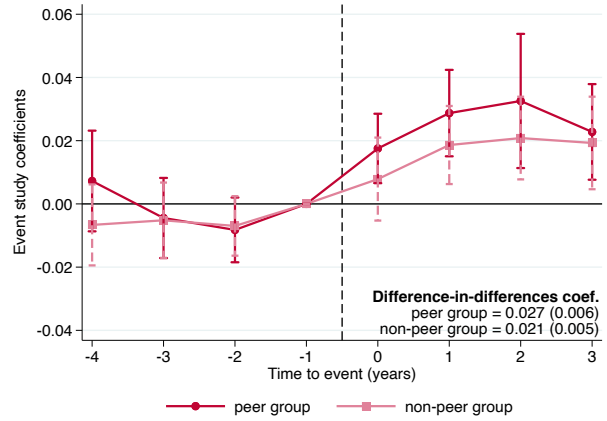
(B) Low-quality leave, peers vs non-peers
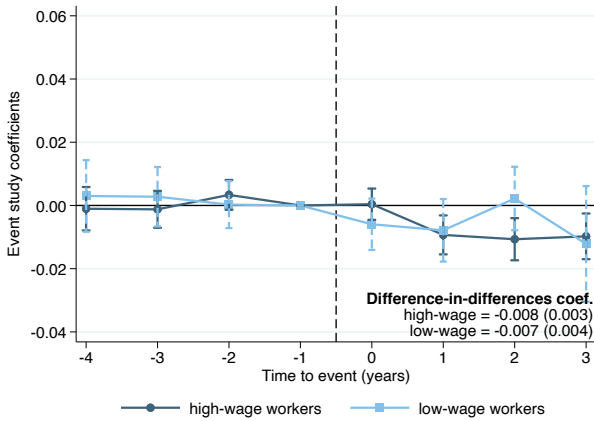
(C) High-quality leave, high- vs low-wage

(D) Low-quality leave, high- vs low-wage

Figure 9: Heterogeneous effects for peers and non-peers (top panels) and high-wage and low-wage coworkers (bottom panels), leave design

Notes. The figure reports estimates of β_k from equation (9) for different groups of workers. Panel A and B compare separations from high- and low-quality workers, respectively, to similar-quality separations, distinguishing the effect for workers belonging to the same or different peer group (i.e., to the same occupation). Panel C and D compare high- and low-quality separations, respectively, to similar-quality separations, distinguishing the effect for high- and low-wage workers (i.e., above or below the median wage in the 2-digit sector they belong to). The dependent variable is the log weekly wage of coworkers in the origin firm. Vertical bars are 95 percent confidence intervals, obtained from cluster-robust standard errors at the firm level.
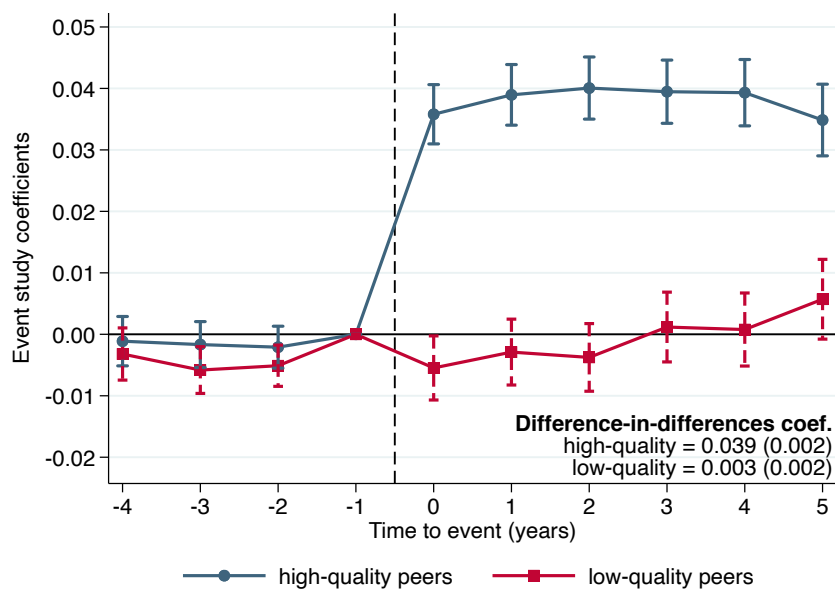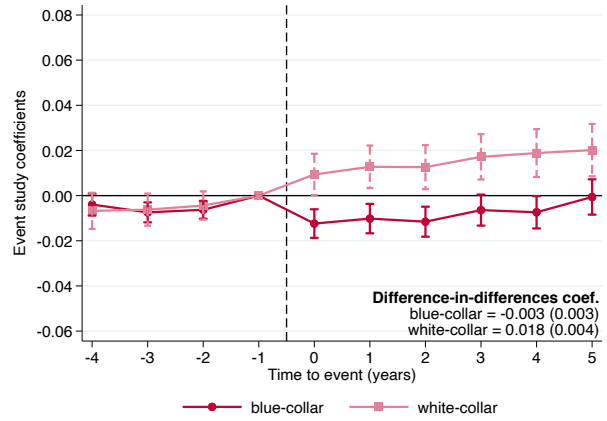
Figure 10: The effect of moving into a high-/low-quality peer group on movers' future wages

Notes. The figure reports estimates of γ_k from equation (10), separately for workers moving into high-quality and low-quality peer groups relative to those moving into similar-quality peer groups. The dependent variable is the log weekly wage of the mover. Vertical bars are 95 percent confidence intervals, obtained from cluster-robust standard errors at the individual level.
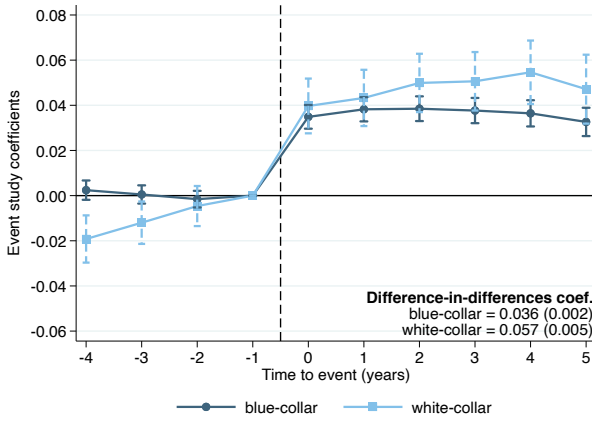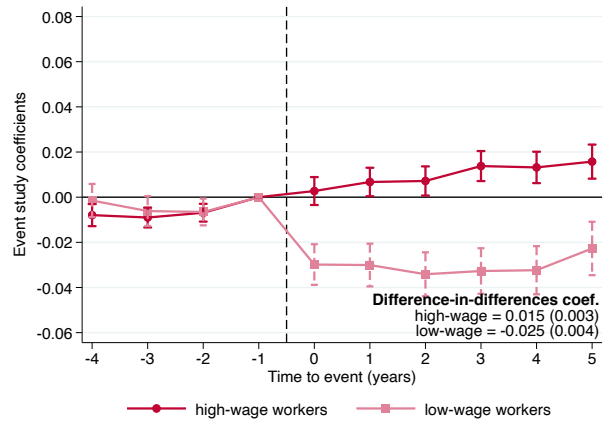
(A) High-quality peers, blue- vs white-c. mover (B) Low-quality peers, blue- vs white-c. mover
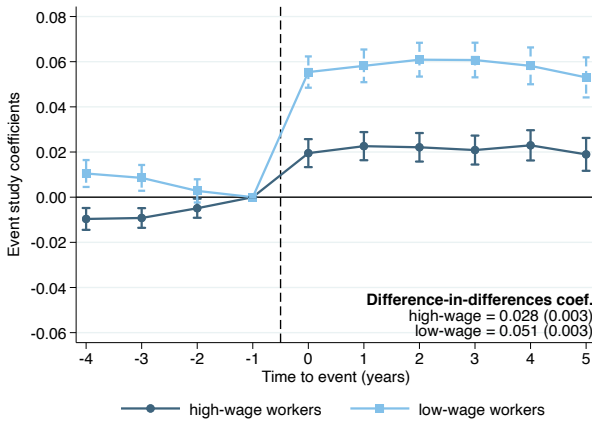
(C) High-quality peers, high- vs low-wage mover (D) Low-quality peers, high- vs low-wage mover

Figure 11: Heterogeneous effects for blue- and white-collar (top panels) and high-wage and low-wage movers (bottom panels), worker-level design

Notes. The figure reports estimates of γ_k from equation (10) for different groups of workers. Panel A and B show the effects for movers into high- and low-quality peers, respectively, relative to similar-quality peers, distinguishing movers that in the year before the move are employed as blue- or white-collar workers. show the effects for movers into high- and low-quality peers, respectively, relative to similar-quality peers, distinguishing high- and low-wage movers (i.e., above or below the median wage in the 1-digit sector they belong to). The dependent variable is the log weekly wage of movers. Vertical bars are 95 percent confidence intervals, obtained from cluster-robust standard errors at the individual level.

Appendix

A Estimation

This section provides more details on the estimation method in Section 3.3. Specifically, Section A.1 shows the detailed construction steps for our key coworker-averaging matrix C. Section A.2 shows the proof of Theorem 1.

A.1 Construction of the C Matrix

As a simple example on how we construct C, suppose we have the following data, where there are only five workers and two peer groups. The first column and second column of the data indicate the worker ID and peer group ID, respectively.

$$
\text{data} = \begin{pmatrix} 1 & 1 \\ 2 & 1 \\ 3 & 2 \\ 4 & 2 \\ 5 & 2 \end{pmatrix}
$$

We first construct an averaging matrix $\tilde{C}$ below to detect who is each worker's peer and what weight they are assigned when calculating the average peer quality. One might read $\tilde{C}$ as follows. The first row of $\tilde{C}$ says: 1 is not a coworker of himself, 2 is her coworker, and 3, 4, 5 are not her coworkers. The third row says, 1 and 2 are not 3's coworkers, 3 is not a coworker of herself, but 4 and 5 are her

coworkers. Both of them weight half when calculating the average coworker quality.

$$\tilde{C} = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.5 & 0.5 \\ 0 & 0 & 0.5 & 0 & 0.5 \\ 0 & 0 & 0.5 & 0.5 & 0 \end{pmatrix}$$

To make sure C and X have the same dimension, we add an auxiliary matrix 0 to $\tilde{C}$ as a final component of C. That is, $C = [\tilde{C}, 0]$.

A.2 Proof of Consistency

Proof of Theorem 1. The essential property that would ensure consistency of the non-linear least squares estimator is that β_0 is the unique minimizer of the population analog to Q_n, i.e., that

$$\beta_0 = \arg\min_{\beta \in B} \mathbb{E}[Q_n(\beta) \mid Z, C] \tag{A.1}$$

Noting that one could write the objective $Q_n(\beta)$ as a function of linear project matrices

$$Q_n(\beta) = ||M(\beta)w||^2/n$$

where $M(\beta) = I_n - P(\beta)$ and $P(\beta)$ is the linear projection onto the span of $Z + C\beta$, i.e.,

$$P(\beta) = (Z + C\beta)\left((Z + C\beta)'(Z + C\beta)\right)^{-1}(Z + C\beta)'.$$

To determine when equation (A.1) holds, one can calculate that

$$nQ_n(\beta) = ||M(\beta)(Z\delta + C\delta\beta_0)||^2 + ||M(\beta)\varepsilon||^2 + 2\varepsilon'M(\beta)(Z\delta + C\delta\beta_0).$$

When taking the conditional expectation of $Q_n(\beta)$ of the above equation, the following happens.

- The exogeneity condition (A1) leads the third term to have zero expectation

- The homoskedasticity condition (A2) leads the second term to have expectation equal to

$$\mathbb{E}\left[||M(\beta)\varepsilon||^2\right] = \text{trace}(M(\beta))\sigma^2 = (n-k)\sigma^2$$

for any value of β.

Finally, since $M(\beta)(Z\delta + C\delta\beta) = 0$, by taking expectation of $Q_n(\beta)$, we obtain that

$$\mathbb{E}[Q_n(\beta) \mid Z, C] = (\beta - \beta_0)^2 ||M(\beta)C\delta||^2/n + \frac{n-k}{n}\sigma^2. \tag{A.2}$$

Clearly, β_0 is a minimizer of equation (A.2). It is also unique if $||M(\beta)C\delta||^2/n \neq 0$ holds, which is ensured by the full-rank condition (A3). Therefore, the consistency of $\widehat{\beta}$ follows under the additional "regularity" condition that $\max_{\beta \in B} |Q_n(\beta) - Q(\beta)| \xrightarrow{p} 0$.

To prove $\mathbb{E}[S_n(\beta_0)] = 0$, we could use the same arguments above. Under homoskedasticity and exogeneity,

$$\mathbb{E}\left[\varepsilon' M(\beta_0)C\left((Z+C\beta_0)'(Z+C\beta_0)\right)^{-1}(Z+C\beta_0)'\varepsilon\right]$$
$$= \text{trace}\left(M(\beta_0)C\left((Z+C\beta_0)'(Z+C\beta_0)\right)^{-1}(Z+C\beta_0)'\right)\sigma^2 = 0,$$

where the last equality follows from $M(\beta)(Z+C\beta) = 0$ and the property of trace where $\text{trace}(AB) = \text{trace}(BA)$. ∎

B   Additional Figures and Tables
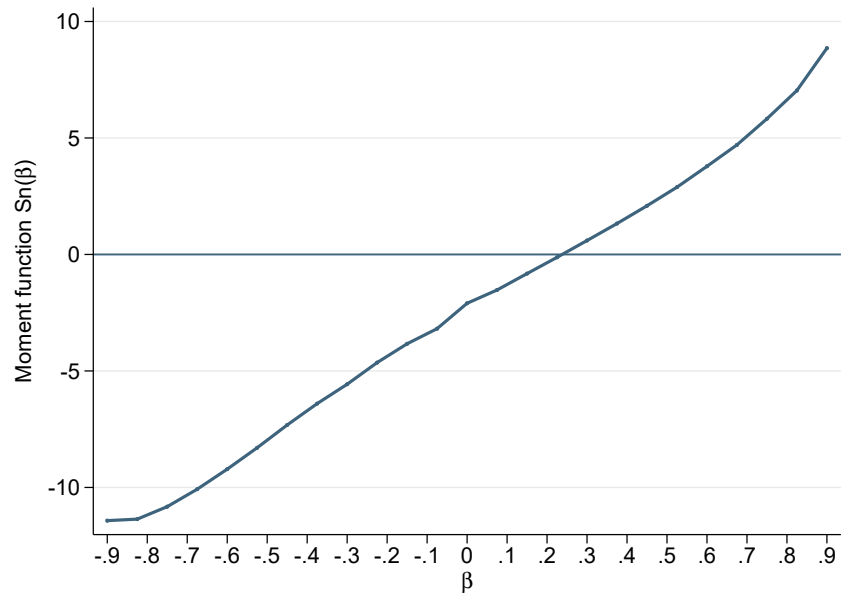
Figure B.1: The behavior of the moment function $S_n(\beta)$

Notes. The figure shows the behavior of the moment function $S_n(\beta)$ derived in equation (8), and the y-axis is scaled down by 1,000.
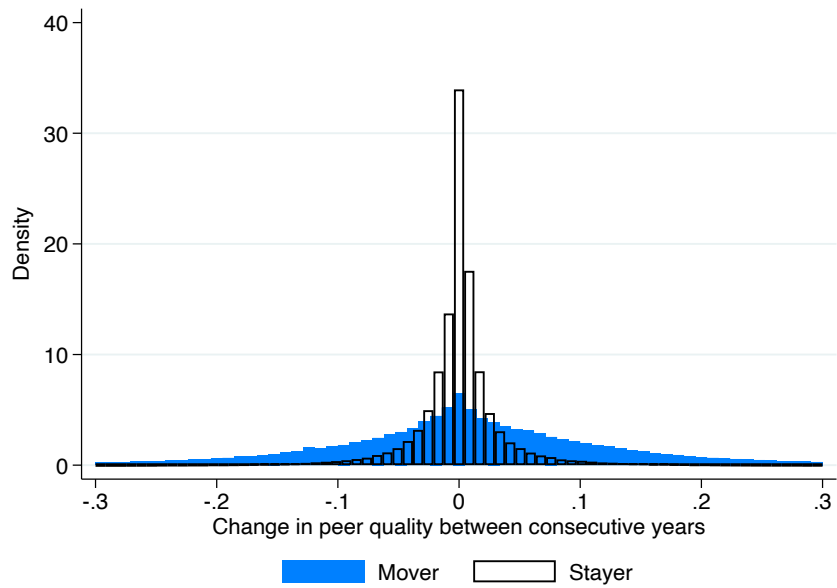
Figure B.2: Density of the change in peer fixed effect between consecutive years for movers and stayers.

Notes. The figure shows the density of changes in peer quality between consecutive years for movers and stayers. The peer quality is measured as the leave-one-out average of AKM worker effects at the peer group level, i.e., $\bar{\alpha}_{-i,t} = \frac{1}{|M_{-it}|} \sum_{k \in M_{-it}} \alpha_k$, where $|M_{-it}|$ is the number of peers of worker i.
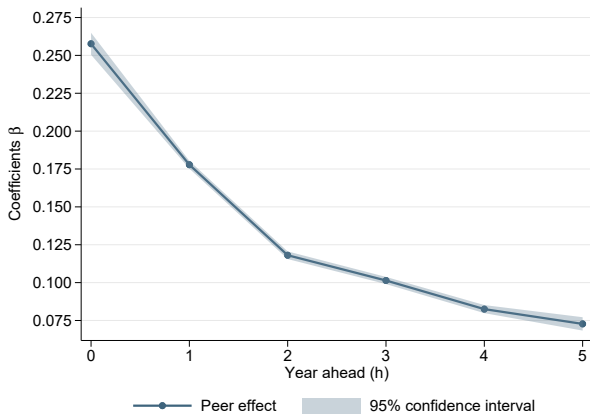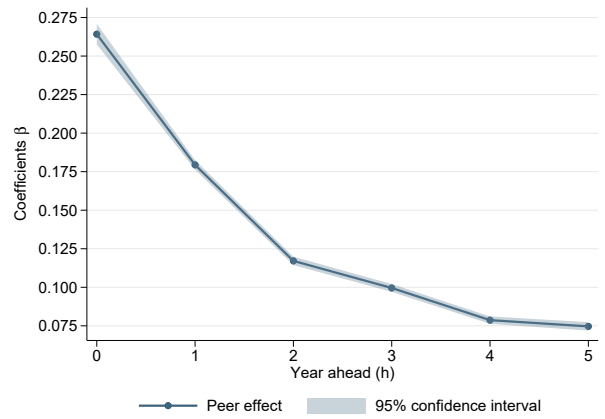
(A) Padua   (B) Venice

Figure B.3: Peer effect estimates in Padua and Venice

Notes. The figures report the peer effect stimates using equation (2) for the two largest local labor markets in Veneto - Padua and Venice.
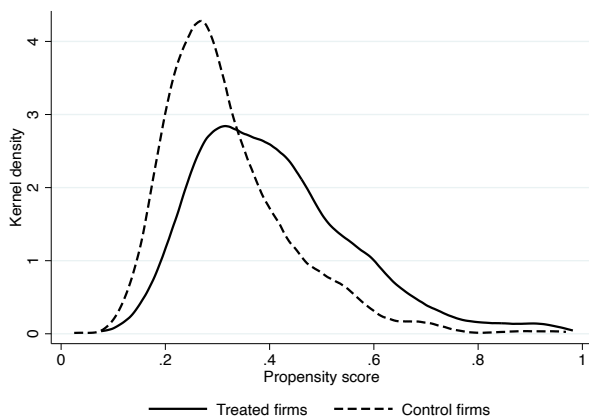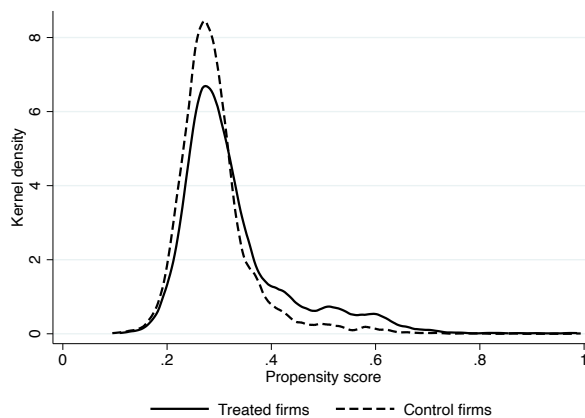
(A) Treatment 1 vs Control group   (B) Treatment 2 vs Control group

Figure B.4: Propensity score density, hire design

Notes. The figure reports the propensity score density for firms hiring high-quality (treatment 1) and similar-quality (control) workers in panel A and for firms hiring low-quality (treatment 1) and similar-quality (control) workers in panel B.
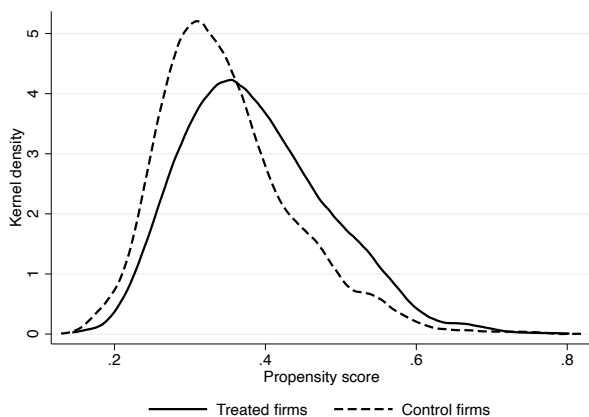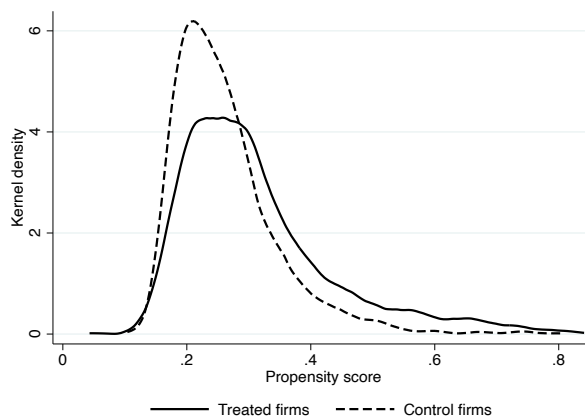
(A) Treatment 1 vs Control group   (B) Treatment 2 vs Control group

Figure B.5: Propensity score density, leave design

Notes. The figure reports the propensity score density for firms separating from high-quality (treatment 1) and similar-quality (control) workers in panel A and for firms hiring low-quality (treatment 1) and similar-quality (control) workers in panel B.
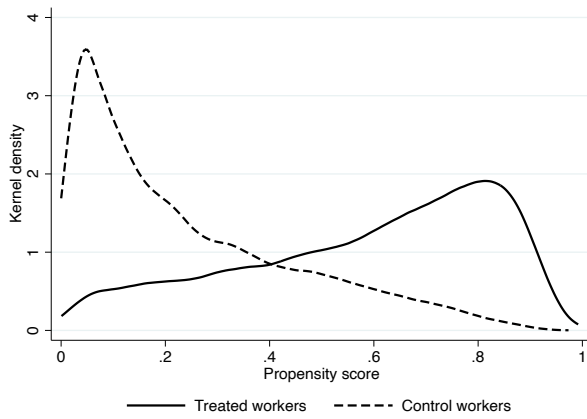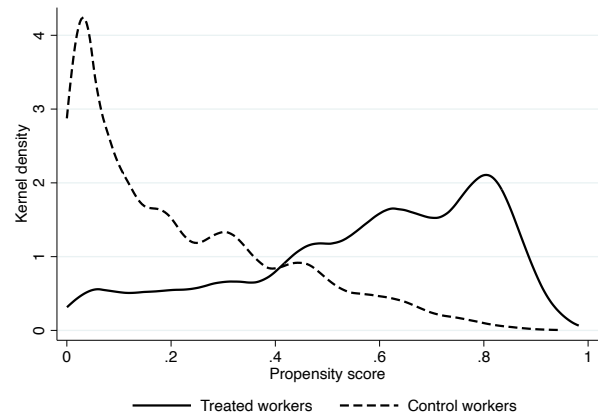
(A) Treatment 1 vs Control group   (B) Treatment 2 vs Control group

Figure B.6: Propensity score density, mover design

Notes. The figure reports the propensity score density for workers moving into high-quality (treatment 1) and similar-quality (control) peer groups in panel A and for workers moving into low-quality (treatment 1) and similar-quality (control) peer groups in panel B.
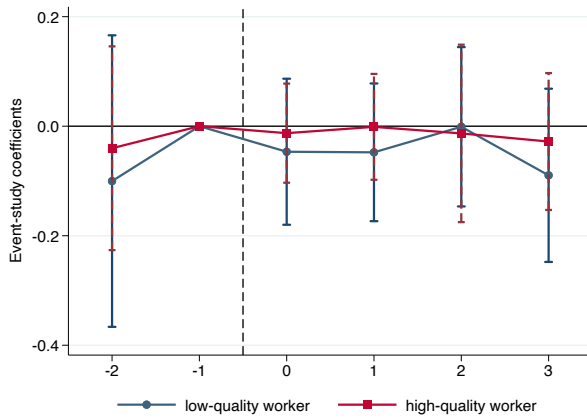
(A) Sales per worker
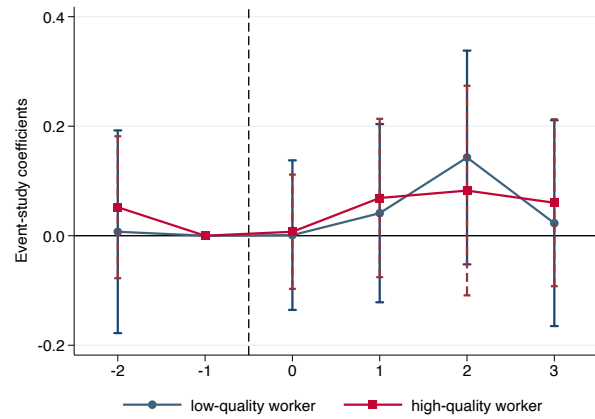
(B) Value added per worker

Figure B.7: Log value added per worker and log sales per worker around mobility, hire design

*Notes.* The figure reports estimates of β_k from equation (9), separately for firms hiring high-quality and low-quality workers relative to firms hiring similar-quality workers. The dependent variable is log sales per worker in panel A and log value added per worker in panel B. Regressions are weighted by firm size. Vertical bars are 95 percent confidence intervals, obtained from cluster-robust standard errors at the firm level.
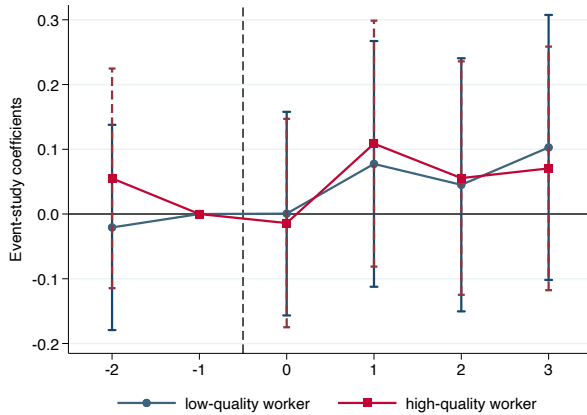
(A) Sales per worker
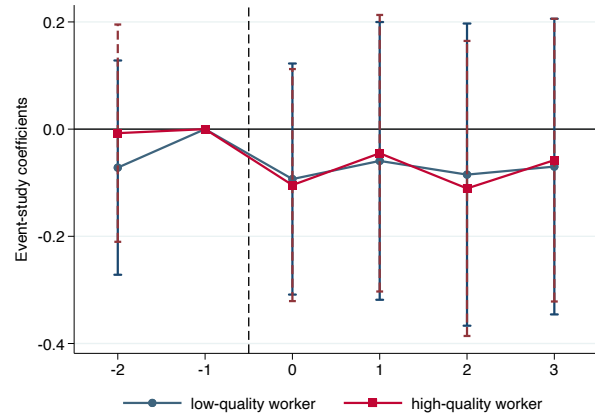
(B) Value added per worker

Figure B.8: Log value added per worker and log sales per worker around mobility, leave design

Notes. The figure reports estimates of β_k from equation (9), separately for firms separating from high-quality and low-quality workers relative to firms separating from similar-quality workers. The dependent variable is log sales per worker in panel A and log value added per worker in panel B. Regressions are weighted by firm size. Vertical bars are 95 percent confidence intervals, obtained from cluster-robust standard errors at the firm level.
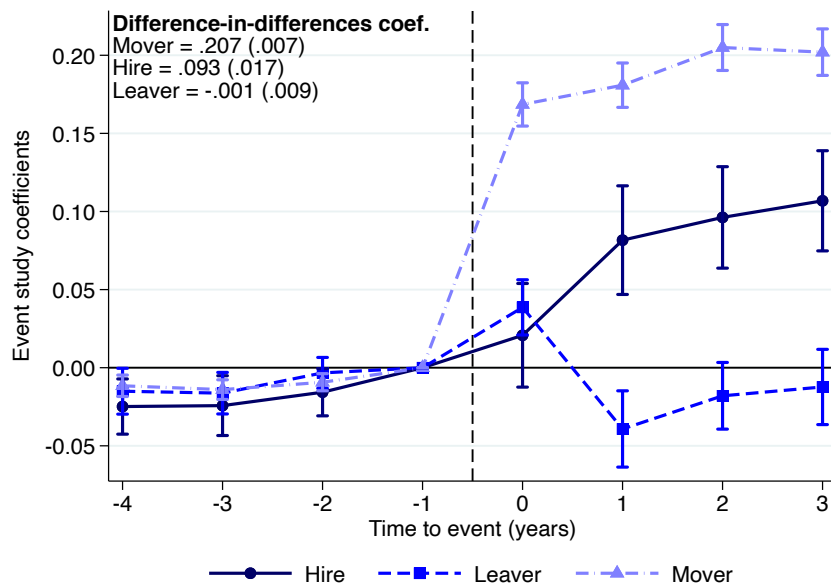
Figure B.9: Event study, continuous treatment

Notes. The figure reports estimates of $\widetilde{\beta}_k$, i.e., the dynamic effects of a 1 percent increase in the quality of a new hire or a separation on coworkers' wages in the origin (*Hire*) and destination firms (*Leave*) from equation (11), and the estimates of $\widetilde{\gamma}_k$, i.e., the dynamic effects of a 1 percent increase in the quality of the peer group a mover joins (*Mover*), from equation (12). Vertical bars are 95 percent confidence intervals, obtained from cluster-robust standard errors at the firm (for $\widetilde{\beta}_k$) and individual (for $\widetilde{\gamma}_k$) level.

Table B.1: Estimates of the peer effect on current and future wages

| Years ahead		Baseline (1)	Mover/Stayer		Peer size			Tenure brackets			Age brackets		
			Mover (2)	Stayer (3)	0−10 (4)	11−50 (5)	50+ (6)	0−1 (7)	2−3 (8)	4+ (9)	16−30 (10)	31−45 (11)	46−65 (12)
$h=0$	$\hat{\beta}$	0.258	0.263	0.182	0.269	0.259	0.250	0.298	0.255	0.192	0.276	0.248	0.224
	s.e.	(0.002)	(0.263)	(0.182)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)
	# obs	17,723,260	4,587,715	6,096,654	4,921,186	5,434,321	7,367,753	6,832,798	3,865,810	7,024,652	7,678,846	6,733,816	3,310,598
$h=1$	$\hat{\beta}$	0.178	0.157	0.100	0.188	0.174	0.172	0.223	0.175	0.109	0.198	0.168	0.146
	s.e.	(0.003)	(0.157)	(0.100)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
	# obs	14,386,952	4,643,066	4,851,831	4,159,930	4,376,922	5,850,100	5,227,468	3,214,061	5,945,423	6,176,693	5,582,025	2,628,234
$h=2$	$\hat{\beta}$	0.118	0.090	0.042	0.126	0.114	0.113	0.166	0.111	0.044	0.137	0.108	0.086
	s.e.	(0.003)	(0.090)	(0.042)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
	# obs	12,268,216	4,610,848	3,884,112	3,675,595	3,703,138	4,889,483	4,398,535	2,780,110	5,089,571	5,339,434	4,810,235	2,118,547
$h=3$	$\hat{\beta}$	0.101	0.077	0.030	0.108	0.098	0.098	0.152	0.091	0.027	0.119	0.091	0.069
	s.e.	(0.003)	(0.077)	(0.030)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
	# obs	10,613,066	4,460,695	3,115,653	3,292,768	3,183,362	4,136,936	3,811,229	2,431,132	4,370,705	4,714,626	4,199,253	1,699,187
$h=4$	$\hat{\beta}$	0.080	0.059	0.013	0.085	0.076	0.078	0.130	0.069	0.006	0.098	0.068	0.047
	s.e.	(0.002)	(0.059)	(0.013)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)
	# obs	9,201,160	4,229,238	2,490,626	2,952,472	2,751,998	3,496,690	3,336,339	2,130,425	3,734,396	4,180,065	3,679,285	1,341,810
$h=5$	$\hat{\beta}$	0.073	0.055	0.008	0.076	0.068	0.072	0.118	0.065	-0.001	0.089	0.060	0.040
	s.e.	(0.002)	(0.055)	(0.008)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)
	# obs	7,959,214	3,938,659	1,977,090	2,633,008	2,373,113	2,953,093	2,929,847	1,880,429	3,148,938	3,694,233	3,227,907	1,037,074

Notes. The table reports estimates of equation (2) for time horizons $h = 0,\dots,5$. Column (1) reports estimates for the full sample. Column (2) and (3) report estimates for workers changing employer at least once between $h = 0$ and $h = 5$ (*Mover*) and for those staying in the same firm (*Stayer*). Note the number of observations of Mover and Stayer does not add up to the one in Column (1). It is because we exclude the workers who are only observed for one period, who moved out of the labor market, and who newly entered. Columns (4) to (6) report estimates for workers in different peer group size brackets: 2-10, 11-50, and more than 50. Columns (7) to (9) report estimates for different tenure brackets: 0-1, 2-3, and more than 3 years of tenure with the firm. Columns (10) to (12) report results for different age groups: younger than 30, between 31 and 45, and older than 45. Robust standard errors, clustered at the firm level, are reported in parentheses.

Table B.2: Return to experience in Veneto from 1982 to 2001

	log(wages)
Experience	0.020
Experience^2	-0.001
$\mathbb{E}[\frac{\partial w_{it}}{\partial e_{it}}] = \gamma_1 + 2\gamma_2 \mathbb{E}[e_{it}] = 1.36\%$	

Notes. The table uses workers who are *not* left-censored so that we could calculate their actual working experience. We then use the following modified Mincer regression

$$w_{it} = \alpha_i + \gamma_1 e_{it} + \gamma_2 e_{it}^2 + \psi_{jt} + \phi_{oj} + \theta_{ot} + \varepsilon_{it},$$

where e_{it} is the years of experience and the average experience in the sample is around 3.2 years. The two coefficients in the table refer to $\widehat{\gamma_1}$ and $\widehat{\gamma_2}$ in the regression.

Table B.3: Balance test of covariates, before and after matching, hiring design

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High-quality mover				Low-quality mover			
	Unmatched		Matched		Unmatched		Matched	
	Diff.	P-value	Diff.	P-value	Diff.	P-value	Diff.	P-value
Mean wage -4	-21.574	0.000***	-5.932	0.141	7.136	0.124	1.291	0.785
Mean wage -3	-21.511	0.000***	-5.905	0.156	7.951	0.093*	4.570	0.342
Mean wage -2	-21.050	0.000***	-5.580	0.165	10.742	0.026**	4.523	0.356
AKM worker effect	-0.088	0.000***	-0.006	0.178	-0.000	0.955	0.006	0.273
AKM firm effect	-0.001	0.721	-0.006	0.155	-0.025	0.000***	-0.001	0.791
Employees' mean age	3.512	0.000***	-0.177	0.399	0.659	0.000***	-0.165	0.456
Share female	0.006	0.534	0.003	0.811	0.028	0.007***	-0.011	0.383
Share blue-collar	0.014	0.145	-0.007	0.513	-0.049	0.000***	0.011	0.400
Firm size	0.293	0.136	-0.069	0.770	0.236	0.233	0.106	0.642
Firm age	0.492	0.000***	-0.107	0.512	0.280	0.047**	-0.021	0.905
Value added	332.034	0.645	-425.186	0.631	-1.2e+03	0.138	-75.134	0.938
Revenues	94.932	0.895	-420.232	0.634	517.826	0.501	-11.555	0.990
Manufacturing	-0.104	0.000***	0.012	0.425	-0.041	0.002***	0.018	0.263
Construction	0.055	0.000***	-0.006	0.548	0.002	0.823	0.008	0.382
Wholesale	-0.020	0.030**	0.001	0.904	-0.038	0.000***	-0.001	0.927
Accommodation	0.018	0.000***	-0.004	0.519	0.008	0.074*	-0.004	0.462
Transports	0.001	0.771	-0.003	0.574	-0.007	0.125	-0.003	0.630
Finance	-0.012	0.000***	0.001	0.733	0.001	0.809	-0.003	0.633
Services	-0.010	0.058*	-0.002	0.783	-0.010	0.100*	-0.005	0.459
Health	0.038	0.000***	0.010	0.062*	0.047	0.000***	-0.009	0.171
Domestic	0.003	0.289	-0.000	0.897	0.005	0.128	0.001	0.784
Other	0.031	0.000***	-0.010	0.237	0.032	0.000***	-0.003	0.751
Belluno	0.019	0.001***	0.002	0.746	0.001	0.882	-0.004	0.590
Padua	-0.023	0.016**	0.005	0.692	-0.001	0.934	0.006	0.617
Rovigo	-0.002	0.722	0.000	0.940	-0.006	0.275	0.005	0.389
Treviso	-0.003	0.766	0.004	0.723	-0.010	0.335	0.006	0.609
Venice	-0.004	0.686	-0.012	0.254	0.004	0.657	-0.015	0.212
Vicenza	-0.008	0.433	0.003	0.820	-0.003	0.784	-0.002	0.903
Verona	0.020	0.036**	-0.002	0.875	0.015	0.152	0.002	0.861
N. treated	2517		2164		2015		1848	
N. control	4636		2164		4636		1848	

Notes. The table reports a balance test of covariates used for matching in the analysis of the effect of a new hire on coworkers' wages. Columns (1) to (4) report the average difference and the p-value of the difference for each variable in the unmatched (columns 1-2) and matched (column 3-4) samples comparing firms hiring a high-quality worker to those hiring a similar-quality worker. Columns (5) to (8) report the average difference and the p-value of the difference for each variable in the unmatched (columns 5-6) and matched (column 7-8) samples comparing firms hiring a low-quality worker to those hiring a similar-quality worker. Heteroskedasticity robust p-values are obtained from univariate regressions of each covariate on a dummy for firms hiring high-quality workers (in columns 2 and 4) or low-quality workers (in columns 6 and 8). Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.4: Balance test of covariates, before and after matching, leave design

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High-quality mover				Low-quality mover			
	Unmatched		Matched		Unmatched		Matched	
	Diff.	P-value	Diff.	P-value	Diff.	P-value	Diff.	P-value
Mean wage -4	-2.060	0.509	-4.895	0.163	-1.729	0.676	-0.362	0.940
Mean wage -3	-1.298	0.682	-3.758	0.292	-0.208	0.960	-1.934	0.688
Mean wage -2	0.039	0.990	-4.018	0.256	4.700	0.285	-1.859	0.693
AKM worker effect	-0.036	0.000***	-0.004	0.327	-0.036	0.000***	-0.002	0.708
AKM firm effect	0.000	0.940	-0.004	0.264	-0.008	0.061*	-0.002	0.735
Employees' mean age	2.109	0.000***	-0.040	0.811	1.972	0.000***	0.202	0.352
Share female	-0.006	0.470	0.009	0.365	0.048	0.000***	-0.017	0.183
Share blue-collar	0.005	0.539	-0.002	0.840	-0.093	0.000***	0.015	0.260
Firm size	0.642	0.000***	-0.046	0.828	-0.149	0.519	-0.385	0.087*
Firm age	0.124	0.309	-0.072	0.616	0.006	0.965	-0.037	0.836
Value added	39.360	0.952	782.142	0.303	709.148	0.354	209.679	0.825
Revenues	-290.164	0.657	176.462	0.816	363.910	0.627	177.693	0.851
Manufacturing	-0.057	0.000***	-0.002	0.895	-0.105	0.000***	0.014	0.392
Construction	0.045	0.000***	0.003	0.682	0.013	0.091*	0.014	0.139
Wholesale	-0.022	0.007***	-0.001	0.915	-0.027	0.004***	-0.006	0.596
Accommodation	0.017	0.000***	-0.002	0.701	0.003	0.528	0.001	0.860
Transports	0.003	0.462	-0.003	0.557	-0.001	0.796	0.002	0.762
Finance	-0.008	0.016**	0.004	0.250	0.003	0.502	-0.007	0.237
Services	-0.025	0.000***	-0.001	0.880	0.004	0.504	-0.007	0.399
Health	0.017	0.000***	0.005	0.231	0.055	0.000***	-0.003	0.676
Domestic	0.006	0.037**	-0.001	0.846	0.009	0.014**	-0.002	0.634
Other	0.023	0.000***	-0.003	0.628	0.046	0.000***	-0.006	0.535
Belluno	0.013	0.009***	-0.003	0.644	0.010	0.079*	-0.002	0.827
Padua	-0.023	0.008***	-0.001	0.892	-0.018	0.070*	-0.002	0.868
Rovigo	0.006	0.200	0.000	0.949	0.004	0.439	0.005	0.411
Treviso	-0.019	0.029**	0.011	0.250	-0.004	0.708	0.008	0.526
Venice	0.020	0.015**	0.001	0.915	0.002	0.808	-0.001	0.964
Vicenza	-0.003	0.785	-0.008	0.447	-0.008	0.429	0.010	0.467
Verona	0.006	0.489	-0.000	0.972	0.014	0.148	-0.019	0.139
N. treated	3065		2905		2046		1885	
N. control	5374		2905		5374		1885	

Notes. The table reports a balance test of covariates used for matching in the analysis of the effect of a separation on coworkers' wages. Columns (1) to (4) report the average difference and the p-value of the difference for each variable in the unmatched (columns 1-2) and matched (column 3-4) samples comparing firms separating from a high-quality worker to those separating from a similar-quality worker. Columns (5) to (8) report the average difference and the p-value of the difference for each variable in the unmatched (columns 5-6) and matched (column 7-8) samples comparing firms separating from a low-quality worker to those separating from a similar-quality worker. Heteroskedasticity robust p-values are obtained from univariate regressions of each covariate on a dummy for firms separating from high-quality workers (in columns 2 and 4) or low-quality workers (in columns 6 and 8). Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.5: Balance test of covariates, before and after matching, mover design

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High-quality peers				Low-quality peers			
	Unmatched		Matched		Unmatched		Matched	
	Diff.	P-value	Diff.	P-value	Diff.	P-value	Diff.	P-value
Wage -4	-0.070	0.000***	0.007	0.513	0.201	0.000***	-0.009	0.658
Wage -3	-0.076	0.000***	0.008	0.490	0.216	0.000***	-0.011	0.578
Wage -2	-0.081	0.000***	0.007	0.567	0.229	0.000***	-0.009	0.681
Weeks worked	-0.420	0.004***	0.105	0.321	0.196	0.017**	0.085	0.618
AKM worker effect decile	-2.682	0.000***	-0.033	0.712	2.881	0.000***	0.094	0.279
Age	6.504	0.000***	-0.303	0.425	0.360	0.407	-0.523	0.068*
Female	0.091	0.000***	0.002	0.957	-0.125	0.000***	-0.023	0.182
Tenure	-0.114	0.038**	0.091	0.074*	-0.012	0.760	0.070	0.328
Blue-collar	0.049	0.001***	0.008	0.658	-0.261	0.000***	0.031	0.209
AKM firm effect	-0.005	0.341	0.002	0.680	-0.003	0.477	0.007	0.231
Log firm size	0.260	0.002***	0.002	0.973	0.319	0.000***	0.033	0.759
Manufacturing	0.015	0.358	0.001	0.964	-0.027	0.052*	-0.019	0.490
Construction	0.004	0.361	0.001	0.867	0.005	0.238	-0.002	0.800
Wholesale	-0.007	0.528	-0.003	0.790	-0.004	0.539	0.012	0.410
Accommodation	-0.000	0.683	0.001	0.259	0.001	0.216	-0.001	0.443
Transports	-0.002	0.706	0.001	0.818	-0.005	0.175	-0.002	0.455
Finance	-0.018	0.235	0.004	0.649	0.010	0.197	0.018	0.161
Services	-0.002	0.605	0.000	0.836	0.002	0.533	-0.002	0.784
Health	0.003	0.267	-0.001	0.409	0.008	0.232	-0.002	0.680
Domestic	0.003	0.148	-0.001	0.286	0.003	0.408	-0.001	0.839
Other	0.003	0.411	-0.003	0.745	0.009	0.147	-0.001	0.945
Belluno	0.001	0.667	0.002	0.512	0.005	0.085*	0.001	0.668
Padua	-0.009	0.429	-0.001	0.963	-0.011	0.078*	0.011	0.571
Rovigo	-0.003	0.408	0.000	0.979	-0.009	0.031**	-0.003	0.494
Treviso	0.000	0.995	0.001	0.936	0.004	0.501	-0.006	0.641
Venice	-0.008	0.510	0.001	0.956	-0.005	0.595	-0.000	0.986
Vicenza	0.018	0.073*	-0.004	0.756	0.019	0.078*	-0.001	0.974
Verona	0.001	0.830	0.001	0.879	-0.002	0.704	-0.003	0.757
N. treated	26194		15511		22547		12778	
N. control	46007		15511		46007		12778	

Notes. The table reports a balance test of covariates used for matching in the analysis of the effect on worker's wages of moving into peer groups of different quality. Columns (1) to (4) report the average difference and the p-value of the difference for each variable in the unmatched (columns 1-2) and matched (column 3-4) samples comparing workers moving into high-quality peers to those moving into similar-quality peers. Columns (5) to (8) report the average difference and the p-value of the difference for each variable in the unmatched (columns 5-6) and matched (column 7-8) samples comparing workers moving into low-quality peers to those moving into similar-quality peers. Heteroskedasticity robust p-values are obtained from univariate regressions of each covariate on a dummy for workers moving into high-quality peers (in columns 2 and 4) or low-quality peers (in columns 6 and 8). Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.