# Follow the Leader: Coworker Networks and Job-to-Job Mobility*

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**Abstract**

This paper studies how coworker departures and former-peer links relate to (i) the decision to leave an employer, (ii) the choice of destination firm conditional on moving, and (iii) wages at the destination. Our analysis reveals that higher recent peer group turnover predicts a higher individual probability of leaving, and the composition of exits matters. Additionally, having at least one former peer at a candidate firm substantially raises the probability of choosing that firm, especially if at least one former peer is of high quality. We show that movers earn modestly higher wages at entry when the destination employs former peers, particularly if a high-quality former peer is present. Peer-linked moves are also associated with stronger positive assortative matching in wages. The results indicate that workplace networks are strongly associated with retention, reallocation, and wage outcomes, and that peer quality is central to understanding these relationships.

**Keywords:** peer effects, employer-employee data, panel data, individual heterogeneity, wage sorting, network centrality

**JEL Codes:** J24, J31, J62, J63, C23, C55, D85

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# 1 Introduction

Social interactions play a key role in shaping workplace dynamics, influencing decisions that significantly impact both individual careers and broader labor market outcomes. The current body of research underscores how peer effects can alter productivity, wages, and employment stability, recognizing that employees do not operate in isolation but are influenced by their coworkers' behaviors and characteristics. However, relatively less focus has been directed towards understanding peer influences on turnover decisions. This gap represents a crucial area of investigation, as employee mobility not only affects individual career trajectories but also impacts firm-level productivity and overall labor market efficiency.

This paper sits at the intersection of the workplace peer-effects literature and the literature on labor-market networks. Evidence from workplace settings shows that coworkers can affect productivity and wages (Bandiera et al., 2010; Cornelissen et al., 2017; Mas & Moretti, 2009), while models and evidence on social networks emphasize that personal ties transmit job information, reduce search frictions, and improve referral screening (Granovetter, 1973; Ioannides & Loury, 2004; Montgomery, 1991; Topa, 2011). More closely related to our setting, matched employer-employee studies show that coworker links and referrals predict transitions, hiring, and wages (Eliason et al., 2023; Hensvik & Skans, 2016; Kramarz & Skans, 2014), and evidence on peer spillovers in separations suggests that coworker exits can shape subsequent mobility (Cingano & Rosolia, 2012; Cornelissen et al., 2017). Relative to this literature, our contribution is to study both sides of peer-linked mobility in the same national administrative setting: how peer departures from the origin are related to leaving, and how former-peer presence at candidate destinations is related to where movers go.

We contribute to the existing literature in four ways:

(i) We provide evidence that peer departures and former-peer links are strongly related to turnover and destination choice in a national administrative setting with low mobility.

(ii) We classify peer quality from worker fixed effects within firm × establishment × oc-

cupation × year cells and quantify how the composition of leavers matters for others' quits.

(iii) We introduce network-centrality controls, i.e., PageRank on a worker-year graph, and show that the results are robust to global versus component normalization.

(iv) We formulate destination choice as a mover-year conditional-logit problem, distinguish between the extensive and intensive margins of former-peer exposure, and show that the main results survive controls for candidate-firm hiring and occupational composition, alternative choice-set sizes and constructions, and a complementary log-log functional form.

The labor market in Portugal provides a well-suited setting for examining these dynamics due to its distinctive characteristics, including notably low worker mobility and a predominance of small and medium-sized enterprises. These features create an environment where peer interactions may be especially pronounced, as tighter-knit relationships can reduce information frictions and amplify peer influences.

We thus use the Quadros de Pessoal (QP), a comprehensive matched employer-employee dataset covering Portugal from 1986 to 2022, to study how peer-group composition is related to worker mobility. The richness of the data allows us to identify peer groups as workers sharing the same firm, establishment, and occupation within a year, and to examine how lagged departures from those groups are associated with subsequent turnover and destination choice. This setting also allows us to control for observed worker and firm characteristics while distinguishing between the role of any former peer and that of more highly ranked peers.

A key empirical contribution of our analysis is the use of high-dimensional fixed-effect wage regressions to classify peer quality systematically. We designate individuals as high-quality peers if they belong to the top quintile of the estimated worker fixed-effect distribution within their peer group in a given year. This classification follows the matched employer-employee

wage-decomposition tradition and allows us to differentiate clearly between the associations of high-quality and low-quality peer exits with turnover decisions (Abowd et al., 1999; Card et al., 2013; Kline et al., 2020). The underlying hypothesis is that departures of high-quality peers send stronger signals about external labor-market opportunities or internal working conditions, or may represent larger losses of retained team capital at the origin.

Our empirical investigation unfolds through two complementary analyses. Initially, we examine the relationship between peer exits and individual turnover probabilities, discerning the differential associations of high-quality and low-quality peer departures. Subsequently, we analyze the destination choices of workers who change firms, namely assessing whether individuals are more likely to choose firms where former peers are already employed. The preferred destination model is a conditional logit that compares candidate firms within the same mover-year choice set. It therefore holds fixed all observed and unobserved mover-year characteristics common to the alternatives and identifies the peer coefficients from variation across the firms faced by the same worker. We complement this specification with complementary log-log models that retain worker characteristics and provide a functional-form robustness check.

Because not all peers are equally influential, we compute a network-centrality measure on a worker-year graph that connects coworkers within firm-years and links each worker across adjacent years. We also account for candidate-firm hiring activity, the share of employment represented by the focal worker's occupation, and broader occupational composition. These controls allow us to assess whether former-peer links are simply proxying for highly connected firms, rapidly expanding firms, or firms with greater demand for labor in the focal worker's occupation.

Our main findings can be summarized as follows. First, coworker turnover in the focal peer group strongly increases a worker's move probability, and who leaves matters. In our baseline model, a one-percentage-point increase in peer-group turnover between $t-2$ and $t-1$ raises the probability of leaving between $t-1$ and $t$ by 0.145 percentage points. Holding

total turnover fixed, shifting its composition toward higher-quality leavers has large effects: a one-percentage-point increase in the high-quality share of leavers raises the move probability by 0.079 percentage points, while a one-percentage-point increase in the low-quality share reduces it by an almost symmetric 0.075 percentage points. These associations survive rich covariates and the PageRank controls described above.

Second, when workers do move, destinations that already employ former peers are chosen much more often. In the preferred conditional-logit model, an ordinary-peer candidate firm, i.e., a firm with at least one former peer but no high-quality former peer, has approximately 80.45 times the relative choice odds of an otherwise comparable no-peer firm. Conditional on the candidate firm already employing a former peer, the presence of at least one high-quality former peer raises its relative choice odds by a further factor of 2.66. These results imply that, counterfactual to a firm with no peers, assigning a candidate firm to the ordinary-peer state, i.e., a firm that employs at least one former peer but no high-quality former peer, raises its probability of being chosen by 22.70 percentage points, while having at least one high-quality peer adds a further 13.85 percentage points. These large estimates mirror a striking feature of the raw data: when a mover's choice set contains exactly one peer-linked candidate firm, that firm is selected in approximately 84.9% of cases.

The intensive-margin results refine this conclusion. Conditional on the extensive peer state, a one-percentage-point increase in ordinary-peer share raises the relative choice odds by approximately 21.9%, or 20.8% after adding the predetermined candidate-firm controls. Holding total former-peer share fixed, however, replacing one percentage point of ordinary-peer share with high-quality-peer share reduces the relative choice odds by approximately 10%. By contrast, increasing high-quality-peer share without displacing ordinary former peers remains positively associated with choice. These results suggest that the high-quality-peer effect operates mainly through the presence of at least one salient high-quality former coworker, rather than increasing monotonically with the high-quality composition of a fixed-size peer network.

The heterogeneity results provide an additional qualification. Higher-ranked focal workers rely less on peer-linked candidate firms and on peer concentration in general. Concomitantly, the importance they attach to the quality composition of those peer links rises with their own estimated worker quality. This evidence points to the possibility that quality-based homophily appears more clearly on the intensive margin than in the mere presence of at least one high-quality former peer.

Third, peer-linked moves are also associated with modest but statistically significant entry-wage premia at the destination firm. The presence of a non-high-quality former peer is associated with an entry wage that is approximately 0.63% higher. The presence of at least one high-quality former peer adds approximately 0.33%, bringing the total premium to roughly 0.97%. Although these wage effects are much smaller than the corresponding destination-choice effects, they suggest that peer networks are related not only to where workers move, but also to the terms under which they are hired.

Lastly, wage sorting is substantially higher when former peers are present at the destination. The overall sample shows an average correlation of 0.310, which breaks down as 0.278 when no former peers are present, 0.385 when any former peer is present, and 0.403 when at least one high-quality former peer is present. These descriptive patterns indicate that peer-linked moves are associated with stronger positive sorting between worker and firm wage components.

The remainder of the paper is organized as follows. Section 2 reviews the related literature on workplace peer effects, labor-market networks, referrals, and coworker spillovers in mobility. Section 3 presents the search framework that guides the empirical interpretation, distinguishing between peer departures at the origin and former-peer links at candidate destinations. Section 4 describes the data, the sample restrictions, and the construction of peer groups. Section 5 presents the empirical strategy, including the construction of the peer-quality measure, the turnover model, the conditional-logit destination-choice model, the extensive- and intensive-margin peer measures, the choice-set exercises, and the PageRank-

based network controls. Section 6 reports the main results on turnover, destination choice, worker-quality heterogeneity, choice-set size, entry wages, the wage decomposition, and wage sorting. Section 7 concludes. The appendices provide the formal model and proofs, details on the choice-set construction, the network-centrality procedure, the additional regression tables, and the variable definitions.

## 2 Literature Review

Exploring peer effects across various settings, including education, neighborhoods, prisons, and, notably, the workplace, has garnered significant interest among researchers. Initially concentrated within the field of education, the empirical study of peer effects has expanded into a broad array of environments, illustrating the diverse contexts in which social interactions can influence individual behavior and outcomes (Bayer et al., 2009; Chetty & Hendren, 2018; Glaeser et al., 1996; Oreopoulos, 2003). The investigation into workplace peer effects, although a relatively recent endeavor, draws on the foundational hypothesis posited that coworker interactions facilitate learning opportunities, thereby enhancing productivity. Observational studies, often limited by their narrow focus on specific occupations or settings, have nonetheless identified peer effects on productivity and wages, albeit with varying degrees of external validity (Bandiera et al., 2010; Jackson & Bruegmann, 2009; Mas & Moretti, 2009).

Empirical research on peer effects has traditionally bifurcated into laboratory experiments and observational studies. Experimental approaches, such as those by Falk and Ichino (2006) and Guryan et al. (2009), have provided mixed evidence on the presence of peer effects, ranging from significant impacts in controlled settings to negligible effects in quasi-experimental designs. Recent literature has begun to leverage more comprehensive datasets, enabling a broader examination of peer effects across different firms and industries. Studies utilizing extensive records from Germany and Italy, as well as a wide-ranging dataset from Portugal,

have enriched our understanding of how peer dynamics influence wages and productivity (Battisti, 2017; Cornelissen et al., 2017; Hong & Lattanzio, 2022; Jarosch et al., 2021; Portugal et al., 2022). However, and to our knowledge, no study has been able to analyze how peers affect turnover decisions in a national setting, and beyond one-time event studies.

Building on this foundation, this paper contributes to the existing literature by focusing on the influence of peers on individual turnover decisions within the Portuguese context of low worker mobility and a labor market dominated by small and medium-sized enterprises. Using Quadros de Pessoal, a rich matched employer-employee dataset, we study how personal connections and the composition of peer groups affect job transitions. We also want to further elucidate the role of personal connections in the labor market, particularly for new employment opportunities. Drawing upon existing literature, we hypothesize that peers play a crucial role in disseminating knowledge about job openings and work-related competencies, potentially influencing individuals' decisions to transition to firms where former peers are employed (Eliason et al., 2023; Garcia-Louzao & Silva, 2021; Kramarz & Skans, 2014).

A large literature argues that social ties transmit job information and referrals, shaping matching and mobility. Seminal work emphasizes weak ties and information transmission (Granovetter, 1973) and models referrals as screening devices that improve match quality (Montgomery, 1991) or reduce search frictions (Ioannides & Loury, 2004; Topa, 2011). In matched employer-employee data, referrals and coworker links predict transitions and wages (Eliason et al., 2023; Glitz, 2017; Hensvik & Skans, 2016; Kramarz & Skans, 2014). Our contribution is to bring peer quality, proxied by worker fixed effects, and network position (PageRank) directly into models of turnover hazards and destination choice, in a national setting with low mobility.

Evidence from Italy and Sweden documents quit clustering and peer spillovers in separations (Cingano & Rosolia, 2012; Cornelissen et al., 2017). We complement this by (i) quantifying how the skill mix of exiting peers differentially affects the focal hazard, and (ii) showing that movers' destination choices heavily favor firms where former peers—especially high-quality

ones—work.

We exploit our rich administrative records to recover network structure at scale. We do this by constructing a worker-year graph that merges within-firm cliques and mobility edges, then controlling for PageRank-based embeddedness when estimating peer-share effects on quits and choices. This guards against mechanical confounding from centrality while explicitly testing whether central peers' exits or presence carry excess influence. Relative to the productivity-oriented peer literature (Bandiera et al., 2010; Jackson & Bruegmann, 2009; Mas & Moretti, 2009), our focus is turnover and firm choice. To our knowledge, no national-scale study has simultaneously modeled: (a) the hazard of quitting as a function of who exits, and (b) the conditional choice of destination as a function of which peers are present there, while also (c) embedding both analyses in an explicit network centrality framework. Our estimates suggest economically relevant peer effects on both the propensity to leave and the destination selected.

# 3 A Search Framework for Peer-Linked Mobility

This section provides a compact framework for interpreting the empirical specifications. A more detailed version with the formal derivations, value functions, propositions, and proofs is available in Appendix A. The model is a partial equilibrium where firm productivity, vacancies, incumbent workforces, and outside-opportunity distributions are taken as given from the perspective of an individual worker, but workers and firms optimize given those objects. The objective is not to estimate a structural model but to clarify why peer departures and former-peer links can enter reduced-form mobility, destination-choice, and wage equations.

The framework builds on dynamic job-mobility models in which workers search across heterogeneous firms and wages depend on match quality, mobility, and worker-firm histories (Adda et al., 2013; Adda & Dustmann, 2023). It also draws on models and evidence on

social networks, referrals, and labor-market information transmission (Eliason et al., 2023; Granovetter, 1973; Hensvik & Skans, 2016; Ioannides & Loury, 2004; Kramarz & Skans, 2014; Montgomery, 1991; Topa, 2011). The distinctive feature here is that the same predetermined peer history generates two empirically linked margins: peer losses at the origin and former-peer stocks at candidate destinations.

The model has two central implications. The first is that on the origin side, coworker departures can lower the value of staying because, for example, they reveal information about latent origin-firm conditions, reveal information about outside opportunities, or remove productive team capital. The second is that on the destination side, former peers can raise the value of a candidate firm because they transmit vacancy information, lower application costs, increase review probabilities, improve referral screening, provide worker-side information about the job, or increase match surplus. The empirical coefficients should therefore be interpreted as reduced-form composite objects, not as structural preference or technology parameters.

### 3.1 Timing, peer groups, and peer-rank objects

Time is discrete and indexed by $t = 1, 2, \ldots$. Worker $i$ is employed at origin firm

$$o \equiv o(i, t-1)$$

before the mobility decision observed between $t-1$ and $t$. The predetermined peer group is defined in $t-2$. Let

$$\mathcal{P}_{i,t-2}$$

denote the set of workers who shared worker $i$'s firm $\times$ establishment $\times$ occupation $\times$ year cell in $t-2$, excluding worker $i$. For each peer $j \in \mathcal{P}_{i,t-2}$, define

$$d^{o}_{j,t-1} = \mathbb{1}\{j \text{ leaves origin firm } o \text{ between } t-2 \text{ and } t-1\} \tag{1}$$

Thus peer departures are observed before worker $i$'s own move between $t-1$ and $t$, and are predetermined relative to the focal mobility outcome.

Each worker $j$ has latent type

$$\theta_j = (a_j, \xi_j, r_j)$$

where $a_j$ is productive ability, $\xi_j$ is search efficiency, and $r_j$ is latent peer influence. The rank $r_j$ should not be assumed to be pure innate ability. It may capture productivity, credibility, centrality, mentoring value, search efficiency, referral value, or access to firms, among others. In the empirical analysis, we proxy $r_j$ using the worker fixed-effect rank within the predetermined peer cell, i.e., high-ranked and low-ranked peers correspond to the high-quality and low-quality peer categories constructed from worker fixed-effect ranks. Lastly, let $\mathcal{R} \subseteq \mathbb{R}$ denote the support of latent peer rank. Define peer $j$'s influence weight by

$$\omega_j \equiv \omega(r_j), \qquad \omega : \mathcal{R} \to (0, \infty), \qquad \omega'(r) > 0 \quad \text{for all } r \in \mathcal{R}$$

Thus every peer receives a strictly positive influence weight, and higher-ranked peers receive larger weights.

The latent weighted origin peer-loss index is

$$D_{i,t-1} = \frac{1}{|\mathcal{P}_{i,t-2}|} \sum_{j \in \mathcal{P}_{i,t-2}} \omega(r_j) d^o_{j,t-1} \tag{2}$$

The empirical total peer-turnover share is

$$T_{i,t-1} = \frac{1}{|\mathcal{P}_{i,t-2}|} \sum_{j \in \mathcal{P}_{i,t-2}} d^o_{j,t-1} \tag{3}$$

Let the predetermined peer group be partitioned into high-, middle-, and low-ranked peers such that:

$$\mathcal{P}_{i,t-2} = \mathcal{H}_{i,t-2} \cup \mathcal{M}_{i,t-2} \cup \mathcal{L}_{i,t-2}$$

The corresponding departure shares are thus:

$$
\begin{aligned}
H_{i,t-1} &= \frac{1}{|\mathcal{P}_{i,t-2}|} \sum_{j \in \mathcal{H}_{i,t-2}} d^o_{j,t-1} \\
M_{i,t-1} &= \frac{1}{|\mathcal{P}_{i,t-2}|} \sum_{j \in \mathcal{M}_{i,t-2}} d^o_{j,t-1} \\
L_{i,t-1} &= \frac{1}{|\mathcal{P}_{i,t-2}|} \sum_{j \in \mathcal{L}_{i,t-2}} d^o_{j,t-1}
\end{aligned} \tag{4}
$$

so that

$$
T_{i,t-1} = H_{i,t-1} + M_{i,t-1} + L_{i,t-1} \tag{5}
$$

The middle-ranked share $M_{i,t-1}$ is useful for the theoretical decomposition, but in the empirical specifications we will only focus on $T_{i,t-1}$, $H_{i,t-1}$, and $L_{i,t-1}$.

For destination firms, let

$$
\mathcal{B}_{i,f,t} = \{j \in \mathcal{P}_{i,t-2} : j \text{ moved to firm } f \text{ between } t-2 \text{ and } t-1 \text{ and remains at } f \text{ in } t\}
$$

be the set of former peers of worker $i$ present at candidate firm $f$. The weighted former-peer stock is

$$
B_{i,f,t} = \sum_{j \in \mathcal{B}_{i,f,t}} \omega(r_j) \tag{6}
$$

and the high-ranked former-peer stock is

$$
B^H_{i,f,t} = \sum_{j \in \mathcal{B}_{i,f,t} \cap \mathcal{H}_{i,t-2}} \omega(r_j) \tag{7}
$$

The empirical destination-side variables are the extensive-margin indicators

$$
\begin{aligned}
P_{i,f,t} &= \mathbb{1}\{\mathcal{B}_{i,f,t} \neq \emptyset\} = \mathbb{1}\{B_{i,f,t} > 0\}, \\
Q_{i,f,t} &= \mathbb{1}\{\mathcal{B}_{i,f,t} \cap \mathcal{H}_{i,t-2} \neq \emptyset\} = \mathbb{1}\{B^H_{i,f,t} > 0\}.
\end{aligned} \tag{8}
$$

The second equality in each line follows from the strict positivity of $\omega(\cdot)$, together with the convention that a sum over an empty set equals zero. Thus $P_{i,f,t}$ equals one exactly when candidate firm $f$ employs at least one former peer of worker $i$, while $Q_{i,f,t}$ equals one exactly when it employs at least one high-ranked former peer.

Lastly, we consider the calligraphic object $\mathcal{B}_{i,f,t}$ to be a set of former peers, while the non-calligraphic object $B_{i,f,t}$ is a scalar weighted stock. This distinction is maintained throughout the paper.

## 3.2 Origin-side mechanism

Let the origin firm have an unobserved state during the peer-departure interval,

$$\Theta_{o,t-1} \in \{G, B\}$$

where $G$ denotes a good state and $B$ denotes a bad state. The state summarizes latent origin-firm conditions relevant for staying, such as wage growth, promotion prospects, management quality, workplace stability, and nonpecuniary job quality. Before observing peer departures, worker $i$'s prior belief that the origin is good is

$$\mu^0_{i,t-2} = \Pr(\Theta_{o,t-1} = G \mid \mathcal{I}^0_{i,t-2})$$

where $\mathcal{I}^0_{i,t-2}$ denotes information available before the departures of the $t-2$ peer group are realized.

Peer departures are informative because peers may observe private signals about the origin firm before deciding whether to leave. We define the state-contingent departure probabilities as:

$$p_G(r_j) \equiv \Pr(d^o_{j,t-1} = 1 \mid \Theta_{o,t-1} = G, r_j) \quad \text{and} \quad p_B(r_j) \equiv \Pr(d^o_{j,t-1} = 1 \mid \Theta_{o,t-1} = B, r_j) \quad (9)$$

The key informational restriction is

$$0 < p_G(r_j) < p_B(r_j) < 1 \tag{10}$$

This restriction means that peer $j$'s departure is more likely when the origin is bad than when it is good. From a Bayesian perspective, this implies that a departure therefore lowers the posterior probability that the origin is in the good state.

The information content of peer $j$'s departure can be summarized by the log-likelihood object

$$\ell(r_j) = \log\left[\frac{p_B(r_j)[1 - p_G(r_j)]}{p_G(r_j)[1 - p_B(r_j)]}\right] \tag{11}$$

Under (10), $\ell(r_j) > 0$. A larger value of $\ell(r_j)$ means that peer $j$'s departure contains stronger negative information about the origin. Furthermore, if $\ell'(r) > 0$, then departures by higher-ranked peers generate larger negative revisions in beliefs.

The focal worker's stay decision between $t-1$ and $t$ depends on the future origin state $\Theta_{o,t}$.[1] The belief relevant for staying is denoted as

$$\widetilde{\mu}_{i,t} = \Pr(\Theta_{o,t} = G \mid \mathcal{I}^0_{i,t-2}, \mathbf{d}^o_{i,t-1})$$

where

$$\mathbf{d}^o_{i,t-1} = \{d^o_{j,t-1} : j \in \mathcal{P}_{i,t-2}\}$$

A peer departure that lowers the posterior probability that $\Theta_{o,t-1} = G$ also lowers $\widetilde{\mu}_{i,t}$ when origin-firm conditions are persistent.

Peer departures may also reduce retained team capital at the origin. Let

$$K^o_{i,t} = \sum_{j \in \mathcal{P}_{i,t-2}} \chi_{ij}\omega(r_j)(1 - d^o_{j,t-1}), \qquad \chi_{ij} \geq 0 \tag{12}$$

[1] Appendix A connects $\Theta_{o,t-1}$ to $\Theta_{o,t}$ through a persistent Markov process.

where $\chi_{ij}$ measures how complementary peer $j$ is to worker $i$ in production. The term $1 - d^o_{j,t-1}$ is an indicator that peer $j$ remains at the origin after the peer-departure interval. Thus peer $j$'s contribution to $K^o_{i,t}$ is $\chi_{ij}\omega(r_j)$ if $j$ stays and zero if $j$ leaves. A departure by peer $j$ lowers $K^o_{i,t}$ by $\chi_{ij}\omega(r_j)$, and the loss is larger for higher-ranked peers when $\omega'(r) > 0$. The subscript $t$ indicates that $K^o_{i,t}$ is the retained team capital relevant for worker $i$'s mobility decision between $t-1$ and $t$. It is constructed from the predetermined $t-2$ peer group and from peer departures observed between $t-2$ and $t-1$.

The value of staying can therefore be written in reduced form as

$$V^S_{i,t} = V^S_i\left(\bar{w}^S_{i,o,t}, K^o_{i,t}, \widetilde{\mu}_{i,t}, X_{i,t-1}, Z_{o,t-1}\right) \tag{13}$$

The object $\bar{w}^S_{i,o,t}$ denotes worker $i$'s expected wage at the origin firm $o$ if she stays through the decision interval between $t-1$ and $t$. This should be interpreted as a counterfactual expected origin wage for movers, not necessarily the realized wage observed at $t$. The predetermined wage $w_{i,o,t-1}$ is observed before the mobility decision and is used empirically as a control or proxy for this expected stay wage.

The remaining arguments are as follows: $K^o_{i,t}$ is retained team capital after peer departures, $\widetilde{\mu}_{i,t}$ is the posterior belief that the origin remains in the good state during the decision interval, $X_{i,t-1}$ contains predetermined worker controls, and $Z_{o,t-1}$ contains predetermined origin-firm controls. The function $V^S_i(\cdot)$ is a reduced-form stay-value function: it summarizes the current and continuation value of remaining at the origin, conditional on worker $i$'s information at the time of the decision. The notation does not impose a specific parametric structure on this value function; it only requires that the value of staying is increasing in retained team capital $K^o_{i,t}$ and in the posterior belief $\widetilde{\mu}_{i,t}$ that the origin remains in the good state.

This mechanism maps naturally into the empirical variables $T_{i,t-1}$, $H_{i,t-1}$, and $L_{i,t-1}$. Suppose that the informational content of departures is approximately constant within rank classes.

Let

$$\ell_H = \mathbb{E}[\ell(r_j) \mid j \in \mathcal{H}_{i,t-2}], \qquad \ell_M = \mathbb{E}[\ell(r_j) \mid j \in \mathcal{M}_{i,t-2}], \qquad \ell_L = \mathbb{E}[\ell(r_j) \mid j \in \mathcal{L}_{i,t-2}]$$

and assume monotone informativeness:

$$\ell_H > \ell_M > \ell_L \geq 0$$

Then the average negative information contained in the observed peer departures can be approximated by

$$\begin{aligned} \frac{1}{|\mathcal{P}_{i,t-2}|} \sum_{j \in \mathcal{P}_{i,t-2}} \ell(r_j) d^o_{j,t-1} &\approx \ell_H H_{i,t-1} + \ell_M M_{i,t-1} + \ell_L L_{i,t-1} \\ &= \ell_M T_{i,t-1} + (\ell_H - \ell_M) H_{i,t-1} + (\ell_L - \ell_M) L_{i,t-1} \end{aligned} \tag{14}$$

This equation is only a mapping from the Bayesian mechanism to the empirical variables. It says that total peer turnover captures the amount of departure information, while the high- and low-ranked departure shares capture the composition of that information. Holding total turnover fixed, a larger high-ranked departure share is a stronger negative signal about the origin, while a larger low-ranked departure share is a weaker negative signal relative to middle-ranked departures.

The retained-team-capital channel works in the same direction. From (12), a departure by peer $j$ removes $\chi_{ij}\omega(r_j)$ units of team capital from the origin job. If complementarity weights are larger for high-ranked peers, then the same empirical variables $T_{i,t-1}$, $H_{i,t-1}$, and $L_{i,t-1}$ also proxy for heterogeneity in team-capital losses. Thus the origin-side coefficients should be interpreted as reduced-form effects of peer departures on the relative value of moving versus staying, combining belief updating, outside-opportunity information, and retained-team-capital mechanisms.

Peer departures may also reveal information about outside opportunities. Let

$$\Omega_{t-1} \in \{\Omega^B, \Omega^G\}$$

be the outside-opportunity state during the peer-departure interval, where $\Omega^G$ denotes a favorable outside market and $\Omega^B$ denotes an unfavorable outside market. A key assumption is that peer departures are more likely when the outside market is favorable, that is, when $\Omega_{t-1} = \Omega^G$. After observing the peer-departure vector $\mathbf{d}^o_{i,t-1}$, worker $i$'s posterior belief that the outside market is favorable is

$$\Pi^{\Omega}_{i,t} \equiv \Pr(\Omega_{t-1} = \Omega^G \mid \mathcal{I}^0_{i,t-2}, \mathbf{d}^o_{i,t-1})$$

where $\Pi^{\Omega}_{i,t}$ is worker $i$'s posterior probability that outside opportunities were good during the peer-departure interval. The subscript $t$ indicates that this belief is relevant for worker $i$'s mobility decision between $t-1$ and $t$, even though the outside-opportunity state being inferred is $\Omega_{t-1}$. This channel raises the value of search even if origin-firm conditions have not deteriorated. In a fully specified Bayesian model, worker $i$ would update over the joint state $(\Theta_{o,t-1}, \Omega_{t-1})$. The origin-side empirical coefficients therefore capture the net effect of peer departures on beliefs about the origin, beliefs about outside opportunities, and retained team capital.

## 3.3 Destination-side mechanism

Workers do not observe or apply to all firms. We propose that former peers at candidate destinations can affect both whether a firm enters the consideration set and the value of that firm conditional on consideration.

Let

$$v_{f,t} \in \{0, 1\}$$

indicate whether candidate firm $f$ has a relevant vacancy during the decision interval and let

$$\mathcal{V}_{i,f,t} = 1$$

if worker $i$ learns about a relevant vacancy at candidate firm $f$ during the decision interval. Vacancy information arrives through a formal channel such as a job posting, and through former-peer links. The formal arrival rate is $\lambda^0_{i,f,t} \geq 0$. Each former peer $j \in \mathcal{B}_{i,f,t}$ contributes a peer-specific information arrival rate $\lambda^{peer}(r_j)$, with $(\lambda^{peer})'(r) > 0$, i.e., high-ranked former peers have larger effects. Assuming independent Poisson information arrivals,

$$\Pr(\mathcal{V}_{i,f,t} = 1 \mid \mathcal{B}_{i,f,t}, v_{f,t} = 1) = 1 - \exp\left\{-\lambda^0_{i,f,t} - \sum_{j \in \mathcal{B}_{i,f,t}} \lambda^{peer}(r_j)\right\} \tag{15}$$

Former peers can also lower application costs:

$$c^a_{i,f,t} = c^0_{i,f,t} - \sum_{j \in \mathcal{B}_{i,f,t}} \rho^c(r_j), \qquad (\rho^c)'(r) > 0 \tag{16}$$

where $c^0_{i,f,t}$ is the baseline cost of applying through non-peer channels and $\rho^c(r_j)$ is the cost reduction generated by former peer $j$'s information.

On the firm side, let

$$\text{Rev}_{i,f,t} = 1$$

denote the event that worker $i$'s application to firm $f$ is reviewed. The baseline review probability without former peers is $q^0_{i,f,t}$. With former peers, the review probability is

$$q^{rev}_{i,f,t}(\mathcal{B}_{i,f,t}) = 1 - (1 - q^0_{i,f,t}) \exp\left\{-\sum_{j \in \mathcal{B}_{i,f,t}} \rho^{rev}(r_j)\right\}, \qquad (\rho^{rev})'(r) > 0 \tag{17}$$

Thus former-peer referrals or information can increase the probability that the application is reviewed. Conditional on review, the firm learns about match surplus. Let

$$S_{i,f,t} = A_{f,t} + a_i + m_{i,f,t} - b_{i,t} \tag{18}$$

denote the surplus from hiring worker $i$ at firm $f$, where $A_{f,t}$ is firm productivity, $a_i$ is worker productivity, $m_{i,f,t}$ is match-specific productivity, and $b_{i,t}$ is the worker's outside option.

Former peers can provide referral information about this surplus. This information may concern worker $i$'s productivity, reliability, fit with the firm's tasks, or compatibility with the destination workplace.[2] The firm then makes an offer only if the application is reviewed and the expected match surplus is nonnegative. Thus former peers can affect the offer margin through two channels: they can raise the probability that the application is reviewed, and they can improve the firm's information about whether the match is valuable.

This screening channel does not imply that former peers mechanically raise offer probabilities for every worker. Better screening can reduce offers for negative-surplus matches. Therefore, when the estimated destination-choice coefficient is positive, it should be interpreted as a net access, information, and screening effect for movers whose peer-linked information improves access to valuable matches.

Worker $i$ may also learn about the job value from former peers. Let $J_{i,f,t}$ be the value of the job if worker $i$ receives and accepts an offer from firm $f$. The worker's information set is $\mathcal{I}^W_{i,f,t}(\mathcal{B})$, and the worker's posterior expected job value is

$$\mu^W_{i,f,t}(\mathcal{B}) = \mathbb{E}[J_{i,f,t} \mid \mathcal{I}^W_{i,f,t}(\mathcal{B})] \tag{19}$$

where $\mathcal{B}$ denotes a generic set of former peers employed at candidate firm $f$. The worker accepts the offer if the posterior expected job value is high enough relative to the fallback

[2] In the formal model in Appendix A, we show that referral signals from former peers increase the precision of the firm's posterior belief about $S_{i,f,t}$.

value $R_{i,t}$.[3] The associated acceptance value is

$$\mathcal{A}_{i,f,t}(\mathcal{B}) = \mathbb{E}\left[\max\{R_{i,t}, \mu^{W}_{i,f,t}(\mathcal{B})\}\right] \tag{20}$$

Additional former-peer information cannot reduce this optimized expected value when it is costless and arrives before the acceptance decision, because the worker can always ignore the extra information. This is the worker-side value-of-information channel.

Finally, former peers may affect destination value through surplus and nonpecuniary mechanisms. If worker $i$ joins firm $f$, output may include former-peer complementarities,

$$Y_{i,f,t} = A_{f,t} + a_i + m_{i,f,t} + \sum_{j \in \mathcal{B}_{i,f,t}} \chi^{f}_{ij}\omega(r_j)$$

and the worker may receive nonpecuniary utility from rejoining former peers,

$$s_{i,f,t} = s^{0}_{i,f,t} + \sum_{j \in \mathcal{B}_{i,f,t}} \upsilon^{f}_{ij}\omega(r_j)$$

where $\chi^{f}_{ij} \geq 0$ and $\upsilon^{f}_{ij} \geq 0$. These channels are not separately identified in the empirical analysis, but they help explain why former-peer presence may be associated with destination choice and entry wages.

## 3.4 Choice, empirical mapping, and interpretation

Let $C_{i,t}$ denote worker $i$'s latent consideration set. Let $\Xi_{i,t}$ collect the information available to worker $i$ when making the mobility decision between $t-1$ and $t$. The worker chooses between staying at the origin and the best available destination:

$$d_{i,t} = \arg\max\left\{V^{S}_{i,t} + \varepsilon^{S}_{i,t}, \max_{f \in C_{i,t}}\left[V^{M}_{i,f,t} + \varepsilon^{M}_{i,f,t}\right]\right\} \tag{21}$$

[3]Given that this is an on-the-job search model, $R_{i,t}$ should be interpreted as the maximum value between staying at the origin firm and accepting any other available offer.

where $V^M_{i,f,t}$ is the deterministic value of destination $f$ conditional on $f$ being in the consideration set and the move being feasible. The shocks $\varepsilon^S_{i,t}$ and $\varepsilon^M_{i,f,t}$ capture idiosyncratic components of the stay and destination-specific values that are observed by the worker but not modeled explicitly, such as unobserved amenities, timing shocks, personal preferences, or other match-specific factors. Here $d_{i,t} = 0$ denotes staying at the origin, while $d_{i,t} = f$ denotes moving to candidate firm $f$.

For tractability, assume the idiosyncratic shocks are iid type-I extreme value. Conditional on $C_{i,t}$, the destination-choice probability among movers is therefore:

$$\Pr(d_{i,t} = f \mid C_{i,t}, d_{i,t} \neq 0) = \frac{\exp(V^M_{i,f,t})}{\sum_{k \in C_{i,t}} \exp(V^M_{i,k,t})} \tag{22}$$

The outside inclusive value is

$$I^M_{i,t} = \log \left[ \sum_{k \in C_{i,t}} \exp(V^M_{i,k,t}) \right] \tag{23}$$

and the probability of moving is

$$\Pr(\text{move}_{i,t} = 1 \mid C_{i,t}) = \frac{\exp(I^M_{i,t})}{\exp(V^S_{i,t}) + \exp(I^M_{i,t})} \tag{24}$$

Thus peer departures increase mobility if they lower $V^S_{i,t}$, raise $I^M_{i,t}$, or both.

The observed destination-choice probability also depends on whether firm $f$ enters the latent consideration set:

$$p_{i,f,t} = \mathbb{E} \left[ \mathbb{1}\{f \in C_{i,t}\} \frac{\exp(V^M_{i,f,t})}{\sum_{k \in C_{i,t}} \exp(V^M_{i,k,t})} \mid \Xi_{i,t} \right] \tag{25}$$

Former peers can raise $p_{i,f,t}$ either by making firm $f$ more likely to enter $C_{i,t}$, or by raising $V^M_{i,f,t}$ conditional on $f \in C_{i,t}$. Therefore, the reduced-form destination-choice coefficient on $P_{i,f,t}$ or $Q_{i,f,t}$ combines consideration-set effects and value effects conditional on consideration.

The origin-side structural object is the difference between the outside inclusive value and

the stay value:

$$\Delta_{i,t}^{O} = I_{i,t}^{M} - V_{i,t}^{S} \tag{26}$$

The coefficients on $T_{i,t-1}$, $H_{i,t-1}$, and $L_{i,t-1}$ estimate reduced-form projections of peer departures on $\Delta_{i,t}^{O}$. They combine belief updating about the origin, information about outside opportunities, and losses of retained team capital.

The destination-side coefficients on $P_{i,f,t}$ and $Q_{i,f,t}$ estimate reduced-form projections of former-peer presence on the probability that a candidate firm is chosen. These coefficients combine vacancy-learning effects, application-cost effects, review and offer effects, worker-side information, social utility, and production complementarities. As mentioned before, they should not be interpreted as structural preference parameters.

The model distinguishes among three sets:

$$\mathcal{F}_t \supset \mathcal{F}_{i,t}^{*} \supset C_{i,t}$$

where $\mathcal{F}_t$ is the full set of firms, $\mathcal{F}_{i,t}^{*}$ is the feasible set, and $C_{i,t}$ is the latent consideration set. The empirical choice set is a sampled approximation to the feasible or salient opportunity set, not an observed consideration set. Including the realized destination plus sampled comparable alternatives is therefore a pragmatic approximation to the set of plausible destinations, not evidence that the worker literally considered all sampled firms.

The correct empirical null is not equal choice probabilities across firms. Even without peer effects,

$$\Pr(d_{i,t} = f \mid C_{i,t}, d_{i,t} \neq 0) \neq \frac{1}{|C_{i,t}|}$$

unless all candidate firms have identical wages, amenities, locations, match qualities, vacancy probabilities, hiring probabilities, and mobility costs. The economically relevant origin-side

null is instead

$$H_0^O : \frac{\partial \Delta_{i,t}^O}{\partial T_{i,t-1}} = \frac{\partial \Delta_{i,t}^O}{\partial H_{i,t-1}} = \frac{\partial \Delta_{i,t}^O}{\partial L_{i,t-1}} = 0 \quad \text{conditional on controls} \tag{27}$$

Therefore, the destination-side null can be defined as:

$$H_0^D : P_{i,f,t} \text{ and } Q_{i,f,t} \text{ do not affect vacancy learning, application costs, review probabilities, offer probabilities, match beliefs, wages, or surplus, conditional on controls} \tag{28}$$

Finally, the wage implication is auxiliary. Peer-linked destinations can generate higher entry wages if former peers improve screening toward positive-surplus matches, raise accepted match surplus, increase productivity through complementarities, or improve worker bargaining position through better information. The empirical wage coefficients should therefore be interpreted as descriptive evidence consistent with these mechanisms, not as separately identifying bargaining, screening, productivity, or selection channels.

# 4 Data

Our analysis uses data from the *Quadros de Pessoal* (QP) dataset, a longitudinal matched employer-employee database spanning from 1986 to 2022, excluding the years 1990 and 2001. Compiled annually by the Portuguese Ministry of Labor, Solidarity, and Social Security, the QP survey is mandatory for all private sector firms that employ at least one wage earner (i.e., excluding business owners). The dataset provides uniquely comprehensive details about firms, including their location (region-wise), industry, number of employees, sales figures, ownership structure, and legal status. It also includes individual worker information such as gender, age, education level, skills, job category, tenure, wages, and hours worked. Wage data is particularly detailed, encompassing monthly base salaries (gross pay for standard work

hours), both regular and irregular benefits, overtime compensation, and the wage negotiation process. Additionally, data on standard and overtime work hours are available. Starting from 1994, QP records pertain to October of each year. Each firm and worker in the dataset is assigned a unique identifier, facilitating the tracking of firms and employees over time. Worker records also include the corresponding firm's identifier for each year, enabling the matching of workers to their employers and the identification of each worker-firm relationship. Importantly, this level of information enables us to monitor the employment relationships of individuals and their employers over time. This capability allows us to form peer groups by identifying coworkers who have shared the same workplace and job category in any given year, thereby creating peers' networks.

Our initial (hereafter, full) dataset includes the population of full-time wage earners in the private sector, aged between 18 and 64, and who earned at least 80 percent of the minimum wage.[4] This dataset encompasses 908,448 firms and 7,923,266 employees between 1986 and 2022. It corresponds to 60,122,627 individuals $\times$ years observations. Its ability to link workers with their employers, the longitudinal structure, and the extensive time coverage make QP ideal for empirically assessing turnover decisions.

The most important restriction concerns the creation of our peer groups: individuals with whom workers share the same establishment and job occupation in a given year. We start by restricting our sample to the largest connected set, which represents close to 92.5% of the full dataset.[5] Next, for identification purposes, we restrict our dataset to individuals with working spells lasting a minimum of three periods,[6] and, for reasons that will become obvious in the next subsection, to peer groups with a minimum of five individuals. These two restrictions severely limit our dataset to 17,198,835 individuals $\times$ years, or approximately

[4]Observations with missing data in the variables of interest were dropped. We also drop observation where a worker holds multiple jobs in a year.

[5]A connected set implies that at least one element of a worker-firm pair links the rest of the group (Abowd et al., 2002). We need this restriction to be satisfied so we can identify the fixed effects.

[6]Some workers, especially women, have multiple spells in the dataset. We only keep those spells that satisfy the three-consecutive years condition.

28.6% of the original dataset.[7]

Next we identify movers in our dataset. These are workers who move from one firm in $t-1$ to $t$.[8] We determine a move by changes in the firm identifier associated to the work. Our next set of restrictions are meant to increase the robustness of our results. We do not consider observations if:

- A worker moves to a new firm and the old firm closes in the same year.
- A worker moves to a new firm and the previous year's turnover in the peer group exceeds 80%.
- A worker appears to have moved to a new firm but her tenure in that year is above 11 months.
- All firms need to exist in $t+1$, i.e., the year after the move.

The first restriction eliminates 188,404 observations, and is meant to avoid moves motivated by firm closures.[9]This restriction allows us to exclude possibilities of mass layoffs.[10] The second restriction eliminates 39,920 observations and is meant to remove any moves that are due to the peer group's instability. This could include possible knowledge of future restructuring or firm closure. Our objective is to capture, as much as possible, moves motivated by external reasons.

The third restriction is purely technical. A firm might change its identifier in our dataset if it suffers some sort of restructuring even if maintaining the same workforce. In those situations employers usually do not restart tenure counting. Eliminating these 48,911 observations allows us to avoid misclassified moves due to firm identifier changes.

The last imposition by far removes the most observations: 1,692,167 or slightly above 9.8%

[7]Despite representing 85.8% of all observations, only 29% firms have five or more workers, which reduces our dataset substantially.

[8]This automatically excludes workers who leave the workforce in $t$, even if temporarily.

[9]We determine firm closures by situations when the firm identifier is no longer present in $t$ the same year the move happens. Unfortunately, data limitations do not allow us to measure if all closures are actual.

[10]We do not possess information on whether a worker is fired or quits on her own volition.

of the previous number of observations. The restriction is meant to avoid situations when the worker quits only months before the firm closes but the majority of the observations being eliminated are due to the automatic dropping of all observations from 1989, 2000, and 2022 as it is impossible to satisfy the $t+1$ existence restriction. These three years comprise a total of 1,007,635 observations. The restriction itself, accounting for the aforementioned technicality, only removes 684,532 observations.

The post-restriction (final) dataset includes 14,344,256 (years $\times$ individuals) observations, which corresponds to 23.9% of the original (full) dataset's observations. We are left with 2,136,229 workers, 54,880 firms, and 976,684 peer groups over the 1986-2021 period. By construction, our identification strategy makes us lose quite a few years if we focus only on the years we can identify workers' moves: 1986, 1989, 1991, 2000, 2002, and the already referenced 2022. The first year in our dataset, 1986, means that it is impossible to identify any moves. It will, however, be useful for computing metrics that might affect the worker's move in 1987. The last year in our dataset, 2022, as well as 1989 and 2000, suffer from the impossibility to satisfy the firm existence in $t+1$ restriction. The last two years, 1991 and 2002, suffer from a similar fate as 1986 as there is no $t-1$ and so there are no movers identified in those years.

Table 1: Number of observations

| VARIABLES | Full | Final | % of Full |
|---|---|---|---|
| Individuals $\times$ years | 60,122,627 | 14,344,256 | 23.9% |
| Individuals | 7,923,266 | 2,136,229 | 27.0% |
| Establishments $\times$ years | 7,706,150 | 539,284 | 7.0% |
| Firms $\times$ years | 6,465,864 | 423,133 | 6.5% |
| Firms | 908,448 | 54,880 | 6.0% |
| Peer groups | 23,570,704 | 976,684 | 4.1% |

These restrictions lead to some changes in our final sample compared to the initial dataset.

Namely, we are left with a sample that is slightly older (by one year), with longer average tenure (by two years), more female, working in bigger firms, more educated, earning higher wages, and more concentrated in Metropolitan Lisbon (47.2% vis-a-vis 38.7% in the full dataset)[11].

Table 2: Summary statistics by estimation sample

| | Full Database | | | Final Sample | | | $\text{Movers}_{t-1}$ | | | $\text{Movers}_t$ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Mean | Min | Max | Mean | Min | Max | Mean | Min | Max | Mean | Min | Max |
| Age | 38.5 | 18 | 64 | 39.5 | 18 | 63 | 34.0 | 18 | 62 | 35.0 | 19 | 63 |
| Tenure | 101.0 | 0 | 600 | 124.2 | 0 | 600 | 37.2 | 0 | 587 | 5.3 | 0 | 11 |
| Male | 57.1% | | | 56.1% | | | 61.9% | | | 61.9% | | |
| Log(Real Hourly Wage) | 0.44 | -0.94 | 7.67 | 0.63 | -0.94 | 7.50 | 0.60 | -0.79 | 6.59 | 0.67 | -0.74 | 5.96 |
| Firm Size | 805.1 | 1 | 26,004 | 1,313.2 | 5 | 25,969 | 1,302.5 | 5 | 25,969 | 871.0 | 5 | 25,958 |
| Observations | 60,122,627 | | | 14,344,256 | | | 309,757 | | | 309,757 | | |

Table 3: Education (% of total)

| Education | Full | Sample | Movers |
|---|---|---|---|
| Less than Elementary School | 1.69 | 1.36 | 0.32 |
| Elementary School (grade 4) | 23.71 | 20.50 | 8.05 |
| Middle School (grade 5) | 17.70 | 16.46 | 10.28 |
| Junior High-School (grade 9) | 21.30 | 20.36 | 21.46 |
| High School (grade 12) | 21.51 | 21.42 | 27.15 |
| Some College | 2.15 | 2.32 | 2.50 |
| Bachelor's degree | 10.74 | 15.55 | 24.82 |
| Master's degree | 1.06 | 1.68 | 5.14 |
| PhD degree | 0.13 | 0.25 | 0.29 |

Full Database: 11.93% of workers have a college degree

Final Sample: 17.47% of workers have a college degree

Movers: 30.25% of workers have a college degree

[11] 58.5% in the Metropolitan region for movers only.

# 5 Empirical model

## 5.1 High-quality peer identification

A central object in the empirical analysis is the distinction between *any* former peer and a *high-quality* former peer. The motivation is that peer influence and informational content are plausibly heterogeneous: some coworkers are more productive, better connected, or more informative about outside opportunities, so their presence (or departure) may have a disproportionate impact on turnover and destination choice. We therefore construct a transparent, scalable proxy for peer "quality" using the worker component of wages, following the matched employer–employee wage-decomposition tradition initiated by Abowd et al. (1999) and widely used in administrative data settings such as in Card et al. (2013).

We estimate a Mincer-type wage equation with high-dimensional fixed effects and year controls:

$$\log(wage_{i,t}) \;=\; \alpha_i \;+\; \psi_f \;+\; \phi_p \;+\; \gamma' X_{i,t} \;+\; \varepsilon_{i,t} \tag{29}$$

where $\alpha_i$ is a worker fixed effect, $\psi_f$ is a firm fixed effect, $\phi_p$ is an occupation fixed effect, and $X_{i,t}$ includes standard Mincerian controls available in the administrative data (e.g., age/experience, tenure, education and other observables). This specification is closely related to standard two-way fixed-effect wage decompositions and their extensions with additional high-dimensional controls, and it is estimated using high-dimensional fixed-effect methods.[12]

The fitted worker effect, $\widehat{\alpha}_i$, is best interpreted as a time-invariant worker-specific component of wages net of firm wage premia and observables. It is not a pure measure of innate ability, but it provides a single-index summary of persistent worker heterogeneity that is widely used as a proxy for worker quality in matched employer-employee settings. Importantly, because firm wage premia are absorbed by $\psi_f$, the worker ranking induced by $\widehat{\alpha}_i$ is not mechanically driven by sorting into high-paying firms in a given year.

The identification of worker and firm fixed effects relies on worker mobility across firms, which

[12] See Guimarães and Portugal (2010) for computational approaches in similar settings

links firm effects through the mobility network. In finite samples, variance components and related objects can be biased when mobility is limited or when the worker-firm graph has weak connectivity. Recent work proposes leave-out and related corrections for inference and variance decomposition in high-dimensional fixed-effect models (e.g., Kline et al., 2020). In our application, the role of Equation (29) is not to estimate structural parameters of wage setting, but to construct an interpretable ranking of workers to classify peer quality. We therefore treat $\widehat{\alpha}_i$ as a convenient and standard proxy for persistent worker quality, while acknowledging that measurement error and mobility structure can affect its precision.

We use the distribution of $\widehat{\alpha}_i$ to assign workers to quality categories. Specifically, within each peer group cell (firm $\times$ establishment $\times$ year $\times$ occupation), we compute quintiles of $\widehat{\alpha}_i$ across employees observed in that cell. A worker is classified as *high-quality* in a given peer group cell if she falls in the top quintile that year,[13] and *low-quality* if she falls in the bottom quintile. This within-cell ranking has two advantages. First, it operationalizes "high-quality" as a coworker-relative concept that is directly relevant for peer interactions inside the workplace. Second, it limits spurious classification driven by cross-firm differences in wage premia, since those differences are absorbed by $\psi_f$ and the ranking is performed within peer groups.

The main empirical hypotheses concern whether peer presence and peer departures shift turnover and destination choice through channels such as information transmission, referrals, social influence, and workplace complementarities. These mechanisms are naturally heterogeneous: high-quality peers may provide more valuable information, be more influential in shaping beliefs about outside options, or be more important complements inside the firm. Using $\widehat{\alpha}_i$ to classify peers provides a tractable, population-wide way to test for such heterogeneity without relying on ad hoc managerial classifications or survey measures.

To mitigate mechanical simultaneity between peer measures and the outcomes of interest, peer quality is measured using lagged information. In the turnover analysis, the quality com-

[13] This inherently implies the classification is not static and can change from year to year. In fact, 592,488 workers (30.4% of all workers) are classified as high-quality peer at least once in their work lifetime.

position of leavers between $t-2$ and $t-1$ is computed using their quality classification in $t-2$ (when they are still coworkers). In the destination-choice analysis, the "high-quality peer exists" indicator at a candidate firm in year $t$ is defined using the $t-2$ quality classification of the relevant former peers. This lag structure ensures that peer quality is predetermined relative to the focal outcome period.

We also control for network centrality measures in the main specifications to ensure that peer-quality effects are not mechanically proxying for the network embeddedness of destination firms or peer groups. We leave a fuller exploration of alternative quality cutoffs and continuous peer-rank measures to future versions of the paper.

## 5.2 Peers leaving the firm

Let $move_{i,t}$ represent a dummy that takes value 1 in $t$ if a given worker is working in a firm different from $t-1$, and 0 otherwise. We do not consider a move if the worker is absent from the database between job spells in different firms. We write the systematic component of the origin-side mobility model as

$$\begin{aligned}\eta^{O}_{i,t} = \beta_0 + \beta_T T_{i,t-1} + \beta_H H_{i,t-1} + \beta_L L_{i,t-1} + \mathbf{X}^{O\prime}_{i,t-1}\boldsymbol{\beta}_X + \mathbf{Z}^{O\prime}_{o,t-1}\boldsymbol{\beta}_Z \\ + \beta_\alpha \widehat{\alpha}_i + \beta_\psi \widehat{\psi}_o + \beta_\phi \widehat{\phi}_{\mathrm{occ}(i,t-1)} + \delta_t \end{aligned} \tag{30}$$

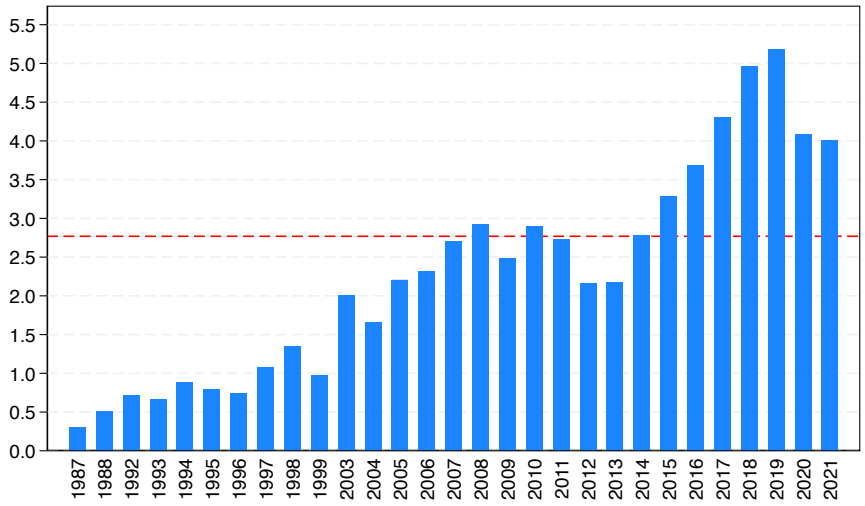
where $o = o(i, t-1)$ is worker $i$'s origin firm. The peer variables correspond to the objects defined in Section 3: $T_{i,t-1}$ is the share of the predetermined $t-2$ peer group that leaves the origin between $t-2$ and $t-1$, $H_{i,t-1}$ is the share of that peer group that leaves and is classified as high-quality in $t-2$, and $L_{i,t-1}$ is the corresponding share classified as low-quality. This definition implies we lose the first year in our sample (1986) and we do not fully exploit 2021, except as the year where we observe the change. It also means we have 4-year gaps in 1989-1993 and 2000-2004 owing to the missing values for 1991 and 2002. In the empirical code, these variables correspond to $turnover_{p,t-1}$, $hpshare_{p,t-1}$, and $lpshare_{p,t-1}$,

respectively.

The vector $\mathbf{X}^{O}_{i,t-1}$ contains the predetermined worker controls used in the turnover regressions: gender, age, tenure, log real hourly wage, squared log real hourly wage, and education indicators. The vector $\mathbf{Z}^{O}_{o,t-1}$ contains the predetermined origin-firm controls, including log firm size and sector indicators. The objects $\widehat{\alpha}_i$, $\widehat{\psi}_o$, and $\widehat{\phi}_{\text{occ}(i,t-1)}$ denote, respectively, the previously estimated worker, origin-firm, and origin-job-occupation wage components included in the relevant specifications. Finally, $\delta_t$ denotes year effects. The specifications reported in the tables are nested versions of (30) and variables not included in a given column are omitted as indicated in the corresponding table.

To estimate the model we resort to a complementary log-log model, a type of generalized linear model used for modeling binary outcomes, especially useful in situations where the event of interest is relatively rare or when the data are skewed. Moving to a new firm is a rare occurrence, particularly in the case of the Portuguese labor market (Addison et al., 2023). On average, only 2.77% of the workers in our database move each year (Figure 1). This value has been increasing with $t$, although not monotonically.

Figure 1: Share of moves per year (% of total workers)




Note: The dashed red line corresponds to the average across years.

Let

$$p_{i,t}^{O} \equiv \Pr\big(move_{i,t} = 1 \mid \mathcal{W}_{i,t}^{O}\big)$$

where $\mathcal{W}_{i,t}^{O}$ collects the regressors included in the relevant origin-side specification. Under the complementary log-log specification,

$$\log\big[-\log\big(1 - p_{i,t}^{O}\big)\big] = \eta_{i,t}^{O} \quad \Longleftrightarrow \quad p_{i,t}^{O} = 1 - \exp\big\{-\exp\big(\eta_{i,t}^{O}\big)\big\} \tag{31}$$

Thus, $p_{i,t}^{O}$ is the conditional probability that worker $i$ moves to a different firm between $t-1$ and $t$, while $\eta_{i,t}^{O}$ is the corresponding linear index before application of the inverse complementary log-log link. The coefficients in equation (30) are therefore complementary log-log index coefficients rather than marginal effects on the probability of moving.

Define the inverse-link function as

$$g(a) \equiv 1 - \exp\{-\exp(a)\}$$

Its derivative is

$$g'(a) = \exp(a)\exp\{-\exp(a)\}$$

Let $\mathcal{S}_O$ denote the origin-side estimation sample and let $n_O = |\mathcal{S}_O|$. For a continuous regressor $x_j$ that enters the linear predictor with coefficient $\beta_j$, the average derivative is

$$\widehat{\mathrm{AME}}_{j}^{O} = \frac{1}{n_O} \sum_{(i,t)\in\mathcal{S}_O} \widehat{\beta}_j \exp\big(\widehat{\eta}_{i,t}^{O}\big)\exp\big\{-\exp\big(\widehat{\eta}_{i,t}^{O}\big)\big\} \tag{32}$$

For a binary regressor $d_j$, the exact average marginal effect is instead the average discrete change

$$\widehat{\mathrm{AME}}_{j,\mathrm{disc}}^{O} = \frac{1}{n_O} \sum_{(i,t)\in\mathcal{S}_O} \big[g\big(\widehat{\eta}_{i,t}^{O}(d_j = 1)\big) - g\big(\widehat{\eta}_{i,t}^{O}(d_j = 0)\big)\big]$$

where all other regressors are held at their observed values. This calculation evaluates the same estimated model twice for each observation; it does not require re-estimating two

separate models.

## 5.3 Destination choice conditional on moving

The second part of our analysis examines where workers go after deciding to change employers. In particular, we ask whether movers are more likely to choose firms that already employ former peers, and whether the presence of a high-quality former peer provides an additional advantage. This is naturally a discrete-choice problem in which each mover selects one destination from a finite set of candidate firms. The relevant comparison is therefore not simply between workers who do and do not use peer links but between the firms available to the same worker at the time of the move.

We begin by identifying workers who change employers between $t-1$ and $t$. For each mover-year, we observe the firm actually joined in $t$, which we denote by $f^{\star}_{i,t}$. Since it is computationally infeasible to include every active firm in Portugal as a potential alternative,[14] we approximate the set of plausible destinations by constructing a sampled choice set. The construction proceeds as follows:

1. **Chosen destination.** The realized destination firm $f^{\star}_{i,t}$ is included in the choice set and receives a choice indicator equal to one.

2. **Alternative firms.** We draw, without replacement, up to 99 firms operating in the same year and belonging to the same sector, NUTS 2 region, and broad firm-size category as the realized destination.[15] These firms receive a choice indicator equal to zero.

3. **Former-peer links.** For each candidate firm, we determine whether it employs any former peer of worker $i$. A former peer is a worker who belonged to the focal worker's

[14] And, probably, would not make much sense given that workers have clear preferences for certain sectors, job positions, and locations.

[15] Firms are classified as micro, small, medium, or large. The sampled firms are intended to approximate a set of broadly comparable destinations. They should not be interpreted as the worker's observed subjective consideration set.

predetermined peer group in $t-2$, moved to candidate firm $f$ between $t-2$ and $t-1$, and remained employed there in $t$. A former peer is classified as high-quality using her worker fixed-effect rank in the predetermined $t-2$ peer cell.

The resulting destination-choice dataset contains 309,757 mover-year observations and 28,928,584 mover-year $\times$ candidate-firm rows. Conditional-logit estimation drops 79 mover-year choice sets containing only one alternative, since these sets provide no within-set comparison. The preferred conditional-logit sample therefore contains 309,678 mover-year choice sets and 28,928,505 candidate-firm observations.

Let

$$\mathcal{C}_{i,t}$$

denote the sampled choice set faced by mover $i$ in year $t$, and define

$$y_{i,f,t}^{choice} = \mathbb{1}\{f = f_{i,t}^{\star}\}$$

Thus, $y_{i,f,t}^{choice} = 1$ for the realized destination and equals zero for the sampled alternatives. As in Section 3, let

$$P_{i,f,t} = \mathbb{1}\{B_{i,f,t} > 0\}$$

indicate that candidate firm $f$ employs at least one former peer of worker $i$, and let

$$Q_{i,f,t} = \mathbb{1}\{B_{i,f,t}^{H} > 0\}$$

indicate that at least one of those former peers is classified as high-quality. By construction,

$$Q_{i,f,t} \leq P_{i,f,t}$$

since a candidate firm cannot employ a high-quality former peer without employing a former peer.

For estimation and interpretation, we combine these two indicators into a single, mutually exclusive peer-state variable:

$$S_{i,f,t} = \begin{cases} 0, & \text{if } P_{i,f,t} = 0 \\ 1, & \text{if } P_{i,f,t} = 1 \text{ and } Q_{i,f,t} = 0 \\ 2, & \text{if } Q_{i,f,t} = 1 \end{cases} \tag{33}$$

Accordingly, $S_{i,f,t} = 0$ denotes a candidate firm with no former peers, $S_{i,f,t} = 1$ denotes a firm with at least one ordinary former peer but no high-quality former peer, and $S_{i,f,t} = 2$ denotes a firm with at least one high-quality former peer. A firm in the third category may also employ other ordinary former peers.

Our preferred estimator is McFadden's conditional logit (McFadden, 1974). The model is built directly around the fact that each mover chooses one firm from a set of mutually exclusive alternatives. Let the latent value that mover $i$ assigns to candidate firm $f$ be

$$U^D_{i,f,t} = \lambda_{i,t} + \gamma_1 \mathbb{1}\{S_{i,f,t} = 1\} + \gamma_2 \mathbb{1}\{S_{i,f,t} = 2\} + \mathbf{Z}^{D\prime}_{f,t}\boldsymbol{\gamma}_Z + \mathbf{R}^{D\prime}_{i,f,t-1}\boldsymbol{\gamma}_R + \gamma_\psi \widehat{\psi}_f + \varepsilon^D_{i,f,t} \tag{34}$$

where $\lambda_{i,t}$ is a mover-year-specific component common to all alternatives in $\mathcal{C}_{i,t}$. The vector $\mathbf{Z}^D_{f,t}$ contains candidate-firm characteristics measured in the destination year, including log firm size, and average firm-year PageRank. The vector $\mathbf{R}^D_{i,f,t-1}$ contains predetermined candidate-firm controls introduced in the robustness analysis, including the firm's hiring share in $t-1$, the share of its $t-1$ workforce employed in the focal worker's occupation, and measures of its occupational concentration. Lastly, $\widehat{\psi}_f$ represents the previously estimated destination-firm fixed effects.

Under the assumption that the destination-specific shocks are independently and identically

distributed type-I extreme value, the probability that mover $i$ chooses candidate firm $f$ is

$$\Pr\left(y_{i,f,t}^{choice} = 1 \mid \mathcal{C}_{i,t}\right) = \frac{\exp\left(V_{i,f,t}^{D}\right)}{\sum_{k \in \mathcal{C}_{i,t}} \exp\left(V_{i,k,t}^{D}\right)} \tag{35}$$

where

$$V_{i,f,t}^{D} = \gamma_1 \mathbb{1}\{S_{i,f,t} = 1\} + \gamma_2 \mathbb{1}\{S_{i,f,t} = 2\} + \mathbf{Z}_{f,t}^{D\prime}\boldsymbol{\gamma}_Z + \mathbf{R}_{i,f,t-1}^{D\prime}\boldsymbol{\gamma}_R + \gamma_\psi \widehat{\psi}_f$$

The coefficient $\gamma_1$ compares an ordinary-peer firm with a no-peer firm and is expressed in log relative choice odds. The difference

$$\gamma_2 - \gamma_1$$

is the incremental high-quality-peer effect, comparing a firm with at least one high-quality former peer with a firm that has ordinary former peers only. Finally, $\gamma_2$ is the total high-quality-peer comparison relative to a no-peer firm. The corresponding relative choice-odds ratios are

$$\exp(\gamma_1), \qquad \exp(\gamma_2 - \gamma_1), \qquad \exp(\gamma_2),$$

respectively.

To translate these coefficients into probability units, we calculate average own-candidate discrete changes. For each candidate-firm row, we change the peer state of that candidate while leaving the characteristics and peer states of every other firm in the mover's choice set at their observed values. We then recompute the denominator in equation (35), since changing the value of one alternative also changes its probability relative to all the others. The resulting candidate-level probabilities are first averaged within mover-year choice sets and then across mover-years, giving equal weight to each move. These calculations provide an economically intuitive probability translation of the conditional-logit coefficients, while statistical inference is based on the worker-clustered coefficient estimates and the associated

relative choice-odds ratios.

Conditional logit identifies coefficients from differences *within* a choice set. Therefore, the mover-year component $\lambda_{i,t}$ does not appear in equation (35), because it enters the value of every candidate firm in the same way and therefore cancels from the numerator and denominator. This implies that our preferred specification does not include gender, age, education, the worker wage component, year effects, or other characteristics that are constant across the alternatives faced by the same mover.

This does not mean that these worker characteristics are being ignored. On the contrary, the mover-year component $\lambda_{i,t}$ absorbs all observed and unobserved factors that are common to the alternatives within that choice set. The peer coefficients are identified by comparing peer-linked and non-peer-linked firms available to the same worker, rather than by comparing different workers who may face very different labor-market circumstances.

The cost of this approach is that we cannot estimate the direct coefficients on alternative-invariant worker characteristics. We cannot, for example, use the baseline conditional logit to estimate whether older workers are generally more or less likely to choose a particular destination, given that the worker's age is not separately identified from $\lambda_{i,t}$. Worker characteristics can nevertheless be used to study heterogeneity by interacting them with variables that vary across candidate firms. This is the approach taken in the homophily analysis (Section 6.3), where focal-worker quality is interacted with former-peer presence and quality.

A second limitation is the familiar independence-of-irrelevant-alternatives assumption. Conditional on the observed candidate-firm characteristics, the relative choice odds between two firms are assumed not to depend on the characteristics of the remaining alternatives. Our use of comparable firms and our robustness exercises with alternative choice-set constructions reduce extreme heterogeneity among alternatives, but they do not eliminate this underlying restriction.

We also examine whether destination choice responds to the intensity of former-peer pres-

ence. Define

$$\mathbf{G}^{I}_{i,f,t} = \begin{pmatrix} \text{sharepeers}_{i,f,t} \\ \text{sharehighpeers}_{i,f,t} \end{pmatrix}$$

where $\text{sharepeers}_{i,f,t}$ is the percentage of workers at candidate firm $f$ who are former peers of worker $i$, and $\text{sharehighpeers}_{i,f,t}$ is the percentage who are former high-quality peers. In these specifications, we add to the extensive-margin peer-state indicators in equation (34) the following:

$$\gamma_{SP}\text{sharepeers}_{i,f,t} + \gamma_{SHP}\text{sharehighpeers}_{i,f,t}$$

The choice-set definition, candidate-firm controls, and conditional-logit estimator are otherwise unchanged.

### 5.3.1 Complementary log-log robustness

As a functional-form robustness check, we also estimate complementary log-log models on the expanded mover-year × candidate-firm dataset. The complementary log-log probability is

$$\Pr\left(y^{choice}_{i,f,t} = 1 \mid \mathcal{W}^{D}_{i,f,t}\right) = 1 - \exp\left\{-\exp\left(\eta^{D}_{i,f,t}\right)\right\} \tag{36}$$

where the full linear predictor can be written as

$$\begin{aligned} \eta^{D}_{i,f,t} = \beta_0 + \beta_1 \mathbb{1}\{S_{i,f,t} = 1\} + \beta_2 \mathbb{1}\{S_{i,f,t} = 2\} + \mathbf{X}^{D\prime}_{i,t-1}\boldsymbol{\beta}_X + \mathbf{Z}^{D\prime}_{f,t}\boldsymbol{\beta}_Z \\ + \mathbf{R}^{D\prime}_{i,f,t-1}\boldsymbol{\beta}_R + \beta_\alpha \widehat{\alpha}_i + \beta_\psi \widehat{\psi}_f + \beta_\phi \widehat{\phi}_{\text{occ}(i,t)} + \delta_t \end{aligned} \tag{37}$$

The vector $\mathbf{X}^{D}_{i,t-1}$ contains mover characteristics measured before the move, including gender, age, and education. The vector $\mathbf{Z}^{D}_{f,t}$ contains candidate-firm characteristics measured in the destination year, while $\mathbf{R}^{D}_{i,f,t-1}$ contains the new predetermined hiring and occupational controls. The remaining terms denote the previously estimated worker, candidate-firm, and job-occupation wage components and year effects.

An advantage of the complementary log-log model is that it allows us to retain and estimate coefficients on worker characteristics and other variables that are constant within a mover-year choice set. It therefore provides a useful check that the peer results are not sensitive to the inclusion of observed differences across movers.

Its main drawback is that it does not model the destination decision as one internally normalized choice among mutually exclusive alternatives. The likelihood treats each mover-year $\times$ candidate-firm row as a separate binary observation. Clustering standard errors at the worker level allows for statistical dependence across rows belonging to the same worker, but it does not impose the restriction that exactly one candidate firm must be chosen or that predicted probabilities must sum to one within a choice set. This is why we regard complementary log-log as a robustness model rather than the preferred destination-choice estimator.

For a direct functional-form comparison, we first estimate a complementary log-log model on the exact conditional-logit estimation sample and using only the same candidate-varying controls. We then report the fuller complementary log-log specification in equation (37), which includes the mover characteristics and wage components that are conditioned out of the conditional logit. In both versions, the peer state is entered as a categorical variable, and the effects are calculated as exact discrete changes between no-peer, ordinary-peer, and high-quality-peer firms. Standard errors are clustered at the worker level.

## 5.4 Choice-set size

The baseline destination-choice analysis approximates each mover's opportunity set using the realized destination and a sample of comparable alternative firms. A natural concern is that the estimated importance of former-peer links may depend on how many alternatives are included in this sampled set. We therefore re-estimate the preferred conditional-logit model using nested choice sets of different intended sizes.

Let $\mathcal{N}$ denote the intended number of firms in the sampled choice set, including the realized

destination, and let

$$K_{i,t}(\mathcal{N}) = |\mathcal{C}_{i,t}(\mathcal{N})|$$

denote the realized number of alternatives for mover $i$ in year $t$. The realized set may contain fewer than $\mathcal{N}$ firms when the relevant sampling pool is too small. The alternative sets are nested within mover-year, so that firms included in a smaller set remain in all larger sets. This limits differences across specifications that would otherwise arise solely from repeated random sampling.

For each intended size $\mathcal{N}$, we estimate

$$\Pr\left(y_{i,f,t}^{choice} = 1 \mid \mathcal{C}_{i,t}(\mathcal{N})\right) = \frac{\exp\left(V_{i,f,t,\mathcal{N}}^{D}\right)}{\sum_{k \in \mathcal{C}_{i,t}(\mathcal{N})} \exp\left(V_{i,k,t,\mathcal{N}}^{D}\right)} \tag{38}$$

where

$$V_{i,f,t,\mathcal{N}}^{D} = \gamma_{1,\mathcal{N}} \mathbb{1}\{S_{i,f,t} = 1\} + \gamma_{2,\mathcal{N}} \mathbb{1}\{S_{i,f,t} = 2\} + \mathbf{Z}_{f,t}^{D\prime} \boldsymbol{\gamma}_{Z,\mathcal{N}} + \mathbf{R}_{i,f,t-1}^{D\prime} \boldsymbol{\gamma}_{R,\mathcal{N}} + \gamma_{\psi} \widehat{\psi}_{f}$$

The peer-state variable $S_{i,f,t}$ follows equation (33): zero denotes no former peer, one denotes at least one ordinary former peer but no high-quality former peer, and two denotes at least one high-quality former peer.

We first compare the relative choice odds across choice-set sizes. For an ordinary-peer firm relative to a no-peer firm, the relevant odds ratio is

$$OR_{\mathcal{N}}^{O} = \exp\left(\gamma_{1,\mathcal{N}}\right) \tag{39}$$

The incremental high-quality-peer odds ratio, comparing a high-quality-peer firm with an ordinary-peer firm, is

$$OR_{\mathcal{N}}^{HQ} = \exp\left(\gamma_{2,\mathcal{N}} - \gamma_{1,\mathcal{N}}\right) \tag{40}$$

These objects are particularly useful for the choice-set-size exercise because absolute choice probabilities necessarily depend on how many alternatives compete for the single observed choice. A decline in a percentage-point effect as $\mathcal{N}$ grows does not, by itself, imply that peer links become less important. Relative choice odds provide a more comparable measure of the peer advantage across sets of different sizes.

We also calculate probability effects. Let

$$p^{(s)}_{i,f,t,\mathcal{N}}, \qquad s \in \{0,1,2\}$$

denote the counterfactual probability of choosing candidate firm $f$ when that candidate is assigned peer state $s$, while the characteristics and peer states of the other alternatives remain at their observed values. For each mover-year, define the average own-candidate probability under state $s$ as

$$\overline{p}^{(s)}_{i,t,\mathcal{N}} = \frac{1}{K_{i,t}(\mathcal{N})} \sum_{f \in \mathcal{C}_{i,t}(\mathcal{N})} p^{(s)}_{i,f,t,\mathcal{N}} \tag{41}$$

The ordinary-peer probability effect is then

$$\Delta^{O}_{\mathcal{N}} = \frac{1}{n_{\mathcal{N}}} \sum_{(i,t)} \left[ \overline{p}^{(1)}_{i,t,\mathcal{N}} - \overline{p}^{(0)}_{i,t,\mathcal{N}} \right] \tag{42}$$

while the incremental high-quality-peer effect is

$$\Delta^{HQ}_{\mathcal{N}} = \frac{1}{n_{\mathcal{N}}} \sum_{(i,t)} \left[ \overline{p}^{(2)}_{i,t,\mathcal{N}} - \overline{p}^{(1)}_{i,t,\mathcal{N}} \right] \tag{43}$$

The total high-quality-peer effect relative to a no-peer candidate is

$$\Delta^{HQ,\text{total}}_{\mathcal{N}} = \frac{1}{n_{\mathcal{N}}} \sum_{(i,t)} \left[ \overline{p}^{(2)}_{i,t,\mathcal{N}} - \overline{p}^{(0)}_{i,t,\mathcal{N}} \right] \tag{44}$$

Each mover-year receives equal weight in these calculations. The purpose of the exercise is not to determine whether probabilities converge as $\mathcal{N} \to \infty$. Instead, we ask two finite-sample questions over the range of choice-set sizes considered. First, do the relative choice odds associated with ordinary and high-quality former peers remain stable as more alternatives are added? Second, does the incremental high-quality-peer probability effect remain economically meaningful even though absolute candidate-level probabilities tend to decline in larger choice sets?

Finally, we repeat the exercise using complementary log-log models estimated on the same samples and with the same candidate-varying controls. These specifications provide a functional-form robustness check, while the conditional-logit estimates remain our preferred results because they model the destination decision as one choice among mutually exclusive alternatives.

## 5.5 Network-Based Peer Centrality

The peer measures used in the main analysis summarize whether former coworkers are present at a destination and which types of coworkers leave the origin. These measures do not, by themselves, capture differences in workers' positions within the broader labor-market network. Yet coworkers are unlikely to be equally connected. Some have worked at more firms, connect otherwise separate groups of workers, or are themselves linked to highly connected coworkers. If workplace networks transmit information about vacancies, firms, or outside opportunities, these differences in network position may matter. We therefore construct a worker-level PageRank measure and use it as an additional control in both the origin and destination analyses, to examine whether the estimated former-peer relationships remain once we account for broader network embeddedness.

The network is defined over worker-year nodes and two types of edges are included. First, workers employed at the same firm in the same year are connected through within-year coworker links. Second, the same worker is connected across adjacent years. These temporal

links allow mobility events to connect firm-year groups over time. A worker's position in the resulting graph therefore reflects both local connectedness within a workplace and broader links created through employment histories and worker mobility.

We calculate PageRank on the full graph and use a component-normalized version as a robustness check. The scores are standardized and winsorized to limit the influence of the long upper tail of the PageRank distribution. Appendix C describes the graph construction, normalization, standardization, and winsorization procedures in detail.

In the origin analysis, the relevant concern is that the effect attributed to peer departures may partly reflect the departure of particularly central workers. A highly connected coworker may have better information about outside opportunities, a wider set of contacts, or greater influence over the remaining members of the peer group. We therefore control for the average PageRank of the peers who leave.

In the destination analysis, the corresponding concern is that firms employing former peers may also be unusually visible or well connected in the labor market. A firm with a highly connected workforce may attract more applicants or appear more frequently in workers' information networks even when no direct former-peer link exists. We address this by controlling for the average PageRank of the workers employed at each candidate firm.

We include the PageRank controls in the conditional logit and complementary log-log robustness specifications. For a direct comparison with conditional logit, we first estimate a cloglog model on the same estimation sample and using the same candidate-varying controls. The main specifications use PageRank calculated and normalized over the full worker-year graph. As a robustness check, we replace it with the component-normalized PageRank measure. The component-based measure changes the scale against which a worker's network position is evaluated but leaves the underlying coworker and temporal links unchanged.

The centrality controls are intended to answer a limited but important question: do the estimated peer relationships remain when we account for the broader network positions of departing peers and candidate firms? They do not separately identify whether PageRank

operates through information, influence, firm visibility, or some other network mechanism. Nor do they turn the estimated peer coefficients into causal effects. They provide a demanding check that the results are not simply reflecting the fact that some workers and firms occupy more central positions in the labor-market network.

# 6 Results

## 6.1 Decision to leave the firm

This section studies whether separations by coworkers predict an incumbent worker's subsequent decision to leave the firm, and whether the *composition* of those separations matters. The underlying idea is that coworker exits can affect the value of staying through several channels: they may directly reduce workplace utility (loss of team complementarities or social capital), signal deteriorating firm conditions, or transmit information about outside opportunities. These mechanisms imply not only that higher recent peer turnover should predict higher individual exit rates, but also that departures by more valuable or more influential coworkers may have disproportionately large effects.

Table 2B in the Appendix reports our main turnover regressions and Table 4 summarizes selected average marginal effects (AMEs) for the key peer group variables. We find a positive and precisely estimated relationship between the peer group turnover rate between $t-2$ and $t-1$ and the probability that worker $i$ moves to a different firm between $t-1$ and $t$. Quantitatively, a 1 percentage point increase in the peer turnover share is associated with an increase of 0.127-0.167 percentage points in the probability of moving, relative to a baseline move probability of 2.77%. This effect is robust to rich controls for worker characteristics, firm characteristics, time effects, and network-centrality controls.

Beyond the overall turnover rate, the composition of leavers is informative. A one-percentage-point increase in the share of the original peer group accounted for by high-quality departures increases the probability of moving by 0.079-0.102 percentage points, whereas a similar in-

crease in low-quality departures reduces the probability of moving by 0.075-0.109 percentage points. This asymmetry is consistent with a model in which departures by high-quality coworkers generate larger negative shocks to the workplace environment (e.g., loss of productive complements or mentoring), convey a stronger signal about outside opportunities, or provide more credible information that leaving is advantageous. Conversely, departures concentrated among low-quality coworkers may reflect idiosyncratic churn or may even improve the incumbent's relative position, attenuating incentives to leave.

Because our baseline specification uses a complementary log-log link, the marginal effects vary with the level of the latent index. Table 2E in the Appendix reports marginal effects evaluated at the covariate means. In this scale, a 1 pp increase in peer turnover raises the leave probability by 0.058-0.076 pp, the high-quality-leaver share raises it by 0.036-0.046 pp, and the low-quality-leaver share reduces it by 0.034-0.049 pp. Importantly, the signs and relative magnitudes mirror the main specification, indicating that the substantive conclusions are not an artifact of scaling.

All specifications include a standard set of worker and firm controls and, crucially, PageRank-based measures of network embeddedness. These centrality controls ensure that the peer-share variables are not simply proxying for differences in the connectedness or visibility of the workplace in the broader labor market. Results are virtually unchanged when using global PageRank controls versus component-winsorized PageRank controls.[16]

The finding that coworker separations predict individual separations is consistent with a growing literature documenting workplace spillovers in quitting and mobility decisions, as well as with models of social interactions in labor markets. The novel element in our results is the strong role of peer *composition*: departures by high-quality peers are associated with larger subsequent exit responses, while departures by low-quality peers are associated with lower exit probabilities. This pattern is suggestive of mechanisms operating through information, coordination, and complementarities rather than through purely mechanical

[16]See Appendix Table 1B: columns 5-8 for global PageRank controls and columns 9-12 for component PageRank controls.

turnover correlation. In the next section, we show that these same peer objects also predict *where* workers move, linking the turnover margin to destination choice and to peer-linked mobility.

Table 4: Probability of worker $i$ moving to a new firm in $t$
(selected average marginal effects from Table 2B - Appendix)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Turnover (%) | 0.148*** | 0.127*** | 0.167*** | 0.145*** |
| Share of high-quality peers (%) | | 0.102*** | | 0.079*** |
| Share of low-quality peers (%) | | | -0.109*** | -0.075*** |
| Observations | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 |
| Nonzero outcomes | 309,757 | 309,757 | 309,757 | 309,757 |

Probabilities have been multiplied by 100

*** p<0.01, ** p<0.05, * p<0.1

Table 1D shows that the benchmark fixed-effects turnover specification is highly stable to a range of additional modeling choices. Column (2) removes the origin job-occupation fixed effects, column (3) excludes lagged wage controls, and columns (4) and (5) re-estimate the same model while clustering standard errors, respectively, at the individual and origin-firm levels rather than at the peer-group level. We keep the column (1) as a carryover specification from table 1C in order to compare. Across all five specifications, the coefficients on the main peer variables are virtually unchanged. Table 2C shows that this stability also carries over to economic magnitudes: the corresponding average marginal effects remain fixed at about 0.145 percentage points for lagged turnover, 0.079 percentage points for the share of high-quality leavers, and -0.075 percentage points for the share of low-quality leavers. Taken together, these exercises indicate that the main turnover results are not sensitive to the inclusion of job-occupation fixed effects, to the treatment of lagged wages, or to the level at which standard errors are clustered.

Table 1E provides an additional set of robustness checks aimed at assessing whether the

main results are affected by future workplace instability. Column (1) again reproduces the preferred fixed-effects specification and is meant to be used for comparison. Column (2) restricts the sample to firms for which future turnover can be observed. The coefficients on the lagged peer variables remain very close to the benchmark, suggesting that the baseline findings are not driven by sample composition. Columns (3) and (4) then consider separate lead-based specifications using future turnover variables, constructed as two-year leads in order to avoid mechanical overlap with the focal worker's own separation period. These regressions show that future turnover is itself positively associated with current mobility, while future low-quality turnover is negatively associated with it. Future high-quality turnover is positive, but much smaller. Importantly, the magnitudes of these future-turnover coefficients are substantially below those of the baseline lagged peer variables. This comparison matters because, if the baseline results were driven entirely by persistent or anticipated workplace instability, we should expect future peer group turnover to have predictive power of a similar order of magnitude. Instead, the fact that the future coefficients are clearly smaller suggests that such confounding forces are present, but cannot account for the full strength of the baseline relationship between lagged peer departures and current mobility. In column (4), the negative interaction between future turnover and lagged peer-group size further suggests that the predictive content of future instability is weaker in larger peer groups.

Overall, these extended robustness checks strengthen the conclusion that the main turnover patterns are not a fragile artifact of specification choice, while also indicating that part of the observed relationship may reflect persistent or anticipated workplace shocks rather than a purely contemporaneous peer effect, although this appears to explain only a small part of the relationship.

## 6.2 Decision to move to a firm

This section examines whether former coworkers shape the destination selected by workers who change employers. The preferred estimates come from the conditional-logit model de-

scribed in Section 5.3. The model compares the firms contained in the same mover-year choice set and therefore asks whether a candidate firm is more likely to be chosen when it employs a former peer, holding fixed both the mover and the other characteristics common to her choice set.

The baseline choice set contains the realized destination and up to 99 alternative firms drawn from the same year, sector, NUTS 2 region, and broad firm-size category. The expanded dataset contains 28,928,584 mover-year $\times$ candidate-firm observations. Conditional-logit estimation drops 79 singleton choice sets, leaving 28,928,505 candidate-firm observations and 309,678 mover-year choice sets. Standard errors are clustered at the worker level.

Table 5 reports the main conditional-logit estimates. The coefficient comparing an ordinary-peer firm with a no-peer firm is 4.591, while the incremental coefficient comparing a high-quality-peer firm with an ordinary-peer firm is 0.968. Both estimates are statistically significant at any reasonable level.

We exponentiate these coefficients to get the relative choice-odds ratios. Conditional on the alternatives and candidate-firm controls included in the model, the relative odds of selecting an ordinary-peer firm rather than an otherwise comparable no-peer firm are approximately 98.6 times larger. Conditional on already having at least one former peer at the candidate firm, the presence of a high-quality former peer raises the relative choice odds by a further factor of 2.63. Taken together, a candidate firm with at least one high-quality former peer has approximately 260 times the relative choice odds of a no-peer firm.

These odds ratios are unusually large, but they mirror a striking feature of the raw data. Among mover-year choice sets containing exactly one peer-linked candidate, that candidate is selected in approximately 84.9% of cases. The conditional logit is therefore fitting a choice pattern in which former-peer firms are selected with exceptional frequency whenever they are available. The odds ratios should nevertheless not be read as probability multipliers: an odds ratio of 98.6 does not imply that the probability of choosing a peer firm is 98.6 times larger for every mover, since the probability also depends on the number and attractiveness

of the competing alternatives.

Table 5: Former-peer presence and destination choice: baseline conditional logit

| Comparison | Log relative choice odds | Relative choice odds | Probability change |
|---|---|---|---|
| Ordinary peer vs. no peer | 4.591*** | 98.63*** | 26.74 pp |
| | (0.015) | [95.74, 101.52] | |
| High-quality peer vs. ordinary peer | 0.968*** | 2.63*** | 15.08 pp |
| | (0.017) | [2.55, 2.72] | |
| High-quality peer vs. no peer | 5.559*** | 259.57*** | 41.82 pp |
| | (0.016) | [251.46, 267.68] | |
| Candidate-firm observations | 28,928,505 | | |
| Mover-year choice sets | 309,678 | | |
| Worker clusters | 248,419 | | |

*Notes:* The dependent variable equals one for the realized destination and zero for the remaining firms in the mover-year choice set. The ordinary-peer category contains firms with at least one former peer but no high-quality former peer. The high-quality-peer category contains firms with at least one high-quality former peer and may also contain other (ordinary) former peers. The baseline model includes the candidate-firm controls described in Section 5.3, including log firm size, average PageRank, and the candidate-firm wage component. Relative choice odds and confidence intervals are obtained from the conditional logit coefficients. Probability changes are mover-year-weighted own-candidate counterfactuals: the peer state of one candidate is changed while all other alternatives remain at their observed values, after which the probabilities are renormalized within the choice set. These probability changes are reported as point estimates. Statistical inference is based on the worker-clustered conditional-logit coefficients and odds ratios.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

The probability translations provide a more intuitive sense of the magnitude. The average own-candidate probability is 0.98% when a candidate firm is assigned the no-peer state, 27.72% when it is assigned the ordinary-peer state, and 42.80% when it is assigned the high-quality-peer state. Thus, moving from no former peer to an ordinary former peer raises the probability assigned to that candidate by 26.74 percentage points. Replacing an ordinary-peer state with a high-quality-peer state adds a further 15.08 percentage points.

These quantities are counterfactual probabilities for a given candidate firm, not unconditional shares of all movers. In particular, the 27.72% estimate does not mean that 27.72% of all workers move to firms with former peers. It means that, after taking the observed choice

set and candidate-firm characteristics as given, assigning ordinary-peer status to a candidate raises the average probability that this candidate is selected to 27.72%. The predicted no-peer probability of 0.98% is close to the mechanical sampling benchmark of approximately 1.07%, but the two objects are conceptually distinct.

A possible concern is that former-peer firms may be selected more often simply because they are expanding or because they already employ many workers in the focal mover's occupation. We address it by adding the candidate firm's hiring share in $t-1$, the share of its $t-1$ workforce employed in the focal worker's occupation, and two broader measures of occupational structure: the occupation Herfindahl index and the number of occupations represented at the firm.

These variables are strongly related to destination choice. Candidate firms that hired a larger share of their workforce in $t-1$, and firms in which the focal worker's occupation already represented a larger share of employment, are more likely to be selected. This is consistent with the idea that recent hiring and occupation-specific employment provide information about whether the candidate firm is likely to have a relevant vacancy.

More importantly, accounting for these dimensions does not remove the former-peer relationship. Table 6 reports the relative choice-odds ratios across the candidate-firm-control specifications. Adding the predetermined hiring share reduces the ordinary-peer odds ratio from 98.63 to 89.14. Controlling for the focal occupation's employment share reduces it to 86.16, while controlling for the broader occupation mix gives an estimate of 93.89. When all predetermined hiring and occupation controls are included jointly, the ordinary-peer odds ratio remains 80.45.

The incremental high-quality-peer effect is even more stable. The relative choice-odds ratio comparing a high-quality-peer firm with an ordinary-peer firm is 2.63 in the baseline model and 2.66 after all predetermined controls are added. The generic former-peer association therefore overlaps partly with candidate-firm hiring activity and occupation-specific employment opportunities. By contrast, these characteristics explain essentially none of the

additional advantage associated with a high-quality former peer.

Table 6: Conditional-logit robustness to candidate-firm controls

| Specification | Ordinary peer vs. no peer | High-quality peer vs. ordinary peer | High-quality peer vs. no peer |
|---|---|---|---|
| Baseline | 98.63*** | 2.63*** | 259.57*** |
| Hiring share in $t-1$ | 89.14*** | 2.64*** | 234.93*** |
| Focal-occupation share in $t-1$ | 86.16*** | 2.59*** | 223.57*** |
| Occupation mix in $t-1$ | 93.89*** | 2.58*** | 242.05*** |
| Combined predetermined controls | 80.45*** | 2.66*** | 214.27*** |
| Contemporaneous leave-one-out hiring | 77.26*** | 2.41*** | 186.46*** |
| Candidate-firm observations | 28,928,505 | | |
| Mover-year choice sets | 309,678 | | |

*Notes:* Entries are conditional-logit relative choice-odds ratios. All specifications include the baseline candidate-firm controls. "Hiring share in $t-1$" adds the share of the candidate firm's workforce hired during the previous year. "Focal-occupation share" adds the share of the candidate firm's $t-1$ workforce employed in the focal worker's occupation. "Occupation mix" adds the candidate firm's occupation Herfindahl index and number of occupations. "Combined predetermined controls" includes all three sets of $t-1$ controls. The contemporaneous leave-one-out measure subtracts the focal mover from hiring and employment at the realized destination; because it is measured in the destination year, it is treated as an additional rather than preferred robustness check. Standard errors are clustered at the worker level.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

The model-based probability changes show the same pattern. With the full set of predetermined controls, the ordinary-peer probability effect declines from 26.74 to 22.70 percentage points, while the incremental high-quality-peer effect declines from 15.08 to 13.85 percentage points. The total high-quality-peer effect becomes 36.55 percentage points. The controls therefore attenuate the estimated magnitudes, particularly for ordinary former peers, but the effects are still economically large.

The contemporaneous leave-one-out hiring measure provides a more demanding but less clearly predetermined check. It controls for the candidate firm's hiring activity in the same year as the focal move, after removing the focal worker from the chosen firm's numerator and denominator. Under this specification, the ordinary-peer odds ratio remains 77.26, and the

incremental high-quality-peer odds ratio remains 2.41. Since this variable may itself reflect the same hiring process that generates the focal move, we do not treat it as the preferred control. Its purpose is to show that the former-peer results are not solely a reflection of broad contemporaneous recruitment at the destination.

We next re-estimate the destination model using complementary log-log. To make the comparison informative, the first cloglog specification uses exactly the same estimation sample and candidate-varying controls as the conditional logit. We also report the fuller cloglog specification which adds the worker characteristics and wage components that are conditioned out of the conditional logit.

Table 7 shows that the probability magnitudes are smaller under cloglog, but the economic ordering is unchanged. In the comparable cloglog model, the predicted probability rises from 0.80% for a no-peer candidate to 10.71% for an ordinary-peer candidate and 15.08% for a high-quality-peer candidate. The corresponding discrete changes are 9.90 percentage points for an ordinary peer and a further 4.38 percentage points for a high-quality peer. The fuller cloglog model gives very similar effects of 10.62 and 4.99 percentage points.

Table 7: Destination-choice effects across estimators

| Estimator | No peer | Ordinary peer | High-quality peer | Ordinary-peer effect | Incremental HQ effect |
|---|---|---|---|---|---|
| Conditional logit | 0.98% | 27.72% | 42.80% | 26.74 pp | 15.08 pp |
| Comparable cloglog | 0.80% | 10.71% | 15.08% | 9.90 pp | 4.38 pp |
| Full cloglog | 0.80% | 11.42% | 16.41% | 10.62 pp | 4.99 pp |

*Notes:* The conditional-logit entries are mover-year-weighted own-candidate counterfactual probabilities and probability changes. The comparable cloglog uses the same estimation sample and candidate-varying controls as the conditional logit. The full cloglog additionally includes mover characteristics, year and sector effects, and the worker and occupation wage components. Cloglog entries are predictive margins and exact discrete changes calculated by treating peer state as a categorical variable. Because conditional logit normalizes probabilities within each mover-year choice set whereas cloglog models each candidate-firm row as a binary outcome, the probability levels are not estimates of an identical structural parameter and need not coincide. Standard errors are clustered at the worker level.

Conditional logit forces the candidate probabilities to sum to one within the mover-year set and estimates how the presence of a peer redistributes probability mass away from the

competing firms. The row-level complementary log-log does not impose this within-set normalization and consequently produces smaller candidate-level probability differences. What matters for the robustness exercise is that both estimators point in the same direction: former-peer firms are substantially more likely to be selected, and high-quality former peers provide an additional and precisely estimated advantage.

We next ask whether the concentration of former peers within a candidate firm matters after allowing separately for these discrete differences in peer presence. We calculate peer shares (excluding the focal worker at the destination firm) relative to the candidate firm's incumbent workforce. Let

$$sharepeers_{i,f,t}$$

denote the percentage of incumbent workers at candidate firm $f$ who are former peers of mover $i$, and let

$$sharehighpeers_{i,f,t}$$

denote the corresponding percentage who are former high-quality peers. Since high-quality former peers are a subset of all former peers, both shares are included in the same regression together with the three peer-state indicators introduced above.

Including the peer-state indicators is important for interpretation. They absorb the discrete difference between a candidate firm with no former peers, one with ordinary former peers, and one with at least one high-quality former peer. The share coefficients then capture variation in peer concentration *conditional on the extensive peer state*. In particular, the coefficient on $sharepeers_{i,f,t}$ corresponds to a one-percentage-point increase in ordinary-peer share, holding the high-quality-peer share fixed. The coefficient on $sharehighpeers_{i,f,t}$ is a composition effect: it corresponds to replacing one percentage point of ordinary-peer share with high-quality-peer share while holding total former-peer share fixed. Finally, the sum of the two coefficients captures a one-percentage-point increase in high-quality-peer share that expands total peer share while leaving ordinary-peer share unchanged.

Table 8 reports the results from the intensive margin regression. In the baseline conditional logit, a one-percentage-point increase in ordinary-peer share raises the relative choice odds by a factor of 1.219, equivalent to an increase of approximately 21.9%. The corresponding exact own-candidate probability change is 2.42 percentage points. After adding candidate-firm hiring and occupational-composition controls, the relative choice-odds ratio remains 1.208 and is statistically significant, and the probability effect remains economically large at 2.25 percentage points.

The high-quality composition, however, yields different results. Holding total former-peer share fixed, replacing one percentage point of ordinary-peer share with high-quality-peer share reduces relative choice odds by approximately 10.0% in the baseline model and 10.4% after adding the predetermined controls. The corresponding exact probability changes are approximately $-1.01$ and $-1.03$ percentage points. Thus, once a candidate firm already has a high-quality former peer and the overall size of the former-peer network is held constant, a larger high-quality share does not provide an additional intensive-margin advantage.

This finding, however, does not overturn the extensive-margin result. The extensive specification shows that the presence of at least one high-quality former peer substantially increases the attractiveness of a candidate firm relative to a firm with ordinary former peers only. The intensive specification addresses a different question: among peer-linked firms, does further shifting a fixed-size former-peer network toward high-quality peers increase the probability of selection? The estimates indicate that it does not. The role of high-quality peers therefore appears to be closer to a threshold effect than to a continuously increasing composition effect.

Consistent with this interpretation, adding high-quality-peer share without displacing ordinary former peers remains positively associated with destination choice. A one-percentage-point increase in high-quality-peer share that also expands total former-peer share raises relative choice odds by approximately 9.7% in the baseline model and 8.3% in the controlled specification. The corresponding exact probability effects are approximately 1.00 and 0.84

percentage points. High-quality former peers therefore remain valuable when they enlarge the worker's overall peer network at the destination; the negative coefficient applies only to a change in the composition of a peer network of fixed size.

Table 8: Former-peer shares and destination choice

| | Relative choice odds | | Exact probability change | |
|---|---|---|---|---|
| One-percentage-point change | Baseline | Combined $t-1$ controls | Baseline | Combined $t-1$ controls |
| Increase in ordinary-peer share | 1.219*** | 1.208*** | 2.42 pp | 2.25 pp |
| | (0.005) | (0.005) | | |
| Replace ordinary-peer share | 0.900*** | 0.896*** | -1.01 pp | -1.03 pp |
| with high-quality-peer share | (0.008) | (0.008) | | |
| Increase in high-quality-peer share, | 1.097*** | 1.083*** | 1.00 pp | 0.84 pp |
| ordinary-peer share unchanged | (0.009) | (0.009) | | |
| Peer-state indicators | Yes | Yes | Yes | Yes |
| Baseline candidate-firm controls | Yes | Yes | Yes | Yes |
| Hiring and occupation controls$_{t-1}$ | No | Yes | No | Yes |
| Candidate-firm observations | 28,928,505 | 28,928,505 | 28,928,505 | 28,928,505 |
| Mover-year choice sets | 309,678 | 309,678 | 309,678 | 309,678 |
| Worker clusters | 248,419 | 248,419 | 248,419 | 248,419 |

*Notes:* Peer shares are calculated relative to the incumbent workforce of the candidate firm. The focal mover is removed from the denominator at the realized destination. All specifications include indicators for no former peer, ordinary former peer, and high-quality former peer, so the share coefficients identify variation conditional on the extensive peer state. The baseline model controls for log firm size, average firm-year PageRank, and the previously estimated candidate-firm wage component. The combined specification additionally controls for the candidate firm's hiring share in $t-1$, the share of its workforce employed in the focal worker's occupation, the occupation Herfindahl index, the number of occupations, and the relevant missing-value indicators. Relative choice odds are obtained from the conditional-logit coefficients, with delta-method standard errors in parentheses. The exact probability changes are mover-year-weighted point estimates obtained by changing the relevant share by one percentage point, holding the remaining candidate characteristics and alternatives fixed, and renormalizing probabilities within each choice set.

The ordinary-share probability effect is evaluated in 100,037 mover-year sets containing a peer-linked candidate for which a one-percentage-point increase is feasible. The composition effect is evaluated in 36,674 sets containing a high-quality-peer candidate with at least one percentage point of ordinary-peer share available to replace. The total high-quality-share effect is evaluated in 62,902 sets containing a high-quality-peer candidate for which the increase is feasible. Statistical inference is based on the clustered conditional-logit coefficients and relative choice-odds ratios; the exact probability changes are reported as point estimates.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

The intensive-margin results also survive the alternative functional form. In the comparable complementary log-log model, a one-percentage-point increase in ordinary-peer share raises the candidate's predicted probability by 1.72 percentage points in the baseline specification and 1.67 percentage points after adding the predetermined controls. Replacing ordinary-peer share with high-quality-peer share lowers the probability by approximately 0.98 and 0.92 percentage points, respectively. Increasing high-quality-peer share while keeping ordinary-peer share fixed remains positive, at approximately 0.86 percentage points in both specifications. The smaller probability magnitudes are consistent with the broader difference between the conditional-logit and cloglog models, while the sign and interpretation of the intensive-margin results remain unchanged.

Taken together, the extensive- and intensive-margin estimates point to two distinct features of peer-linked destination choice. First, the presence of former peers, and especially the presence of at least one high-quality former peer, has a large discrete association with the probability that a firm is selected. Second, conditional on that presence, destination choice rises with the overall concentration of former coworkers. The high-quality advantage, however, does not increase monotonically with the high-quality share once the total size of the peer network is held fixed. This distinction suggests that peer quality is especially relevant through the presence of a salient high-quality contact, whereas the broader intensive margin is more closely related to the overall reach of the former-coworker network.

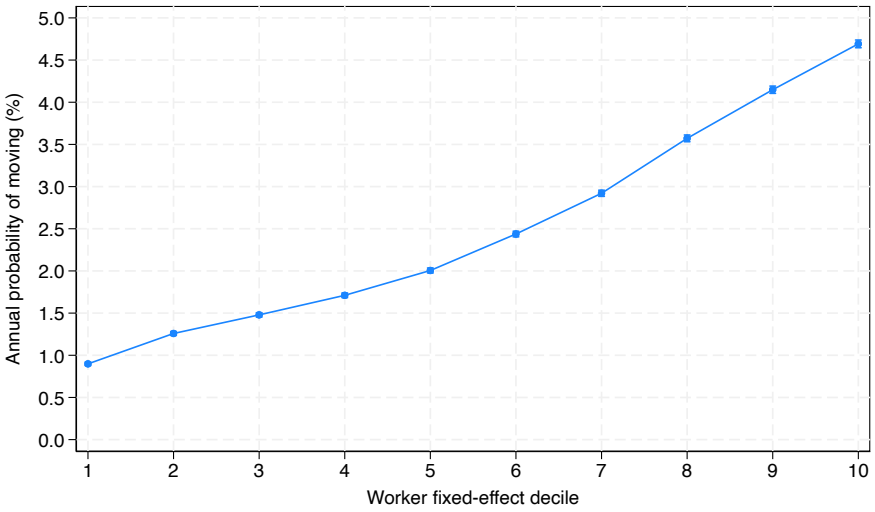
These results are consistent with several mechanisms discussed in the search framework. Former peers may transmit information about vacancies and working conditions, reduce the cost of applying, facilitate review or referral, or help workers and firms assess match quality, among many others. Rejoining former coworkers may also generate social or production complementarities. The stability of the high-quality peer premium after controlling for destination hiring and occupational composition is particularly informative. It suggests that the high-quality result is not simply capturing the fact that high-quality peers tend to work at firms that are expanding or that employ more workers in the focal occupation.

The results remain descriptive rather than causal. The presence of former peers is not randomly assigned across candidate firms and unobserved vacancies, amenities, or match-specific factors, among others, may be correlated with both peer links and destination choice. Nevertheless, the consistency across conditional logit and the complementary log-log specifications indicate that former-peer links are an unusually strong and robust predictor of where movers go.

## 6.3 Homophily and Heterogeneity by Worker Quality

A potential interpretation of the destination-choice results is that workers do not necessarily follow informative or influential coworkers, but instead follow former peers who are similar to themselves. If high-quality focal workers disproportionately select destinations containing high-quality former peers, the estimated high-quality-peer premium could thus partly reflect homophily in persistent worker characteristics rather than a distinct role for peer quality.

Figure 2: Probability of any given worker moving to a new firm




*Notes:* The figure reports the mean annual mobility rate by worker fixed-effect decile. Confidence intervals are based on standard errors clustered by worker and are narrower than the plotted markers.

Figure 2 shows that mobility is strongly positively associated with persistent worker quality.

The annual probability of moving rises monotonically from approximately 0.9% in the bottom worker fixed-effect decile to 4.7% in the top decile. This result indicates that both focal movers and former peers observed at potential destinations may be selected on worker quality. We examine whether homophily is present by allowing the destination-choice effects to vary with the focal worker's own estimated quality. Namely, we augment the baseline conditional-logit specification by interacting the peer variables with an indicator for whether the focal worker is classified as high quality. Let $O_{i,f,t}$ indicate that candidate firm $f$ contains at least one ordinary former peer of focal worker $i$, but no high-quality former peer, and let $H_{i,f,t}$ indicate that it contains at least one high-quality former peer. The omitted category is therefore a candidate firm containing no former peers. The conditional probability is thus:

$$\Pr\left(choice_{i,f,t} = 1 \mid \mathcal{C}_{i,t}\right) = \frac{\exp\left(\eta_{i,f,t}\right)}{\sum_{g \in \mathcal{C}_{i,t}} \exp\left(\eta_{i,g,t}\right)} \tag{45}$$

where $\mathcal{C}_{i,t}$ denotes the choice set of worker $i$ in year $t$, and

$$\begin{aligned} \eta_{i,f,t} = {} & \gamma_O O_{i,f,t} + \gamma_H H_{i,f,t} \\ & + \delta_O O_{i,f,t} \times HighWorker_{i,t} + \delta_H H_{i,f,t} \times HighWorker_{i,t} + \Psi Z_{f,t} \end{aligned} \tag{46}$$

Here, $HighWorker_{i,t}$ is an indicator equal to one if the focal worker belongs to the high-quality group, and $Z_{f,t}$ contains the candidate-firm characteristics included in the baseline conditional-logit specification. $HighWorker_{i,t}$ and all the focal worker-year characteristics are constant across the alternatives in $\mathcal{C}_{i,t}$ and are therefore conditioned out. The interaction terms allow both the general former-peer effect and the relative attractiveness of a high-quality rather than ordinary former peer to differ by focal-worker quality.

We also estimate an intensive-margin specification in which the peer-state indicators and

their interactions remain in the model:

$$\begin{aligned}\eta_{i,f,t} = {} & \gamma_O O_{i,f,t} + \gamma_H H_{i,f,t} + \delta_O O_{i,f,t} \times HighWorker_{i,t} + \delta_H H_{i,f,t} \times HighWorker_{i,t} \\ & + \beta_P PeerShare_{i,f,t} + \beta_H HighPeerShare_{i,f,t} \\ & + \rho_P PeerShare_{i,f,t} \times HighWorker_{i,t} + \rho_H HighPeerShare_{i,f,t} \times HighWorker_{i,t} + \Psi Z_{f,t}\end{aligned} \tag{47}$$

The peer shares are calculated relative to the candidate firm's incumbent workforce. At the destination firm, the focal mover is removed from the denominator. Including the peer-state indicators may be relevant because they separate the discrete difference between no-peer, ordinary-peer, and high-quality-peer candidate firms from variation in peer concentration within those states.

Table 9 reports the conditional odds ratios from the extensive- and intensive-margin specifications. In Panel A, the first two rows compare ordinary and high-quality peer-linked candidate firms with otherwise comparable candidate firms containing no former peers. The third row compares a high-quality peer-linked candidate firm directly with an ordinary peer-linked candidate firm. Panel B reports the odds ratios associated with one-percentage-point changes in the peer-share variables, conditional on the extensive peer state.

The results reveal two distinct patterns. First, high-quality focal workers appear to rely less on former-peer links in general. For non-high-quality focal workers, an ordinary peer-linked candidate firm has 108.43 times the conditional odds of being selected as an otherwise comparable candidate firm containing no former peers. The corresponding odds ratio is 68.58 for high-quality focal workers, and the difference between the two groups is statistically significant at any reasonable level of significance. The same pattern holds for candidate firms containing high-quality former peers: the conditional odds ratios relative to a no-peer candidate firm are 285.17 for non-high-quality focal workers and 189.56 for high-quality focal workers.

Table 9: Heterogeneity in destination-choice effects by focal-worker quality

| | Non-high-quality | High-quality | $p$-value for equality |
|---|---|---|---|
| *Panel A: Extensive margin* | | | |
| Ordinary peer versus no peer | 108.43*** | 68.58*** | $< 0.001$ |
| High-quality peer versus no peer | 285.17*** | 189.56*** | $< 0.001$ |
| High-quality peer versus ordinary peer | 2.63*** | 2.76*** | 0.212 |
| *Panel B: Intensive margin* | | | |
| Increase in ordinary-peer share | 1.226*** | 1.197*** | 0.019 |
| Replace ordinary-peer share with high-quality-peer share | 0.903*** | 0.890*** | 0.491 |
| Increase in high-quality-peer share, ordinary-peer share unchanged | 1.106*** | 1.065*** | 0.045 |
| Observations | 28,928,505 | | |
| Choice sets | 309,678 | | |
| Focal workers | 248,419 | | |

*Notes:* Entries are conditional odds ratios from conditional-logit destination-choice models. In Panel A, ordinary-peer and high-quality-peer candidate firms are mutually exclusive states, and firms containing no former peers constitute the omitted category. The third row compares a high-quality peer-linked candidate firm directly with an ordinary peer-linked candidate firm. Panel B includes the extensive peer-state indicators and their focal-worker-quality interactions, so the reported share effects identify variation in peer concentration conditional on the extensive peer state. Peer shares are measured relative to the incumbent workforce, excluding the focal mover at the realized destination. The first row in Panel B increases ordinary-peer share by one percentage point. The second replaces one percentage point of ordinary-peer share with high-quality-peer share while holding total peer share fixed. The third increases high-quality-peer share by one percentage point while leaving ordinary-peer share unchanged. The final column reports Wald tests of equality between high-quality and non-high-quality focal workers. Standard errors are clustered by focal worker. Seventy-nine singleton choice sets are omitted because they contain no within-choice-set variation.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

These results imply that both groups place substantial additional weight on peer quality when comparing peer-linked candidate firms. For non-high-quality focal workers, a candidate firm containing a high-quality former peer has 2.63 times the conditional odds of being selected as a candidate firm containing only ordinary former peers. The corresponding odds ratio is 2.76 for high-quality focal workers. However, and although the point estimate is slightly larger for high-quality focal workers, the difference is statistically insignificant ($p = 0.212$), providing no evidence that high-quality workers place greater relative weight on the mere

presence of a high-quality former peer.

The intensive-margin results reinforce the conclusion that higher-quality workers rely somewhat less on peer concentration in general. A one-percentage-point increase in ordinary-peer share multiplies the conditional odds of choosing a candidate firm by 1.226 for non-high-quality focal workers and by 1.197 for high-quality focal workers. Although the difference is considerably smaller than in the extensive-margin comparisons, it is statistically significant at the 5% level ($p = 0.019$).

The high-quality composition effect does not provide evidence of homophily in the binary specification. Holding total peer share fixed, replacing one percentage point of ordinary-peer share with high-quality-peer share reduces the conditional odds of selection for both groups. The odds ratio is 0.903 for non-high-quality focal workers and 0.890 for high-quality focal workers. The difference is small and statistically insignificant ($p = 0.491$).

Increasing high-quality-peer share without displacing ordinary former peers remains positively associated with destination choice for both groups. A one-percentage-point increase in high-quality-peer share that also expands total peer share produces an odds ratio of 1.106 for non-high-quality focal workers and 1.065 for high-quality focal workers. The difference between the two groups is statistically significant at the 5%.

Taken together, the results provide little evidence that high-quality focal workers are disproportionately attracted to high-quality former peers. Higher-quality workers rely less on both the presence and concentration of former peers in general. The incremental high-quality-peer premium at the extensive margin does not differ significantly across the two worker groups, while the intensive high-quality composition effect is negative and statistically indistinguishable between them.

### 6.3.1 Continuous worker-quality gradient

The binary classification may, nevertheless, conceal heterogeneity within the two worker-quality groups. We therefore replace $HighWorker_{i,t}$ with the focal worker's continuous

estimated worker fixed effect:

$$\begin{aligned}\eta_{i,f,t} = \gamma_O O_{i,f,t} + \gamma_H H_{i,f,t} \\ + \theta_O O_{i,f,t} \times \widehat{\alpha}_i + \theta_H H_{i,f,t} \times \widehat{\alpha}_i + \Psi Z_{f,t}\end{aligned} \tag{48}$$

where $\widehat{\alpha}_i$ is the focal worker's estimated worker fixed effect. The corresponding intensive-margin specification retains both the extensive peer states and the peer shares:

$$\begin{aligned}\eta_{i,f,t} = \gamma_O O_{i,f,t} + \gamma_H H_{i,f,t} + \theta_O O_{i,f,t} \times \widehat{\alpha}_i + \theta_H H_{i,f,t} \times \widehat{\alpha}_i \\ + \beta_P PeerShare_{i,f,t} + \beta_H HighPeerShare_{i,f,t} \\ + \kappa_P PeerShare_{i,f,t} \times \widehat{\alpha}_i + \kappa_H HighPeerShare_{i,f,t} \times \widehat{\alpha}_i + \Psi Z_{f,t}\end{aligned} \tag{49}$$

Table 10 reports conditional odds ratios evaluated at the 25th, 50th, and 75th percentiles of the focal-worker fixed-effect distribution.

Table 10: Former-peer effects across the focal-worker fixed-effect distribution

| | 25th percentile | 50th percentile | 75th percentile | $p$-value for gradient |
|---|---|---|---|---|
| *Panel A: Extensive margin* | | | | |
| Ordinary peer versus no peer | 172.51*** | 109.06*** | 68.94*** | $< 0.001$ |
| High-quality peer versus no peer | 502.00*** | 296.26*** | 174.83*** | $< 0.001$ |
| High-quality peer versus ordinary peer | 2.91*** | 2.72*** | 2.54*** | $< 0.001$ |
| *Panel B: Intensive margin* | | | | |
| Increase in ordinary-peer share | 1.215*** | 1.206*** | 1.198*** | 0.011 |
| Replace ordinary-peer share with high-quality-peer share | 0.867*** | 0.904*** | 0.942*** | $< 0.001$ |
| Increase in high-quality-peer share, ordinary-peer share unchanged | 1.053*** | 1.090*** | 1.129*** | $< 0.001$ |
| Observations | 28,928,505 | | | |
| Choice sets | 309,678 | | | |
| Focal workers | 248,419 | | | |

*Notes:* Entries are conditional odds ratios evaluated at the 25th, 50th, and 75th percentiles of the focal-worker fixed-effect distribution. Panel A compares the indicated peer state with the relevant omitted category. In the third row, the comparison is a high-quality peer-linked firm relative to an ordinary peer-linked firm. Panel B includes the peer-state indicators and their interactions with the continuous worker fixed effect. The first row increases ordinary-peer share by one percentage point. The second replaces one percentage point of ordinary-peer share with high-quality-peer share while holding total peer share fixed. The third increases high-quality-peer share by one percentage point while holding ordinary-peer share fixed. The final column reports tests of whether the corresponding conditional-logit effect changes with the continuous worker fixed effect. Standard errors are clustered by focal worker.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

The continuous specification reinforces the finding that higher-quality workers rely less on peer-linked candidate firms overall. The conditional odds ratio for an ordinary peer-linked firm relative to a no-peer candidate firm declines from 172.51 at the 25th percentile of the worker fixed-effect distribution to 68.94 at the 75th percentile. The corresponding odds ratio for a high-quality peer-linked firm declines from 502.00 to 174.83. Both gradients are negative and statistically significant at the 1% level.

The relative premium associated with a high-quality rather than ordinary former peer also declines with focal-worker quality. A high-quality peer-linked candidate firm has 2.91 times the conditional odds of an ordinary peer-linked firm at the 25th percentile of the worker fixed-effect distribution, compared with 2.72 at the median and 2.54 at the 75th percentile.

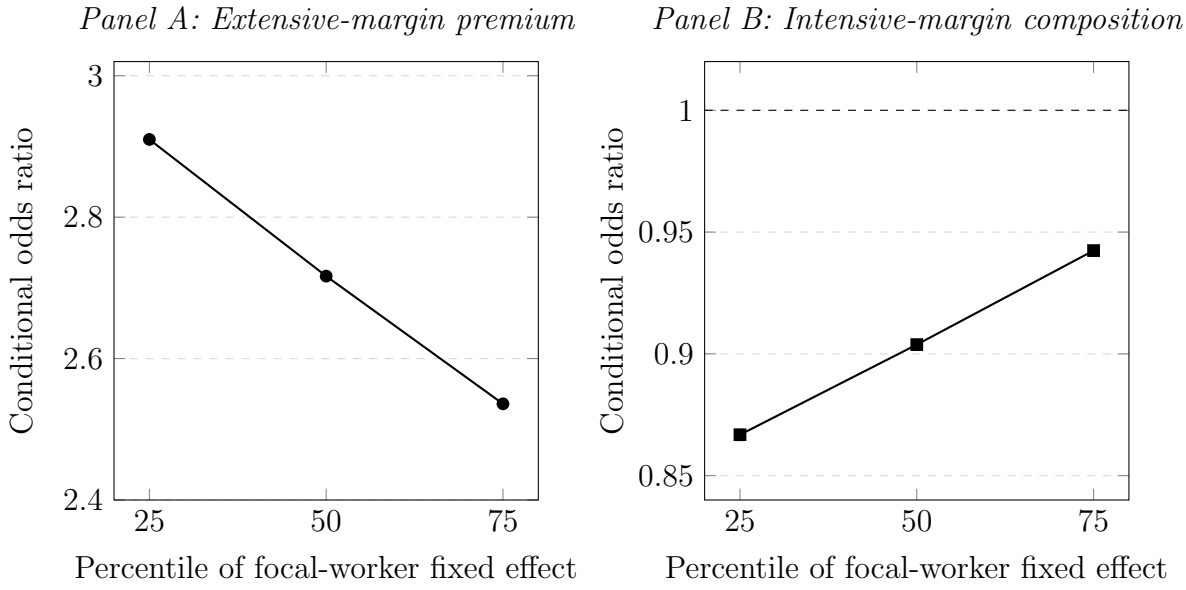
The decline between the 25th and 75th percentiles is statistically significant. Higher-quality workers therefore continue to exhibit a strong preference for high-quality rather than ordinary former peers, but this extensive-margin premium becomes moderately smaller, rather than larger, as focal-worker quality rises.

The intensive-margin gradients are more nuanced. The effect of ordinary-peer exposure declines modestly with focal-worker quality: the conditional odds ratio associated with a one-percentage-point increase falls from 1.215 at the 25th percentile to 1.206 at the median and 1.198 at the 75th percentile. The gradient is statistically significant ($p = 0.011$), which, like in the extensive-margin, reinforces the conclusion that higher-quality workers rely less on the concentration of ordinary former peers.

As with the previous exercise, the high-quality composition effect moves in the opposite direction, but remains negative throughout the observed portion of the worker-quality distribution. Holding total peer share fixed, replacing one percentage point of ordinary-peer share with high-quality-peer share produces an odds ratio of 0.867 at the 25th percentile, 0.904 at the median, and 0.942 at the 75th percentile. Thus, the negative composition effect becomes progressively weaker as focal-worker quality rises, but it does not become positive even at the 75th percentile. The gradient is statistically significant at the 1% level.

When high-quality-peer share increases without displacing ordinary former peers, the pattern is positive and increasing. The corresponding odds ratio rises from 1.053 at the 25th percentile to 1.090 at the median and 1.129 at the 75th percentile. Higher-quality workers therefore respond more strongly to an expansion of the high-quality-peer network, even though they do not respond positively to replacing ordinary peers with high-quality peers within a peer network of fixed size.

Figure 3: High-quality-peer selectivity across focal-worker quality




*Notes:* Panel A reports the conditional odds ratio for a candidate firm containing a high-quality rather than ordinary former peer. Panel B reports the conditional odds ratio associated with replacing one percentage point of ordinary-peer share with high-quality-peer share while holding total peer share fixed.

In sum, the results provide limited evidence of simple homophily but reveal meaningful heterogeneity in how workers use peer links. The extensive-margin specifications do not support the hypothesis that higher-quality workers place greater weight on the mere presence of a high-quality former peer. The high-quality-peer premium does not differ significantly across the binary worker-quality groups and declines with the continuous worker fixed effect. High-quality former peers nevertheless remain substantially more attractive than ordinary former peers throughout the worker-quality distribution.

The more consistent pattern is that workers with higher estimated fixed effects, i.e., higher quality, rely less on peer links and ordinary-peer concentration in general. In the binary specification, high-quality focal workers also exhibit a slightly smaller total response to an increase in high-quality-peer share, while the pure composition effect does not differ signifi-

cantly across groups.

The continuous specification provides a more nuanced form of quality-based heterogeneity. As focal-worker quality rises, the negative effect of replacing ordinary peers with high-quality peers becomes smaller, and the positive effect of expanding high-quality-peer share without displacing ordinary peers becomes larger. The results therefore do not support simple assortative following in which higher-quality workers are always more attracted to a greater high-quality composition. They do suggest that higher-quality workers are relatively more responsive to additions of high-quality former peers when those additions expand, rather than merely reallocate, the overall peer network.

## 6.4 Choice-set size

The previous section quantified how the presence of former peers at a candidate firm affects the probability that a mover selects that firm, holding constant the candidate-firm controls included in the regression. A remaining question is whether these effects depend on the number of alternatives in the mover's sampled choice set. A larger choice set provides a useful test of whether peer-linked destinations retain their advantage when movers face more plausible alternatives. If the estimated peer effect is driven mainly by small or weakly competitive choice sets, it should diminish as additional firms are introduced. If former peers instead provide information or facilitate access to particular jobs, the peer advantage should remain constant, or rise, as the number of alternatives increases.

Since workers' actual opportunity sets are unobserved, we approximate plausible destinations using firms that match the realized destination on sector, region, and broad firm-size category.[17] We then repeat the conditional-logit estimation using nested choice sets of different intended sizes. Firms included in a smaller choice set remain in the corresponding larger sets, which reduces differences caused solely by repeated random sampling.

The direct conditional-logit comparisons are remarkably stable across choice-set sizes,[18] al-

[17] We classify firms as micro, small, medium, and large.

[18] See Table 5A in the Tables Appendix.

beit declining ever so slightly. For intended sets of 20, 50, and 100 firms, the relative choice odds of an ordinary-peer firm compared with a no-peer firm are approximately 88.0, 84.1, and 81.1, respectively. However, the incremental relative choice odds of a high-quality-peer firm compared with an ordinary-peer firm barely changes, being approximately 2.67, 2.60, and 2.67, for the same sets of firms.

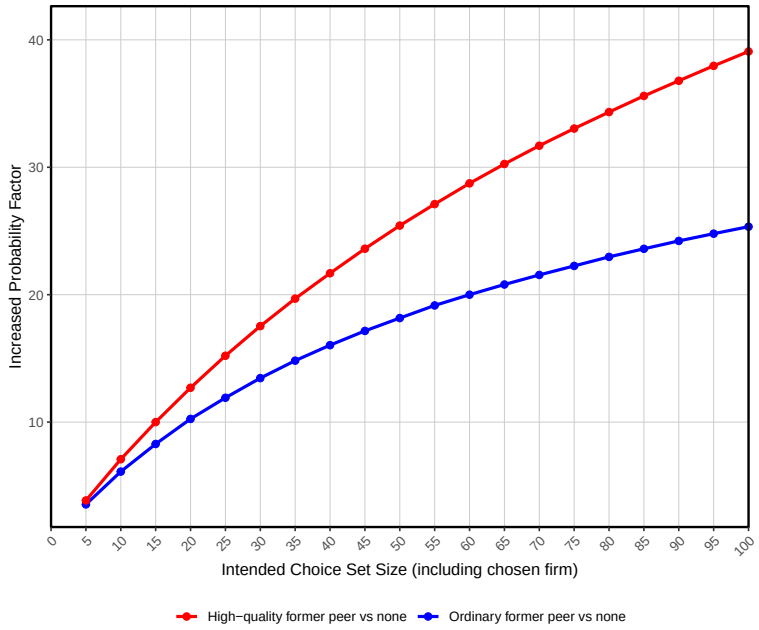
The absolute probability changes display a different pattern. The ordinary-peer effect declines from 41.10 percentage points in the 20-firm specification to 30.67 percentage points in the 50-firm specification and 22.93 percentage points in the 100-firm specification. This decline is partly mechanical: conditional logit requires the candidate probabilities to sum to one within each mover-year choice set, so the probability assigned to an individual candidate generally falls as additional alternatives are introduced. By contrast, the incremental high-quality-peer effect remains close to 14 percentage points across the three specifications: 13.57, 14.51, and 14.07 percentage points for the 20-, 50-, and 100-firm choice sets, respectively.

Figure 4 presents the same probability effects after scaling them by the mechanical benchmark implied by uniform random choice over each realized choice set. Let $K_{i,t}(\mathcal{N})$ denote the realized number of alternatives for mover $i$ under intended choice-set size $\mathcal{N}$. For peer state $s$, the plotted quantity is

$$1 + \frac{\Delta^s_{i,t}(\mathcal{N})}{1/K_{i,t}(\mathcal{N})}$$

where $\Delta^s_{i,t}$ can be $\Delta^O_{i,t} = p^O_{i,t} - p^0_{i,t}$ for the ordinary-peer effect relative to no peer, and $\Delta^H_{i,t} = p^H_{i,t} - p^0_{i,t}$ for the total high-quality-peer effect relative to no peer. The figure reports averages of these mover-year-level quantities.

Figure 4: Peer-state probability effects relative to the uniform-choice benchmark




*Notes:* The figure plots $1 + \Delta^{s}_{i,t}(\mathcal{N})/[1/K_{i,t}(\mathcal{N})]$, averaged across mover-years, where $\Delta^{O}_{i,t} = p^{O}_{i,t} - p^{0}_{i,t}$ for an ordinary-peer candidate and $\Delta^{H}_{i,t} = p^{H}_{i,t} - p^{0}_{i,t}$ for a high-quality-peer candidate. A value of one indicates no peer-state probability effect. The denominator is a descriptive benchmark implied by uniform random selection over the realized choice set and not the model-predicted no-peer probability.

The benchmark-normalized effects increase as the choice set expands. At the largest intended choice-set size, the ordinary-peer curve is approximately 25, meaning that the ordinary-peer probability increment is approximately 24 times the uniform-choice benchmark. The corresponding value for a high-quality-peer candidate is approximately 39, meaning that the total high-quality-peer probability increment is approximately 38 times that benchmark.

This increase is consistent with the decline in the absolute ordinary-peer effect reported above. As the choice set grows, the uniform-choice benchmark falls approximately in proportion to $1/K_{i,t}$. The ordinary-peer probability effect also falls, as expected when more firms compete for one choice, but retains a large and relatively stable choice-odds advantage. However, it declines substantially more slowly than $1/K_{i,t}$ so its value relative to the benchmark

increases. The widening distance between the two curves should be interpreted similarly. At the mover-year level, the difference between them is the incremental high-quality-peer effect scaled by the uniform-choice benchmark. Since the incremental effect remains close to 14 percentage points while $1/K_{i,t}$ becomes smaller, the normalized gap widens even though the underlying incremental effect remains stable.

One important caveat: we do not make claims about convergence as $\mathcal{N} \to \infty$. The purpose of this exercise is simply to assess whether the estimated peer advantage is sensitive to the range of choice-set sizes that can be constructed credibly from the data. Over this range, the main conclusion remains unchanged: the ordinary-peer advantage declines only modestly in relative-odds terms, while the additional advantage associated with a high-quality former peer remains economically meaningful and stable.

## 6.5 Wage impact

The destination-choice analysis establishes that movers are more likely to select firms that employ former peers, and that this effect is stronger when at least one former peer is classified as high-quality. A natural follow-up question is whether these peer-linked transitions are also associated with higher pay at the destination. This section examines whether movers earn a wage premium upon entry into the destination firm when former peers are present, and whether this premium is larger when at least one former peer is high-quality.

We restrict attention to mover-year observations and measure the wage outcome at the destination firm in the year of the move. Let $w_{i,f^\star,t}$ denote worker $i$'s real hourly wage at the destination firm $f^\star$ in year $t$. The estimation sample is the same set of movers used in the destination-choice analysis.

As in the previous analysis, we employ the two main indicators at the mover $\times$ destination-firm $\times$ year level: $\mathbb{1}\{peer_{i,f^\star,t}\}$ equals one if the destination firm employs at least one former peer of worker $i$ (as defined by prior coworker links), and $\mathbb{1}\{highpeer_{i,f^\star,t}\}$ equals one if the destination employs at least one former peer classified as high-quality (as defined above),

measured at $t-2$. We also consider intensity measures: $sharepeers_{i,f^\star,t}$, the share of workers at $f^\star$ in $t$ who are former peers of $i$, and $sharehighpeers_{i,f^\star,t}$, the share of workers at $f^\star$ in $t$ who are former high-quality peers of $i$.

We thus estimate log wage regressions of the form

$$\log(w_{i,f^\star,t}) = \beta_0 + \beta_1 \mathbb{1}\{peer_{i,f^\star,t}\} + \beta_2 \mathbb{1}\{highpeer_{i,f^\star,t}\} + \Theta \mathbf{X}_{i,t} + \Psi \mathbf{Z}_{f^\star,t} + \delta_t + \varepsilon_{i,f^\star,t} \quad (50)$$

where $\mathbf{X}_{i,t}$ includes worker controls and $\mathbf{Z}_{f^\star,t}$ includes destination-firm controls. Table 11 reports the results of regression specified in equation 50. We report coefficients as semi-elasticities (multiplied by 100), so that $\beta_1$ and $\beta_2$ can be read as percent differences in wages at the destination associated with peer presence. Standard errors are clustered at the worker level. Columns (3)–(4) add the peer-share measures to test whether wage effects scale with the intensity of peer exposure at the destination.

Table 11: Impact of wage at destination firm in $t$
(selected coefficients from Table 8 - Appendix)

| VARIABLES | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Peer exists | 0.84*** | 0.63*** | 0.69*** | 0.59*** |
| High-quality peer exists | | 0.33** | | 0.18 |
| Share of peers (%) | | | 0.02*** | 0.01 |
| Share of high-quality peers (%) | | | | 0.04 |
| Observations | 309,757 | 309,757 | 309,757 | 309,757 |

Coefficients have been multiplied by 100

*** p<0.01, ** p<0.05, * p<0.1

The results show that joining a destination firm that employs at least one former peer is associated with higher wages at entry. In the extensive-margin specification, the presence of any former peer corresponds to a wage premium of approximately 0.84% in column (1). When we additionally condition on whether at least one former peer is high-quality (column (2)), moving to an ordinary-peer destination is associated with an entry wage approximately

0.63% higher than moving to a no-peer destination, while the presence of at least one high-quality former peer is associated with an additional 0.33% premium, bringing the total wage premium to approximately 0.97%. The decomposition is consistent with heterogeneity in peer influence: conditional on having any former peer at the destination, the wage gains are about 50% larger when at least one of those peers is high-quality.

The intensive-margin specifications suggest that wage effects also increase with the intensity of peer exposure at the destination, although the value is extremely small in economic terms. Furthermore, the share coefficients are no longer statistically significant when we introduce the high-quality peers variables (both indicator and share). We therefore find no robust evidence that the entry-wage premium rises with peer concentration beyond the extensive presence of former peers.

The wage premium associated with the presence of former peers is consistent with a large body of work showing that referrals and coworker networks improve match formation and can generate entry-wage premia. In learning and screening models of referrals, incumbent employees transmit information to firms about applicants and/or to workers about vacancies and job attributes, reducing match uncertainty and raising surplus at the time of hiring (Dustmann et al., 2016; Montgomery, 1991). Empirically, referred hires often exhibit higher starting wages and longer tenure, with the wage advantage typically diminishing over time as the firm learns about match quality (Brown et al., 2016). Using administrative data, coworker-based referral measures similarly predict destination choices and wage outcomes (Hensvik and Skans, 2016), and recent evidence on recruiting former coworkers to new firms finds sizeable entry wage premia for former coworkers relative to other hires (Muendler et al., 2024).

Our finding that the existence of high-quality former peers in the destination-firm is associated with a larger destination-wage premium is also consistent with theories in which referrals differ in informational content. In the Montgomery (1991) framework, firms optimally place greater weight on referrals originating from more productive incumbents because

their networks are more likely to contain workers of higher unobserved ability. Such referrals can therefore affect both hiring decisions and wage setting at entry (Hensvik & Skans, 2016; Montgomery, 1991). More generally, high-quality former coworkers may provide more informative signals about vacancies, facilitate access to more desirable employers, or strengthen workers' bargaining positions during the hiring process, among others discussed in the theoretical section.

While these mechanisms are consistent with the empirical patterns documented in Table 11, the estimates reported here do not distinguish among them. In particular, the observed wage premium could reflect differences in permanent worker heterogeneity, destination-firm wage policies, occupational sorting, or genuine improvements in match quality. The next subsection uses the decomposition proposed by Gelbach (2016), where we quantify the extent to which the estimated peer-linked mobility association with higher destination wages is accounted for by permanent worker heterogeneity, destination-firm wage premiums, and occupation wage premiums before turning to the broader question of assortative matching between workers and firms.

## 6.6 Explaining the Wage Premium Associated with High-Quality Former Peers

The previous subsection established that workers who move to firms employing former coworkers earn higher wages upon entry, particularly when at least one of those former coworkers is classified as high-quality. While these results are consistent with the idea that peer networks facilitate access to better labor-market opportunities, they do not reveal the source of the observed wage premium. In particular, the premium may arise because peer-linked movers differ systematically in permanent productivity, because they sort into firms paying systematically higher wages, because they enter better-paying occupations, or because peer networks improve match quality through mechanisms not captured by these dimensions. To examine this issue, we apply the decomposition proposed by Gelbach (2016). The method

exploits the omitted-variable-bias identity to partition the change in a coefficient after introducing additional regressors into the contribution of each newly added variable. Unlike sequential decompositions, the Gelbach decomposition is invariant to the order in which controls are introduced. Here, the decomposition compares the preferred wage specification in Table 11 with an otherwise identical specification that excludes the worker, firm, and occupation wage components obtained from the AKM decomposition.

Let,

$$\widehat{\beta}^{U} - \widehat{\beta}^{R} = -\sum_{k} \widehat{\Gamma}_{k} \widehat{\delta}_{k} \tag{51}$$

where $\widehat{\beta}^{R}$ and $\widehat{\beta}^{U}$ denote the coefficients from the restricted and the unrestricted specifications, respectively. The term $\widehat{\delta}_{k}$ is the coefficient on the $k$-th wage component in the unrestricted regression, while $\widehat{\Gamma}_{k}$ measures the conditional association between the peer variable and that wage component after partialling out all regressors included in the restricted specification. A positive contribution therefore means that adding the relevant wage component increases the estimated peer coefficient, while a negative contribution means that it reduces the coefficient.

Table 12 reports the decomposition for three related estimands. The first column considers the ordinary-peer destination, i.e., a firm employing at least one former peer but no high-quality former peer. The second column considers the incremental association with the presence of at least one high-quality former peer, conditional on ordinary-peer presence. The third column reports the total association with a high-quality-peer destination, equal to the sum of the ordinary-peer and incremental high-quality-peer coefficients.

The results from the Gelbach decomposition reveal that the worker, firm, and occupation wage components play markedly different roles depending on the type of peer relationship considered. For moves into ordinary-peer destinations, introducing the AKM wage components produces only a modest reduction in the estimated wage premium, namely from 0.80% to 0.63%. However, this comparatively small net change masks sizable offsetting effects. Con-

trolling for the worker wage component increases the estimated premium by approximately 1.16 percentage points, whereas controlling for the destination-firm wage component reduces it by approximately 1.40 percentage points. The occupation wage component contributes only 0.07 percentage points. These results indicate that workers who move to ordinary-peer destinations tend to have lower estimated worker wage components, conditional on the other controls. However, the same workers end up in firms with higher estimated firm wage components, i.e., firms paying better, all else equal.

Table 12: Decomposition of destination wage premia associated with former coworkers

| | Ordinary-peer destination | Incremental HQ-peer association | Total HQ-peer association |
|---|---|---|---|
| Unrestricted model: with AKM components | 0.6329 | 0.3339 | 0.9668 |
| Restricted model: without AKM components | 0.7972 | -1.0579 | -0.2607 |
| **Change** | **-0.1643** | **1.3918** | **1.2275** |
| *Contribution to the change* | | | |
| Worker wage component | 1.1637 | -1.6545 | -0.4908 |
| Firm wage component | -1.4007 | 2.1527 | 0.7520 |
| Occupation wage component | 0.0727 | 0.8936 | 0.9664 |
| **Sum of contributions** | **-0.1643** | **1.3918** | **1.2275** |

*Notes:* The first column reports the decomposition of the estimated wage premium associated with moving to a destination firm employing at least one ordinary former peer but no high-quality former peer. The second column reports the incremental association with the presence of at least one high-quality former peer. The third column reports the total association with a high-quality-peer destination, equal to the sum of the coefficients on *Peer exists* and *High-quality peer exists*. The restricted model excludes the AKM-estimated worker, firm, and occupation wage components, while the unrestricted model includes them and corresponds to the preferred wage specification in Table 11. All coefficient changes and component contributions are defined as the unrestricted minus the restricted models estimates. A positive contribution means that adding the relevant component increases the estimated association, whereas a negative contribution means that it reduces it. The decomposition follows Gelbach (2016). Entries have been multiplied by 100 and can be interpreted approximately as percentage differences in wages. Minor discrepancies may arise from rounding.

The pattern is different for moves to high-quality-peer destinations. The total wage association changes from $-0.26\%$ in the short model to $0.97\%$ in the full model. The firm and

occupation wage components increase the coefficient by 0.75 and 0.97 percentage points, respectively, while the worker component reduces it by 0.49 percentage points. These results imply that relative to no-peer destinations, and conditional on the controls in the restricted model, these movers have higher worker wage components, but enter firms and occupations with lower estimated wage components.

One possible interpretation is that the presence of a high-quality former coworker makes destinations with otherwise less favorable wage characteristics more attractive. At the same time, the positive residual wage premium indicates that these workers earn more than would be predicted from their own, the firm's, and the occupation's additive wage components. The decomposition is therefore consistent both with workers valuing the peer relationship itself and with former peers helping them obtain relatively favorable terms within otherwise lower-paying firms or occupations.

## 6.7 Wage sorting

The previous subsection showed that the wage premium associated with peer-linked mobility cannot be fully explained by permanent worker heterogeneity or by the additive worker, firm and occupation wage components obtained from the AKM decomposition. An important remaining question is therefore whether peer-linked mobility is associated with better worker–firm matches more generally. Examining assortative matching between worker and firm wage components may provide a complementary perspective on this broader allocation mechanism.

A large theoretical and empirical literature predicts that search frictions, heterogeneous workers and heterogeneous firms generate positive assortative matching, whereby more productive workers disproportionately match with more productive firms (e.g., Shimer, 2005 or Eeckhout and Kircher, 2011). Search frictions, imperfect information, and referral networks may further strengthen this relationship if they facilitate better matches between workers and firms. We thus examine whether peer-linked mobility is associated with stronger as-

sortative matching in wage components. The analysis is descriptive and is not intended to identify a causal effect of peer networks on sorting. Rather, it documents whether workers moving through former coworkers are systematically observed in better worker-firm matches. Let $\widehat{\alpha}_i$ denote the worker wage component and $\widehat{\psi}_f$ the firm wage component obtained from the AKM decomposition described in Section 5.1. For each year $t$, we compute the unweighted correlation

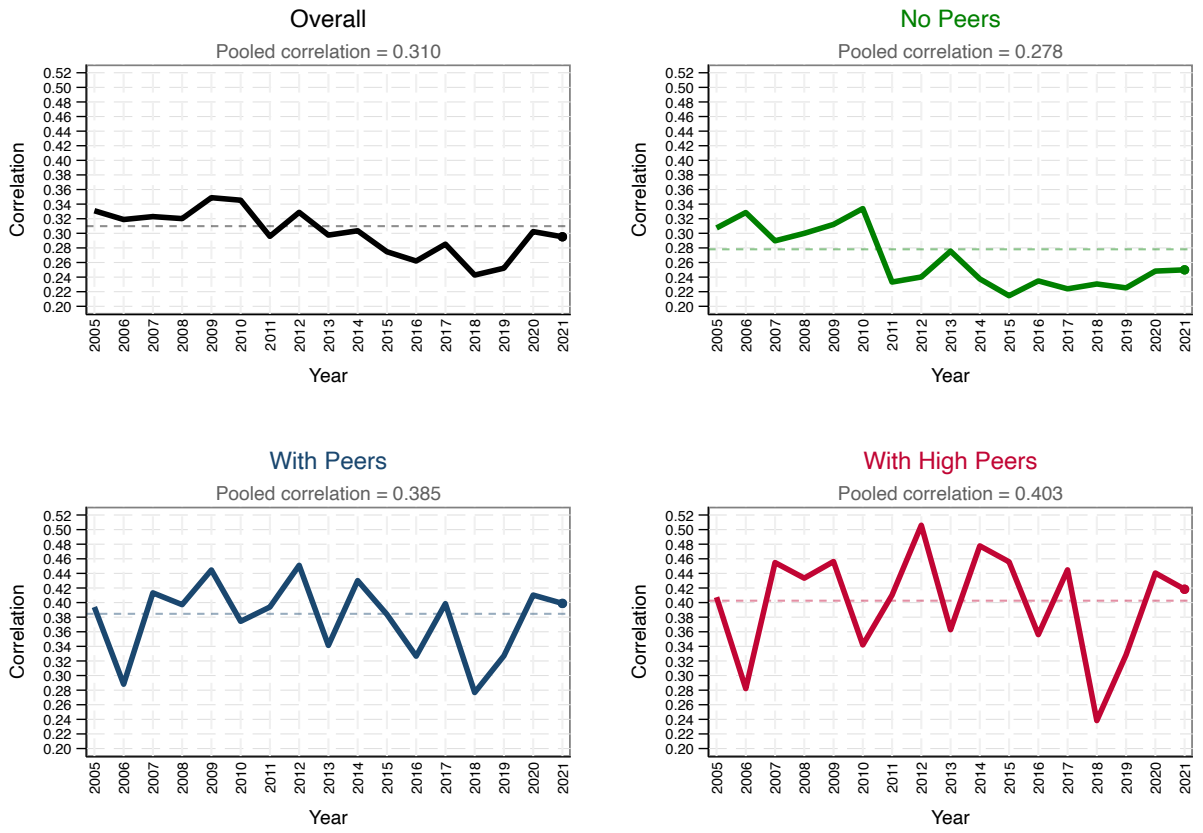
$$\rho_t = \text{Corr}\left(\widehat{\alpha}_i, \widehat{\psi}_{f(i,t)}\right)$$

where $f(i,t)$ denotes worker $i$'s employer in year $t$. Figure 5 reports the annual correlations together with pooled correlations obtained across all years.

The overall correlation between worker and firm wage components is approximately 0.31, indicating a moderate degree of positive assortative matching in the Portuguese labor market. This estimate is somewhat larger than the correlation reported by Torres et al. (2013) for Portugal (approximately 0.27) and broadly consistent with the moderate sorting typically documented in matched employer–employee data once search frictions and bargaining are taken into account. Because these correlations are computed mechanically from estimated wage components, however, they should be interpreted as descriptive summaries of worker–firm sorting rather than structural parameters.

Conditioning on whether the destination firm employs the mover's former coworkers reveals substantial heterogeneity in assortative matching. When movers join firms employing no former peers, the pooled correlation equals approximately 0.28. In contrast, the correlation rises to approximately 0.39 when the destination employs at least one former coworker and increases further to roughly 0.40 when at least one former coworker is classified as high-quality. Figure 5 shows that these differences are remarkably persistent over time. In almost every year of the sample, destinations employing former coworkers exhibit systematically stronger worker–firm sorting than destinations without former coworkers, with the strongest sorting observed when high-quality former coworkers are present.

Figure 5: Wage Sorting




Note: The dashed lines correspond to the annual correlations between firm and worker fixed effects calculated as a weighted average across all years. The black dashed line corresponds to the overall correlation calculated over the whole period in our sample. The full lines correspond to the actual correlations for the year in question.

These findings naturally complement the decomposition presented in the previous subsection where we showed that the wage premium associated with high-quality former coworkers cannot be fully explained by permanent worker heterogeneity or by the additive worker, firm and occupation wage components. The evidence presented here suggests that peer-linked mobility is also associated with stronger assortative matching between workers and firms. In other words, workers following former coworkers, and especially high-quality former coworkers, are disproportionately observed in matches combining higher worker wage components

with higher firm wage components.

This pattern is consistent with several mechanisms emphasized in the literature on referrals and labor-market networks, already discussed in Section 3. Former coworkers may transmit valuable information about vacancies, working conditions or career opportunities, reducing search frictions and improving workers' ability to identify employers where they are a better fit. Alternatively, referrals may provide firms with more informative signals about applicants, allowing them to screen workers more effectively and allocate them to more productive matches. High-quality former coworkers may be particularly informative or influential referrers, consistent with the stronger assortative matching documented here (Brown et al., 2016; Dustmann et al., 2016; Hensvik & Skans, 2016; Montgomery, 1991). More broadly, these findings are also consistent with recent evidence that search frictions and information play an important role in shaping worker–firm matching and the allocation of talent across employers (Card et al., 2018; Lopes De Melo, 2018).

Two caveats should nevertheless be emphasized. First, the observed correlations are computed using realized matches and therefore conflate assortative matching with selection. Workers relying on former coworkers may differ systematically from other movers, and peer-linked mobility may target firms or occupations where sorting is stronger for reasons unrelated to peer networks. Second, conditioning on peer presence is endogenous, as firms attracting peer-linked movers may themselves differ in unobserved ways, including recruitment practices, internal labor markets or compensation policies. Consequently, Figure 5 should not be interpreted as causal evidence that peer networks improve assortative matching.

Taken together, the destination-choice, wage, decomposition, and assortative-matching results present a coherent descriptive pattern. Peer-linked moves are associated with greater destination choice probabilities, modestly higher entry wages, and stronger positive sorting between worker and firm wage components. These findings are consistent with peer networks facilitating access to different, and potentially better-aligned, worker-firm matches, but they

do not establish that peer links causally improve match quality.

# 7 Conclusion

This paper provides evidence that peer departures and former-peer links are closely related to both turnover and the focal worker's destination firm. Using matched employer-employee data from Quadros de Pessoal and a high-dimensional fixed-effects framework, we classify peer quality from worker fixed effects within firm × establishment × occupation × year cells and estimate two linked margins of mobility: (i) the decision to leave the current firm and (ii) the decision to join a particular destination. We supplement the peer measures with a PageRank-based measure of network centrality computed on a worker-year graph that combines within-firm coworker links and workers' employment histories.

Four findings stand out. First, coworker turnover raises the focal worker's move probability, and who leaves matters. Exits by high-quality peers increase that probability substantially, while exits by low-quality peers reduce it. In our preferred model, a one-percentage-point increase in peer-group turnover raises the move probability by 0.145 percentage points, a one-percentage-point increase in the high-quality share adds 0.079 percentage points, and a one-percentage-point increase in the low-quality share subtracts an almost symmetric 0.075 percentage points. These patterns survive rich covariates and controls for global and component-normalized PageRank, suggesting that they do not simply reflect differences in network centrality.

Second, destination choice is strongly tilted toward firms employing former peers. In our baseline model, a firm employing at least one non-high-quality former peer (and no high-quality one) has approximately 80.45 times the relative choice odds of a no-peer candidate, while a candidate firm with at least one high-quality former peer has 2.66 times the relative odds of a firm containing ordinary former peers only. The corresponding within-choice-set probability calculations imply an ordinary-peer effect of 22.70 percentage points and an addi-

tional high-quality-peer effect of 13.85 percentage points. The magnitude of these estimates reflects the unusually strong concentration of realized choices among peer-linked alternatives: when a choice set contains exactly one peer-linked candidate firm, that firm is selected in approximately 84.9% of cases.

Conditional on peer presence, a one-percentage-point increase in ordinary-peer share raises relative choice odds by approximately 20.8%. Holding total former-peer share fixed, however, replacing ordinary-peer share with high-quality-peer share lowers relative choice odds by approximately 10%. Increasing high-quality-peer share without displacing ordinary former peers remains positively associated with destination choice. The high-quality-peer advantage therefore appears to operate primarily through the presence of at least one salient high-quality contact rather than through a monotonically increasing high-quality share within a fixed-size peer network.

The heterogeneity results are consistent with this distinction. Workers with higher estimated worker quality rely less on peer-linked destinations and peer concentration overall. At the same time, their response to the high-quality composition of the peer network is more positive. There is therefore little evidence of homophily, namely that higher-quality workers place greater weight on the mere presence of a high-quality former peer. There is, however, some evidence of quality-related heterogeneity in how they respond to the composition of their peer exposure.

Third, former-peer links are associated with modest but statistically significant entry-wage premia at the destination. Compared to a no-peer situation, the presence of any former peer is associated with an entry wage that is approximately 0.63% higher, while the presence of at least one high-quality former peer adds approximately 0.33%, bringing the total premium to roughly 0.97%. The Gelbach decomposition shows that these wage differences cannot be summarized as simple sorting on permanent worker quality. For the any-peer premium, the modest net attenuation after including the worker, firm, and occupation wage components masks sizable offsetting contributions from worker and firm heterogeneity. For the

total high-quality-peer premium, controlling for the additive wage components makes the estimated association larger rather than smaller. The high-quality-peer premium is therefore not mechanically generated by higher-paid workers following one another or by simple additive sorting into higher-paying firms and occupations.

Fourth, wage sorting is substantially higher when former peers, especially high-quality former peers, are present at the destination. The unweighted correlation is 0.310 overall, 0.278 when no former peers are present, 0.385 when any former peer is present, and 0.403 when at least one high-quality former peer is present. This descriptive exercise is consistent with peer-linked moves being disproportionately associated with matches between higher-worker-component workers and higher-firm-component firms.

We refrain from causal language throughout the paper. Correlated shocks at the peer-group or firm-year level remain possible even after the sample restrictions, covariates, candidate-firm controls, and PageRank measures. The origin-side robustness checks produce two relevant results. First, when the sample is restricted to firms for which future turnover can be observed, the coefficients on lagged peer turnover and the composition of leavers remain stable, indicating that the main findings are not driven by the change in sample composition. Second, future peer-group turnover also predicts current mobility, which is consistent with persistent or anticipated workplace shocks. Its coefficients are, however, materially smaller than those on lagged peer-group turnover. We therefore interpret the turnover results as robust reduced-form evidence that peer-group exits are strongly associated with subsequent worker mobility, while recognizing that some part of the relationship may reflect broader workplace instability rather than a purely contemporaneous peer effect.

For firms, the results are practically consequential. The marginal peer who exits is not average: departures by high-quality coworkers are associated with disproportionately large increases in the mobility of those who remain. Retention policies focused on high-quality employees may therefore have second-order effects by limiting subsequent peer-linked turnover. On the recruitment side, firms employing former coworkers appear substantially more likely

to attract additional workers from the same prior networks. The destination results also suggest a distinction between the presence and composition of these links. Having at least one high-quality former coworker is strongly associated with destination choice, but increasing the high-quality share of a fixed-size peer network does not generate a further advantage. Broader former-coworker reach and the presence of a salient high-quality contact appear to be different margins.

For policymakers, a network view helps rationalize why mobility and sorting can remain limited even in otherwise competitive labor markets. Information, trust, and referral channels travel through coworker ties whose quality, concentration, and network position vary markedly. Policies or institutions that affect labor-market information and access to vacancies may therefore have heterogeneous effects depending on the workplace networks through which that information travels.

Four margins deserve further attention:

(i) **Timing and dynamics.** We aggregate peer exits between $t-2$ and $t-1$ to predict moves in $t$. More granular data would allow sharper event-study designs and more direct tests of diffusion and decay following the first departure.

(ii) **Mechanisms and consideration sets.** Distinguishing information transmission from workplace amenities, morale, referrals, and production complementarities would benefit from data on vacancies, applications, referral records, and team production. Such information would also permit a more direct measurement of the firms workers genuinely consider before moving.

(iii) **Heterogeneity.** The present results show that higher-quality workers rely less on peer-linked destinations overall but respond more positively to the quality composition of their peer networks. Extending this analysis across occupations, tenure groups, firm sizes, and local labor markets would help identify where peer presence, peer concentration, and peer quality matter most.

(iv) **Peer dynamics.** Extending the model to include peers that departed before $t-2$ would yield insights into how quickly the effect on turnover decisions decays. It would, however, seriously constrain the final sample.

Overall, the results indicate that, in a national administrative setting, coworker links are strongly associated with both the decision to leave and the destination chosen conditional on moving. Accounting for peer rank, network position, candidate-firm hiring and occupational composition, and the internal structure of the choice set helps clarify why these relationships vary across workers and destinations. The evidence does not isolate a single mechanism, but it consistently points to workplace networks as an important part of labor-market retention, reallocation, and matching.

# Tables

Table 1A: Probability that worker $i$ moved to a new firm in year $t$ (cloglog coefficients)

| | Dependent variable: $\mathbb{1}\{move_{i,t}\}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Turnover$_{t-1}$ (%) | 0.0870*** | 0.0764*** | 0.0967*** | 0.0854*** | 0.0749*** | 0.0654*** | 0.0840*** | 0.0739*** |
| | (0.0001) | (0.0002) | (0.0002) | (0.0003) | (0.0001) | (0.0002) | (0.0002) | (0.0003) |
| High-quality peers$_{t-1}$ (%) | | 0.0511*** | | 0.0395*** | | 0.0466*** | | 0.0359*** |
| | | (0.0006) | | (0.0007) | | (0.0006) | | (0.0007) |
| Low-quality peers$_{t-1}$ (%) | | | -0.0535*** | -0.0364*** | | | -0.0500*** | -0.0347*** |
| | | | (0.0008) | (0.0008) | | | (0.0008) | (0.0008) |
| Male | | | | | 0.1537*** | 0.1518*** | 0.1525*** | 0.1515*** |
| | | | | | (0.0040) | (0.0040) | (0.0040) | (0.0040) |
| Age$_{t-1}$ | | | | | -0.0116*** | -0.0119*** | -0.0120*** | -0.0121*** |
| | | | | | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| Tenure$_{t-1}$ | | | | | -0.0107*** | -0.0106*** | -0.0106*** | -0.0106*** |
| | | | | | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Log (wage)$_{t-1}$ | | | | | 0.3926*** | 0.3949*** | 0.3868*** | 0.3904*** |
| | | | | | (0.0078) | (0.0077) | (0.0077) | (0.0077) |
| Log (wage)$^2{}_{t-1}$ | | | | | -0.0755*** | -0.0732*** | -0.0717*** | -0.0711*** |
| | | | | | (0.0038) | (0.0038) | (0.0038) | (0.0038) |
| Log (firm size)$_{t-1}$ | | | | | -0.0012 | 0.0008 | 0.0030*** | 0.0031*** |
| | | | | | (0.0011) | (0.0011) | (0.0011) | (0.0011) |
| **Controls:** | | | | | | | | |
| Education$_{t-1}$ | No | No | No | No | No | No | No | No |
| Firm sector$_{t-1}$ | No | No | No | No | No | No | No | No |
| Year$_t$ | No | No | No | No | No | No | No | No |
| **Page Rank Calculations:** | | | | | | | | |
| Global$_{t-1}$ | No | No | No | No | No | No | No | No |
| Components$_{t-1}$ | No | No | No | No | No | No | No | No |
| **Fixed Effects:** | | | | | | | | |
| Worker | No | No | No | No | No | No | No | No |
| Origin Firm | No | No | No | No | No | No | No | No |
| Origin Job Occupation | No | No | No | No | No | No | No | No |
| Constant | -4.1549*** | -4.1670*** | -4.1650*** | -4.1733*** | -3.1740*** | -3.1926*** | -3.1942*** | -3.2016*** |
| | (0.0023) | (0.0023) | (0.0023) | (0.0023) | (0.0101) | (0.0102) | (0.0101) | (0.0102) |
| Observations | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 |
| Nonzero outcomes | 309,757 | 309,757 | 309,757 | 309,757 | 309,757 | 309,757 | 309,757 | 309,757 |

*Notes:* The unit of observation is a worker-year. The dependent variable equals one if worker $i$ is observed working at a different firm in year $t$ than in year $t-1$, and zero otherwise. The table reports complementary log-log coefficients, not marginal effects. The peer group is defined in $t-2$ as workers in the same firm × establishment × occupation × year cell, excluding worker $i$. Turnover$_{t-1}$ is the percentage of this predetermined peer group that leaves the origin firm between $t-2$ and $t-1$. High-quality peers$_{t-1}$ and low-quality peers$_{t-1}$ are the percentages of the same predetermined peer group that leave and are classified, respectively, in the top and bottom quintiles of the worker fixed-effect distribution within the $t-2$ peer cell. Because these variables are expressed in percentage points, a one-unit change corresponds to a one-percentage-point increase. Worker and firm controls are measured in $t-1$. This table reports specifications without education controls, firm-sector controls, year effects, PageRank controls, or fixed effects, as indicated in the rows above. Standard errors, clustered at the $t-1$ peer-group level, are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 1B: Probability that worker $i$ moved to a new firm in year $t$ (cloglog coefficients)

| Dependent variable: $\mathbb{1}\{move_{i,t}\}$ | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Turnover$_{t-1}$ (%) | 0.0686*** | 0.0593*** | 0.0775*** | 0.0675*** | 0.0588*** | 0.0625*** | 0.0774*** | 0.0672*** | 0.0684*** | 0.0588*** | 0.0773*** | 0.0672*** |
| | (0.0006) | (0.0007) | (0.0008) | (0.0009) | (0.0006) | (0.0007) | (0.0008) | (0.0010) | (0.0006) | (0.0007) | (0.0008) | (0.0010) |
| High-qual. peers$_{t-1}$ (%) | | 0.0454*** | | 0.0351*** | | 0.0464*** | | 0.0358*** | | 0.0463*** | | 0.0357*** |
| | | (0.0021) | | (0.0021) | | (0.0021) | | (0.0022) | | (0.0021) | | (0.0022) |
| Low-qual. peers$_{t-1}$ (%) | | | -0.0485*** | -0.0335*** | | | -0.0496*** | -0.0342*** | | | -0.0494*** | -0.0341*** |
| | | | (0.0030) | (0.0030) | | | (0.0030) | (0.0031) | | | (0.0030) | (0.0031) |
| Male | 0.1534*** | 0.1522*** | 0.1512*** | 0.1510*** | 0.1530*** | 0.1517*** | 0.1506*** | 0.1505*** | 0.1532*** | 0.1519*** | 0.1508*** | 0.1507*** |
| | (0.0091) | (0.0092) | (0.0091) | (0.0092) | (0.0092) | (0.0092) | (0.0091) | (0.0092) | (0.0091) | (0.0092) | (0.0091) | (0.0092) |
| Age$_{t-1}$ | -0.0166*** | -0.0169*** | -0.0169*** | -0.0171*** | -0.0167*** | -0.0170*** | -0.0171*** | -0.0172*** | -0.0167*** | -0.0170*** | -0.0171*** | -0.0172*** |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Tenure$_{t-1}$ | -0.0087*** | -0.0087*** | -0.0087*** | -0.0087*** | -0.0087*** | -0.0087*** | -0.0087*** | -0.0087*** | -0.0087*** | -0.0087*** | -0.0087*** | -0.0087*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Log (wage)$_{t-1}$ | -0.1312*** | -0.1178*** | -0.1291*** | -0.1191*** | -0.1356*** | -0.1222*** | -0.1336*** | -0.1236*** | -0.1381*** | -0.1248*** | -0.1361*** | -0.1261*** |
| | (0.0220) | (0.0218) | (0.0217) | (0.0217) | (0.0220) | (0.0218) | (0.0217) | (0.0217) | (0.0220) | (0.0218) | (0.0217) | (0.0216) |
| Log (wage)$^2{}_{t-1}$ | 0.0686*** | 0.0678*** | 0.0700*** | 0.0689*** | 0.0696*** | 0.0688*** | 0.0711*** | 0.0700*** | 0.0702*** | 0.0694*** | 0.0717*** | 0.0706*** |
| | (0.0073) | (0.0073) | (0.0072) | (0.0072) | (0.0073) | (0.0072) | (0.0072) | (0.0072) | (0.0073) | (0.0072) | (0.0071) | (0.0071) |
| Log (firm size)$_{t-1}$ | -0.0192*** | -0.0171*** | -0.0150*** | -0.0149*** | -0.0332*** | -0.0318*** | -0.0296*** | -0.0297*** | -0.0340*** | -0.0326*** | -0.0303*** | -0.0304*** |
| | (0.0042) | (0.0041) | (0.0041) | (0.0041) | (0.0044) | (0.0043) | (0.0043) | (0.0043) | (0.0044) | (0.0043) | (0.0043) | (0.0043) |
| **Controls:** | | | | | | | | | | | | |
| Education$_{t-1}$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm sector$_{t-1}$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year$_t$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **Page Rank Calculations:** | | | | | | | | | | | | |
| Global$_{t-1}$ | No | No | No | No | Yes | Yes | Yes | Yes | No | No | No | No |
| Components$_{t-1}$ | No | No | No | No | No | No | No | No | Yes | Yes | Yes | Yes |
| **Fixed Effects:** | | | | | | | | | | | | |
| Worker | No | No | No | No | No | No | No | No | No | No | No | No |
| Origin Firm | No | No | No | No | No | No | No | No | No | No | No | No |
| Origin Job Occupation | No | No | No | No | No | No | No | No | No | No | No | No |
| Constant | -5.2326*** | -5.2376*** | -5.2489*** | -5.2467*** | -5.1020*** | -5.0997*** | -5.1123*** | -5.1071*** | -5.0937*** | -5.0914*** | -5.1041*** | -5.0989*** |
| | (0.7055) | (0.7060) | (0.7045) | (0.7053) | (0.7063) | (0.7069) | (0.7053) | (0.7062) | (0.7064) | (0.7070) | (0.7053) | (0.7062) |
| Observations | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 |
| Nonzero outcomes | 309,757 | 309,757 | 309,757 | 309,757 | 309,757 | 309,757 | 309,757 | 309,757 | 309,757 | 309,757 | 309,757 | 309,757 |

*Notes:* The unit of observation is a worker-year. The dependent variable equals one if worker $i$ is observed working at a different firm in year $t$ than in year $t-1$, and zero otherwise. The table reports complementary log-log coefficients, not marginal effects. Peer variables are constructed from the predetermined $t-2$ firm × establishment × occupation × year cell, excluding worker $i$, and measure peer departures between $t-2$ and $t-1$. Turnover, high-quality peers, and low-quality peers are expressed in percentage points. High-quality and low-quality peers are classified using the top and bottom quintiles of worker fixed-effect rank within the $t-2$ peer cell. Columns (5)–(8) add global PageRank controls, and columns (9)–(12) add component-normalized PageRank controls. Standard errors, clustered at the $t-1$ peer-group level, are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 1C: Probability that worker $i$ moved to a new firm in year $t$ (cloglog coefficients)

| Dependent variable: $\mathbb{1}\{move_{i,t}\}$ | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Turnover$_{t-1}$ (%) | 0.0685*** | 0.0588*** | 0.0777 *** | 0.0674*** |
| | (0.0006) | (0.0007) | (0.0008) | (0.0096) |
| High-qual. peers$_{t-1}$ (%) | | 0.0474*** | | 0.0366*** |
| | | (0.0021) | | (0.0022) |
| Low-qual. peers$_{t-1}$ (%) | | | -0.0505*** | -0.0348*** |
| | | | (0.0030) | (0.0030) |
| Male | 0.1191*** | 0.1163*** | 0.1157*** | 0.1147*** |
| | (0.0089) | (0.0090) | (0.0089) | (0.0090) |
| Age$_{t-1}$ | -0.0047*** | -0.0045*** | -0.0048*** | -0.0046*** |
| | (0.0009) | (0.0009) | (0.0009) | (0.0008) |
| Tenure$_{t-1}$ | -0.0088*** | -0.0087*** | -0.0087*** | -0.0087*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Log (wage)$_{t-1}$ | -0.3239*** | -0.3210*** | -0.3271*** | -0.3235*** |
| | (0.0300) | (0.0298) | (0.0297) | (0.0297) |
| Log (wage)$^2{}_{t-1}$ | 0.0525*** | 0.0516*** | 0.0539*** | 0.0526*** |
| | (0.0081) | (0.0081) | (0.0080) | (0.0080) |
| Log (firm size)$_{t-1}$ | -0.0274*** | -0.0259*** | -0.0237*** | -0.0237*** |
| | (0.0044) | (0.0043) | (0.0043) | (0.0043) |
| **Controls:** | | | | |
| Education$_{t-1}$ | Yes | Yes | Yes | Yes |
| Firm sector$_{t-1}$ | Yes | Yes | Yes | Yes |
| Year$_t$ | Yes | Yes | Yes | Yes |
| **Page Rank Calculations:** | | | | |
| Global$_{t-1}$ | Yes | Yes | Yes | Yes |
| Components$_{t-1}$ | No | No | No | No |
| **Fixed Effects:** | | | | |
| Worker | Yes | Yes | Yes | Yes |
| Origin Firm | Yes | Yes | Yes | Yes |
| Origin Job Occupation | Yes | Yes | Yes | Yes |
| Constant | -4.6560*** | -4.6362*** | -4.6527*** | -4.638*** |
| | (0.7107) | (0.7117) | (0.7098) | (0.7110) |
| Observations | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 |
| Nonzero outcomes | 309,757 | 309,757 | 309,757 | 309,757 |

*Notes:* The unit of observation is a worker-year. The dependent variable equals one if worker $i$ is observed working at a different firm in year $t$ than in year $t-1$, and zero otherwise. The table reports complementary log-log coefficients, not marginal effects. The peer group is defined in $t-2$ as workers in the same firm × establishment × occupation × year cell, excluding worker $i$. Turnover$_{t-1}$, high-quality peers$_{t-1}$, and low-quality peers$_{t-1}$ are measured from peer departures between $t-2$ and $t-1$. The high- and low-quality classifications are based on quintiles of the worker fixed-effect distribution within the predetermined $t-2$ peer cell. All peer variables are expressed in percentage points. Worker and firm controls are measured in $t-1$. All specifications include education controls, firm-sector controls, year effects, global PageRank controls, worker fixed effects, origin-firm fixed effects, and origin job-occupation fixed effects, as indicated in the rows above. Standard errors, clustered at the $t-1$ peer-group level, are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 1D: Probability that worker $i$ moved to a new firm in year $t$ (cloglog coefficients)

| Dependent variable: $\mathbb{1}\{move_{i,t}\}$ | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Turnover$_{t-1}$ (%) | 0.0674*** | 0.0674*** | 0.0674*** | 0.0674*** | 0.0674*** |
| | (0.0096) | (0.0096) | (0.0096) | (0.0004) | (0.0029) |
| High-qual. peers$_{t-1}$ (%) | 0.0366*** | 0.0366*** | 0.0367*** | 0.0366*** | 0.0366*** |
| | (0.0022) | (0.0022) | (0.0022) | (0.0010) | (0.0024) |
| Low-qual. peers$_{t-1}$ (%) | -0.0348*** | -0.0348*** | -0.0347*** | -0.0348*** | -0.0348*** |
| | (0.0030) | (0.0030) | (0.0030) | (0.0014) | (0.0038) |
| Male | 0.1147*** | 0.1148*** | 0.1009*** | 0.1147*** | 0.1147*** |
| | (0.0090) | (0.0090) | (0.0090) | (0.0052) | (0.0153) |
| Age$_{t-1}$ | -0.0046*** | -0.0046*** | -0.0107*** | -0.0046*** | -0.0046*** |
| | (0.0008) | (0.0009) | (0.0006) | (0.0005) | (0.0013) |
| Tenure$_{t-1}$ | -0.0087*** | -0.0087*** | -0.0089*** | -0.0087*** | -0.0087*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0000) | (0.0004) |
| Log (wage)$_{t-1}$ | -0.3235*** | -0.3231*** | — | -0.3235*** | -0.3235*** |
| | (0.0297) | (0.0292) | | (0.0153) | (0.0649) |
| Log (wage)$^2_{t-1}$ | 0.0526*** | 0.0527*** | — | 0.0526*** | 0.0526*** |
| | (0.0080) | (0.0079) | | (0.0044) | (0.0171) |
| Log (firm size)$_{t-1}$ | -0.0237*** | -0.0237*** | -0.0237*** | -0.0237*** | -0.0237* |
| | (0.0043) | (0.0043) | (0.0043) | (0.0013) | (0.0136) |
| **Controls:** | | | | | |
| Education$_{t-1}$ | Yes | Yes | Yes | Yes | Yes |
| Firm sector$_{t-1}$ | Yes | Yes | Yes | Yes | Yes |
| Year$_t$ | Yes | Yes | Yes | Yes | Yes |
| **Page Rank Calculations:** | | | | | |
| Global$_{t-1}$ | Yes | Yes | Yes | Yes | Yes |
| Components$_{t-1}$ | No | No | No | No | No |
| **Fixed Effects:** | | | | | |
| Worker | Yes | Yes | Yes | Yes | Yes |
| Origin Firm | Yes | Yes | Yes | Yes | Yes |
| Origin Job Occupation | Yes | No | Yes | Yes | Yes |
| Constant | -4.638*** | -4.6382*** | -4.7077*** | -4.638*** | -4.638*** |
| | (0.7110) | (0.7109) | (0.7102) | (0.7016) | (0.2057) |
| Observations | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 |
| Nonzero outcomes | 309,757 | 309,757 | 309,757 | 309,757 | 309,757 |

*Notes:* The unit of observation is a worker-year. The dependent variable equals one if worker $i$ is observed working at a different firm in year $t$ than in year $t-1$, and zero otherwise. The table reports complementary log-log coefficients, not marginal effects. Peer variables are constructed from the predetermined $t-2$ peer group and measure departures between $t-2$ and $t-1$. Turnover$_{t-1}$ is the percentage of peers leaving the origin firm. High-quality peers$_{t-1}$ and low-quality peers$_{t-1}$ are the percentages of departing peers classified, respectively, in the top and bottom quintiles of the worker fixed-effect distribution within the $t-2$ peer cell. Column (1) reproduces column (4) of Table 1C. Column (2) removes origin job-occupation fixed effects. Column (3) removes lagged log wage and lagged squared log wage. Columns (4) and (5) reproduce the benchmark specification with standard errors clustered, respectively, at the individual and origin-firm levels. Unless otherwise indicated, standard errors are clustered at the $t-1$ peer-group level and are reported in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 1E: Probability that worker $i$ moved to a new firm in year $t$ (cloglog coefficients)

| Dependent variable: $\mathbb{1}\{move_{i,t}\}$ | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Turnover$_{t-1}$ (%) | 0.0674*** | 0.0663*** | | |
| | (0.0096) | (0.0010) | | |
| High-qual. peers$_{t-1}$ (%) | 0.0366*** | 0.0370*** | | |
| | (0.0022) | (0.0024) | | |
| Low-qual. peers$_{t-1}$ (%) | -0.0348*** | -0.0323*** | | |
| | (0.0030) | (0.0032) | | |
| Turnover$_{t+1}$ (%) | | | 0.0154*** | 0.0173*** |
| | | | (0.0015) | (0.0005) |
| High-qual. peers$_{t+1}$ (%) | | | 0.0045 | 0.0047*** |
| | | | (0.0031) | (0.0013) |
| Low-qual. peers$_{t+1}$ (%) | | | -0.0139*** | -0.0135*** |
| | | | (0.0043) | (0.0016) |
| Peersize$_{t-1}$ | | | | -0.0004*** |
| | | | | (0.0001) |
| Turnover$_{t+1}$ (%) $\times$ Peersize$_{t-1}$ | | | | -0.0000*** |
| | | | | (0.0000) |
| Male | 0.1147*** | 0.1106*** | 0.0292*** | 0.0582*** |
| | (0.0090) | (0.0100) | (0.0010) | (0.0046) |
| Age$_{t-1}$ | -0.0046*** | -0.0036*** | -0.0133*** | -0.0131*** |
| | (0.0008) | (0.0009) | (0.0010) | (0.0004) |
| Tenure$_{t-1}$ | -0.0087*** | -0.0087*** | -0.0126*** | -0.0126*** |
| | (0.0001) | (0.0002) | (0.0002) | (0.0000) |
| Log (wage)$_{t-1}$ | -0.3235*** | -0.3388*** | -0.5503*** | -0.5413*** |
| | (0.0297) | (0.0325) | (0.0333) | (0.0127) |
| Log (wage)$^2{}_{t-1}$ | 0.0526*** | 0.0527*** | 0.1229*** | 0.1193*** |
| | (0.0080) | (0.0089) | (0.0077) | (0.0032) |
| Log (firm size)$_{t-1}$ | -0.0237*** | -0.0379*** | 0.0660*** | 0.1170*** |
| | (0.0043) | (0.0050) | (0.0062) | (0.0013) |
| **Controls:** | | | | |
| Education$_{t-1}$ | Yes | Yes | Yes | Yes |
| Firm sector$_{t-1}$ | Yes | Yes | Yes | Yes |
| Year$_t$ | Yes | Yes | Yes | Yes |
| **Page Rank Calculations:** | | | | |
| Global$_{t-1}$ | Yes | Yes | Yes | Yes |
| Components$_{t-1}$ | No | No | No | No |
| **Fixed Effects:** | | | | |
| Worker | Yes | Yes | Yes | Yes |
| Origin Firm | Yes | Yes | Yes | Yes |
| Origin Job Occupation | Yes | Yes | Yes | Yes |
| Constant | -4.638*** | -4.3937*** | -4.6774*** | -4.9891*** |
| | (0.7110) | (1.0826) | (1.1081) | (1.0009) |
| Observations | 11,187,776 | 9,167,906 | 9,167,906 | 9,167,906 |
| Nonzero outcomes | 309,757 | 258,218 | 258,218 | 258,218 |

*Notes:* The unit of observation is a worker-year. The dependent variable equals one if worker $i$ is observed working at a different firm in year $t$ than in year $t-1$, and zero otherwise. The table reports complementary log-log coefficients, not marginal effects. Column (1) reproduces column (4) of Table 1C. Columns (2)–(4) restrict the sample to observations for which future peer-group turnover can be observed. Baseline peer variables are constructed from the predetermined $t-2$ peer group and measure departures between $t-2$ and $t-1$. Future turnover variables are constructed as two-year leads of the baseline turnover variables to avoid overlap with the focal worker's own separation period. Peersize$_{t-1}$ is the size of the predetermined peer group. All specifications include education controls, firm-sector controls, year effects, global PageRank controls, worker fixed effects, origin-firm fixed effects, and origin job-occupation fixed effects. Standard errors, clustered at the $t-1$ peer-group level, are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 2A: Average Marginal Effects (multiplied by 100)

| Dependent variable: $\mathbb{1}\{move_{i,t}\}$ | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Turnover$_{t-1}$ (%) | 0.147*** | 0.127*** | 0.167*** | 0.145*** |
| | (0.001) | (0.001) | (0.001) | (0.002) |
| Share of high-quality peers$_{t-1}$ (%) | | 0.100*** | | 0.077*** |
| | | (0.004) | | (0.005) |
| Share of low-quality peers$_{t-1}$ (%) | | | -0.107*** | -0.074*** |
| | | | (0.007) | (0.007) |
| Male | 0.325*** | 0.322*** | 0.320*** | 0.320*** |
| | (0.019) | (0.019) | (0.019) | (0.019) |
| Age$_{t-1}$ | -0.036*** | -0.037*** | -0.037*** | -0.037*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Tenure$_{t-1}$ | -0.019*** | -0.019*** | -0.019*** | -0.019*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Log (wage)$_{t-1}$ | -0.292*** | -0.263*** | -0.288*** | -0.266*** |
| | (0.047) | (0.047) | (0.047) | (0.047) |
| Log (wage)$^2_{t-1}$ | 0.150*** | 0.148*** | 0.153*** | 0.151*** |
| | (0.016) | (0.016) | (0.015) | (0.015) |
| Log (firm size)$_{t-1}$ | -0.072*** | -0.069*** | -0.064*** | -0.064*** |
| | (0.009) | (0.009) | (0.009) | (0.009) |
| **Controls:** | | | | |
| Education$_{t-1}$ | Yes | Yes | Yes | Yes |
| Firm sector$_{t-1}$ | Yes | Yes | Yes | Yes |
| Year$_t$ | Yes | Yes | Yes | Yes |
| **Page Rank Calculations:** | | | | |
| Global$_{t-1}$ | Yes | Yes | Yes | Yes |
| Components$_{t-1}$ | No | No | No | No |
| **Fixed Effects:** | | | | |
| Worker | No | No | No | No |
| Origin Firm | No | No | No | No |
| Origin Job Occupation | No | No | No | No |
| Observations | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 |
| Nonzero outcomes | 309,757 | 309,757 | 309,757 | 309,757 |

*Notes:* The unit of observation is a worker-year. The dependent variable equals one if worker $i$ is observed working at a different firm in year $t$ than in year $t-1$, and zero otherwise. The table reports average marginal effects from complementary log-log models, multiplied by 100, so coefficients are in percentage points. Marginal effects are calculated using specifications (9)–(12) from Table 1B. The margins are calculated for each individual observation and then averaged over the estimation sample. Peer variables are constructed from the predetermined $t-2$ peer group and measure departures between $t-2$ and $t-1$. All peer variables are expressed in percentage points. Standard errors, clustered at the $t-1$ peer-group level, are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 2B: Average Marginal Effects (multiplied by 100)

| Dependent variable: $\mathbb{1}\{move_{i,t}\}$ | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Turnover$_{t-1}$ (%) | 0.148*** | 0.127*** | 0.167*** | 0.145*** |
| | (0.001) | (0.001) | (0.002) | (0.002) |
| High-qual. peers$_{t-1}$ (%) | | 0.102*** | | 0.079*** |
| | | (0.005) | | (0.005) |
| Low-qual. peers$_{t-1}$ (%) | | | -0.109*** | -0.075*** |
| | | | (0.007) | (0.007) |
| Male | 0.254*** | 0.248*** | 0.247*** | 0.245*** |
| | (0.019) | (0.019) | (0.019) | (0.019) |
| Age$_{t-1}$ | -0.010*** | -0.010*** | -0.010*** | -0.010*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Tenure$_{t-1}$ | -0.019*** | -0.019*** | -0.019*** | -0.019*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Log (wage)$_{t-1}$ | -0.697*** | -0.691*** | -0.704*** | -0.696*** |
| | (0.064) | (0.064) | (0.064) | (0.064) |
| Log (wage)$^2{}_{t-1}$ | 0.113*** | 0.111*** | 0.116*** | 0.113*** |
| | (0.017) | (0.017) | (0.017) | (0.017) |
| Log (firm size)$_{t-1}$ | -0.059*** | -0.056*** | -0.051*** | -0.051*** |
| | (0.009) | (0.009) | (0.009) | (0.009) |
| **Controls:** | | | | |
| Education$_{t-1}$ | Yes | Yes | Yes | Yes |
| Firm sector$_{t-1}$ | Yes | Yes | Yes | Yes |
| Year$_t$ | Yes | Yes | Yes | Yes |
| **Page Rank Calculations:** | | | | |
| Global$_{t-1}$ | Yes | Yes | Yes | Yes |
| Components$_{t-1}$ | No | No | No | No |
| **Fixed Effects:** | | | | |
| Worker | Yes | Yes | Yes | Yes |
| Origin Firm | Yes | Yes | Yes | Yes |
| Origin Job Occupation | Yes | Yes | Yes | Yes |
| Observations | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 |
| Nonzero outcomes | 309,757 | 309,757 | 309,757 | 309,757 |

*Notes:* The unit of observation is a worker-year. The dependent variable equals one if worker $i$ is observed working at a different firm in year $t$ than in year $t-1$, and zero otherwise. The table reports average marginal effects from complementary log-log models, multiplied by 100, so coefficients are in percentage points. Marginal effects are calculated using specifications (1)–(4) from Table 1C. The margins are calculated for each individual observation and then averaged over the estimation sample. Peer variables are constructed from the predetermined $t-2$ peer group and measure departures between $t-2$ and $t-1$. High-quality and low-quality peer variables are based on the top and bottom quintiles of worker fixed-effect ranks within the $t-2$ peer cell. All specifications include the controls and fixed effects indicated in the rows above. Standard errors, clustered at the $t-1$ peer-group level, are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 2C: Average Marginal Effects (multiplied by 100)

| Dependent variable: $\mathbb{1}\{move_{i,t}\}$ | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Turnover$_{t-1}$ (%) | 0.145*** | 0.145*** | 0.145*** | 0.145*** | 0.145*** |
| | (0.002) | (0.002) | (0.002) | (0.001) | (0.004) |
| High-qual. peers$_{t-1}$ (%) | 0.079*** | 0.079*** | 0.079*** | 0.079*** | 0.079*** |
| | (0.005) | (0.005) | (0.005) | (0.002) | (0.005) |
| Low-qual. peers$_{t-1}$ (%) | -0.075*** | -0.075*** | -0.075*** | -0.075*** | -0.075*** |
| | (0.007) | (0.007) | (0.007) | (0.003) | (0.008) |
| Male | 0.245*** | 0.245*** | 0.230*** | 0.245*** | 0.245*** |
| | (0.019) | (0.019) | (0.019) | (0.011) | (0.032) |
| Age$_{t-1}$ | -0.010*** | -0.010*** | -0.023*** | -0.010*** | -0.010*** |
| | (0.002) | (0.002) | (0.001) | (0.001) | (0.003) |
| Tenure$_{t-1}$ | -0.019*** | -0.019*** | -0.019*** | -0.019*** | -0.019*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| Log (wage)$_{t-1}$ | -0.696*** | -0.696*** | — | -0.696*** | -0.696*** |
| | (0.064) | (0.063) | | (0.033) | (0.136) |
| Log (wage)$^2_{t-1}$ (%) | 0.113*** | 0.113*** | — | 0.113*** | 0.113*** |
| | (0.017) | (0.017) | | (0.010) | (0.037) |
| Log (firm size)$_{t-1}$ (%) | -0.051*** | -0.051*** | -0.051*** | -0.051*** | -0.051* |
| | (0.009) | (0.009) | (0.009) | (0.003) | (0.029) |
| **Controls:** | | | | | |
| Education$_{t-1}$ | Yes | Yes | Yes | Yes | Yes |
| Firm sector$_{t-1}$ | Yes | Yes | Yes | Yes | Yes |
| Year$_t$ | Yes | Yes | Yes | Yes | Yes |
| **Page Rank Calculations:** | | | | | |
| Global$_{t-1}$ | Yes | Yes | Yes | Yes | Yes |
| Components$_{t-1}$ | No | No | No | No | No |
| **Fixed Effects:** | | | | | |
| Worker | Yes | Yes | Yes | Yes | Yes |
| Origin Firm | Yes | Yes | Yes | Yes | Yes |
| Origin Job Occupation | Yes | No | Yes | Yes | Yes |
| Observations | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 |
| Nonzero outcomes | 309,757 | 309,757 | 309,757 | 309,757 | 309,757 |

*Notes:* The unit of observation is a worker-year. The dependent variable equals one if worker $i$ is observed working at a different firm in year $t$ than in year $t-1$, and zero otherwise. The table reports average marginal effects from complementary log-log models, multiplied by 100, so coefficients are in percentage points. Marginal effects are calculated using specifications (1)–(5) from Table 1D. The margins are calculated for each individual observation and then averaged over the estimation sample. Column (1) reproduces the benchmark marginal effects from Table 1C, column (2) removes origin job-occupation fixed effects, column (3) removes lagged wage controls, and columns (4)–(5) use alternative clustering levels corresponding to Table 1D. Unless otherwise indicated, standard errors are clustered at the $t-1$ peer-group level and are reported in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 2D: Marginal Effects at the Mean (multiplied by 100)

| Dependent variable: $\mathbb{1}\{move_{i,t}\}$ | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | Average value |
| Turnover$_{t-1}$ (%) | 0.068*** | 0.058*** | 0.076*** | 0.066*** | 2.02 |
| | (0.001) | (0.001) | (0.001) | (0.001) | |
| Share of high-quality peers$_{t-1}$ (%) | | 0.046*** | | 0.035*** | 0.54 |
| | | (0.002) | | (0.002) | |
| Share of low-quality peers$_{t-1}$ (%) | | | -0.049*** | -0.034*** | 0.29 |
| | | | (0.003) | (0.003) | |
| Male | 0.150*** | 0.148*** | 0.147*** | 0.147*** | 0.56 |
| | (0.009) | (0.009) | (0.009) | (0.009) | |
| Age$_{t-1}$ | -0.017*** | -0.017*** | -0.017*** | -0.017*** | 39.2 |
| | (0.001) | (0.001) | (0.001) | (0.001) | |
| Tenure$_{t-1}$ | -0.009*** | -0.009*** | -0.009*** | -0.009*** | 122.4 |
| | (0.000) | (0.000) | (0.000) | (0.000) | |
| Log (wage)$_{t-1}$ | -0.134*** | -0.120*** | -0.132*** | -0.122*** | 0.64 |
| | (0.022) | (0.022) | (0.022) | (0.021) | |
| Log (wage)$^2{}_{t-1}$ | 0.069*** | 0.068*** | 0.069*** | 0.065*** | 0.79 |
| | (0.007) | (0.007) | (0.007) | (0.007) | |
| Log (firm size)$_{t-1}$ | -0.033*** | -0.031*** | -0.029*** | -0.029*** | 5.63 |
| | (0.004) | (0.004) | (0.004) | (0.004) | |
| **Controls:** | | | | | |
| Education$_{t-1}$ | Yes | Yes | Yes | Yes | |
| Firm sector$_{t-1}$ | Yes | Yes | Yes | Yes | |
| Year$_t$ | Yes | Yes | Yes | Yes | |
| **Page Rank Calculations:** | | | | | |
| Global$_{t-1}$ | Yes | Yes | Yes | Yes | |
| Components$_{t-1}$ | No | No | No | No | |
| **Fixed Effects:** | | | | | |
| Worker | No | No | No | No | |
| Origin Firm | No | No | No | No | |
| Origin Job Occupation | No | No | No | No | |
| Observations | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 | |
| Nonzero outcomes | 309,757 | 309,757 | 309,757 | 309,757 | |

*Notes:* The unit of observation is a worker-year. The dependent variable equals one if worker $i$ is observed working at a different firm in year $t$ than in year $t-1$, and zero otherwise. The table reports marginal effects from complementary log-log models, multiplied by 100, evaluated at the sample mean of each covariate rather than averaged over individual observations. Marginal effects are calculated using specifications (9)–(12) from Table 1B. The final column reports the sample mean of each variable used for the evaluation. Peer variables are constructed from the predetermined $t-2$ peer group and measure departures between $t-2$ and $t-1$. Standard errors, clustered at the $t-1$ peer-group level, are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 2E: Marginal Effects at the Mean (multiplied by 100)

| Dependent variable: $\mathbb{1}\{move_{i,t}\}$ | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | Average value |
| Turnover$_{t-1}$ (%) | 0.067*** | 0.058*** | 0.076*** | 0.066*** | 2.02 |
| | (0.001) | (0.001) | (0.001) | (0.001) | |
| Share of high-quality peers$_{t-1}$ (%) | | 0.046*** | | 0.036*** | 0.54 |
| | | (0.002) | | (0.002) | |
| Share of low-quality peers$_{t-1}$ (%) | | | -0.049*** | -0.034*** | 0.29 |
| | | | (0.003) | (0.003) | |
| Male | 0.116*** | 0.113*** | 0.113*** | 0.113*** | 0.56 |
| | (0.009) | (0.008) | (0.009) | (0.009) | |
| Age$_{t-1}$ | -0.005*** | -0.004*** | -0.005*** | -0.004*** | 39.2 |
| | (0.001) | (0.001) | (0.001) | (0.001) | |
| Tenure$_{t-1}$ | -0.009*** | -0.009*** | -0.009*** | -0.009*** | 122.4 |
| | (0.000) | (0.000) | (0.000) | (0.000) | |
| Log (wage)$_{t-1}$ | -0.319*** | -0.314*** | -0.321*** | -0.316*** | 0.64 |
| | (0.030) | (0.030) | (0.029) | (0.029) | |
| Log (wage)$^2{}_{t-1}$ | 0.052*** | 0.050*** | 0.053*** | 0.051*** | 0.79 |
| | (0.008) | (0.008) | (0.008) | (0.008) | |
| Log (firm size)$_{t-1}$ | -0.027*** | -0.025*** | -0.023*** | -0.023*** | 5.63 |
| | (0.004) | (0.004) | (0.004) | (0.004) | |
| **Controls:** | | | | | |
| Education$_{t-1}$ | Yes | Yes | Yes | Yes | |
| Firm sector$_{t-1}$ | Yes | Yes | Yes | Yes | |
| Year$_t$ | Yes | Yes | Yes | Yes | |
| **Page Rank Calculations:** | | | | | |
| Global$_{t-1}$ | Yes | Yes | Yes | Yes | |
| Components$_{t-1}$ | No | No | No | No | |
| **Fixed Effects:** | | | | | |
| Worker | Yes | Yes | Yes | Yes | |
| Origin Firm | Yes | Yes | Yes | Yes | |
| Origin Job Occupation | Yes | Yes | Yes | Yes | |
| Observations | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 | |
| Nonzero outcomes | 309,757 | 309,757 | 309,757 | 309,757 | |

*Notes:* The unit of observation is a worker-year. The dependent variable equals one if worker $i$ is observed working at a different firm in year $t$ than in year $t-1$, and zero otherwise. The table reports marginal effects from complementary log-log models, multiplied by 100, evaluated at the sample mean of each covariate rather than averaged over individual observations. Marginal effects are calculated using specifications (1)–(4) from Table 1C. The final column reports the sample mean of each variable used for the evaluation. Peer variables are constructed from the predetermined $t-2$ peer group and measure departures between $t-2$ and $t-1$. All specifications include the controls and fixed effects indicated in the rows above. Standard errors, clustered at the $t-1$ peer-group level, are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 2F: Marginal Effects at the Mean (multiplied by 100)

| Dependent variable: $\mathbb{1}\{move_{i,t}\}$ | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | Average value |
| Turnover$_{t-1}$ (%) | 0.066*** | 0.066*** | 0.066*** | 0.066*** | 0.066*** | 2.02 |
| | (0.001) | (0.001) | (0.001) | (0.000) | (0.003) | |
| Share of high-quality peers$_{t-1}$ (%) | 0.036*** | 0.036*** | 0.036*** | 0.036*** | 0.036*** | 0.54 |
| | (0.002) | (0.002) | (0.002) | (0.001) | (0.002) | |
| Share of low-quality peers$_{t-1}$ (%) | -0.034*** | -0.034*** | -0.034*** | -0.034*** | -0.034*** | 0.29 |
| | (0.003) | (0.003) | (0.004) | (0.001) | (0.004) | |
| Male | 0.113*** | 0.111*** | 0.104*** | 0.113*** | 0.113*** | 0.56 |
| | (0.009) | (0.009) | (0.009) | (0.005) | (0.015) | |
| Age$_{t-1}$ | -0.004*** | -0.004*** | -0.010*** | -0.004*** | -0.004*** | 39.2 |
| | (0.001) | (0.001) | (0.001) | (0.000) | (0.001) | |
| Tenure$_{t-1}$ | -0.009*** | -0.009*** | -0.009*** | -0.009*** | -0.009*** | 122.4 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | |
| Log (wage)$_{t-1}$ | -0.316*** | -0.316*** | — | -0.316*** | -0.316*** | 0.64 |
| | (0.029) | (0.029) | | (0.015) | (0.062) | |
| Log (wage)$^2_{t-1}$ | 0.051*** | 0.051*** | — | 0.051*** | 0.051*** | 0.79 |
| | (0.008) | (0.008) | | (0.004) | (0.017) | |
| Log (firm size)$_{t-1}$ | -0.023*** | -0.023*** | -0.023*** | -0.023*** | -0.023* | 5.63 |
| | (0.004) | (0.004) | (0.004) | (0.001) | (0.013) | |
| **Controls:** | | | | | | |
| Education$_{t-1}$ | Yes | Yes | Yes | Yes | Yes | |
| Firm sector$_{t-1}$ | Yes | Yes | Yes | Yes | Yes | |
| Year$_t$ | Yes | Yes | Yes | Yes | Yes | |
| **Page Rank Calculations:** | | | | | | |
| Global$_{t-1}$ | Yes | Yes | Yes | Yes | Yes | |
| Components$_{t-1}$ | No | No | No | No | No | |
| **Fixed Effects:** | | | | | | |
| Worker | Yes | Yes | Yes | Yes | Yes | |
| Origin Firm | Yes | Yes | Yes | Yes | Yes | |
| Origin Job Occupation | Yes | No | Yes | Yes | Yes | |
| Observations | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 | 11,187,776 | |
| Nonzero outcomes | 309,757 | 309,757 | 309,757 | 309,757 | 309,757 | |

*Notes:* The unit of observation is a worker-year. The dependent variable equals one if worker $i$ is observed working at a different firm in year $t$ than in year $t-1$, and zero otherwise. The table reports marginal effects from complementary log-log models, multiplied by 100, evaluated at the sample mean of each covariate rather than averaged over individual observations. Marginal effects are calculated using specifications (1)–(5) from Table 1D. The final column reports the sample mean of each variable used for the evaluation. Column definitions correspond to Table 1D. Unless otherwise indicated, standard errors are clustered at the $t-1$ peer-group level and are reported in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3A: Destination choice conditional on moving (conditional-logit coefficients)
Realized destination plus up to 99 comparable alternative firms

| Dependent variable: $\mathbb{1}\{choice_{i,f,t}\}$ | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ordinary former peer | 4.5914*** | 4.4902*** | 4.4562*** | 4.5421*** | 4.3877*** | 4.3472*** |
| | (0.0150) | (0.0149) | (0.0150) | (0.0149) | (0.0151) | (0.0143) |
| High-quality former peer | 5.5590*** | 5.4593*** | 5.4097*** | 5.4891*** | 5.3673*** | 5.2282*** |
| | (0.0159) | (0.0158) | (0.0161) | (0.0159) | (0.0161) | (0.0154) |
| Log (firm size) | 0.9297*** | 0.9428*** | 0.9506*** | 1.0097*** | 0.9695*** | 0.9204*** |
| | (0.0015) | (0.0015) | (0.0015) | (0.0017) | (0.0017) | (0.0015) |
| Average PageRank | -0.1049*** | -0.0421*** | -0.0513*** | -0.0490*** | -0.0630*** | -0.0112*** |
| | (0.0019) | (0.0019) | (0.0020) | (0.0019) | (0.0019) | (0.0017) |
| Candidate-firm wage component | 0.6343*** | 0.6884*** | 0.5994*** | 0.6846*** | 0.6452*** | 0.6776*** |
| | (0.0102) | (0.0100) | (0.0101) | (0.0101) | (0.0101) | (0.0100) |
| Hiring share$_{t-1}$ | | 0.0152*** | | | 0.0143*** | |
| | | (0.0001) | | | (0.0001) | |
| Focal-occupation share$_{t-1}$ | | | 0.0129*** | | 0.0125*** | |
| | | | (0.0001) | | (0.0001) | |
| Occupation HHI$_{t-1}$ | | | | 0.2473*** | -0.3198*** | |
| | | | | (0.0094) | (0.0100) | |
| Number of occupations$_{t-1}$ | | | | -0.0206*** | -0.0164*** | |
| | | | | (0.0005) | (0.0004) | |
| Hiring share$_t$ (leave-one-out) | | | | | | 0.0230*** |
| | | | | | | (0.0001) |
| **Controls:** | | | | | | |
| Education$_t$ | No | No | No | No | No | No |
| Firm sector$_t$ | No | No | No | No | No | No |
| Year$_t$ | No | No | No | No | No | No |
| **Page Rank Calculations:** | | | | | | |
| Global$_t$ | Yes | Yes | Yes | Yes | Yes | Yes |
| Components$_t$ | No | No | No | No | No | No |
| **Fixed Effects:** | | | | | | |
| Worker | No | No | No | No | No | No |
| Origin Firm | Yes | Yes | Yes | Yes | Yes | Yes |
| Origin Job Occupation | No | No | No | No | No | No |
| Pseudo $R^2$ | 0.3892 | 0.4016 | 0.4007 | 0.3947 | 0.4108 | 0.4161 |
| Candidate-firm observations | 28,928,505 | 28,928,505 | 28,928,505 | 28,928,505 | 28,928,505 | 28,928,505 |
| Mover-year choice sets | 309,678 | 309,678 | 309,678 | 309,678 | 309,678 | 309,678 |
| Worker clusters | 248,419 | 248,419 | 248,419 | 248,419 | 248,419 | 248,419 |

*Notes:* The unit of observation is a mover-year × candidate-firm alternative. The dependent variable equals one for the realized destination and zero for sampled alternatives. "Ordinary former peer" denotes a candidate firm with at least one former peer but no high-quality former peer. "High-quality former peer" denotes a candidate firm with at least one high-quality former peer. The omitted category is a candidate firm with no former peers. The two peer-state coefficients therefore compare each category with a no-peer firm; the incremental high-quality-peer effect is the difference between the two reported coefficients. All specifications include log firm size, average firm-year PageRank, and the previously estimated candidate-firm wage component. Column (5) is the preferred specification with all predetermined conference controls. Column (6) uses contemporaneous leave-one-out hiring as an additional robustness check. Conditional logit conditions out all mover-year characteristics common to the alternatives in a choice set. Standard errors, clustered at the worker level, are in parentheses. Seventy-nine singleton choice sets are omitted.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3B: Destination choice conditional on moving (comparable cloglog coefficients)
Realized destination plus up to 99 comparable alternative firms

| Dependent variable: $\mathbb{1}\{choice_{i,f,t}\}$ | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ordinary former peer | 2.7918*** | 2.7071*** | 2.7086*** | 2.7673*** | 2.6105*** | 2.6261*** |
| | (0.0085) | (0.0088) | (0.0088) | (0.0088) | (0.0089) | (0.0091) |
| High-quality former peer | 3.2087*** | 3.1984*** | 3.1474*** | 3.2216*** | 3.1123*** | 3.1294*** |
| | (0.0084) | (0.0083) | (0.0084) | (0.0083) | (0.0083) | (0.0081) |
| Log (firm size) | 0.7185*** | 0.7292*** | 0.7295*** | 0.7801*** | 0.7439*** | 0.7112*** |
| | (0.0012) | (0.0012) | (0.0012) | (0.0015) | (0.0015) | (0.0012) |
| Average PageRank | -0.0532*** | -0.0089*** | -0.0198*** | -0.0147*** | -0.0213*** | 0.0029* |
| | (0.0018) | (0.0017) | (0.0018) | (0.0018) | (0.0017) | (0.0016) |
| Candidate-firm wage component | 0.3425*** | 0.4258*** | 0.3203*** | 0.3912*** | 0.3787*** | 0.4762*** |
| | (0.0089) | (0.0085) | (0.0088) | (0.0087) | (0.0086) | (0.0083) |
| Hiring share$_{t-1}$ | | 0.0112*** | | | 0.0110*** | |
| | | (0.0001) | | | (0.0001) | |
| Focal-occupation share$_{t-1}$ | | | 0.0070*** | | 0.0072*** | |
| | | | (0.0001) | | (0.0001) | |
| Occupation HHI$_{t-1}$ | | | | -0.0036 | -0.4900*** | |
| | | | | (0.0083) | (0.0088) | |
| Number of occupations$_{t-1}$ | | | | -0.0213*** | -0.0171*** | |
| | | | | (0.0004) | (0.0004) | |
| Hiring share$_t$ (leave-one-out) | | | | | | 0.0185*** |
| | | | | | | (0.0001) |
| Constant | -7.8696*** | -8.2256*** | -8.0911*** | -8.1481*** | -7.9726*** | -8.2331*** |
| | (0.0060) | (0.0067) | (0.0063) | (0.0103) | (0.0104) | (0.0064) |
| **Controls:** | | | | | | |
| Education$_t$ | No | No | No | No | No | No |
| Firm sector$_t$ | No | No | No | No | No | No |
| Year$_t$ | No | No | No | No | No | No |
| **Page Rank Calculations:** | | | | | | |
| Global$_t$ | Yes | Yes | Yes | Yes | Yes | Yes |
| Components$_t$ | No | No | No | No | No | No |
| **Fixed Effects:** | | | | | | |
| Worker | No | No | No | No | No | No |
| Origin Firm | Yes | Yes | Yes | Yes | Yes | Yes |
| Origin Job Occupation | No | No | No | No | No | No |
| Candidate-firm observations | 28,928,505 | 28,928,505 | 28,928,505 | 28,928,505 | 28,928,505 | 28,928,505 |
| Nonzero outcomes | 309,678 | 309,678 | 309,678 | 309,678 | 309,678 | 309,678 |
| Worker clusters | 248,419 | 248,419 | 248,419 | 248,419 | 248,419 | 248,419 |

*Notes:* The peer-state definitions and column specifications follow Table 3A. The table reports complementary log-log coefficients, not probability effects. Each model is estimated on the corresponding conditional-logit estimation sample and uses the same candidate-varying controls. Unlike conditional logit, cloglog treats each candidate-firm row as a binary observation and does not impose probabilities summing to one within mover-year choice sets. Standard errors are clustered at the worker level.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 4A: Conditional-logit relative choice odds and probability effects
Extensive-margin former-peer states

**Panel A: Relative choice-odds ratios**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Ordinary peer vs. no peer | 98.63*** | 89.14*** | 86.16*** | 93.89*** | 80.45*** | 77.26*** |
| | (1.48) | (1.32) | (1.29) | (1.40) | (1.21) | (1.11) |
| High-quality peer vs. ordinary peer | 2.632*** | 2.636*** | 2.595*** | 2.578*** | 2.663*** | 2.413*** |
| | (0.044) | (0.044) | (0.045) | (0.043) | (0.045) | (0.039) |
| High-quality peer vs. no peer | 259.57*** | 234.93*** | 223.57*** | 242.05*** | 214.27*** | 186.46*** |
| | (4.14) | (3.71) | (3.61) | (3.85) | (3.45) | (2.88) |
| Candidate-firm observations | 28,928,505 | 28,928,505 | 28,928,505 | 28,928,505 | 28,928,505 | 28,928,505 |
| Mover-year choice sets | 309,678 | 309,678 | 309,678 | 309,678 | 309,678 | 309,678 |

**Panel B: Mover-year-weighted own-candidate probability effects**

| | Baseline | Combined $t-1$ controls |
|---|---|---|
| Ordinary peer vs. no peer | 26.74 pp | 22.70 pp |
| High-quality peer vs. ordinary peer | 15.08 pp | 13.85 pp |
| High-quality peer vs. no peer | 41.82 pp | 36.55 pp |

*Notes:* Columns in Panel A report the following specifications: (1) baseline; (2) candidate-firm hiring share in $t-1$; (3) focal-occupation share in $t-1$; (4) occupational-composition controls in $t-1$; (5) all predetermined conference controls; and (6) contemporaneous leave-one-out hiring. Relative choice odds are obtained by exponentiating the relevant conditional-logit coefficient or coefficient difference. Standard errors are delta-method standard errors. Panel B reports model-based point estimates obtained by changing one candidate firm's peer state while holding the characteristics and peer states of all other alternatives at their observed values. Probabilities are then renormalized within each mover-year choice set and averaged by giving each mover-year equal weight. These probability effects are reported as point estimates and do not have the delta-method standard errors reported in Panel A.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 4B: Comparable cloglog discrete probability effects (percentage points)
Exact changes between the three categorical peer states

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Ordinary peer vs. no peer | 9.904*** | 9.038*** | 9.097*** | 9.631*** | 8.244*** | 8.210*** |
| | (0.077) | (0.073) | (0.073) | (0.076) | (0.068) | (0.068) |
| High-quality peer vs. ordinary peer | 4.375*** | 4.877*** | 4.313*** | 4.700*** | 4.620*** | 4.584*** |
| | (0.111) | (0.109) | (0.107) | (0.112) | (0.102) | (0.102) |
| High-quality peer vs. no peer | 14.279*** | 13.914*** | 13.410*** | 14.332*** | 12.864*** | 12.795*** |
| | (0.101) | (0.096) | (0.096) | (0.100) | (0.090) | (0.086) |
| Candidate-firm observations | 28,928,505 | 28,928,505 | 28,928,505 | 28,928,505 | 28,928,505 | 28,928,505 |
| Nonzero outcomes | 309,678 | 309,678 | 309,678 | 309,678 | 309,678 | 309,678 |

*Notes:* Columns follow the specifications in Table 3B. Entries are predictive-margin contrasts from complementary log-log models, multiplied by 100 and expressed in percentage points. The peer-state variable is entered categorically, so the reported effects are finite discrete changes rather than derivatives that treat the indicators as continuous. Standard errors, clustered at the worker level, are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 4C: Full complementary log-log specification
Realized destination plus up to 99 comparable alternative firms

| | (1) Baseline | (2) Combined $t-1$ controls |
|---|---|---|
| Ordinary former peer | 2.8881*** | 2.6746*** |
| | (0.0087) | (0.0092) |
| High-quality former peer | 3.3398*** | 3.1899*** |
| | (0.0082) | (0.0082) |
| Male | 0.0200*** | 0.0250*** |
| | (0.0036) | (0.0039) |
| Age | -0.0037*** | -0.0035*** |
| | (0.0002) | (0.0002) |
| Log (firm size) | 0.7698*** | 0.8137*** |
| | (0.0013) | (0.0016) |
| Average PageRank | -0.0717*** | -0.0273*** |
| | (0.0018) | (0.0018) |
| Worker wage component | -0.0918*** | -0.0850*** |
| | (0.0055) | (0.0059) |
| Candidate-firm wage component | 0.5962*** | 0.6176*** |
| | (0.0091) | (0.0090) |
| Occupation wage component | 0.2255*** | 0.1624*** |
| | (0.0139) | (0.0136) |
| Hiring share$_{t-1}$ | | 0.0132*** |
| | | (0.0001) |
| Focal-occupation share$_{t-1}$ | | 0.0072*** |
| | | (0.0001) |
| Occupation HHI$_{t-1}$ | | -0.3773*** |
| | | (0.0093) |
| Number of occupations$_{t-1}$ | | -0.0181*** |
| | | (0.0004) |
| Constant | -6.8284*** | -7.2241*** |
| | (0.0499) | (0.0479) |
| **Controls:** | | |
| Education$_t$ | Yes | Yes |
| Firm sector$_t$ | Yes | Yes |
| Year$_t$ | Yes | Yes |
| **Page Rank Calculations:** | | |
| Global$_t$ | Yes | Yes |
| Components$_t$ | No | No |
| **Fixed Effects:** | | |
| Worker | Yes | Yes |
| Origin Firm | Yes | Yes |
| Origin Job Occupation | Yes | Yes |
| **Predictive margins and discrete changes:** | | |
| No former peer | 0.802% | 0.807% |
| Ordinary former peer | 11.425% | 9.390% |
| High-quality former peer | 16.413% | 14.217% |
| Ordinary peer vs. no peer | 10.623 pp*** | 8.583 pp*** |
| High-quality peer vs. ordinary peer | 4.988 pp*** | 4.827 pp*** |
| High-quality peer vs. no peer | 15.611 pp*** | 13.410 pp*** |
| Observations | 28,928,584 | 28,928,584 |
| Nonzero outcomes | 309,757 | 309,757 |
| Worker clusters | 248,485 | 248,485 |

*Notes:* This table expands on the baseline specification from Table 3B. Column (1) includes the controls used in the fuller origin-side specification (at time $t$). Column (2) adds the predetermined hiring and occupational-composition controls. The peer-state coefficients compare ordinary-peer and high-quality-peer firms with the omitted no-peer category. Predictive margins and contrasts treat peer state as a categorical variable. Standard errors are clustered at the worker level.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 5A: Destination-choice results by sampled choice-set size
Conditional logit with predetermined hiring and focal-occupation controls

| Intended choice-set size | 20 | 50 | 100 |
|---|---|---|---|
| Ordinary former peer coefficient | 4.4772*** | 4.4321*** | 4.3951*** |
| | (0.0225) | (0.0173) | (0.0150) |
| High-quality former peer coefficient | 5.4609*** | 5.3864*** | 5.3764*** |
| | (0.0282) | (0.0196) | (0.0161) |
| Ordinary peer vs. no peer: relative odds | 87.99*** | 84.11*** | 81.05*** |
| | (1.98) | (1.46) | (1.22) |
| High-quality peer vs. ordinary peer: relative odds | 2.674*** | 2.597*** | 2.668*** |
| | (0.082) | (0.055) | (0.046) |
| High-quality peer vs. no peer: relative odds | 235.31*** | 218.41*** | 216.23*** |
| | (6.64) | (4.28) | (3.48) |
| Ordinary peer vs. no peer: probability effect | 41.10 pp | 30.67 pp | 22.93 pp |
| High-quality peer vs. ordinary peer: probability effect | 13.57 pp | 14.51 pp | 14.07 pp |
| High-quality peer vs. no peer: probability effect | 54.67 pp | 45.18 pp | 37.00 pp |
| Average realized choice-set size | 19.88 | 48.77 | 93.41 |
| Pseudo $R^2$ | 0.4991 | 0.4450 | 0.4102 |
| Candidate-firm observations | 6,155,901 | 15,103,983 | 28,928,505 |
| Mover-year choice sets | 309,678 | 309,678 | 309,678 |
| Worker clusters | 248,419 | 248,419 | 248,419 |

*Notes:* Alternative sets are nested within mover-year. All specifications control for log firm size, average PageRank, the candidate-firm wage component, candidate-firm hiring share in $t-1$, and the share of the candidate firm's $t-1$ workforce employed in the focal worker's occupation. Relative choice odds use delta-method inference. Probability effects are mover-year-weighted own-candidate point estimates. Absolute probability effects decline as more alternatives compete for the single observed choice; the relative choice-odds ratios provide the more directly comparable measure across set sizes.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 6A: Former-peer shares and destination choice (conditional-logit coefficients)
Realized destination plus up to 99 comparable alternative firms

| Dependent variable: $\mathbb{1}\{choice_{i,f,t}\}$ | | |
|---|---|---|
| | (1) Baseline | (2) Combined $t-1$ controls |
| Ordinary former-peer state | 3.9789*** | 3.8158*** |
| | (0.0162) | (0.0163) |
| High-quality former-peer state | 4.4804*** | 4.3771*** |
| | (0.0204) | (0.0204) |
| Share of former peers (%) | 0.1978*** | 0.1890*** |
| | (0.0045) | (0.0044) |
| Share of high-quality former peers (%) | -0.1049*** | -0.1096*** |
| | (0.0087) | (0.0090) |
| Log (firm size) | 0.9442*** | 0.9826*** |
| | (0.0015) | (0.0017) |
| Average PageRank | -0.0794*** | -0.0480*** |
| | (0.0020) | (0.0020) |
| Candidate-firm wage component | 0.6363*** | 0.6443*** |
| | (0.0103) | (0.0102) |
| Hiring share$_{t-1}$ | | 0.0142*** |
| | | (0.0001) |
| Focal-occupation share$_{t-1}$ | | 0.0125*** |
| | | (0.0001) |
| Occupation HHI$_{t-1}$ | | -0.3292*** |
| | | (0.0099) |
| Number of occupations$_{t-1}$ | | -0.0168*** |
| | | (0.0004) |
| **Specification:** | | |
| Peer-state indicators | Yes | Yes |
| Hiring and occupation controls$_{t-1}$ | No | Yes |
| Missing-value indicators | No | Yes |
| Mover-year choice-set effects | Yes | Yes |
| Pseudo $R^2$ | 0.3954 | 0.4164 |
| Candidate-firm observations | 28,928,505 | 28,928,505 |
| Mover-year choice sets | 309,678 | 309,678 |
| Worker clusters | 248,419 | 248,419 |

*Notes:* The unit of observation is a mover-year × candidate-firm alternative. The dependent variable equals one for the realized destination and zero for sampled alternatives. Peer shares are calculated relative to the candidate firm's incumbent workforce; the focal mover is removed from the denominator at the realized destination. Since high-quality former peers are a subset of all former peers, the coefficient on the total former-peer share measures a one-percentage-point increase in ordinary-peer share, holding the high-quality share fixed. The coefficient on the high-quality-peer share is the incremental composition effect of replacing ordinary-peer share with high-quality-peer share while holding total peer share fixed. The sum of the two share coefficients gives the effect of increasing high-quality-peer share while holding ordinary-peer share fixed. The peer-state indicators absorb the discrete extensive-margin differences between no-peer, ordinary-peer, and high-quality-peer candidate firms. Their coefficients are reported for completeness but are not used as the paper's extensive-margin estimates; those estimates are reported in Tables 3A–4A. Standard errors, clustered at the worker level, are in parentheses. Seventy-nine singleton choice sets are omitted.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 6B: Conditional-logit intensive-margin effects
Effects of a one-percentage-point change in former-peer shares

**Panel A: Log relative choice odds**

| One-percentage-point change | (1) Baseline | (2) Combined $t-1$ controls |
|---|---|---|
| Increase in ordinary-peer share | 0.1978*** | 0.1890*** |
| | (0.0045) | (0.0044) |
| Replace ordinary-peer share with high-quality-peer share | -0.1049*** | -0.1096*** |
| | (0.0087) | (0.0090) |
| Increase in high-quality-peer share, ordinary-peer share unchanged | 0.0929*** | 0.0794*** |
| | (0.0080) | (0.0082) |

**Panel B: Relative choice-odds ratios**

| One-percentage-point change | (1) Baseline | (2) Combined $t-1$ controls |
|---|---|---|
| Increase in ordinary-peer share | 1.2187*** | 1.2080*** |
| | (0.0055) | (0.0053) |
| Replace ordinary-peer share with high-quality-peer share | 0.9004*** | 0.8962*** |
| | (0.0078) | (0.0081) |
| Increase in high-quality-peer share, ordinary-peer share unchanged | 1.0974*** | 1.0826*** |
| | (0.0088) | (0.0089) |

**Panel C: Exact own-candidate probability changes**

| One-percentage-point change | (1) Baseline | (2) Combined $t-1$ controls | Mover-year sets |
|---|---|---|---|
| Increase in ordinary-peer share | 2.424 pp | 2.249 pp | 100,037 |
| Replace ordinary-peer share with high-quality-peer share | -1.011 pp | -1.034 pp | 36,674 |
| Increase in high-quality-peer share, ordinary-peer share unchanged | 0.999 pp | 0.837 pp | 62,902 |
| Candidate-firm observations | 28,928,505 | 28,928,505 | |
| Mover-year choice sets | 309,678 | 309,678 | |
| Worker clusters | 248,419 | 248,419 | |

*Notes:* The baseline and controlled specifications are those reported in Table 6A. Panel A reports the relevant conditional-logit coefficient or coefficient sum. Panel B exponentiates these quantities; the reported standard errors are delta-method standard errors, and the null hypothesis is that the relative choice-odds ratio equals one.
Panel C reports mover-year-weighted point estimates of exact one-percentage-point finite changes. The ordinary-share effect is evaluated for peer-linked candidate firms for which the increase is feasible. The composition effect is evaluated for high-quality-peer firms with at least one percentage point of ordinary-peer share available to replace. The total high-quality-share effect is evaluated for high-quality-peer firms for which both total and high-quality shares can increase by one percentage point. Candidate probabilities are renormalized within each mover-year choice set after the counterfactual change. Statistical inference is based on Panels A and B; the exact probability changes are reported as point estimates.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 7A: Former-peer shares and destination choice
(complementary log-log coefficients)
Realized destination plus up to 99 comparable alternative firms

Dependent variable: $\mathbb{1}\{choice_{i,f,t}\}$

| | Comparable cloglog | | Full cloglog | |
|---|---|---|---|---|
| | (1) Baseline | (2) Controlled | (3) Baseline | (4) Controlled |
| Ordinary former-peer state | 2.6980*** | 2.5150*** | 2.7871*** | 2.5768*** |
| | (0.0093) | (0.0097) | (0.0095) | (0.0101) |
| High-quality former-peer state | 2.8625*** | 2.7703*** | 2.9876*** | 2.8516*** |
| | (0.0119) | (0.0117) | (0.0120) | (0.0122) |
| Share of former peers (%) | 0.0708*** | 0.0693*** | 0.0678*** | 0.0661*** |
| | (0.0026) | (0.0026) | (0.0026) | (0.0027) |
| Share of high-quality former peers (%) | -0.0372*** | -0.0355*** | -0.0327*** | -0.0325*** |
| | (0.0105) | (0.0104) | (0.0109) | (0.0109) |
| Male | | | 0.0216*** | 0.0258*** |
| | | | (0.0041) | (0.0044) |
| Age | | | -0.0048*** | -0.0045*** |
| | | | (0.0003) | (0.0003) |
| Log (firm size) | 0.7402*** | 0.7625*** | 0.7902*** | 0.8299*** |
| | (0.0016) | (0.0019) | (0.0017) | (0.0020) |
| Average PageRank | -0.0437*** | -0.0168*** | -0.0618*** | -0.0236*** |
| | (0.0019) | (0.0018) | (0.0019) | (0.0019) |
| Worker wage component | | | -0.1077*** | -0.1006*** |
| | | | (0.0075) | (0.0084) |
| Candidate-firm wage component | 0.3027*** | 0.3379*** | 0.5662*** | 0.5852*** |
| | (0.0105) | (0.0097) | (0.0104) | (0.0098) |
| Occupation wage component | | | 0.2458*** | 0.1856*** |
| | | | (0.0154) | (0.0155) |
| Hiring share$_{t-1}$ | | 0.0111*** | | 0.0132*** |
| | | (0.0001) | | (0.0001) |
| Focal-occupation share$_{t-1}$ | | 0.0071*** | | 0.0072*** |
| | | (0.0001) | | (0.0001) |
| Occupation HHI$_{t-1}$ | | -0.5094*** | | -0.3833*** |
| | | (0.0090) | | (0.0094) |
| Number of occupations$_{t-1}$ | | -0.0163*** | | -0.0171*** |
| | | (0.0004) | | (0.0004) |
| Constant | -7.9730*** | -8.0452*** | -6.9231*** | -7.2578*** |
| | (0.0076) | (0.0115) | (0.0508) | (0.0487) |
| **Controls:** | | | | |
| Worker characteristics | No | No | Yes | Yes |
| Education controls | No | No | Yes | Yes |
| Sector effects | No | No | Yes | Yes |
| Year effects | No | No | Yes | Yes |
| Hiring and occupation controls$_{t-1}$ | No | Yes | No | Yes |
| Missing-value indicators | No | Yes | No | Yes |
| Same sample as corresponding clogit | Yes | Yes | No | No |
| Log pseudolikelihood | -1,220,221.7 | -1,196,929.8 | -1,201,937.4 | -1,174,866.0 |
| Candidate-firm observations | 28,928,505 | 28,928,505 | 28,928,584 | 28,928,584 |
| Nonzero outcomes | 309,678 | 309,678 | 309,757 | 309,757 |
| Worker clusters | 248,419 | 248,419 | 248,485 | 248,485 |

*Notes:* The peer-share definitions and interpretations follow Table 6A. Columns (1)–(2) use the same samples and candidate-varying controls as the corresponding conditional-logit models. Columns (3)–(4) add mover characteristics, education, year and sector effects, and the worker and occupation wage components retained from the previous paper specification. The peer-state indicators are included to separate the extensive and intensive margins; their coefficients are reported for completeness but should not replace the extensive-margin estimates in Tables 3A–4C. Standard errors are clustered at the worker level.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 7B: Complementary log-log intensive-margin effects
Effects of a one-percentage-point change in former-peer shares

**Panel A: Coefficient effects**

| | Comparable cloglog | | Full cloglog | |
|---|---|---|---|---|
| One-percentage-point change | (1) Baseline | (2) Controlled | (3) Baseline | (4) Controlled |
| Increase in ordinary-peer share | 0.0708*** | 0.0693*** | 0.0678*** | 0.0661*** |
| | (0.0026) | (0.0026) | (0.0026) | (0.0027) |
| Replace ordinary-peer share with high-quality-peer share | -0.0372*** | -0.0355*** | -0.0327*** | -0.0325*** |
| | (0.0105) | (0.0104) | (0.0109) | (0.0109) |
| Increase in high-quality-peer share, ordinary-peer share unchanged | 0.0336*** | 0.0338*** | 0.0351*** | 0.0335*** |
| | (0.0089) | (0.0087) | (0.0092) | (0.0092) |

**Panel B: Exact own-candidate probability changes**

| | Comparable cloglog | | Full cloglog | |
|---|---|---|---|---|
| One-percentage-point change | (1) Baseline | (2) Controlled | (3) Baseline | (4) Controlled |
| Increase in ordinary-peer share | 1.722 pp | 1.669 pp | 1.623 pp | 1.554 pp |
| Replace ordinary-peer share with high-quality-peer share | -0.981 pp | -0.920 pp | -0.846 pp | -0.822 pp |
| Increase in high-quality-peer share, ordinary-peer share unchanged | 0.856 pp | 0.856 pp | 0.874 pp | 0.825 pp |
| Candidate-firm observations | 28,928,505 | 28,928,505 | 28,928,584 | 28,928,584 |
| Nonzero outcomes | 309,678 | 309,678 | 309,757 | 309,757 |
| Worker clusters | 248,419 | 248,419 | 248,485 | 248,485 |

*Notes:* Panel A reports the relevant cloglog coefficient or coefficient sum. The coefficient on the total peer share is the ordinary-peer-share effect, the coefficient on high-quality-peer share is the incremental composition effect, and their sum is the total effect of increasing high-quality-peer share while holding ordinary-peer share fixed. Panel B reports mover-year-weighted exact one-percentage-point finite changes, evaluated over the logically feasible support described in Table 6B. Candidate characteristics and all other alternatives remain fixed during the counterfactual calculation. The probability effects are point estimates; statistical inference is based on the clustered coefficients in Panel A.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 8: Impact of wage at destination firm

| Dependent variable: log (wage)$_t$ | | | | |
|---|---|---|---|---|
| | Extensive margin | | Share measures | |
| | OLS (1) | OLS (2) | OLS (3) | OLS (4) |
| Peer exists | 0.0084*** | 0.0064*** | 0.0069*** | 0.0059*** |
| | (0.0008) | (0.0012) | (0.0009) | (0.0012) |
| High-quality peer exists | | 0.0033** | | 0.0018 |
| | | (0.0014) | | (0.0015) |
| Share of peers (%) | | | 0.0002*** | 0.0001 |
| | | | (0.0001) | (0.0001) |
| Share of high-quality peers (%) | | | | 0.0004 |
| | | | | (0.0006) |
| Log (wage)$_{t-1}$ | 0.0073*** | 0.0072*** | 0.0072*** | 0.0072*** |
| | (0.0018) | (0.0018) | (0.0018) | (0.0018) |
| Male | 0.0012 | 0.0012 | 0.0012 | 0.0012 |
| | (0.0008) | (0.0008) | (0.0008) | (0.0008) |
| Age | 0.0500*** | 0.0500*** | 0.0500*** | 0.0500*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Age$^2$ | -0.0003*** | -0.0003*** | -0.0003*** | -0.0003*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Tenure$_{t-1}$ | 0.0017*** | 0.0017*** | 0.0017*** | 0.0017*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Log (firm size) | 0.0026*** | 0.0026*** | 0.0028*** | 0.0027*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Constant | -0.0696*** | -0.0693*** | -0.0698*** | -0.0695*** |
| | (0.0160) | (0.0160) | (0.0160) | (0.0160) |
| **Controls:** | | | | |
| Education$_t$ | Yes | Yes | Yes | Yes |
| Firm sector$_t$ | Yes | Yes | Yes | Yes |
| Year$_t$ | Yes | Yes | Yes | Yes |
| **Page Rank Calculations:** | | | | |
| Global | Yes | Yes | Yes | Yes |
| Components | No | No | No | No |
| **Fixed Effects:** | | | | |
| Worker | Yes | Yes | Yes | Yes |
| Destination Firm | Yes | Yes | Yes | Yes |
| Destination Job Occupation | Yes | Yes | Yes | Yes |
| $R^2$ | 0.8803 | 0.8803 | 0.8804 | 0.8804 |
| Observations | 309,757 | 309,757 | 309,757 | 309,757 |
| Worker clusters | 248,485 | 248,485 | 248,485 | 248,485 |

*Notes:* The unit of observation is a mover-year. The sample includes workers who move to a different firm between $t-1$ and $t$. The dependent variable is log wage at the destination firm in year $t$. Columns (1) and (2) use extensive-margin former-peer indicators. Peer exists equals one if the destination firm employs at least one former peer of worker $i$ in year $t$. High-quality peer exists equals one if at least one such former peer is classified in the top quintile of the predetermined peer-quality distribution within the $t-2$ peer cell. Columns (3) and (4) use destination peer shares. Share of peers is the percentage of workers at the destination firm in year $t$ who are former peers of worker $i$. Share of high-quality peers is the percentage of workers at the destination firm in year $t$ who are former peers of worker $i$ and are classified in the top quintile of the predetermined peer-quality distribution within the $t-2$ peer cell. Standard errors, clustered at the individual level in $t$, are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

# A Formal Search Model and Proofs

This appendix provides the formal details behind the search framework in Section 3. The model is a partial equilibrium where firm productivity, vacancies, incumbent workforces, and outside-opportunity distributions are taken as given from the perspective of an individual worker, but workers and firms optimize given those objects. We do not intend to estimate the model structurally. Instead, its purpose is to show why peer departures and former-peer links can enter reduced-form mobility and destination-choice equations through primitive search, information, referral, screening, and production mechanisms.

The framework builds on dynamic job-mobility and wage-growth models in which workers search across heterogeneous firms and wages depend on worker-firm matches, mobility, and accumulated labor-market histories (Adda et al., 2013; Adda & Dustmann, 2023). It also draws on network and referral models in which social ties transmit information, lower search frictions, and improve screening (Granovetter, 1973; Ioannides & Loury, 2004; Montgomery, 1991; Topa, 2011), as well as empirical work on referrals, coworker links, and job mobility in matched employer-employee data (Eliason et al., 2023; Hensvik & Skans, 2016; Kramarz & Skans, 2014). Relative to this literature, the model below modifies the standard search/referral framework by using the same predetermined peer history to generate two linked margins: peer losses at the origin and former-peer stocks at candidate destinations. The framework also uses the matched employer-employee wage-decomposition tradition to motivate the empirical proxy for peer rank (Abowd et al., 1999; Card et al., 2013; Kline et al., 2020).

## A.1 Workers, firms, peer groups, and timing

Time is discrete and indexed by $t = 1, 2, \ldots$. Worker $i$ is employed at origin firm

$$o \equiv o(i, t-1)$$

before the mobility decision observed between $t-1$ and $t$. Worker $i$'s predetermined peer group is defined in $t-2$. Let

$$\mathcal{P}_{i,t-2}$$

denote worker $i$'s peer group, i.e., the set of workers who shared worker $i$'s firm $\times$ establishment $\times$ occupation $\times$ year cell in $t-2$, excluding worker $i$. Peer departures between $t-2$ and $t-1$ are therefore predetermined with respect to worker $i$'s move between $t-1$ and $t$. Each worker $j$ has a latent type

$$\theta_j = (a_j, \xi_j, r_j)$$

where $a_j$ is productive ability, $\xi_j$ is search efficiency, and $r_j$ is latent peer influence. The rank $r_j$ is not assumed to be pure ability, but the extent to which peer $j$'s actions and information are useful to other workers. This may reflect productivity, credibility, centrality, mentoring value, search efficiency, or access to firms, among many others. The empirical proxy is measured in the predetermined $t-2$ peer cell, so all high- and low-ranked classifications used in the empirical mapping are predetermined relative to departures between $t-2$ and $t-1$. For notational simplicity, the latent rank is written as $r_j$.

Let $\mathcal{R} \subseteq \mathbb{R}$ denote the support of latent peer rank. Define peer $j$'s influence weight by

$$\omega_j \equiv \omega(r_j), \qquad \omega : \mathcal{R} \to (0, \infty), \qquad \omega'(r) > 0 \quad \text{for all } r \in \mathcal{R}.$$

Thus every peer receives a strictly positive influence weight, and higher-ranked peers receive larger weights.. We assume that higher-ranked peers have larger influence weights. This is a reduced-form way of allowing some peers to be more informative, more credible, or more productive for their coworkers, consistent with workplace peer-effect evidence showing that coworkers can affect productivity and wages (Bandiera et al., 2010; Bayer et al., 2009; Cornelissen et al., 2017; Mas & Moretti, 2009). In the empirical analysis, $r_j$ is proxied by worker fixed-effect rank within the predetermined peer cell.

Each firm $f$ has state

$$Z_{f,t} = (A_{f,t}, \psi_f, \text{loc}_f, \kappa_{f,t}, v_{f,t})$$

where $A_{f,t}$ is productivity, $\psi_f$ is a firm wage or amenity component, $\text{loc}_f$ is location, $\kappa_{f,t}$ is hiring capacity, and $v_{f,t} \in \{0, 1\}$ indicates whether firm $f$ has a relevant vacancy.
The timing of the model is as follows:

1. There is a peer group $\mathcal{P}_{i,t-2}$ observed at $t-2$.
2. Peers $j \in \mathcal{P}_{i,t-2}$ may leave the origin firm between $t-2$ and $t-1$.
3. Worker $i$ observes peer departures and updates beliefs about the origin firm and outside opportunities.
4. Vacancies and information about candidate firms arrive through formal search and former-peer links.
5. Firms observe applicant signals and decide whether to review applications and make offers.
6. Worker $i$ chooses whether to stay or accept the best available outside offer.

## A.2 Origin-side peer departures

For each peer $j \in \mathcal{P}_{i,t-2}$, we define departure as:

$$d^o_{j,t-1} = \mathbb{1}\{j \text{ leaves origin firm } o \text{ between } t-2 \text{ and } t-1\} \tag{52}$$

The latent weighted peer-loss index is composed of the share of peers departing and their aggregate weight, such that:

$$D_{i,t-1} = \frac{1}{|\mathcal{P}_{i,t-2}|} \sum_{j \in \mathcal{P}_{i,t-2}} \omega(r_j) d^o_{j,t-1} \tag{53}$$

The empirical total peer-turnover share removes the unobserved weight, becoming:

$$T_{i,t-1} = \frac{1}{|\mathcal{P}_{i,t-2}|} \sum_{j \in \mathcal{P}_{i,t-2}} d^o_{j,t-1} \tag{54}$$

Let the predetermined peer group be partitioned into high-, middle-, and low-ranked peers such that:

$$\mathcal{P}_{i,t-2} = \mathcal{H}_{i,t-2} \cup \mathcal{M}_{i,t-2} \cup \mathcal{L}_{i,t-2}$$

where $\mathcal{H}_{i,t-2}$, $\mathcal{M}_{i,t-2}$, and $\mathcal{L}_{i,t-2}$ are sets. The corresponding empirical departure shares are

$$H_{i,t-1} = \frac{1}{|\mathcal{P}_{i,t-2}|} \sum_{j \in \mathcal{H}_{i,t-2}} d^o_{j,t-1}, \tag{55}$$

$$M_{i,t-1} = \frac{1}{|\mathcal{P}_{i,t-2}|} \sum_{j \in \mathcal{M}_{i,t-2}} d^o_{j,t-1}, \tag{56}$$

$$L_{i,t-1} = \frac{1}{|\mathcal{P}_{i,t-2}|} \sum_{j \in \mathcal{L}_{i,t-2}} d^o_{j,t-1} \tag{57}$$

Thus

$$T_{i,t-1} = H_{i,t-1} + M_{i,t-1} + L_{i,t-1} \tag{58}$$

### A.2.1 Coworker departures as Bayesian signals

In canonical social-learning models, agents' actions are informative because those actions partly reflect private signals (Banerjee, 1992; Bikhchandani et al., 1992). Here, coworkers' departures play that role: they are equilibrium actions that may reveal private information about the origin workplace or the outside market. The job-learning component is also related to models in which workers and firms learn about match quality over time (Jovanovic, 1979). Let the origin firm have an unobserved state during the peer-departure interval $(t-2, t-1]$:

$$\Theta_{o,t-1} \in \{G, B\},$$

where $G$ denotes a good state and $B$ denotes a bad state. The subscript $t-1$ indicates that this state governs the interval over which peer departures are realized. The state summarizes latent origin-firm conditions relevant for staying, such as wage growth, promotion prospects, management quality, workplace stability, and nonpecuniary job quality, among others.

Before observing peer departures, worker $i$'s prior belief that the origin is in the good state is

$$\mu^0_{i,t-2} = \Pr(\Theta_{o,t-1} = G \mid \mathcal{I}^0_{i,t-2})$$

where $\mathcal{I}^0_{i,t-2}$ denotes information available before the departures of the $t-2$ peer group are realized. The worker does not observe $\Theta_{o,t-1}$ directly. Instead, worker $i$ observes the departure decisions of peers in $\mathcal{P}_{i,t-2}$. The Bayesian channel arises because those departure decisions may reflect private information held by the peers.

Each peer $j \in \mathcal{P}_{i,t-2}$ may observe information about the origin firm that is not directly observed by worker $i$. Let

$$z_{j,t-1} \in \mathbb{R}$$

denote peer $j$'s private signal about $\Theta_{o,t-1}$. A larger value of $z_{j,t-1}$ means that peer $j$ receives more favorable information about the origin firm.

The signal distribution is

$$z_{j,t-1} \mid \Theta_{o,t-1} = G, r_j \sim N\left(1, \tau_j^{-1}\right), \qquad z_{j,t-1} \mid \Theta_{o,t-1} = B, r_j \sim N\left(0, \tau_j^{-1}\right) \tag{59}$$

Thus the signal is centered around one when the origin is in the good state and around zero when the origin is in the bad state. The term $\tau_j > 0$ is the precision of peer $j$'s signal. Since the variance is $\tau_j^{-1}$, a larger value of $\tau_j$ means that the signal is less noisy. We allow the signal precision to depend on peer rank:

$$\tau_j = \tau(r_j), \qquad \tau'(r) > 0 \tag{60}$$

This condition says that higher-ranked peers receive more precise information about the origin state.

Peer $j$'s departure decision is determined once both the private signal $z_{j,t-1}$ and the outside opportunity $x_{j,t-1}$ are realized. Specifically, peer $j$ leaves the origin firm between $t-2$ and $t-1$ if

$$d^o_{j,t-1} = \mathbb{1}\{x_{j,t-1} - c^m_j \geq S_j(z_{j,t-1})\} \tag{61}$$

where $x_{j,t-1}$ is peer $j$'s outside opportunity, $c^m_j$ is peer $j$'s mobility cost, and $S_j(z_{j,t-1})$ is peer $j$'s perceived value of staying at the origin after observing signal $z_{j,t-1}$. This implies that peer $j$ leaves the origin between $t-2$ and $t-1$ if the outside opportunity net of the mobility cost is at least as large as the perceived value of staying. We assume

$$S'_j(z) > 0$$

so that a more favorable signal about the origin raises the perceived value of staying.

For the Bayesian-learning argument, it is useful to define the probability that peer $j$ leaves conditional only on the signal. Let

$$q_j(z) \equiv \Pr(d^o_{j,t-1} = 1 \mid z_{j,t-1} = z) \tag{62}$$

The function $q_j(z)$ is peer $j$'s signal-contingent departure probability, not an empirical variable. It integrates over the outside opportunity $x_{j,t-1}$, which is not observed by worker $i$. Since peer $j$ leaves when

$$x_{j,t-1} \geq c^m_j + S_j(z)$$

we have

$$q_j(z) = 1 - F_{x,j}\left(c^m_j + S_j(z)\right) \tag{63}$$

where $F_{x,j}$ is the cumulative distribution function of peer $j$'s outside opportunity $x_{j,t-1}$.

If $F_{x,j}$ is differentiable with density $f_{x,j}$, then

$$q_j'(z) = -f_{x,j}\left(c_j^m + S_j(z)\right) S_j'(z)$$

Intuitively, $q_j(z)$ is the probability that peer $j$'s outside opportunity is high enough to compensate for the mobility cost and the perceived value of staying. Because $f_{x,j}(\cdot) \geq 0$ and $S_j'(z) > 0$, we obtain

$$q_j'(z) < 0$$

whenever the outside-opportunity density is positive at the relevant threshold. Thus, a better signal $z$ raises the value of staying $S_j(z)$, which raises the outside-offer threshold $c_j^m + S_j(z)$. Therefore the upper-tail probability $1 - F_{x,j}(\cdot)$ falls, so $q_j'(z) < 0$ whenever the outside-offer density is positive at the threshold. This implies that a better signal about the origin makes peer $j$ less likely to leave.

Define the state-contingent departure probabilities:

$$p_G(r_j) \equiv \Pr(d_{j,t-1}^o = 1 \mid \Theta_{o,t-1} = G, r_j) \quad \text{and} \quad p_B(r_j) \equiv \Pr(d_{j,t-1}^o = 1 \mid \Theta_{o,t-1} = B, r_j) \tag{64}$$

Because the signal distribution under $G$ first-order stochastically dominates the signal distribution under $B$, and because $q_j(z)$ is decreasing in $z$,

$$p_B(r_j) > p_G(r_j) \tag{65}$$

Thus peer $j$'s departure is more likely when the origin is in the bad state.

To obtain the posterior, assume that peer departures are conditionally independent across peers given the origin state $\Theta_{o,t-1}$ and peer ranks $\{r_j\}_{j \in \mathcal{P}_{i,t-2}}$. The vector

$$\mathbf{d}_{i,t-1}^o = \{d_{j,t-1}^o : j \in \mathcal{P}_{i,t-2}\}$$

contains the observed departure decisions of all peers in worker $i$'s predetermined $t-2$ peer group. For each peer $j$, the term

$$p_G(r_j)^{d^o_{j,t-1}}[1-p_G(r_j)]^{1-d^o_{j,t-1}}$$

is the probability of observing peer $j$'s realized departure decision if the origin is in the good state. If $d^o_{j,t-1}=1$, this term equals $p_G(r_j)$; if $d^o_{j,t-1}=0$, it equals $1-p_G(r_j)$. The analogous term using $p_B(r_j)$ is the probability of observing the same departure decision if the origin is in the bad state. Therefore, the product over $j \in \mathcal{P}_{i,t-2}$ is the likelihood of the entire observed peer-departure vector under each possible origin state.

The Bayes' rule thus gives

$$\mu^+_{i,t-1} = \frac{\mu^0_{i,t-2}\prod_{j\in\mathcal{P}_{i,t-2}} p_G(r_j)^{d^o_{j,t-1}}[1-p_G(r_j)]^{1-d^o_{j,t-1}}}{\mu^0_{i,t-2}\prod_{j\in\mathcal{P}_{i,t-2}} p_G(r_j)^{d^o_{j,t-1}}[1-p_G(r_j)]^{1-d^o_{j,t-1}} + (1-\mu^0_{i,t-2})\prod_{j\in\mathcal{P}_{i,t-2}} p_B(r_j)^{d^o_{j,t-1}}[1-p_B(r_j)]^{1-d^o_{j,t-1}}} \tag{66}$$

The numerator is the prior probability that the origin is good multiplied by the likelihood of observing the peer-departure vector if the origin is good. The denominator is the total probability of observing the same peer-departure vector, summing over the two possible origin states. Hence $\mu^+_{i,t-1}$ is worker $i$'s posterior belief that the origin is good after observing which peers left.

Equivalently, in posterior odds form,

$$\frac{\mu^+_{i,t-1}}{1-\mu^+_{i,t-1}} = \frac{\mu^0_{i,t-2}}{1-\mu^0_{i,t-2}} \prod_{j\in\mathcal{P}_{i,t-2}} \left[\frac{p_G(r_j)}{p_B(r_j)}\right]^{d^o_{j,t-1}} \left[\frac{1-p_G(r_j)}{1-p_B(r_j)}\right]^{1-d^o_{j,t-1}} \tag{67}$$

The odds representation makes the learning mechanism transparent. A departure by peer $j$ multiplies the posterior odds that the origin is good by

$$\frac{p_G(r_j)}{p_B(r_j)}$$

Since $p_B(r_j) > p_G(r_j)$, this ratio is smaller than one, so observing a departure lowers the posterior odds that the origin is good. Conversely, observing that peer $j$ stays multiplies the posterior odds by

$$\frac{1 - p_G(r_j)}{1 - p_B(r_j)} > 1$$

so non-departure is favorable news about the origin. Thus peer departures affect the value of staying because they reveal information about latent origin-firm conditions, not because peer turnover is directly inserted into the worker's utility function.

Assume throughout that

$$0 < p_G(r_j) < p_B(r_j) < 1$$

so that departures and non-departures both occur with positive probability under each origin state. To connect this Bayesian mechanism to the empirical high- and low-quality departure shares, define the log-likelihood content of peer $j$'s departure as

$$\ell(r_j) \equiv \log \left[ \frac{p_B(r_j)[1 - p_G(r_j)]}{p_G(r_j)[1 - p_B(r_j)]} \right] \tag{68}$$

Under (65), we have the implication that $\ell(r_j) > 0$. Holding all other peer departures fixed, changing $d^o_{j,t-1}$ from zero to one changes the posterior log odds that the origin is good by

$$\Delta_j \log \left( \frac{\mu^+_{i,t-1}}{1 - \mu^+_{i,t-1}} \right) = -\ell(r_j) \tag{69}$$

Thus a departure by peer $j$ lowers the posterior probability that the origin is good.

Assume that departures by higher-ranked peers are more informative:

$$\ell'(r) > 0 \tag{70}$$

This condition is the formal counterpart of the idea that high-quality or high-influence peers have more precise information, more credible outside options, stronger knowledge of work-

place conditions, or any other information that would lead them to departure with a higher probability.

The focal worker's stay value between $t-1$ and $t$ may depend on the next-period origin state $\Theta_{o,t}$. To connect the peer-departure signal to this future state, assume the origin state follows a Markov process:

$$\Pr(\Theta_{o,t} = G \mid \Theta_{o,t-1} = G) = \rho_G, \qquad \Pr(\Theta_{o,t} = G \mid \Theta_{o,t-1} = B) = \rho_B, \qquad \rho_G > \rho_B \tag{71}$$

The condition $\rho_G > \rho_B$ imposes persistence in origin-firm conditions: if the origin was in the good state during the peer-departure interval, it is more likely to remain good during worker $i$'s subsequent decision interval than if it was previously in the bad state. Then the belief relevant for worker $i$'s stay decision is

$$\widetilde{\mu}_{i,t} \equiv \Pr(\Theta_{o,t} = G \mid \mathcal{I}^0_{i,t-2}, \mathbf{d}^o_{i,t-1}) = \rho_G \mu^+_{i,t-1} + \rho_B(1 - \mu^+_{i,t-1}) \tag{72}$$

Because $\rho_G > \rho_B$, any peer departure that lowers $\mu^+_{i,t-1}$ also lowers $\widetilde{\mu}_{i,t}$, the expected quality of staying at the origin during worker $i$'s decision interval.

The belief-based peer-loss signal is given by

$$\mathcal{S}^o_{i,t-1} = \frac{1}{|\mathcal{P}_{i,t-2}|} \sum_{j \in \mathcal{P}_{i,t-2}} \ell(r_j) d^o_{j,t-1} \tag{73}$$

Equation (73) is the Bayesian counterpart of the weighted origin peer-loss index, i.e., (53). However, instead of weighting each departure by the latent influence weight $\omega(r_j)$, (73) weights each departure by the log-likelihood content $\ell(r_j)$, defined in (68). This implies that a larger value of $\mathcal{S}^o_{i,t-1}$ means that the observed peer-departure vector contains stronger negative information about the origin state.

If we assume that the informational content of departures is approximately constant within

rank classes, then we can write

$$\ell_H = \mathbb{E}[\ell(r_j) \mid j \in \mathcal{H}_{i,t-2}],$$
$$\ell_M = \mathbb{E}[\ell(r_j) \mid j \in \mathcal{M}_{i,t-2}],$$
$$\ell_L = \mathbb{E}[\ell(r_j) \mid j \in \mathcal{L}_{i,t-2}]$$

Under monotone informativeness,

$$\ell_H > \ell_M > \ell_L \geq 0$$

Therefore

$$\begin{aligned} \mathcal{S}^o_{i,t-1} &\approx \ell_H H_{i,t-1} + \ell_M M_{i,t-1} + \ell_L L_{i,t-1} \\ &= \ell_M T_{i,t-1} + (\ell_H - \ell_M) H_{i,t-1} + (\ell_L - \ell_M) L_{i,t-1} \end{aligned} \tag{74}$$

Under (74) we conclude that holding total peer turnover fixed, a larger high-quality departure share raises the negative signal about the origin, while a larger low-quality departure share weakens the negative signal relative to middle-quality departures.

### A.2.2 Peer departures as information about outside opportunities

The same logic as the previous subsection also applies to the outside market. This channel is related to evidence that coworker networks transmit information about outside opportunities and shape subsequent mobility (Cingano & Rosolia, 2012; Hensvik & Skans, 2016; Kramarz & Skans, 2014). Let

$$\Omega_{t-1} \in \{\Omega^B, \Omega^G\}$$

be the outside-opportunity state during the peer-departure interval, where a good state $\Omega^G$ means that workers are more likely to receive attractive outside offers. Suppose the peer

outside offer distribution satisfies first-order stochastic dominance:

$$F_{x|\Omega^G,r}(x) \leq F_{x|\Omega^B,r}(x) \quad \text{for all } x \tag{75}$$

Equation (75) means that for any offer threshold $x$, peers are weakly less likely to draw an offer below $x$ when $\Omega_{t-1} = \Omega^G$ than when $\Omega_{t-1} = \Omega^B$. Hence, holding mobility costs and stay values fixed, peers are more likely to receive outside offers large enough to leave when outside opportunities are favorable.

It follows that the probability of departure is higher when outside opportunities are favorable:

$$\Pr(d^o_{j,t-1} = 1 \mid \Omega_{t-1} = \Omega^G, r_j) > \Pr(d^o_{j,t-1} = 1 \mid \Omega_{t-1} = \Omega^B, r_j) \tag{76}$$

Thus, observed peer departures can also raise the posterior probability that outside opportunities are attractive. This channel increases the value of search even if the origin firm itself has not deteriorated. Let

$$\Pi^{\Omega}_{i,t} \equiv \Pr(\Omega_{t-1} = \Omega^G \mid \mathcal{I}^0_{i,t-2}, \mathbf{d}^o_{i,t-1})$$

denote worker $i$'s posterior belief that outside opportunities were favorable during the peer-departure interval. Since departures are more likely when $\Omega_{t-1} = \Omega^G$, observed peer departures can raise $\Pi^{\Omega}_{i,t}$, increasing the perceived value of search.

The origin-state and outside-opportunity channels are presented separately for clarity. In a fully specified Bayesian model, worker $i$ would update over the joint state $(\Theta_{o,t-1}, \Omega_{t-1})$. A peer departure may be informative about a deterioration of the origin, an improvement in outside opportunities, or both. The reduced-form origin-side coefficient therefore captures the net effect of these belief revisions on the relative value of moving versus staying.

### A.2.3 Coworker-specific production capital

Peer departures may also reduce the current production value of the origin job. This channel follows the workplace peer-effects literature, which treats coworkers as potential inputs into productivity through effort, learning, monitoring, or complementarities (Bandiera et al., 2010; Cornelissen et al., 2017; Mas & Moretti, 2009). Let output generated by worker $i$ at origin $o$ be:

$$Y_{i,o,t} = A_{o,t} + a_i + m_{i,o,t} + \sum_{j \in \mathcal{P}_{i,t-2}} \chi_{ij}\omega(r_j)(1 - d^o_{j,t-1}) \tag{77}$$

In (77), output has four components. The term $A_{o,t}$ is the productivity of the origin firm, $a_i$ is worker $i$'s own productive component, and $m_{i,o,t}$ is the match-specific productivity of worker $i$ at the origin. The final term captures coworker-specific team capital. For each peer $j \in \mathcal{P}_{i,t-2}$, the indicator

$$1 - d^o_{j,t-1}$$

equals one if peer $j$ remains at the origin after the peer-departure interval and equals zero if peer $j$ leaves. Therefore peer $j$'s contribution to worker $i$'s origin output is present only when $j$ stays.

The magnitude of this contribution is defined by

$$\chi_{ij}\omega(r_j)$$

where the parameter $\chi_{ij} \geq 0$ measures how complementary peer $j$ is to worker $i$ in production. This can reflect task-specific knowledge, coordination, mentoring, or any other forms of team-specific capital. The term $\omega(r_j)$ weights this complementarity by peer $j$'s influence rank. Since $\omega'(r) > 0$, losing a higher-ranked peer removes a larger amount of team capital, holding $\chi_{ij}$ fixed.

Thus, holding everything else constant, a peer departure affects worker $i$'s origin output

mechanically:

$$d^o_{j,t-1} : 0 \to 1 \quad \Rightarrow \quad \Delta_j Y_{i,o,t} = -\chi_{ij}\omega(r_j) \leq 0$$

This channel does not assume that peer turnover enters utility directly but that peer departures matter because the production technology uses retained coworkers as inputs.

If wages share surplus with worker bargaining weight $\beta_i \in (0,1)$, then the flow wage at the origin satisfies:

$$w_{i,o,t} = b_{i,t} + \beta_i \left[ Y_{i,o,t} - b_{i,t} \right] \tag{78}$$

Equation (78) is a simple surplus-sharing wage equation. The worker receives her outside option $b_{i,t}$ plus a fraction $\beta_i$ of the match surplus generated at the origin. The surplus from the origin job is

$$Y_{i,o,t} - b_{i,t},$$

such that $\beta_i \in (0,1)$ measures the share of this surplus accruing to worker $i$. When $\beta_i$ is larger, changes in origin output translate more strongly into changes in the worker's wage. Holding the outside option $b_{i,t}$ fixed, the only way peer $j$'s departure affects the origin wage in this channel is through its effect on origin output $Y_{i,o,t}$. From (77), changing $d^o_{j,t-1}$ from zero to one removes peer $j$'s team-capital contribution:

$$\Delta_j Y_{i,o,t} = -\chi_{ij}\omega(r_j)$$

Substituting this output loss into the surplus-sharing equation gives

$$\Delta_j w_{i,o,t} = \beta_i \Delta_j Y_{i,o,t} = -\beta_i \chi_{ij}\omega(r_j) \leq 0 \tag{79}$$

Therefore, a peer departure lowers the worker's origin wage component whenever the departing peer was productive for worker $i$, that is, whenever $\chi_{ij} > 0$. The magnitude of the loss is larger when the peer is more complementary to worker $i$, when the worker captures

a larger share of match surplus, or when the departing peer has a higher influence weight $\omega(r_j)$.

(79) should be interpreted as the wage effect operating through the production or team-capital channel. If peer departures also affect worker $i$'s outside option $b_{i,t}$, for example by revealing better outside opportunities, then the total wage effect would include an additional outside-option component. The expression above isolates the direct effect of losing peer $j$'s contribution to origin output. Meanwhile, the expression also tells us that the loss is larger for higher-ranked peers whenever $\omega'(r) > 0$ and $\chi_{ij} > 0$.

Next, define the production loss from peer departures as

$$\mathcal{K}^{o,\text{loss}}_{i,t-1} = \frac{1}{|\mathcal{P}_{i,t-2}|} \sum_{j \in \mathcal{P}_{i,t-2}} \chi_{ij}\omega(r_j) d^o_{j,t-1} \tag{80}$$

If the average complementarity weight is larger for high-ranked peers than for middle-ranked peers and larger for middle-ranked peers than for low-ranked peers, then we can define

$$\begin{aligned} k_H &= \mathbb{E}[\chi_{ij}\omega(r_j) \mid j \in \mathcal{H}_{i,t-2}], \\ k_M &= \mathbb{E}[\chi_{ij}\omega(r_j) \mid j \in \mathcal{M}_{i,t-2}], \\ k_L &= \mathbb{E}[\chi_{ij}\omega(r_j) \mid j \in \mathcal{L}_{i,t-2}], \end{aligned}$$

with

$$k_H > k_M > k_L \geq 0$$

Then

$$\begin{aligned} \mathcal{K}^{o,\text{loss}}_{i,t-1} &\approx k_H H_{i,t-1} + k_M M_{i,t-1} + k_L L_{i,t-1} \\ &= k_M T_{i,t-1} + (k_H - k_M) H_{i,t-1} + (k_L - k_M) L_{i,t-1} \end{aligned} \tag{81}$$

(81) allows us to conclude that, holding total turnover fixed, departures by high-quality peers generate larger losses of team capital, while departures by low-quality peers generate smaller losses relative to middle-quality departures.

## A.3 Destination-side former peers

Now consider a candidate destination firm $f$. Let

$$\mathcal{B}_{i,f,t} = \{j \in \mathcal{P}_{i,t-2} : j \text{ moved to firm } f \text{ between } t-2 \text{ and } t-1 \text{ and remains at } f \text{ in } t\}$$

be the set of former peers of $i$ present at firm $f$. We can define the weighted former-peer stock as

$$B_{i,f,t} = \sum_{j \in \mathcal{B}_{i,f,t}} \omega(r_j) \tag{82}$$

and the high-ranked former-peer stock

$$B^H_{i,f,t} = \sum_{j \in \mathcal{B}_{i,f,t} \cap \mathcal{H}_{i,t-2}} \omega(r_j) \tag{83}$$

The empirical indicators for the extensive margin are

$$\begin{aligned} P_{i,f,t} &= \mathbb{1}\{\mathcal{B}_{i,f,t} \neq \emptyset\} = \mathbb{1}\{B_{i,f,t} > 0\}, \\ Q_{i,f,t} &= \mathbb{1}\{\mathcal{B}_{i,f,t} \cap \mathcal{H}_{i,t-2} \neq \emptyset\} = \mathbb{1}\{B^H_{i,f,t} > 0\}. \end{aligned} \tag{84}$$

The second equality in each line follows from the strict positivity of $\omega(\cdot)$, together with the convention that a sum over an empty set equals zero. Thus $P_{i,f,t}$ equals one exactly when candidate firm $f$ employs at least one former peer of worker $i$, while $Q_{i,f,t}$ equals one exactly when it employs at least one high-ranked former peer.

### A.3.1 Vacancy information and consideration-set formation

Worker $i$ does not observe all vacancies before making the move decision between $t-1$ and $t$. This search-friction channel follows network job-search models in which social contacts reveal vacancies and lower information frictions (Granovetter, 1973; Ioannides & Loury, 2004; Topa, 2011). Let

$$\mathcal{V}_{i,f,t} = 1$$

denote that, during the decision interval $(t-1, t]$ and before the employment state at $t$ is realized, worker $i$ learns about a relevant vacancy at candidate firm $f$. The subscript $t$ indexes the destination-choice year, not the moment at which the information is first received. Vacancy information arrives through a formal channel and through former peers. Recall that $\mathcal{B}_{i,f,t}$ denotes the set of former peers of worker $i$ who moved to candidate firm $f$ between $t-2$ and $t-1$ and remain at $f$ in $t$. These former peers are already linked to destination firm $f$ before worker $i$'s move is observed in $t$, and therefore can transmit information about vacancies, applications, or working conditions during the decision interval.

The formal channel has an arrival rate $\lambda^0_{i,f,t} \geq 0$. This object captures the rate at which worker $i$ learns about a vacancy at candidate firm $f$ through non-peer sources during the decision interval $(t-1, t]$. These sources may include public job postings, direct applications, recruiters, firm visibility, occupation-specific search channels, or other formal search mechanisms. The superscript 0 denotes the baseline no-peer information channel: it is the vacancy-information arrival rate that would apply even if worker $i$ had no former peers at firm $f$.

At the same time, each former peer $j \in \mathcal{B}_{i,f,t}$ may provide an additional peer-network information channel. Let the peer-specific arrival rate be

$$\lambda^{peer}_j = \lambda^{peer}(r_j), \qquad (\lambda^{peer})'(r) > 0$$

The superscript "peer" distinguishes this network-based information channel from the formal search channel $\lambda^0_{i,f,t}$. The condition $(\lambda^{peer})'(r) > 0$ means that higher-ranked former peers transmit vacancy information at a higher rate.

Assuming independent Poisson information arrivals, the probability that worker $i$ learns about a relevant vacancy at firm $f$ is

$$\Pr(\mathcal{V}_{i,f,t} = 1 \mid \mathcal{B}_{i,f,t}, v_{f,t} = 1) = 1 - \exp\left\{-\lambda^0_{i,f,t} - \sum_{j \in \mathcal{B}_{i,f,t}} \lambda^{peer}(r_j)\right\} \tag{85}$$

The expression inside the exponential is the total information-arrival rate. It is the sum of the formal arrival rate, $\lambda^0_{i,f,t}$, and the peer-network arrival rates generated by former peers at the candidate firm. If no former peers are present at $f$, then $\mathcal{B}_{i,f,t} = \emptyset$ and the learning probability reduces to the formal-search probability

$$1 - \exp\{-\lambda^0_{i,f,t}\}$$

If former peers are present, the total arrival rate is larger, so the probability of learning about the vacancy is weakly higher. Adding a former peer $j$ to firm $f$ changes the probability of learning about the vacancy by

$$\Delta_j \Pr(\mathcal{V}_{i,f,t} = 1) = \exp\left\{-\lambda^0_{i,f,t} - \sum_{k \in \mathcal{B}^{-j}_{i,f,t}} \lambda^{peer}(r_k)\right\} [1 - \exp\{-\lambda^{peer}(r_j)\}] > 0 \tag{86}$$

In this expression, $\mathcal{B}^{-j}_{i,f,t}$ denotes the set of former peers already present at candidate firm $f$ before adding peer $j$. The first factor,

$$\exp\left\{-\lambda^0_{i,f,t} - \sum_{k \in \mathcal{B}^{-j}_{i,f,t}} \lambda^{peer}(r_k)\right\}$$

is the probability that none of the existing information channels transmit the vacancy to worker $i$. The second factor,

$$1 - \exp\{-\lambda^{peer}(r_j)\}$$

is the probability that the newly added former peer $j$ transmits the vacancy. Their product is therefore the probability that peer $j$'s information channel is pivotal. Since $\lambda^{peer}(r_j) > 0$, this probability is strictly positive, so adding a former peer raises the probability that worker $i$ learns about the vacancy. This effect follows from a search technology in which network links transmit vacancy information.

Application costs are also affected by former-peer information. Let

$$c^a_{i,f,t} = c^0_{i,f,t} - \sum_{j \in \mathcal{B}_{i,f,t}} \rho^c(r_j), \qquad (\rho^c)'(r) > 0 \tag{87}$$

The term $c^0_{i,f,t}$ is the baseline cost for worker $i$ to apply to candidate firm $f$ through non-peer channels. It may reflect the time cost of finding the relevant posting, identifying the appropriate contact, preparing an application, or learning whether the vacancy is suitable, among many others. Each former peer $j \in \mathcal{B}_{i,f,t}$ reduces this cost by $\rho^c(r_j)$, because former peers can provide information about whom to contact, how to apply, which vacancy is relevant, or what the firm is likely to value. The condition $(\rho^c)'(r) > 0$ means that higher-ranked former peers generate larger application-cost reductions. We interpret $c^a_{i,f,t}$ as a net application cost and we can impose a parameter restriction such that $c^a_{i,f,t} \geq 0$.

Let $C_{i,t}$ be worker $i$'s latent consideration set. A candidate firm enters $C_{i,t}$ if worker $i$ learns about the vacancy and the expected net value of applying is at least as large as the fallback value. Let

$$\pi^O_{i,f,t} \equiv \Pr(O_{i,f,t} = 1 \mid \mathcal{I}_{i,f,t}, \mathcal{V}_{i,f,t} = 1)$$

denote the probability that applying to firm $f$ generates an offer, conditional on worker $i$'s information set $\mathcal{I}_{i,f,t}$ and on learning about the vacancy. Here $\mathcal{I}_{i,f,t}$ denotes the information

available at the application stage. In the referral-screening model below, this offer probability can be decomposed as

$$\pi^{O}_{i,f,t} = q^{rev}_{i,f,t}(\mathcal{B}_{i,f,t}) \Pr\left(M^{F}_{i,f,t}(\mathcal{B}_{i,f,t}) \geq 0 \mid \mathcal{I}_{i,f,t}, \mathcal{V}_{i,f,t} = 1, \mathrm{Rev}_{i,f,t} = 1\right)$$

Thus $\pi^{O}_{i,f,t}$ summarizes both the probability that the application is reviewed and the probability that, conditional on review, the firm believes the expected match surplus is nonnegative. Let $J_{i,f,t}$ denote the value of the job if an offer is received and accepted, and let $R_{i,t}$ denote the fallback value. The object $R_{i,t}$ is the fallback value in the worker's apply-or-accept decision, expressed in value-function units. The object $b_{i,t}$ is the outside option entering the match-surplus and wage-bargaining equations. In the simplest case they coincide, but the notation allows the value-function fallback to include continuation values and other available options. Then

$$f \in C_{i,t} \quad \Longleftrightarrow \quad \mathcal{V}_{i,f,t} = 1 \quad \text{and} \quad \pi^{O}_{i,f,t}\left(\mathbb{E}[J_{i,f,t} \mid \mathcal{I}_{i,f,t}, O_{i,f,t} = 1] - R_{i,t}\right) \geq c^{a}_{i,f,t} \tag{88}$$

The first condition, $\mathcal{V}_{i,f,t} = 1$, says that a firm cannot enter the consideration set unless worker $i$ learns about a relevant vacancy. The second condition says that applying must have nonnegative expected surplus relative to the fallback option. The term in parentheses is the expected gain from receiving and accepting an offer from firm $f$, relative to fallback value $R_{i,t}$. Multiplying by $\pi^{O}_{i,f,t}$ accounts for the fact that applying does not guarantee an offer. Former peers can therefore increase consideration through three primitive channels: they can raise the probability of learning about the vacancy, lower the application cost $c^{a}_{i,f,t}$, or increase the expected offer probability $\pi^{O}_{i,f,t}$.

### A.3.2 Referral screening and firm-side offer decisions

Former peers can also affect whether firm $f$ reviews worker $i$'s application. This mechanism adapts referral models in which social contacts generate informative signals about applicant

productivity or match quality (Montgomery, 1991; Simon & Warner, 1992), and connects to empirical evidence that referrals and coworker links affect hiring, mobility, and wages (Dustmann et al., 2016; Eliason et al., 2023; Hensvik & Skans, 2016; Kramarz & Skans, 2014). Firm $f$ has limited review capacity $\kappa_{f,t}$, which means that not all applications are necessarily evaluated. Let

$$\text{Rev}_{i,f,t} = 1$$

denote the event that worker $i$'s application to firm $f$ is reviewed. Without a referral, the application enters the regular review process. With a former-peer referral, the application may receive additional attention or enter a priority queue. Let

$$q^0_{i,f,t} \equiv \Pr(\text{Rev}_{i,f,t} = 1 \mid \mathcal{B}_{i,f,t} = \emptyset)$$

denote the baseline probability that worker $i$'s application is reviewed when no former peers are present at firm $f$ and let

$$q^{rev}_{i,f,t}(\mathcal{B}_{i,f,t}) \equiv \Pr(\text{Rev}_{i,f,t} = 1 \mid \mathcal{B}_{i,f,t})$$

denote the review probability when the set of former peers at firm $f$ is $\mathcal{B}_{i,f,t}$.[19]

A capacity-constrained review technology is

$$q^{rev}_{i,f,t}(\mathcal{B}_{i,f,t}) = 1 - (1 - q^0_{i,f,t}) \exp\left\{ - \sum_{j \in \mathcal{B}_{i,f,t}} \rho^{rev}(r_j) \right\}, \qquad (\rho^{rev})'(r) > 0 \tag{89}$$

The term $\rho^{rev}(r_j) \geq 0$ measures the additional review intensity generated by former peer $j$'s referral or information. The condition $(\rho^{rev})'(r) > 0$ means that higher-ranked former peers generate stronger review effects. Equation (89) says that the probability of review is one minus the probability that no review channel succeeds. If no former peers are present,

[19] The set $\mathcal{B}_{i,f,t}$ contains the former peers of worker $i$ who moved to candidate firm $f$ between $t-2$ and $t-1$ and remain at $f$ in $t$.

then $\mathcal{B}_{i,f,t} = \emptyset$, the summation is zero, and the review probability reduces to the baseline probability $q^0_{i,f,t}$. If former peers are present, the exponential term falls, so the probability of review rises.

Let $\mathcal{B}^{-j}_{i,f,t}$ denote the set of former peers already present at firm $f$ before adding peer $j$. Adding former peer $j$ changes the review probability by

$$\begin{aligned}\Delta_j q^{rev}_{i,f,t} &= q^{rev}_{i,f,t}(\mathcal{B}^{-j}_{i,f,t} \cup \{j\}) - q^{rev}_{i,f,t}(\mathcal{B}^{-j}_{i,f,t}) \\ &= (1 - q^0_{i,f,t}) \exp\left\{ - \sum_{k \in \mathcal{B}^{-j}_{i,f,t}} \rho^{rev}(r_k) \right\} [1 - \exp\{-\rho^{rev}(r_j)\}] > 0 \end{aligned} \tag{90}$$

The first factor, $1 - q^0_{i,f,t}$, is the probability that the application would not be reviewed through the baseline channel. The exponential term is the probability that none of the existing former-peer channels generates review. The bracketed term is the probability that the newly added former peer $j$'s channel generates review. Their product is therefore the probability that peer $j$'s referral is pivotal. Since $\rho^{rev}(r_j) > 0$, adding a former peer strictly increases the probability that the application is reviewed.

Conditional on review, the firm observes signals about the surplus from hiring worker $i$. Let the true match surplus from hiring worker $i$ at firm $f$ be

$$S_{i,f,t} = A_{f,t} + a_i + m_{i,f,t} - b_{i,t} \tag{91}$$

where $A_{f,t}$ is firm productivity, $a_i$ is worker $i$'s productive component, $m_{i,f,t}$ is match-specific productivity between worker $i$ and firm $f$, and $b_{i,t}$ is worker $i$'s outside option. Thus $S_{i,f,t}$ is the net surplus generated by the match relative to worker $i$'s outside option. The firm does not observe $S_{i,f,t}$ perfectly before making an offer. Instead, before receiving application or referral information, the firm has a prior belief that follows the given distribution:

$$S_{i,f,t} \sim N\left(\mu^{F,0}_{i,f,t}, \sigma^2_S\right)$$

where $\mu^{F,0}_{i,f,t}$ is the firm's prior expected surplus from hiring worker $i$, and $\sigma^2_S$ measures the prior uncertainty about that surplus. A formal application produces a noisy signal about match surplus, namely:

$$s^0_{i,f,t} = S_{i,f,t} + \varepsilon^0_{i,f,t} \quad \text{with} \quad \varepsilon^0_{i,f,t} \sim N(0, \sigma^2_0) \tag{92}$$

The superscript 0 denotes the formal, non-referral application channel. The signal $s^0_{i,f,t}$ may summarize information contained in the application, CV, interview, observable credentials, or other standard screening inputs. The noise term $\varepsilon^0_{i,f,t}$ captures the fact that formal screening is imperfect and a smaller $\sigma^2_0$ means that the formal application signal is more precise. Each former peer $j \in \mathcal{B}_{i,f,t}$ can provide an additional referral signal:

$$s^j_{i,f,t} = S_{i,f,t} + \varepsilon^j_{i,f,t}, \quad \text{with} \quad \varepsilon^j_{i,f,t} \sim N(0, \tau_j^{-1}), \qquad \tau_j = \tau(r_j), \qquad \tau'(r) > 0 \tag{93}$$

The signal $s^j_{i,f,t}$ is former peer $j$'s information about the expected surplus from hiring worker $i$. This information may concern worker $i$'s productivity, reliability, fit with the firm's tasks, or compatibility with the destination workplace, among other information that $j$ might have about $i$. The parameter $\tau_j$ is the precision of peer $j$'s referral signal. Similar to what we discussed in (59), since the variance is $\tau_j^{-1}$, a larger $\tau_j$ means that the referral signal is less noisy. The condition $\tau'(r) > 0$ says that higher-ranked former peers provide more precise referral information.

We can assume that the prior, formal signal, and referral signals are normally distributed and conditionally independent given $S_{i,f,t}$. In that case, let the firm's information set after observing the formal application and any referral signals be

$$\mathcal{I}^F_{i,f,t} = \left\{ s^0_{i,f,t}, \{ s^j_{i,f,t} : j \in \mathcal{B}_{i,f,t} \} \right\}$$

in which case the firm's posterior mean surplus is

$$M^F_{i,f,t}(\mathcal{B}_{i,f,t}) = \mathbb{E}\left[S_{i,f,t} \mid \mathcal{I}^F_{i,f,t}\right] \tag{94}$$

Under normal learning, this posterior mean is a precision-weighted average of the prior mean, the formal application signal, and the referral signals:

$$M^F_{i,f,t}(\mathcal{B}_{i,f,t}) = \frac{\frac{1}{\sigma_S^2}\mu^{F,0}_{i,f,t} + \frac{1}{\sigma_0^2}s^0_{i,f,t} + \sum_{j\in\mathcal{B}_{i,f,t}} \tau(r_j)s^j_{i,f,t}}{\frac{1}{\sigma_S^2} + \frac{1}{\sigma_0^2} + \sum_{j\in\mathcal{B}_{i,f,t}} \tau(r_j)} \tag{95}$$

Equation (95) makes the referral mechanism imply that a former peer affects the firm's belief because her signal enters the posterior mean with weight proportional to its precision $\tau(r_j)$. A high-ranked former peer receives a larger weight when $\tau'(r) > 0$.

The posterior precision is

$$\frac{1}{\mathrm{Var}(S_{i,f,t} \mid \mathcal{I}^F_{i,f,t})} = \frac{1}{\sigma_S^2} + \frac{1}{\sigma_0^2} + \sum_{j\in\mathcal{B}_{i,f,t}} \tau(r_j) \tag{96}$$

i.e., precision is the inverse of variance. Therefore, equation (96) says that each additional former-peer referral signal increases the precision of the firm's belief about match surplus. If no former peers are present, the posterior precision is only the sum of the prior precision and the formal-application precision. If former peers are present, the firm receives additional information, and uncertainty about $S_{i,f,t}$ falls. This is the screening channel in the sense that former peers can improve the firm's ability to identify positive-surplus matches. The firm makes an offer if expected surplus is nonnegative:

$$O_{i,f,t} = 1 \quad \Longleftrightarrow \quad \mathrm{Rev}_{i,f,t} = 1 \quad \text{and} \quad M^F_{i,f,t}(\mathcal{B}_{i,f,t}) \geq 0 \tag{97}$$

Equation (97) separates two firm-side margins. The first implies that the application must be reviewed, $\mathrm{Rev}_{i,f,t} = 1$. The second, conditional on review, implies that the firm must believe

that hiring worker $i$ generates nonnegative expected surplus, $M^F_{i,f,t}(\mathcal{B}_{i,f,t}) \geq 0$. Former peers can affect both margins: they can increase the probability that the application is reviewed, and they can provide referral information that changes the firm's posterior belief about match surplus. For workers who are good matches for firm $f$, referral information can raise the probability that the firm recognizes the match as positive surplus and makes an offer. For workers who are poor matches, better information can instead reduce the probability of an offer. Therefore, the destination-side peer effect should be interpreted as a net screening and access effect: former peers help workers reach firms where the expected match surplus is more likely to be positive, rather than mechanically increasing offers for every worker.

### A.3.3 Worker-side match information and the value of information

Worker $i$ also has imperfect information about the value of a potential job at candidate firm $f$. Similarly to the firm-side screening channel above, former peers can help worker $i$ learn about firm $f$. This channel uses a standard value-of-information argument: more informative signals cannot reduce the value of an optimized accept-or-reject decision when information is costless and available before the decision (Blackwell, 1953).

Let $J_{i,f,t}$ denote the value of the job if worker $i$ receives and accepts an offer from firm $f$. Before accepting an offer, worker $i$ may not know $J_{i,f,t}$ perfectly. The worker may be uncertain about managers, coworkers, working conditions, schedule flexibility, promotion prospects, wage growth, task fit, or other attributes of the destination job. Let

$$\mathcal{I}^W_{i,f,t}(\mathcal{B})$$

denote worker $i$'s information set about candidate firm $f$ when the set of former peers at $f$ is $\mathcal{B}$. The superscript $W$ indicates that this is the worker's information set, similar to how the superscript $F$ indicated that it was the firm's information set. The argument $\mathcal{B}$ indicates that the information available to the worker depends on which former peers are employed

at the candidate firm. Here $\mathcal{B}$ denotes a generic set of former peers employed at candidate firm $f$.

To make this channel explicit, suppose each former peer $j \in \mathcal{B}$ can send worker $i$ a signal about the job value,

$$z^W_{j,i,f,t} = J_{i,f,t} + u^W_{j,i,f,t}$$

where $u^W_{j,i,f,t}$ is signal noise which can represent imperfect information about working conditions, managers, expected pay, firm culture, or the suitability of the job for worker $i$, among others. The worker's information set can then be written as

$$\mathcal{I}^W_{i,f,t}(\mathcal{B}) = \mathcal{I}^{W,0}_{i,f,t} \cup \{z^W_{j,i,f,t} : j \in \mathcal{B}\}$$

where $\mathcal{I}^{W,0}_{i,f,t}$ is the information available from non-peer sources, such as public information, interviews, recruiters, or the formal application process. The worker accepts the job only if the expected job value is high enough relative to the fallback value.[20] Let $R_{i,t}$ denote worker $i$'s fallback value. Given information set $\mathcal{I}^W_{i,f,t}(\mathcal{B})$, worker $i$'s posterior expected job value is

$$\mu^W_{i,f,t}(\mathcal{B}) \equiv \mathbb{E}[J_{i,f,t} \mid \mathcal{I}^W_{i,f,t}(\mathcal{B})]$$

The worker's acceptance value from candidate firm $f$ is

$$\mathcal{A}_{i,f,t}(\mathcal{B}) = \mathbb{E}\left[\max\{R_{i,t}, \mu^W_{i,f,t}(\mathcal{B})\}\right]$$

This expression implies that if the posterior expected job value is below the fallback value, the worker rejects the offer and receives $R_{i,t}$. If the posterior expected job value is above the fallback value, the worker accepts the offer. The maximum operator captures this accept-or-reject option.

[20] Given that this is an on-the-job search model, $R_{i,t}$ should be interpreted as the maximum value between staying at the origin firm and accepting any other available offer.

Now compare two former-peer sets, $\mathcal{B}$ and $\mathcal{B}'$, with $\mathcal{B}' \supset \mathcal{B}$. Since $\mathcal{B}'$ gives the worker all the information available under $\mathcal{B}$ plus additional former-peer signals, the worker can always ignore the extra information and behave as if only $\mathcal{B}$ were available. This argument assumes that additional former-peer information is costless to process and arrives before the worker must accept or reject the offer. Under this timing, additional former-peer information cannot reduce the optimized expected acceptance value:

$$\mathcal{A}_{i,f,t}(\mathcal{B}') \geq \mathcal{A}_{i,f,t}(\mathcal{B})$$

A formal way to see this is that the posterior mean under the smaller information set equals the conditional expectation of the posterior mean under the larger information set:

$$\mu^W_{i,f,t}(\mathcal{B}) = \mathbb{E}[\mu^W_{i,f,t}(\mathcal{B}') \mid \mathcal{I}^W_{i,f,t}(\mathcal{B})]$$

Because $x \mapsto \max\{R_{i,t}, x\}$ is convex, Jensen's inequality implies

$$\mathbb{E}\left[\max\{R_{i,t}, \mu^W_{i,f,t}(\mathcal{B}')\}\right] \geq \mathbb{E}\left[\max\{R_{i,t}, \mu^W_{i,f,t}(\mathcal{B})\}\right] \tag{98}$$

which is exactly

$$\mathcal{A}_{i,f,t}(\mathcal{B}') \geq \mathcal{A}_{i,f,t}(\mathcal{B})$$

Thus, former peers can increase the value of a destination even if their signals are unbiased and even if the worker receives no direct social utility from rejoining them. The reason is that former peers reduce the uncertainty about the destination, i.e., better information helps the worker avoid bad matches and accept good matches. This worker-side information channel is one mechanism through which former-peer presence can raise the probability that candidate firm $f$ is chosen.

### A.3.4 Additional surplus channels

The information and referral mechanisms above are sufficient to generate peer-linked destination effects, but additional surplus channels may also be present. For example, if worker $i$ joins firm $f$, output may include complementarities with former peers:

$$Y_{i,f,t} = A_{f,t} + a_i + m_{i,f,t} + \sum_{j \in \mathcal{B}_{i,f,t}} \chi_{ij}^{f} \omega(r_j), \qquad \chi_{ij}^{f} \geq 0 \tag{99}$$

The worker may also receive nonpecuniary utility from rejoining former peers:

$$s_{i,f,t} = s_{i,f,t}^{0} + \sum_{j \in \mathcal{B}_{i,f,t}} \upsilon_{ij}^{f} \omega(r_j), \qquad \upsilon_{ij}^{f} \geq 0 \tag{100}$$

These channels are not separately identified in the empirical analysis, but they are included to show that former-peer stocks can also affect destination value through surplus and nonpecuniary mechanisms. The complementarity channel follows the same economic logic as the workplace peer-effects literature, while the social-utility channel is a reduced-form way to allow coworker ties to enter nonpecuniary job value (Bandiera et al., 2010; Cornelissen et al., 2017; Mas & Moretti, 2009).

## A.4 The worker's dynamic problem

The previous subsections derive the primitive channels through which peers affect mobility. Origin-side peer departures can change worker $i$'s beliefs about the origin firm, beliefs about outside opportunities, and retained team capital. Destination-side former peers can affect vacancy information, application costs, review probabilities, offer probabilities, firm-side posterior beliefs, worker-side information, and match surplus. This subsection collects those objects into a single dynamic decision problem. No new peer effect is assumed here and the state vector and value functions only summarize the mechanisms already defined above. The discrete-choice representation follows the logic of random-utility models McFadden (1974)

and dynamic discrete-choice models used in labor-market mobility settings (Adda et al., 2013; Adda & Dustmann, 2023; Rust, 1987). Unlike those structural papers, however, the present model is not estimated structurally; it is used to discipline the reduced-form empirical variables.

Let $\Xi_{i,t}$ denote the information available to worker $i$ when making the mobility decision between $t-1$ and $t$. A convenient representation is

$$\Xi_{i,t} = \big(\theta_i, o(i,t-1), w_{i,o,t-1}, \mathcal{P}_{i,t-2}, \mathbf{d}^o_{i,t-1}, \widetilde{\mu}_{i,t}, \Pi^{\Omega}_{i,t}, K^o_{i,t}, \{Z_{f,t}\}_{f\in\mathcal{F}_t}, \{\mathcal{B}_{i,f,t}\}_{f\in\mathcal{F}_t}, \mathfrak{M}_{i,t}\big) \quad (101)$$

The state vector is only a compact way of listing the payoff-relevant objects defined in the previous subsections, namely:

- $\theta_i$ is worker $i$'s type.
- $o(i,t-1)$ is the origin firm before the move.
- $w_{i,o,t-1}$ is the worker's lagged wage at the origin firm.
- The set $\mathcal{P}_{i,t-2}$ is the predetermined peer group.
- $\mathbf{d}^o_{i,t-1}$ is the vector of peer departures observed between $t-2$ and $t-1$.
- The belief $\widetilde{\mu}_{i,t}$, defined in (72), is worker $i$'s posterior probability that the origin is in the good state during the decision interval.
- $\Pi^{\Omega}_{i,t}$ denotes worker $i$'s posterior belief about the outside-opportunity state after observing peer departures.
- $K^o_{i,t}$ is retained team capital at the origin, such that $K^o_{i,t} = \sum_{j\in\mathcal{P}_{i,t-2}} \chi_{ij}\omega(r_j)(1-d^o_{j,t-1})$.
- $\{Z_{f,t}\}_{f\in\mathcal{F}_t}$ are candidate-firm states.
- $\{\mathcal{B}_{i,f,t}\}_{f\in\mathcal{F}_t}$ are the former-peer sets at candidate firms.

- $\mathfrak{M}_{i,t}$ collects destination-specific beliefs and probabilities generated by the search and referral channels.

Namely,

$$\mathfrak{M}_{i,t} = \left\{ \Pr(\mathcal{V}_{i,f,t} = 1), c^a_{i,f,t}, q^{rev}_{i,f,t}(\mathcal{B}_{i,f,t}), \pi^O_{i,f,t}, M^F_{i,f,t}(\mathcal{B}_{i,f,t}), \mu^W_{i,f,t}(\mathcal{B}_{i,f,t}) \right\}_{f \in \mathcal{F}_t}$$

has objects that were defined in Sections A.3.1, A.3.2, and A.3.3. They summarize, for each candidate firm $f$, the probability that worker $i$ learns about a vacancy, the application cost, the probability of review, the offer probability, the firm's posterior mean surplus, and the worker's posterior expected job value.

Before writing the stay value, define worker $i$'s expected stay wage as

$$\bar{w}^S_{i,o,t} \equiv \mathbb{E}[w_{i,o,t} \mid \text{stay}, \Xi_{i,t}]$$

This is the expected wage at the origin if worker $i$ stays through the decision interval. It is not necessarily the realized wage observed at $t$ for movers. The lagged wage $w_{i,o,t-1}$ is observed before the mobility decision and can be viewed empirically as a predetermined control or proxy for this expected stay wage. The value of staying at the origin is

$$V^S_{i,t} = u^S_i \left( \bar{w}^S_{i,o,t}, K^o_{i,t}, \widetilde{\mu}_{i,t}, X_{i,t-1}, Z_{o,t-1} \right) + \delta \mathbb{E} \left[ V_{i,t+1}(\Xi_{i,t+1}) \mid \text{stay}, \Xi_{i,t} \right] \tag{102}$$

The flow payoff from staying depends on the expected origin wage if the worker stays, $\bar{w}^S_{i,o,t}$, retained team capital $K^o_{i,t}$, beliefs about the future quality of the origin $\widetilde{\mu}_{i,t}$, worker characteristics $X_{i,t-1}$, and origin-firm characteristics $Z_{o,t-1}$. Peer departures affect (102) only through these primitive objects, i.e., they can lower $K^o_{i,t}$, lower $\widetilde{\mu}_{i,t}$, change the perceived outside-opportunity state, or lower the expected stay wage through the production channel. The continuation term captures the fact that staying today affects the distribution of future wages, future peer groups, and future mobility opportunities.

For destination firms, let $J_{i,f,t}$ denote the value of the job if worker $i$ receives and accepts an offer from firm $f$:

$$J_{i,f,t} = u_i^M\left(w_{i,f,t}, s_{i,f,t}, m_{i,f,t}, X_{i,t-1}, Z_{f,t}\right) + \delta \mathbb{E}\left[V_{i,t+1}(\Xi_{i,t+1}) \mid \text{join } f, \Xi_{i,t}\right] \tag{103}$$

The current payoff from joining firm $f$ depends on the entry wage $w_{i,f,t}$, nonpecuniary value $s_{i,f,t}$, match quality $m_{i,f,t}$, worker characteristics, and candidate-firm characteristics. Former peers can affect $J_{i,f,t}$ through worker-side information, firm-side screening, production complementarities, social utility, or wages, as described in Section A.3. Before the job is accepted, worker $i$ may have to learn about the vacancy, apply, be reviewed, and receive an offer. The ex ante value of pursuing candidate firm $f$ is thus

$$\begin{aligned}\mathcal{W}_{i,f,t}^M = R_{i,t} + \Pr(\mathcal{V}_{i,f,t}=1)\Bigg[ & -c_{i,f,t}^a + q_{i,f,t}^{rev}(\mathcal{B}_{i,f,t}) \\ & \times \mathbb{E}\left[\mathbb{1}\{M_{i,f,t}^F(\mathcal{B}_{i,f,t}) \geq 0\}\left(J_{i,f,t} - R_{i,t}\right) \mid \Xi_{i,t}\right]\Bigg]\end{aligned} \tag{104}$$

This expression is the destination-side analogue of the stay value. The fallback value $R_{i,t}$ is what the worker obtains if pursuing candidate firm $f$ does not lead to an accepted job. The application cost $c_{i,f,t}^a$ is paid only if worker $i$ learns about the vacancy and applies. The probability $\Pr(\mathcal{V}_{i,f,t}=1)$ captures the vacancy-learning channel. The probability $q_{i,f,t}^{rev}(\mathcal{B}_{i,f,t})$ captures the review channel. The indicator $\mathbb{1}\{M_{i,f,t}^F(\mathcal{B}_{i,f,t}) \geq 0\}$ captures the firm's offer rule: conditional on review, an offer is made only if the firm's posterior mean surplus is nonnegative. Finally, $J_{i,f,t} - R_{i,t}$ is the gain from receiving and accepting the offer relative to the fallback value. Former peers enter (104) only through the primitive channels derived earlier: vacancy learning, application costs, review probability, firm-side posterior beliefs, worker-side information, and surplus.

The latent consideration set $C_{i,t}$ contains the candidate firms for which worker $i$ learns about the vacancy and for which the expected value of applying is high enough. This corresponds

to the condition in (88). Conditional on this consideration set, worker $i$ chooses between staying at the origin and the best available destination:

$$d_{i,t} = \arg\max \left\{ V_{i,t}^{S} + \varepsilon_{i,t}^{S}, \max_{f \in C_{i,t}} \left[ V_{i,f,t}^{M} + \varepsilon_{i,f,t}^{M} \right] \right\} \tag{105}$$

where $V_{i,f,t}^{M}$ is the deterministic value of destination $f$ conditional on $f$ being in the consideration set and the move being feasible. In applications, $V_{i,f,t}^{M}$ can be interpreted as the relevant choice-specific component of $\mathcal{W}_{i,f,t}^{M}$ once the worker is comparing considered alternatives. The shocks $\varepsilon_{i,t}^{S}$ and $\varepsilon_{i,f,t}^{M}$ capture idiosyncratic factors in the stay and destination-specific values, respectively, that are not explicitly modeled. Here $d_{i,t} = 0$ denotes staying at the origin, while $d_{i,t} = f$ denotes moving to candidate firm $f$.

Assume that the idiosyncratic shocks are iid type-I extreme value. Conditional on the latent consideration set $C_{i,t}$, the probability of choosing destination $f$ is

$$\Pr(d_{i,t} = f \mid C_{i,t}) = \frac{\exp(V_{i,f,t}^{M})}{\exp(V_{i,t}^{S}) + \sum_{k \in C_{i,t}} \exp(V_{i,k,t}^{M})} \tag{106}$$

The probability of staying is

$$\Pr(d_{i,t} = 0 \mid C_{i,t}) = \frac{\exp(V_{i,t}^{S})}{\exp(V_{i,t}^{S}) + \sum_{k \in C_{i,t}} \exp(V_{i,k,t}^{M})} \tag{107}$$

Conditional on moving, the destination-choice probability is

$$\Pr(d_{i,t} = f \mid C_{i,t}, d_{i,t} \neq 0) = \frac{\exp(V_{i,f,t}^{M})}{\sum_{k \in C_{i,t}} \exp(V_{i,k,t}^{M})} \tag{108}$$

This conditional probability is the theoretical counterpart of the destination-choice regressions, where the empirical choice set contains the realized destination and sampled comparable alternatives.

We can define the outside inclusive value as

$$I_{i,t}^{M} = \log \left[ \sum_{k \in C_{i,t}} \exp(V_{i,k,t}^{M}) \right] \tag{109}$$

The inclusive value summarizes the attractiveness of all considered outside options. The probability of moving can then be written as

$$\Pr(\text{move}_{i,t} = 1 \mid C_{i,t}) = \frac{\exp(I_{i,t}^{M})}{\exp(V_{i,t}^{S}) + \exp(I_{i,t}^{M})} \tag{110}$$

Equation (110) makes the origin-side comparative statics transparent. Peer departures increase mobility if they lower $V_{i,t}^{S}$, raise $I_{i,t}^{M}$, or both. Namely, the Bayesian-origin channel and the team-capital channel lower $V_{i,t}^{S}$, the outside-opportunity channel can raise $I_{i,t}^{M}$, and the destination former-peer links can raise $I_{i,t}^{M}$ by increasing the value of candidate firms that employ former peers.

The observed destination-choice probability also depends on whether firm $f$ enters the latent consideration set:

$$p_{i,f,t} = \mathbb{E}\left[ \mathbb{1}\{f \in C_{i,t}\} \frac{\exp(V_{i,f,t}^{M})}{\sum_{k \in C_{i,t}} \exp(V_{i,k,t}^{M})} \mid \Xi_{i,t} \right] \tag{111}$$

This expression implies that a former peer at candidate firm $f$ can raise $p_{i,f,t}$ either by making $f$ more likely to enter $C_{i,t}$, or by raising $V_{i,f,t}^{M}$ conditional on $f \in C_{i,t}$. Therefore, the reduced-form destination-choice coefficient on former-peer presence combines consideration-set effects and value effects conditional on consideration.

## A.5 Propositions and proofs

**Proposition 1 (Origin peer departures reduce the value of staying)**

Suppose:

(i) peers leave according to (61)

(ii) private signals satisfy (59)

(iii) (65) holds

(iv) the value of staying is increasing in $\widetilde{\mu}_{i,t}$

(v) coworker production complementarities satisfy $\chi_{ij} \geq 0$

(vi) at least one of the Bayesian-learning or production-complementarity channels is strict

Then a departure by peer $j$ weakly lowers worker $i$'s value of staying:

$$V_{i,t}^{S}(d_{j,t-1}^{o} = 1) \leq V_{i,t}^{S}(d_{j,t-1}^{o} = 0)$$

with strict inequality if either $j$'s departure changes value-relevant beliefs or $\chi_{ij} > 0$. Moreover, the loss is larger for higher-ranked peers if $\ell'(r) > 0$, $\omega'(r) > 0$, and $\chi_{ij}$ does not decline sufficiently with $r_j$.

*Proof.* First consider the Bayesian channel. From (65),

$$p_B(r_j) > p_G(r_j)$$

Hence a departure by $j$ multiplies the posterior odds that the origin is good by

$$\frac{p_G(r_j)}{p_B(r_j)} < 1$$

Therefore

$$\Pr(\Theta_{o,t-1} = G \mid d_{j,t-1}^{o} = 1, \mathbf{d}_{-j,t-1}^{o}) < \Pr(\Theta_{o,t-1} = G \mid d_{j,t-1}^{o} = 0, \mathbf{d}_{-j,t-1}^{o})$$

where $\mathbf{d}_{-j,t-1}^{o}$ denotes the peer-departure vector excluding peer $j$. By (72), if $\rho_G > \rho_B$, this also lowers $\widetilde{\mu}_{i,t}$, the belief relevant for worker $i$'s stay decision. Since the value of staying is increasing in $\widetilde{\mu}_{i,t}$, this lowers $V_{i,t}^{S}$.

Second, from (77) and (78), peer $j$'s departure changes the origin wage component by

$$-\beta_i \chi_{ij} \omega(r_j) \leq 0$$

Combining the Bayesian and production channels gives

$$V_{i,t}^S(d_{j,t-1}^o = 1) \leq V_{i,t}^S(d_{j,t-1}^o = 0)$$

The inequality is strict if either the posterior changes value-relevant beliefs or $\chi_{ij} > 0$. Finally, if $\ell'(r) > 0$, higher-ranked peer departures have larger likelihood-ratio content. If $\omega'(r) > 0$, higher-ranked peers also carry larger production weights. Therefore the value loss from a high-ranked peer departure is larger under the stated monotonicity conditions. ■

**Proposition 2 (Origin peer departures increase mobility)**

Suppose the conditions of Proposition 1 hold. Suppose also that peer departures weakly increase the outside inclusive value by revealing favorable outside opportunities. Then a stronger peer-loss history, in the sense of a higher belief-based signal $\mathcal{S}_{i,t-1}^o$ or a higher production-loss index $\mathcal{K}_{i,t-1}^{o,\text{loss}}$, increases the probability of mobility:

$$\frac{\partial}{\partial \mathcal{X}_{i,t-1}} \Pr(\text{move}_{i,t} = 1 \mid C_{i,t}) > 0$$

where $\mathcal{X}_{i,t-1}$ denotes any scalar peer-loss index that lowers $V_{i,t}^S$ and weakly raises $I_{i,t}^M$, such as $\mathcal{S}_{i,t-1}^o$, $\mathcal{K}_{i,t-1}^{o,\text{loss}}$, or a positive weighted combination of the two.

*Proof.* Let $\mathcal{X}_{i,t-1}$ be a scalar peer-loss index satisfying

$$\frac{\partial V_{i,t}^S}{\partial \mathcal{X}_{i,t-1}} < 0$$

and

$$\frac{\partial I_{i,t}^{M}}{\partial \mathcal{X}_{i,t-1}} \geq 0$$

The first condition holds when $\mathcal{X}_{i,t-1}$ captures either a stronger negative signal about the origin or a larger loss of retained team capital. The second condition holds when peer departures reveal favorable outside opportunities and thereby raise the attractiveness of search. From (110),

$$\Pr(\text{move}_{i,t} = 1 \mid C_{i,t}) = \Lambda(I_{i,t}^{M} - V_{i,t}^{S})$$

where $\Lambda(x) = \exp(x)/(1+\exp(x))$. Therefore

$$\begin{aligned}\frac{\partial \Pr(\text{move}_{i,t} = 1 \mid C_{i,t})}{\partial \mathcal{X}_{i,t-1}} &= \Lambda(I_{i,t}^{M} - V_{i,t}^{S}) \left[1 - \Lambda(I_{i,t}^{M} - V_{i,t}^{S})\right] \\ &\quad \times \left[\frac{\partial I_{i,t}^{M}}{\partial \mathcal{X}_{i,t-1}} - \frac{\partial V_{i,t}^{S}}{\partial \mathcal{X}_{i,t-1}}\right] \end{aligned} \tag{112}$$

The first two factors are strictly positive. The bracketed term is strictly positive because $I_{i,t}^{M}$ weakly increases and $V_{i,t}^{S}$ strictly decreases. Hence the derivative is strictly positive. ■

**Proposition 3 (Former peers increase destination value through primitive channels)**

Consider candidate firm $f$. Adding a former peer $j$ to $\mathcal{B}_{i,f,t}$ weakly increases the value of destination $f$ for workers for whom the former-peer link improves access to positive-surplus matches, lowers search or application costs, or improves worker-side information. For workers whose match surplus is negative, better screening may reduce the probability of an offer. Therefore, when the estimated destination coefficient is positive, it should be interpreted as a net access, information, and screening effect for the empirically relevant mover-choice population.

*Proof.* Adding former peer $j$ affects $V_{i,f,t}^{M}$ through five primitive channels. First, by (86), adding $j$ strictly raises the probability that worker $i$ learns about a vacancy at $f$ whenever

$\lambda^{peer}(r_j) > 0$. Second, by (87), adding $j$ lowers application cost by $\rho^c(r_j) \geq 0$. Third, by (90), adding $j$ raises the probability that the firm reviews the application whenever $\rho^{rev}(r_j) > 0$. Fourth, by (96), adding $j$'s referral signal weakly increases the precision of firm-side beliefs about match surplus. This improves screening. For workers whose true or expected match surplus is positive but noisily observed, better screening can increase access to positive-surplus matches. For workers whose match surplus is negative, better screening may reduce the probability of receiving an offer. Fifth, adding $j$'s worker-side information makes $\mathcal{I}^W_{i,f,t}$ more informative. Since $x \mapsto \max\{R_{i,t}, x\}$ is convex, (98) implies that the worker's option value from the candidate firm weakly increases.

The move value in (104), the theoretical correspondent to $V^M_{i,f,t}$, is increasing in vacancy learning, review probability, worker-side option value, and access to positive-surplus offers, and decreasing in application cost. Therefore adding a former peer weakly increases $V^M_{i,f,t}$ for workers for whom the former-peer link improves access to positive-surplus matches or improves worker-side information. The result should not be read as implying that former peers mechanically raise offer probabilities for every applicant. Rather, former peers increase destination value on average for the population of movers for whom peer-linked information improves access to valuable matches. ■

**Proposition 4 (High-ranked former peers have larger destination effects)**
Suppose peer rank increases information-transmission intensity, referral-review intensity, signal precision, and influence weight:

$$(\lambda^{peer})'(r) > 0, \qquad (\rho^{rev})'(r) > 0, \qquad \tau'(r) > 0, \qquad \omega'(r) > 0, \qquad (\rho^c)'(r) > 0$$

Then the marginal increase in destination value from adding a former peer is increasing in that peer's rank:

$$r_j > r_k \quad \Longrightarrow \quad \Delta_j V^M_{i,f,t} \geq \Delta_k V^M_{i,f,t}$$

where

$$\Delta_j V^M_{i,f,t} \equiv V^M_{i,f,t}(\mathcal{B}_{i,f,t} \cup \{j\}) - V^M_{i,f,t}(\mathcal{B}_{i,f,t})$$

The inequality is strict if at least one rank-dependent channel is strict.

*Proof.* From (85), the marginal contribution of peer $j$ to vacancy learning is increasing in $\lambda^{peer}(r_j)$, hence increasing in $r_j$. From (89), the marginal contribution to review probability is increasing in $\rho^{rev}(r_j)$, hence increasing in $r_j$. From (96), the marginal contribution to posterior precision is $\tau(r_j)$, which is increasing in $r_j$. Finally, any production or social-complementarity component is weighted by $\omega(r_j)$, which is increasing in $r_j$. For workers for whom these channels raise access to positive-surplus matches or improve worker-side information, $V^M_{i,f,t}$ is increasing in the active primitive channels under Proposition 3. The result follows. ■

**Proposition 5 (Destination-choice coefficients combine consideration and value effects)**

Let the observed destination-choice probability for candidate firm $f$ be

$$p_{i,f,t} = \mathbb{E}\left[\mathbb{1}\{f \in C_{i,t}\}\frac{\exp(V^M_{i,f,t})}{\sum_{k\in C_{i,t}}\exp(V^M_{i,k,t})} \mid \Xi_{i,t}\right] \tag{113}$$

Then the reduced-form coefficient on $P_{i,f,t}$ or $Q_{i,f,t}$ combines:

1. The effect of former peers on consideration-set inclusion.
2. The effect of former peers on application costs and review probabilities.
3. The effect of former peers on offer probabilities.
4. The effect of former peers on expected match surplus conditional on consideration.
5. Any production or social-complementarity effect.

Therefore, it is not a structural preference parameter.

*Proof.* The expression in (113) contains two distinct margins. The indicator $\mathbb{1}\{f \in C_{i,t}\}$ captures whether firm $f$ enters the latent consideration set. The logit term captures the probability that $f$ is chosen conditional on being in the realized consideration set. Former peers can affect either margin: they can make $f$ more likely to be considered, or they can raise $V^M_{i,f,t}$ conditional on consideration. Since changes in $V^M_{i,f,t}$ itself may reflect application costs, offer probabilities, posterior match quality, wages, social utility, and production complementarities, a single reduced-form coefficient cannot isolate one structural channel without additional restrictions. ■

**Proposition 6 (Peer-linked destinations can generate higher entry wages)** Suppose accepted-job wages satisfy Nash bargaining:

$$w_{i,f,t} = b_{i,t} + \beta_i M^F_{i,f,t}, \qquad \beta_i \in (0,1) \tag{114}$$

where $M^F_{i,f,t}$ is the firm's posterior expected surplus conditional on making an offer. If former-peer links improve screening toward positive-surplus matches or improve worker bargaining position through better outside information, then peer-linked destinations have higher expected entry wages:

$$\mathbb{E}[w_{i,f,t} \mid P_{i,f,t} = 1, \text{offer}] \geq \mathbb{E}[w_{i,f,t} \mid P_{i,f,t} = 0, \text{offer}]$$

The inequality is strict if peer links strictly raise expected accepted surplus.

*Proof.* From (114),

$$\mathbb{E}[w_{i,f,t} \mid \text{offer}] = \mathbb{E}[b_{i,t} \mid \text{offer}] + \beta_i \mathbb{E}[M^F_{i,f,t} \mid \text{offer}]$$

Referral information can raise $\mathbb{E}[M^F_{i,f,t} \mid \text{offer}]$ by improving selection into positive-surplus matches. Better worker information can raise the outside option or bargaining position $b_{i,t}$.

Since $\beta_i > 0$, any strict increase in expected accepted surplus or bargaining position raises expected entry wages. ■

## A.6 Mapping to the empirical design

The previously discussed model is not estimated structurally. Instead, it provides micro-foundations for the reduced-form variables used in the empirical analysis.

### A.6.1 Origin-side mapping

The structural object on the origin side is the difference between the outside inclusive value and the stay value:

$$\Delta^O_{i,t} = I^M_{i,t} - V^S_{i,t} \tag{115}$$

Peer departures affect this object because they change posterior beliefs about the origin state, posterior beliefs about outside opportunities, and retained team capital.

The empirical variables

$$T_{i,t-1}, \qquad H_{i,t-1}, \qquad L_{i,t-1}$$

are observable approximations to latent weighted peer-loss objects. If influence weights are approximately constant within rank classes, then

$$\begin{aligned} D_{i,t-1} &\approx \omega_H H_{i,t-1} + \omega_M M_{i,t-1} + \omega_L L_{i,t-1} \\ &= \omega_M T_{i,t-1} + (\omega_H - \omega_M) H_{i,t-1} + (\omega_L - \omega_M) L_{i,t-1} \end{aligned} \tag{116}$$

where $\omega_H > \omega_M > \omega_L$. Similarly, the belief-based peer-loss signal satisfies (74), and the production-loss component satisfies (81). These expressions rationalize why the empirical turnover specification includes both total peer turnover and the composition of leavers.

A reduced-form mobility equation can therefore be written as

$$\Pr(\text{move}_{i,t} = 1) = \mathcal{G}\left(\beta_T T_{i,t-1} + \beta_H H_{i,t-1} + \beta_L L_{i,t-1} + X'_{i,t-1}\beta_X + Z'_{o,t-1}\beta_Z + \delta_t\right) \quad (117)$$

where $\mathcal{G}(\cdot)$ is the empirical link function. The coefficients $\beta_T, \beta_H, \beta_L$ are the reduced-form projections of the effect of peer departures on $\Delta^O_{i,t}$.

Importantly, the sign of the coefficient associated with $L_{i,t-1}$ should be interpreted carefully. Under the Bayesian condition $p_B(r) > p_G(r)$, even low-quality departures can be weakly bad news in absolute terms. However, conditional on total turnover $T_{i,t-1}$, a larger low-quality departure share means that departures are less concentrated among middle- or high-ranked peers. Therefore, a negative coefficient on $L_{i,t-1}$ is naturally interpreted as a composition effect: for a given amount of turnover, departures concentrated among low-ranked peers are less informative or less costly than departures concentrated among higher-ranked peers.

### A.6.2 Destination-side mapping

The structural destination object is

$$p_{i,f,t} = \Pr(f \in C_{i,t}) \Pr(d_{i,t} = f \mid f \in C_{i,t}, \text{move}_{i,t} = 1) \quad (118)$$

The empirical variables

$$P_{i,f,t} = \mathbf{1}\{B_{i,f,t} > 0\}, \qquad Q_{i,f,t} = \mathbf{1}\{B^H_{i,f,t} > 0\}$$

are extensive-margin proxies for the latent former-peer stock and high-ranked former-peer stock.

The reduced-form destination-choice equation can be written as

$$\Pr(y^{choice}_{i,f,t} = 1) = \mathcal{G}\left(\gamma_P P_{i,f,t} + \gamma_Q Q_{i,f,t} + X'_{i,t-1}\gamma_X + Z'_{f,t}\gamma_Z + \delta_t\right) \quad (119)$$

where $y_{i,f,t}^{choice} = 1$ if mover $i$ chooses candidate firm $f$. The coefficients $\gamma_P$ and $\gamma_Q$ combine vacancy-learning effects, consideration-set effects, application-cost effects, review-probability effects, offer-probability effects, match-information effects, and any complementarity or social-utility effects. They should therefore be interpreted as reduced-form composite parameters.

### A.6.3 Empirical proxy for peer rank

The model's latent influence rank is $r_j$. The empirical proxy is

$$\widehat{r}_{j,t-2} = \text{rank}\left(\widehat{\alpha}_j \mid \text{firm} \times \text{establishment} \times \text{job occupation} \times (t-2)\right) \tag{120}$$

where $\widehat{\alpha}_j$ is the estimated worker fixed effect. This mapping follows the matched employer-employee wage-decomposition literature, where worker fixed effects summarize persistent wage-relevant worker heterogeneity net of firm wage premia (Abowd et al., 1999; Card et al., 2013). This proxy is valid for the reduced-form purpose if

$$\text{Cov}(\widehat{r}_{j,t-2}, r_j) > 0 \tag{121}$$

The model does not require $\widehat{\alpha}_j$ to equal innate ability. It only requires the rank proxy to be positively correlated with influence, credibility, informativeness, or referral value, among other characteristics that can influence turnover and firm-choice decisions. As in other applications of high-dimensional fixed effects, the proxy may be measured with error when mobility is sparse or the worker-firm graph is weakly connected (Kline et al., 2020).

### A.6.4 Feasible and sampled choice sets

The model distinguishes among three sets:

$$\mathcal{F}_t \supset \mathcal{F}_{i,t}^{*} \supset C_{i,t}$$

where $\mathcal{F}_t$ is the full set of firms, $\mathcal{F}^*_{i,t}$ is the feasible set, and $C_{i,t}$ is the latent consideration set. The empirical choice set is a sampled approximation to the feasible or salient opportunity set, not an observed consideration set. Including the realized destination plus sampled comparable alternatives is therefore a pragmatic approximation to the set of plausible destinations. It should not be interpreted as evidence that the worker literally considered all sampled firms. This distinction is standard in empirical discrete-choice work, where the econometrician often observes or samples alternatives rather than observing the agent's full subjective consideration set (McFadden, 1974).

### A.6.5 Correct empirical null

The correct null is not equal choice probabilities across firms. In the model, even without peer effects,

$$\Pr(d_{i,t} = f \mid C_{i,t}, \text{move}_{i,t} = 1) \neq \frac{1}{|C_{i,t}|}$$

This is true unless all candidate firms have identical wages, amenities, locations, match qualities, vacancy probabilities, hiring probabilities, and mobility costs. That symmetry is economically irrelevant.

The correct origin-side null is

$$H_0^O : \frac{\partial \Delta^O_{i,t}}{\partial T_{i,t-1}} = \frac{\partial \Delta^O_{i,t}}{\partial H_{i,t-1}} = \frac{\partial \Delta^O_{i,t}}{\partial L_{i,t-1}} = 0 \quad \text{conditional on controls} \tag{122}$$

That is, peer departures provide no incremental information about origin value, outside opportunities, or retained team capital once observed worker, firm, peer-group, and time controls are included.

The correct destination-side null is

$$H_0^D : P_{i,f,t} \text{ and } Q_{i,f,t} \text{ do not affect vacancy learning, application costs, review probabilities, offer probabilities, match beliefs, wages, or surplus, conditional on controls.} \tag{123}$$

### A.6.6 Interpretation

Lastly, the origin coefficients on $T_{i,t-1}$, $H_{i,t-1}$, and $L_{i,t-1}$ estimate the net relationship between observed peer departures and the relative value of moving versus staying. The destination coefficients on $P_{i,f,t}$ and $Q_{i,f,t}$ estimate the composite relationship between former-peer presence and the probability of choosing a candidate destination. The wage coefficients test whether peer-linked moves are associated with higher entry wages, as the model predicts when peer links improve accepted match surplus, but they do not separately identify bargaining, screening, productivity, or selection mechanisms.

The model should therefore be read as a set of microfoundations for the reduced-form variables, not as a structural object taken directly to the data. The origin-side coefficients combine belief updating about the origin, information about outside opportunities, and losses of retained team capital. The destination-side coefficients combine vacancy learning, application costs, review, offers, worker-side information, and surplus. The wage coefficients are auxiliary implications of improved accepted match surplus and should not be interpreted as separately identifying bargaining, productivity, or screening mechanisms.

# B Choice Set Construction

Because workers' true opportunity sets are unobserved, any empirical implementation of destination choice must rely on an approximation to the set of firms that were plausibly feasible or salient at the time of the move. Our approach is to construct sampled alternatives using firms that match the realized destination on broad observable dimensions such as sector, region, and size. The rationale is that the realized match is informative about the type of jobs the worker was plausibly targeting, even if it does not reveal the full set of applications, offers, or firms considered.

This procedure should only be viewed as a pragmatic sampling device designed to reduce gross heterogeneity across candidate firms, not as a literal observation of the worker's full consideration set. Under this design, we do not interpret the sampled firms as identical, nor do we treat the resulting mechanical reference probability as the economic null of no peer effect. Instead, the relevant empirical question is whether former-peer variables predict the chosen destination over and above these broad comparability restrictions and the observed candidate-firm characteristics included in the regression.

## B.1 Baseline choice-set construction

Let $f^{\star}_{i,t}$ denote the realized destination firm of mover $i$ in year $t$. For each mover-year $(i,t)$, we construct a finite choice set

$$\mathcal{C}_{i,t}(\mathcal{N})$$

of intended size $\mathcal{N}$, including the realized destination. The feasible universe for sampling alternatives is year-specific given that we require that candidate firms are active in the same year as the move happens. In addition, we restrict the choice set to firms in the same NUTS

2 region, sector, and broad size category as the realized destination firm $f_{i,t}^{\star}$.[21] Let

$$\mathcal{F}_{i,t}$$

denote the resulting pool of firms satisfying these requirements for mover-year $(i,t)$. For each mover-year, we sample alternatives uniformly without replacement from

$$\mathcal{F}_{i,t} \setminus \left\{ f_{i,t}^{\star} \right\}$$

To reduce variation across different intended choice-set sizes, we use a nested sampling design:

1. Fix a maximum intended size
$$\mathcal{N}_{\max} = 100$$
2. For each mover-year $(i,t)$, draw a single ordered list
$$\widetilde{\mathcal{A}}_{i,t} \subseteq \mathcal{F}_{i,t} \setminus \left\{ f_{i,t}^{\star} \right\}$$
of up to $\mathcal{N}_{\max} - 1$ alternatives, sampled uniformly without replacement.
3. For each intended size
$$\mathcal{N} \leq \mathcal{N}_{\max}$$
define
$$\mathcal{A}_{i,t}(\mathcal{N})$$
as the first
$$\min\left\{ \mathcal{N} - 1, \left| \widetilde{\mathcal{A}}_{i,t} \right| \right\}$$
firms in the ordered list $\widetilde{\mathcal{A}}_{i,t}$.

[21] For more information on the classification of firms, please see Appendix D.

This construction ensures that

$$\mathcal{A}_{i,t}(5) \subseteq \mathcal{A}_{i,t}(10) \subseteq \cdots \subseteq \mathcal{A}_{i,t}(100)$$

for each mover-year. The corresponding choice set is

$$\mathcal{C}_{i,t}(\mathcal{N}) = \left\{ f_{i,t}^{\star} \right\} \cup \mathcal{A}_{i,t}(\mathcal{N})$$

Because sampling is without replacement and $\mathcal{F}_{i,t}$ is finite, some mover-years contain fewer than $\mathcal{N} - 1$ eligible alternatives. The realized choice-set size is therefore

$$K_{i,t}(\mathcal{N}) = |\mathcal{C}_{i,t}(\mathcal{N})| = 1 + \min \left\{ \mathcal{N} - 1, \left| \widetilde{\mathcal{A}}_{i,t} \right| \right\}$$

## B.2 Expanded estimation dataset

For each intended size $\mathcal{N}$, we construct an expanded dataset containing one observation for every mover-year $\times$ candidate-firm combination

$$(i, f, t) \qquad \text{such that} \qquad f \in \mathcal{C}_{i,t}(\mathcal{N})$$

The dependent variable is

$$y_{i,f,t}^{choice} = \mathbb{1} \left\{ f = f_{i,t}^{\star} \right\}$$

It equals one for the realized destination and zero for the sampled alternatives. Contemporaneous candidate-firm characteristics are measured at $(f, t)$. The predetermined candidate-firm controls introduced in the robustness analysis, including hiring and occupational-composition measures, are measured in $t - 1$. Worker characteristics are retained in the expanded dataset for the complementary log-log and heterogeneity specifications, but they are conditioned out of the preferred conditional logit unless they are interacted with variables

that vary across candidate firms.

Former-peer variables are constructed at the mover-year × candidate-firm level. Let

$$P_{i,f,t} = \mathbb{1}\left\{\text{candidate firm } f \text{ employs at least one former peer of worker } i\right\}$$

and let

$$Q_{i,f,t} = \mathbb{1}\left\{\text{candidate firm } f \text{ employs at least one high-quality former peer}\right\}.$$

Since a high-quality former peer is necessarily a former peer,

$$Q_{i,f,t} \leq P_{i,f,t}.$$

We therefore define the mutually exclusive peer-state variable

$$S_{i,f,t} = \begin{cases} 0, & \text{if } P_{i,f,t} = 0, \\ 1, & \text{if } P_{i,f,t} = 1 \text{ and } Q_{i,f,t} = 0, \\ 2, & \text{if } Q_{i,f,t} = 1. \end{cases}$$

The three states correspond to no former peer, at least one ordinary former peer but no high-quality former peer, and at least one high-quality former peer, respectively.

## B.3 Second-stage conditional-logit model

For each intended choice-set size $\mathcal{N}$, we estimate a conditional-logit model. Let the latent value that mover $i$ assigns to candidate firm $f$ be

$$\begin{aligned} U_{i,f,t,\mathcal{N}} = \lambda_{i,t,\mathcal{N}} &+ \gamma_{1,\mathcal{N}}\mathbb{1}\left\{S_{i,f,t} = 1\right\} + \gamma_{2,\mathcal{N}}\mathbb{1}\left\{S_{i,f,t} = 2\right\} \\ &+ \mathbf{Z}'_{f,t}\boldsymbol{\gamma}_{Z,\mathcal{N}} + \mathbf{R}'_{i,f,t-1}\boldsymbol{\gamma}_{R,\mathcal{N}} + \varepsilon_{i,f,t,\mathcal{N}} \end{aligned} \tag{124}$$

where $\lambda_{i,t,\mathcal{N}}$ is a mover-year-specific component shared by all candidate firms in the same choice set. The vector $\mathbf{Z}_{f,t}$ contains contemporaneous candidate-firm characteristics, including log firm size, average firm-year PageRank, and the candidate-firm wage component. The vector $\mathbf{R}_{i,f,t-1}$ contains the predetermined candidate-firm controls used in the extended specifications.

Assuming that $\varepsilon_{i,f,t,\mathcal{N}}$ is i.i.d., the probability that mover $i$ chooses candidate firm $f$ is

$$\Pr\left(y_{i,f,t}^{choice} = 1 \mid \mathcal{C}_{i,t}(\mathcal{N})\right) = \frac{\exp\left(V_{i,f,t,\mathcal{N}}\right)}{\sum_{g \in \mathcal{C}_{i,t}(\mathcal{N})} \exp\left(V_{i,g,t,\mathcal{N}}\right)} \tag{125}$$

where

$$\begin{aligned} V_{i,f,t,\mathcal{N}} = {} & \gamma_{1,\mathcal{N}} \mathbb{1}\left\{S_{i,f,t} = 1\right\} + \gamma_{2,\mathcal{N}} \mathbb{1}\left\{S_{i,f,t} = 2\right\} \\ & + \mathbf{Z}'_{f,t} \boldsymbol{\gamma}_{Z,\mathcal{N}} + \mathbf{R}'_{i,f,t-1} \boldsymbol{\gamma}_{R,\mathcal{N}} \end{aligned} \tag{126}$$

The mover-year component

$$\lambda_{i,t,\mathcal{N}}$$

cancels from the numerator and denominator. Consequently, worker characteristics, worker wage components, year effects, and other variables that are common to all alternatives in a mover-year choice set are conditioned out. Identification comes from differences across candidate firms faced by the same mover. Choice sets containing only one alternative provide no within-set comparison and are omitted from conditional-logit estimation. Standard errors are clustered at the worker level.

The coefficient

$$\gamma_{1,\mathcal{N}}$$

compares an ordinary-peer candidate with a no-peer candidate. The coefficient difference

$$\gamma_{2,\mathcal{N}} - \gamma_{1,\mathcal{N}}$$

is the incremental high-quality-peer effect, comparing a high-quality-peer candidate with an ordinary-peer candidate. The corresponding relative choice-odds ratios are

$$\exp\left(\gamma_{1,\mathcal{N}}\right), \qquad \exp\left(\gamma_{2,\mathcal{N}} - \gamma_{1,\mathcal{N}}\right), \quad \text{and} \quad \exp\left(\gamma_{2,\mathcal{N}}\right)$$

for an ordinary-peer candidate relative to no peer, a high-quality-peer candidate relative to an ordinary-peer candidate, and a high-quality-peer candidate relative to no peer, respectively.

## B.4 Counterfactual probability effects

In addition to the relative choice odds, we calculate exact own-candidate probability effects. For each candidate firm $f$, we successively assign the candidate to the no-peer, ordinary-peer, and high-quality-peer states while holding the characteristics and peer states of all remaining firms in the mover-year choice set at their observed values. The conditional-logit denominator is recomputed after each change.

Let

$$p^{s}_{i,f,t,\mathcal{N}}, \qquad s \in \{0, O, H\}$$

denote the resulting probability of selecting candidate firm $f$ when that candidate is assigned peer state $s$. For each mover-year, define

$$\overline{p}^{s}_{i,t,\mathcal{N}} = \frac{1}{K_{i,t}(\mathcal{N})} \sum_{f \in \mathcal{C}_{i,t}(\mathcal{N})} p^{s}_{i,f,t,\mathcal{N}}$$

The ordinary-peer probability effect is

$$\Delta_{\mathcal{N}}^{O} = \frac{1}{n_{\mathcal{N}}} \sum_{(i,t)\in\mathcal{S}_{\mathcal{N}}} \left[\overline{p}_{i,t,\mathcal{N}}^{O} - \overline{p}_{i,t,\mathcal{N}}^{0}\right] \tag{127}$$

and the incremental high-quality-peer effect is

$$\Delta_{\mathcal{N}}^{H,I} = \frac{1}{n_{\mathcal{N}}} \sum_{(i,t)\in\mathcal{S}_{\mathcal{N}}} \left[\overline{p}_{i,t,\mathcal{N}}^{H} - \overline{p}_{i,t,\mathcal{N}}^{O}\right] \tag{128}$$

The total high-quality-peer effect relative to no peer is

$$\Delta_{\mathcal{N}}^{H,T} = \frac{1}{n_{\mathcal{N}}} \sum_{(i,t)\in\mathcal{S}_{\mathcal{N}}} \left[\overline{p}_{i,t,\mathcal{N}}^{H} - \overline{p}_{i,t,\mathcal{N}}^{0}\right] \tag{129}$$

By construction,

$$\Delta_{\mathcal{N}}^{H,T} = \Delta_{\mathcal{N}}^{O} + \Delta_{\mathcal{N}}^{H,I}$$

Each mover-year receives equal weight in these calculations. The probability changes are reported as model-based point estimates. Statistical inference is based on the worker-clustered conditional-logit coefficients and the associated relative choice-odds ratios. The benchmark-normalized effects reported in Appendix B.6 rescale these probability changes using the mechanical uniform-choice probability

$$1/K_{i,t}(\mathcal{N}).$$

## B.5 Complementary log-log robustness

As a functional-form robustness check, we also estimate complementary log-log models on the expanded mover-year × candidate-firm dataset. For direct comparison, the comparable cloglog specifications use the same conditional-logit estimation samples and the same

candidate-varying controls:

$$\Pr\left(y_{i,f,t}^{choice} = 1 \mid \mathcal{W}_{i,f,t}\right) = 1 - \exp\left\{-\exp\left(\eta_{i,f,t}\right)\right\}$$

The peer state is entered categorically, and its effects are calculated as exact discrete changes between no-peer, ordinary-peer, and high-quality-peer candidates. Unlike conditional logit, cloglog treats each mover-year × candidate-firm row as a binary observation and does not impose probabilities that sum to one within the mover-year choice set. Standard errors are clustered at the worker level. We therefore treat cloglog as a functional-form robustness check rather than as the preferred destination-choice estimator.

## B.6 Peer-state probability effects by choice-set size

To assess how peer effects scale with the size of the choice set, we calculate benchmark-normalized peer-state effects for each intended size $\mathcal{N}$. For mover-year $(i, t)$, the probability implied by uniform random choice over the realized set is

$$b_{i,t,\mathcal{N}} \equiv \frac{1}{K_{i,t}(\mathcal{N})}$$

where $K_{i,t}(\mathcal{N})$ is the realized number of alternatives. When $K_{i,t}(\mathcal{N}) = \mathcal{N}$, this benchmark equals $1/\mathcal{N}$. It is used only to place probability effects from differently sized choice sets on a common scale. It is not the conditional-logit probability of choosing a no-peer candidate. For each candidate firm $f$, let $p^0_{i,f,t,\mathcal{N}}$, $p^O_{i,f,t,\mathcal{N}}$, and $p^H_{i,f,t,\mathcal{N}}$ denote the conditional-logit probabilities obtained when the focal candidate is assigned, respectively, the no-peer, ordinary-peer, and high-quality-peer states, while all other alternatives retain their observed characteristics and peer states. The corresponding mover-year average own-candidate probability effects are

$$\Delta^O_{i,t,\mathcal{N}} = \frac{1}{K_{i,t}(\mathcal{N})} \sum_{f \in \mathcal{C}_{i,t}(\mathcal{N})} \left(p^O_{i,f,t,\mathcal{N}} - p^0_{i,f,t,\mathcal{N}}\right)$$

and

$$\Delta^{H}_{i,t,\mathcal{N}} = \frac{1}{K_{i,t}(\mathcal{N})} \sum_{f \in \mathcal{C}_{i,t}(\mathcal{N})} \left( p^{H}_{i,f,t,\mathcal{N}} - p^{0}_{i,f,t,\mathcal{N}} \right)$$

The first is the ordinary-peer effect relative to no peer. The second is the total high-quality-peer effect relative to no peer. We then define the benchmark-normalized effect for peer state $s \in \{O, H\}$ as

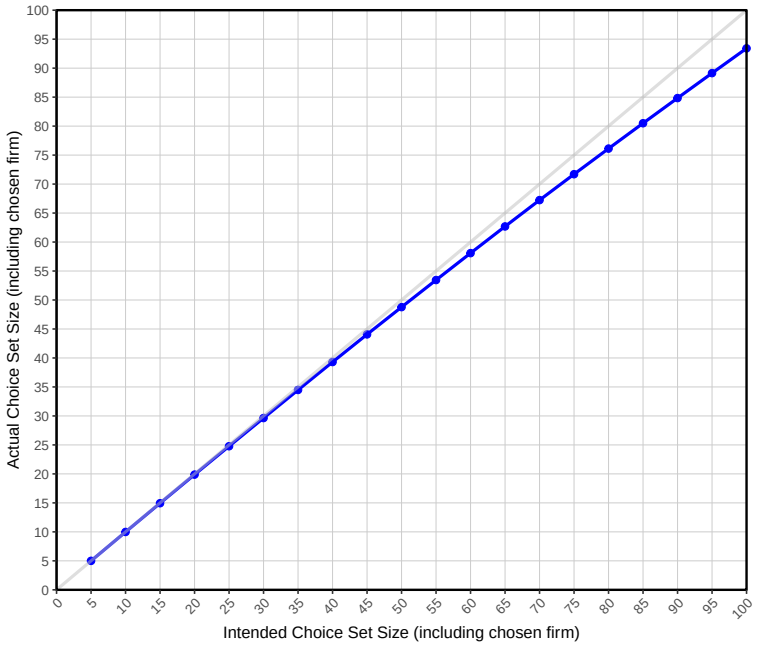
$$\mathcal{B}^{s}_{\mathcal{N}} = \frac{1}{n_{\mathcal{N}}} \sum_{(i,t) \in \mathcal{S}_{\mathcal{N}}} \left[ 1 + \frac{\Delta^{s}_{i,t,\mathcal{N}}}{b_{i,t,\mathcal{N}}} \right] \tag{130}$$

where $\mathcal{S}_{\mathcal{N}}$ is the set of mover-years used at intended size $\mathcal{N}$, and $n_{\mathcal{N}}$ is its cardinality. A value of one indicates no peer-state probability effect. A value of $x$ means that the probability increment associated with the relevant peer state is $x - 1$ times the probability implied by uniform random choice over the realized set. We calculate $\mathcal{B}^{s}_{\mathcal{N}}$ for $\mathcal{N} \in \{5, 10, \ldots, 100\}$.

Figure 6 compares intended and average realized choice-set sizes in the baseline construction. The realized size closely follows the intended size over most of the range. The difference becomes more visible for the largest sets because some year $\times$ sector $\times$ region $\times$ size cells contain fewer than 99 eligible nonchosen firms.[22] At an intended size of 100 firms, the average realized choice set contains approximately 93 firms.

[22] In fact, for some workers, the actual set size can be smaller than five choices.

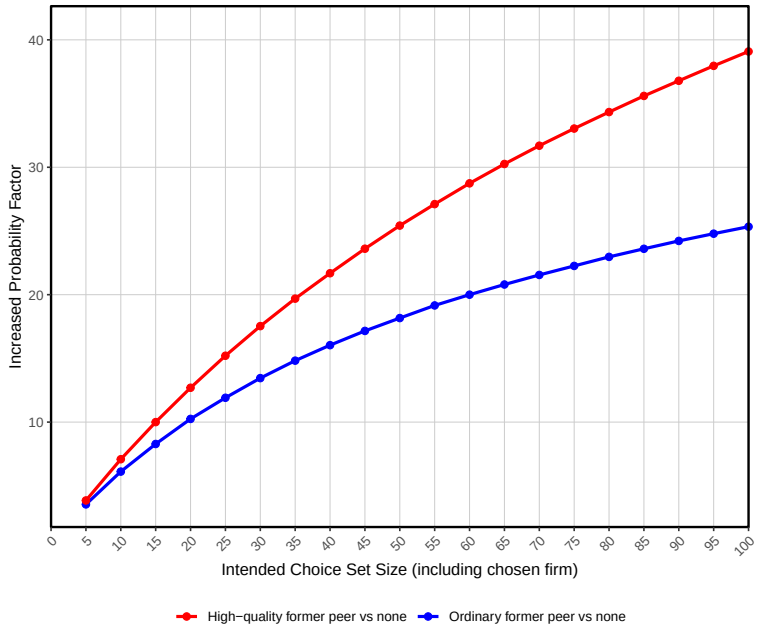
Figure 6: Actual and intended choice-set size




*Note:* The solid line reports the average realized number of firms in the mover-year choice set. The grey line is the 45-degree line. Choice sets contain the realized destination and up to $\mathcal{N} - 1$ sampled alternatives.

Figure 7 reports the benchmark-normalized effects when the conditional-logit model controls for average global PageRank. Both profiles increase sharply for small intended choice sets and continue to rise, although at a diminishing rate, as $\mathcal{N}$ becomes larger. At an intended size of 100 firms, the ordinary-peer profile is approximately 25. This means that the ordinary-peer probability increment is approximately 24 times the probability implied by uniform random choice over the realized set. The corresponding value for a high-quality-peer candidate is approximately 39, so the total high-quality-peer probability increment is approximately 38 times the same benchmark.

Figure 7: Peer-state effects relative to the uniform-choice benchmark: global PageRank

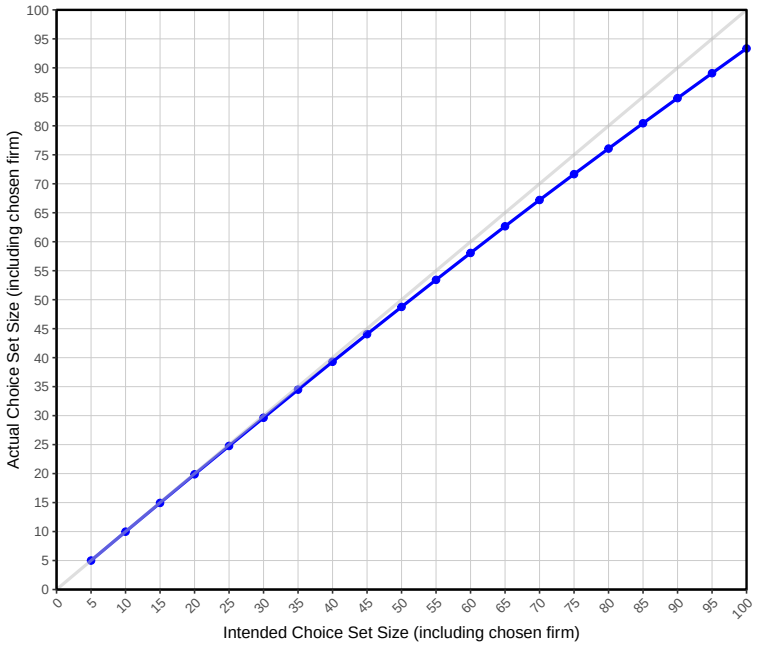



*Note:* The figure reports $\mathcal{B}_{\mathcal{N}}^{O}$ and $\mathcal{B}_{\mathcal{N}}^{H}$ as defined in equation (130). The ordinary-peer series uses the probability effect of changing a candidate from the no-peer state to the ordinary-peer state. The high-quality-peer series uses the total effect of changing a candidate from the no-peer state to the high-quality-peer state. The conditional-logit model controls for average global PageRank and the remaining candidate-firm characteristics described in the main text. The plotted quantities are not conditional-logit odds ratios.

The increasing profiles do not imply that the absolute peer effects become larger as additional alternatives are introduced. As shown in Table 5A in the Tables Appendix, the ordinary-peer probability effect becomes smaller as the choice set expands, while the incremental high-quality-peer effect remains close to 14 percentage points. The benchmark $1/K_{i,t}(\mathcal{N})$, however, declines more rapidly than the ordinary-peer effect. Consequently, the ordinary-peer effect becomes larger relative to that benchmark. The widening distance between the two curves has a similar mechanical component: at the mover-year level, it is the incremental high-quality-peer effect divided by $1/K_{i,t}(\mathcal{N})$. The figure should therefore not be interpreted as showing that the incremental high-quality-peer effect itself increases with the choice-set size.

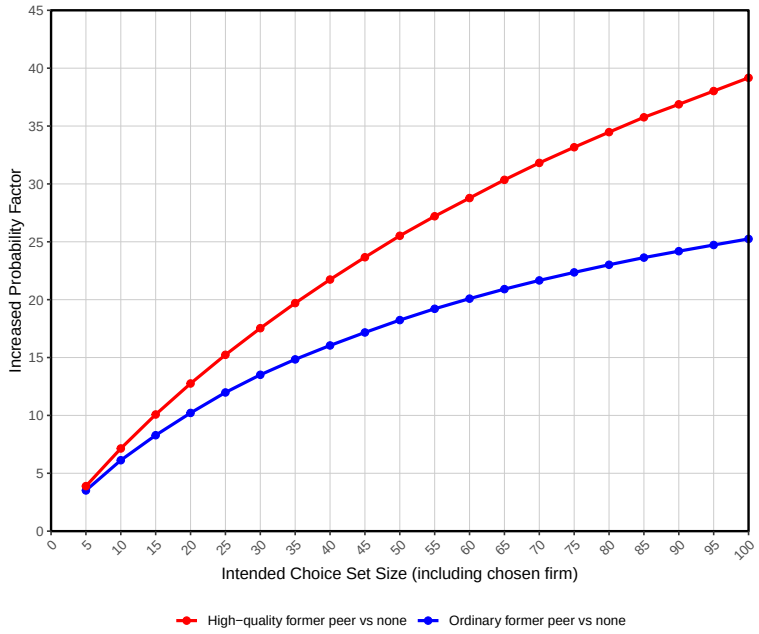
The profiles are essentially unchanged when average component-normalized PageRank replaces global PageRank. Figure 8 confirms that the relationship between actual and intended choice-set size is identical, as expected, because changing the PageRank control does not alter how candidate firms are sampled. Figure 9 shows that the benchmark-normalized ordinary-peer and high-quality-peer effects also follow nearly identical trajectories under the component-normalized measure.

Figure 8: Actual and intended choice-set size: component PageRank specification




*Note:* The choice sets are the same as in Figure 6. Component-normalized PageRank replaces global PageRank only in the second-stage conditional-logit model.

Figure 9: Peer-state effects relative to the uniform-choice benchmark: component PageRank




*Note:* The figure reports the benchmark-normalized effects defined in equation (130). The conditional-logit specification controls for average component-normalized PageRank instead of average global PageRank.

Overall, the simulation does not show that peer effects grow mechanically with the number of sampled firms. Instead, it shows that former-peer effects decline more slowly than the probability implied by uniform random choice. The direct conditional-logit results provide the more economically meaningful comparison: the ordinary-peer relative choice-odds ratio declines only modestly as the choice set expands, while the incremental high-quality-peer odds ratio and probability effect remain remarkably stable. The near-equivalence of the global and component PageRank specifications also indicates that this conclusion is not driven by the particular normalization of the network-centrality control.

## B.7 Robustness 1: Upward-quintile restriction on movers and alternatives

As a robustness check, we repeat the simulation and estimation procedure under a restriction motivated by firm-quality "job ladder" considerations. Let $q_{f^\star,t} \in \{1,2,3,4,5\}$ denote the quality quintile of the realized destination firm in year $t$, and let $q_{-f,t-1}$ denote the origin-firm quintile for mover-year $(i,t)$. We restrict the sample in two ways.

**Mover restriction** We retain only movers whose realized destination firm is in the same or a higher quintile than the origin firm:

$$q_{f^\star,t} \geq q_{-f,t-1}$$

**Alternative-pool restriction** For each retained mover-year, let $\mathcal{F}_{i,t}$ denote the candidate-firm pool satisfying the comparability restrictions in B.1 plus the mover restriction discussed above. Alternatives are sampled without replacement from

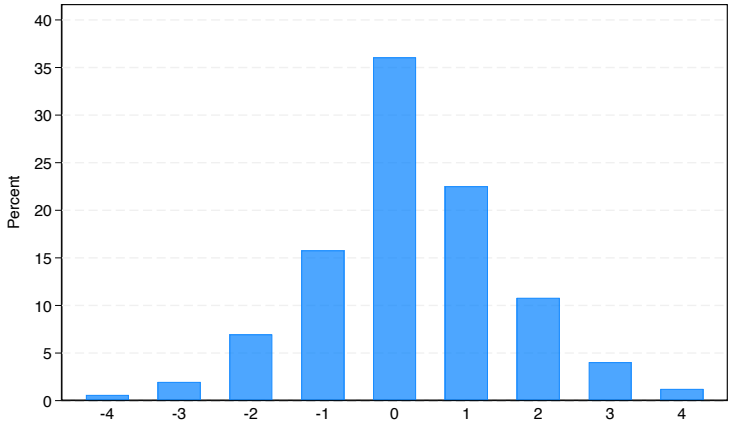
$$\mathcal{F}^{\uparrow}_{i,t} \equiv \{f \in \mathcal{F}_{i,t} : q_{f,t} \geq q_{-f,t-1}\} \setminus \{f^\star_{i,t}\}$$

We then apply the same nested sampling procedure described in Appendix B.1. For each mover-year, we draw a single ordered list $\widetilde{\mathcal{A}}^{\uparrow}_{i,t}$ containing up to $\mathcal{N}_{\max} - 1$ eligible alternatives and use its first $\mathcal{N} - 1$ elements to construct $\mathcal{C}^{\uparrow}_{i,t}(\mathcal{N})$. All subsequent steps, including the construction of the expanded dataset, conditional-logit estimation, calculation of discrete peer-state probability effects, and normalization relative to $1/K_{i,t}(\mathcal{N})$, are identical to the baseline exercise.

The purpose of the upward-quintile restrictions is to reduce contamination from involuntary separations and other transitions that may not reflect the worker's preferred ordering of firms. Displaced workers may accept jobs at lower-quality firms because of a variety of reasons, including liquidity constraints, short search horizons, or limited outside options. If

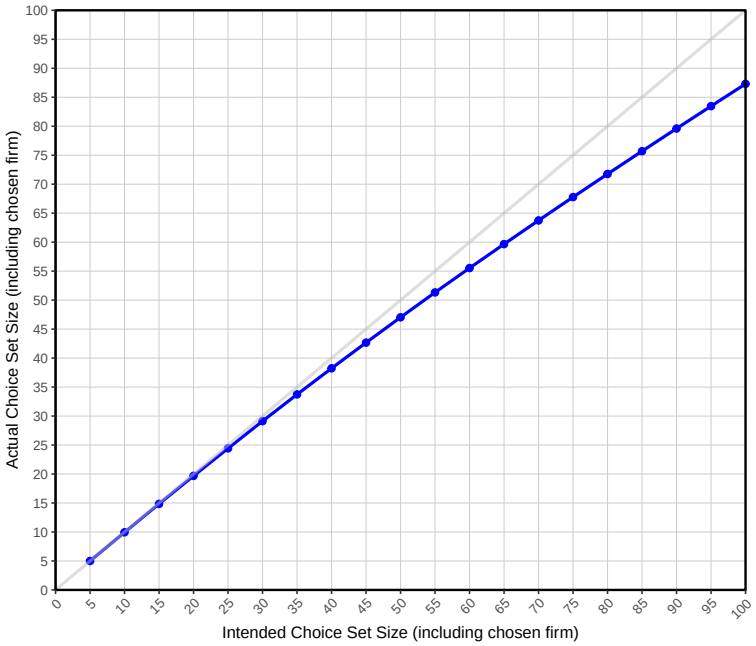
that is the case, then the realized destination may provide incomplete, wrong, or at least less information about the types of firms the worker would have selected under a less constrained search. Figure 10 shows that the largest share of moves occurs within the same firm-quality quintile. The remaining distribution is tilted toward moves to higher-quintile firms.

Figure 10: Change between firm-quality quintiles




Operationally, the restriction limits both the set of mover-years used for estimation and the set of feasible alternatives available to each retained mover. Figure 11 shows that the average realized choice-set size remains close to the intended size for smaller values of $\mathcal{N}$, but the difference increases for larger intended sets. At an intended size of 100 firms, the average realized set contains approximately 87 firms. The growing wedge reflects the finite number of firms in the mover's sector-region cell whose quality quintile is weakly greater than that of the origin firm. It is particularly pronounced for workers whose origin firms already belong to the upper part of the quality distribution.

Figure 11: Actual and intended choice-set size: upward-quintile restriction

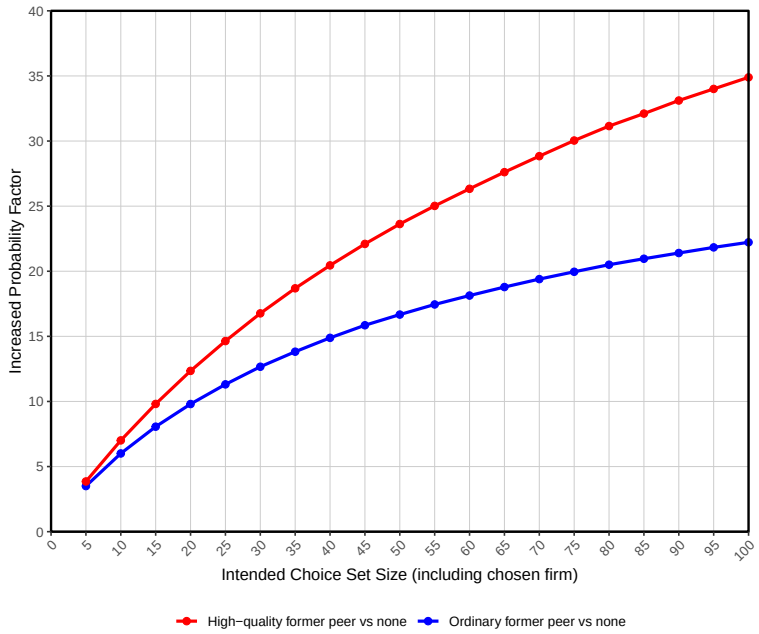



*Note:* The solid line reports the average realized choice-set size after restricting both realized destinations and candidate alternatives according to the origin-firm quality quintile. The grey line is the 45-degree line.

Despite the smaller feasible set, the qualitative conclusions from the baseline simulation remain. Figure 12 shows that the benchmark-normalized ordinary-peer and high-quality-peer effects continue to increase over the range of intended choice-set sizes. At $\mathcal{N} = 100$, the ordinary-peer profile is approximately 22 and the high-quality-peer profile is approximately 35. Thus, the ordinary-peer probability increment remains approximately 21 times the uniform-choice benchmark, while the total high-quality-peer increment remains approximately 34 times that benchmark.[23]

[23] 24 and 38, respectively, in the unconstrained exercise

Figure 12: Peer-state effects relative to the uniform-choice benchmark: upward-quintile restriction




*Note:* The figure reports the benchmark-normalized peer-state effects defined in equation (130) after imposing the upward-quintile restrictions. The conditional-logit model controls for average global PageRank and the remaining candidate-firm characteristics described in the main text.

Although the normalized profiles are somewhat lower than in the baseline construction, the difference between ordinary-peer and high-quality-peer destinations remains substantial throughout the simulated range. As in the baseline exercise, the widening distance between the benchmark-normalized curves should not be interpreted as evidence that the incremental high-quality-peer effect itself increases with $\mathcal{N}$. Overall, the results indicate that the destination-choice findings are not driven by movers whose realized destinations lie below their origin firms on the estimated firm-quality ladder.

## B.8 Robustness 2: Machine-learning-based choice-set construction

Rather than imposing only deterministic rules to define the sampling frame, as in the main analysis and Robustness 1, we implement a data-driven, two-stage procedure in which an

ML screening model ranks potential destination firms and the mover-specific choice set is drawn from a scored proposal pool. This design is consistent with the consideration-set perspective in discrete choice, where agents first form a possibly unobserved set of salient or feasible alternatives and then choose within it (Horowitz & Louviere, 1995; Swait, 2001). The exercise is intended as a robustness check on how alternatives are generated, not as a structural estimate of workers' latent consideration sets.

### B.8.1 Stage 1: ML screening model

Let $i$ index mover-year observations and $t$ calendar years. Let $\mathcal{F}_t$ denote the set of firms observed in year $t$. For mover $(i,t)$, let $f^\star_{i,t} \in \mathcal{F}_t$ denote the realized destination firm and let $-f_{i,t-1}$ denote the origin firm. Let $\mathbf{X}_{i,t}$ contain worker-year covariates, $\mathbf{Z}_{f,t}$ candidate-firm covariates, $\mathbf{Z}_{-f,t-1}$ origin-firm covariates, and $\mathbf{M}_{i,f,t}$ characteristics of the potential mover-firm match, including indicators and differences comparing the candidate and origin firms. To avoid using a worker's realized destination to train the model that later constructs that worker's alternatives, we assign 30% of workers to an ML-training sample and exclude them from the downstream conditional-logit sample. For each mover-year in the training sample, we construct one ranking group containing the realized destination and $R = 20$ nonchosen firms sampled uniformly from $\mathcal{F}_t \setminus \{f^\star_{i,t}\}$. The chosen pair receives label one and the sampled nonchosen pairs receive label zero. This procedure is related to choice-based sampling in econometrics and to negative sampling in large-alternative prediction problems (Gutmann & Hyvarinen, 2010; Manski & Lerman, 1977; Mikolov et al., 2013; Scott & Wild, 1986). Because the nonchosen firms are sampled and the resulting scores are used only for ranking, they are not interpreted as calibrated population choice probabilities.

For each training pair $(i,f,t)$, we construct a feature vector

$$\boldsymbol{\phi}_{i,f,t} = \phi(\mathbf{X}_{i,t}, \mathbf{Z}_{f,t}, \mathbf{Z}_{-f,t-1}, \mathbf{M}_{i,f,t}, t)$$

The worker features include the observed characteristics used in the destination analysis. The candidate- and origin-firm features include firm size, firm quality, network centrality, sector, and region. The match variables include indicators for whether the candidate shares the origin firm's sector or NUTS 2 region and differences between candidate- and origin-firm characteristics.

We estimate an XGBoost learning-to-rank model using the pairwise ranking objective `rank:pairwise` (Chen & Guestrin, 2016). The model therefore targets the ordering of candidate firms within each mover-year ranking group rather than a calibrated binary-choice probability. We use `NDCG@10` as the validation criterion and set `max_depth` $= 6$, `eta` $= 0.05$, `subsample` $= 0.8$, `colsample_bytree` $= 0.8$, and `min_child_weight` $= 1$. Later years are used for validation whenever the time structure permits, and early stopping selects the number of boosting rounds. The final ranker is then refitted on all ML-training groups using the selected number of rounds. For each candidate firm, the fitted model produces a ranking score

$$s_{i,f,t} = \widehat{h}(\boldsymbol{\phi}_{i,f,t})$$

where higher values indicate that the candidate is ranked as a more plausible destination. The score is not treated as a probability.

### B.8.2 Stage 2: ML-screened choice-set construction

For each mover-year in the downstream estimation sample, we draw a same-year proposal pool $\widetilde{\mathcal{F}}_{i,t}$ containing up to $L = 500$ firms sampled uniformly without replacement from $\mathcal{F}_t \setminus \{f^{\star}_{i,t}\}$. We then use the fitted ranker to calculate $s_{i,f,t}$ for each proposal firm.

The ranking scores are not used to infer an effective number of available alternatives. Because these scores are not calibrated probabilities, their concentration should not determine the size of a worker's choice set. Instead, we construct a maximum set containing up to $m_{\max} = 99$ nonchosen alternatives. We rank the proposal firms by $s_{i,f,t}$, select 70% of the maximum set

from the highest-ranked firms, and draw the remaining 30% uniformly from the rest of the proposal pool. This mixture retains the behavioral content of the ML screen while preserving variation from firms outside the top of the ranking.

Let $\widetilde{\mathcal{A}}_{i,t}^{ML}$ denote the resulting maximum alternative set. We randomly reorder this set once and define the alternatives at intended size $\mathcal{N}$ as

$$\mathcal{A}_{i,t}^{ML}(\mathcal{N}) = \text{the first } \min\left\{\mathcal{N}-1, \left|\widetilde{\mathcal{A}}_{i,t}^{ML}\right|\right\} \text{ firms in } \widetilde{\mathcal{A}}_{i,t}^{ML}$$

The ML-screened choice set is therefore

$$\mathcal{C}_{i,t}^{ML}(\mathcal{N}) = \left\{f_{i,t}^{\star}\right\} \cup \mathcal{A}_{i,t}^{ML}(\mathcal{N})$$

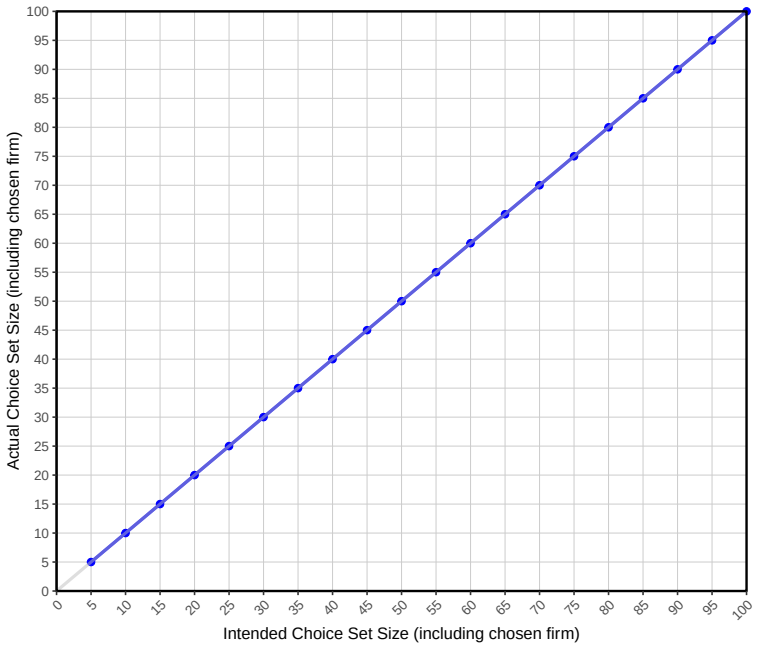
The one-time reordering ensures that the smaller sets remain nested within the larger sets and contain approximately the same mixture of top-ranked and randomly selected firms, rather than consisting only of the very highest-ranked candidates.

For each intended size, we estimate a conditional-logit model with the mutually exclusive no-peer, ordinary-peer, and high-quality-peer states. The specification includes the candidate-firm characteristics used in the ML robustness exercise, including indicators for whether the candidate matches the origin firm's sector and NUTS 2 region. Absolute destination-sector and destination-region indicators are not included because they generate separation within the ML-screened sets. We calculate the same discrete own-candidate probability effects and benchmark-normalized quantities used in the baseline analysis. Since the ML procedure samples alternatives nonuniformly and we do not model the exact candidate-inclusion probabilities, the resulting estimates should be interpreted as an ML-screened robustness exercise rather than as a sampling-corrected structural choice model.

Figure 13 shows that the average realized ML-screened choice-set size perfectly follows the intended size across the full range from 5 to 100 firms. This differs from the earlier score-concentration procedure, under which the number of alternatives varied with an effective-

number calculation. In the present implementation, the ranker determines which firms enter the maximum proposal set but does not determine how many firms are included. Since the same-year proposal pool contains up to 500 firms and the maximum choice set requires only 99 nonchosen alternatives, the intended set sizes can be attained quite easily.

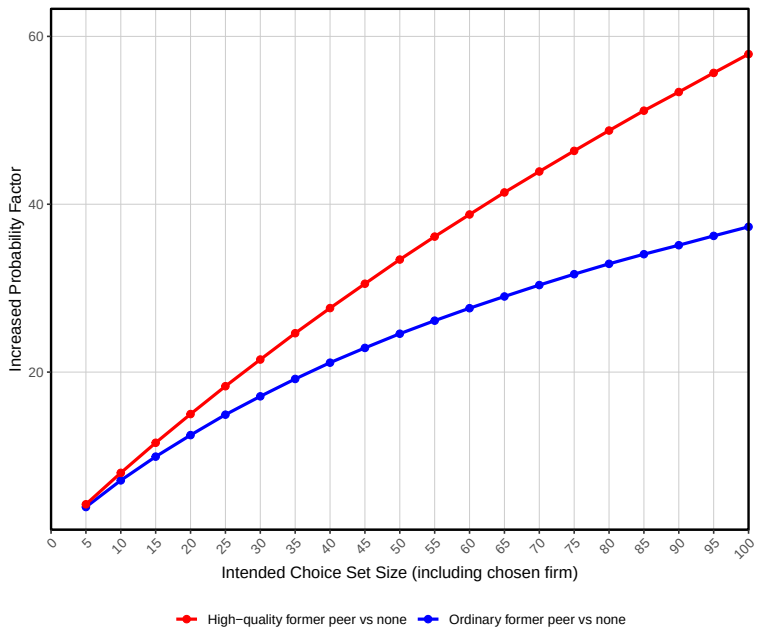
Figure 13: Actual and intended choice-set size: ML-screened alternatives




*Note:* The solid line reports the average realized size of the nested ML-screened choice sets. The grey line is the 45-degree line. The ranking model determines the composition of the maximum alternative set, not its intended size.

Figure 14 shows that the benchmark-normalized effects remain large under the ML-screened construction. At an intended size of 100 firms, the ordinary-peer profile is approximately 37, while the high-quality-peer profile is approximately 58. The corresponding ordinary-peer and total high-quality-peer probability increments are therefore approximately 36 and 57 times the probability implied by uniform random choice over the realized set.

Figure 14: Peer-state effects relative to the uniform-choice benchmark: ML-screened alternatives




*Note:* The figure reports the benchmark-normalized peer-state effects defined in equation (130) for the ML-screened choice sets. Workers used to train the ranking model are excluded from the downstream conditional-logit sample. The ranking procedure samples alternatives nonuniformly, and the plotted estimates do not incorporate a sampled-alternatives correction.

The higher profiles relative to the baseline and upward-quintile constructions should not be interpreted as evidence that ML screening causally increases the peer effect. The ranker deliberately changes the composition of the alternative set by concentrating it on firms that resemble plausible destinations according to observed worker, firm, and match characteristics. In addition, the exact nonuniform sampling probabilities are not incorporated into the conditional-logit estimator. What the results indicate is that even when the comparison firms are selected using a data-driven ranking model, ordinary-peer candidates retain a large destination-choice advantage and high-quality-peer candidates retain a substantial additional advantage. Across the baseline, upward-quintile, and ML-screened exercises, the main qualitative conclusion is unchanged: former-peer presence remains strongly predictive of destination choice, and the incremental role of high-quality former peers does not

disappear as the nominal choice environment expands.

# C Network-Based Peer Centrality

Peer counts and peer quality shares treat all coworkers symmetrically. In practice, influence is heterogeneous: some workers are structurally better connected and more visible, and potentially more influential in shaping turnover decisions. For robustness checks, we go beyond peer counts and introduce a measure of peer centrality that captures the embeddedness of each worker in a network of professional relationships. We operationalize this concept by constructing a time-evolving firm-level social network and deriving a time-varying centrality measure using the PageRank algorithm.

**Graph construction** Our core unit of analysis is the worker-year pair $(i, t)$, which corresponds to worker $i$ employed in year $t$. We define an undirected graph $G = (V, E)$, where each vertex $v \in V$ represents a unique worker-year node and edges $E$ capture two types of relationships: (i) within-year coworker ties and (ii) temporal continuity.

**(i) Within-year coworker ties.** For each firm $f$ in year $t$, we construct a complete subgraph (clique) among all employees observed in $f$ at time $t$. Let $W_{f,t}$ denote the set of workers in firm $f$ at year $t$. For every unordered pair $i, j \in W_{f,t}$ with $i \neq j$, we create an undirected edge $e_{(i,t),(j,t)}$ in the graph. These edges reflect co-presence in a firm-year cell and are assigned a weight of 1. The overall set of these edges creates disconnected components when viewed within a single year. However, connectivity across years emerges via temporal edges.

Formally, if workers $i$ and $j$ belong to the same firm in year $t$, add an edge between the nodes $(i, t)$ and $(j, t)$ such that:

$$A^{(f)}_{(i,t),(j,t)} = \begin{cases} 1, & \text{if } i \neq j \text{ and } \text{firm}_{(i,t)} = \text{firm}_{(j,t)} \\ 0, & \text{otherwise} \end{cases}$$

**(ii) Temporal continuity.** We introduce inter-temporal edges that link a worker to

herself across adjacent years. For every worker $i$ observed in consecutive years $t$ and $t+1$, we create an undirected edge $e_{(i,t),(i,t+1)}$ with unit weight. These temporal links serve to propagate structure over time, allowing influence to travel across firm boundaries whenever a worker changes employers.

Formally, for a given worker $i$ and for each year $t$, add an edge between the nodes $(i,t)$ and $(i,t+1)$

$$A^{(t)}_{(i,t),(i,t+1)} = \begin{cases} 1, & \text{if } i \text{ is observed in } t \text{ and } t+1 \\ 0, & \text{otherwise} \end{cases}$$

**Adjacency matrix representation** Having created within-year coworker ties and temporal continuity, we can create our adjacency matrix. Let $A$ denote the weighted adjacency matrix of $G$, where $A_{(i,t),(j,s)} = 1$ if an edge exists between nodes $(i,t)$ and $(j,s)$, and 0 otherwise. More formally,

$$A_{(i,t),(j,s)} = \begin{cases} 1 & \text{if } i \neq j, t = s, \text{ and } \text{firm}_{(i,t)} = \text{firm}_{(j,t)} \\ 1 & \text{if } i = j \text{ and } |t-s| = 1 \\ 0 & \text{otherwise} \end{cases}$$

The resulting matrix $A$ is symmetric and sparse. The network $G$ contains as many connected components as needed to link workers through firm-year cores and intertemporal paths. Workers who remain in the same firm will accumulate links within the same component, while workers who change firms provide the bridges between firm-year subgraphs.

**Centrality computation** To quantify how embedded each worker is in this temporal labor network, we compute PageRank centrality over the full graph $G$. PageRank, originally developed for web graphs (Brin and Page, 1998), is particularly well-suited for large-scale, sparse, undirected networks. Let $PR_{(i,t)}$ denote the PageRank score of worker $i$ in year $t$.

These scores are defined recursively:

$$PR_{(i,t)} = \alpha \sum_{(j,s)\in N(i,t)} \frac{PR_{(j,s)}}{d_{(j,s)}} + (1-\alpha)\cdot\frac{1}{|V|} \tag{131}$$

where $N(i,t)$ is the set of neighbors of node $(i,t)$, $d_{(j,s)}$ is the degree of node $(j,s)$, $|V|$ is the number of nodes in the graph, and $\alpha \in (0,1)$ is the damping factor, which we set to the canonical value 0.85. This equation admits a unique solution under mild conditions and is computed via power iteration.

The interpretation of $PR_{(i,t)}$ is that it reflects the long-run probability that a random walk on the graph would visit node $(i,t)$, taking into account not just the number of ties but their quality, i.e., whether a node is connected to other well-connected nodes.

There are several advantages to this graph-based centrality approach. First, it allows us to move beyond counting how many peers are present or moving, and instead weight their influence by their structural importance. Second, centrality is computed on the *entire* graph, meaning it captures both local embeddedness (via within-year firm links) and global position (via mobility across firms over time). Third, by including temporal edges, we ensure that structure propagates forward, allowing influence to accumulate across a worker's career.

PageRank values are normalized to sum to 1, which means that for large networks the absolute magnitude of individual scores tends to be extremely small. This can lead to estimation challenges in nonlinear models, as variation becomes hard to interpret or overly sensitive to extreme values. Moreover, the long-tailed distribution of PageRank, where a few highly connected nodes account for a large share of the centrality mass, implies that even standardized scores (i.e., z-scores) can span multiple standard deviations above or below the mean.

**Component structure** Instead of computing PageRank on the whole graph, we can compute the value per component, i.e., mostly separated clusters. By construction[24], the

[24]We kept only the largest connected set when identifying the peers.

worker-year graph exhibits a very dominant component with 16,849,533 observations in the original computation, and many small components with less than 1,000 individual × years. The results in the next section take the global PageRank as the main control and treat the component-normalized PageRank as a robustness variant, given that estimates are nearly identical. See Figures 3–4 for choice-set simulations controlling for the relevant PageRank aggregates.

**Winsorization** To mitigate the influence of outliers and reduce sensitivity to highly skewed centrality scores, we apply winsorization to the standardized PageRank values. Winsorization is a transformation technique in which extreme values in the tails of a distribution are set to a specified percentile threshold. Specifically, we winsorize the standardized PageRank scores at the 1st and 99th percentiles. Formally, let $PR^*_{(i,t)}$ denote the winsorized centrality score:

$$PR^*_{(i,t)} = \begin{cases} q_{0.01} & \text{if } PR_{(i,t)} < q_{0.01} \\ PR_{(i,t)} & \text{if } q_{0.01} \leq PR_{(i,t)} \leq q_{0.99} \\ q_{0.99} & \text{if } PR_{(i,t)} > q_{0.99} \end{cases}$$

where $q_{0.01}$ and $q_{0.99}$ represent the 1st and 99th percentiles of the standardized distribution. This transformation ensures that extreme centrality values do not disproportionately influence regression estimates, while preserving meaningful variation across most of the distribution. For the global measure, standardization and winsorization is done at the year level. For the component variant, standardization and winsorization are within component × year.

# D Variables List

| VARIABLES LIST | |
|---|---|
| Turnover (%) | Share of peers in a given peer group that left the group between $t-2$ and $t-1$ (as a % of peers in $t-2$) |
| Share of high-quality peers (%) | Share of high-quality peers in a given peer group that left the group between $t-2$ and $t-1$ (as a % of peers in $t-2$). A high-quality peer is a worker that belongs to the top quintile of individual fixed effects for his job category in his workplace in a given year. |
| Share of low-quality peers (%) | Share of low-quality peers in a given peer group that left the group between $t-2$ and $t-1$ (as a % of peers in $t-2$). A low-quality peer is a worker that belongs to the bottom quintile of individual fixed effects for his job category in his workplace in a given year. |
| Share of managers (%) | Share of managers in a given firm that left it between $t-2$ and $t-1$. |
| Tenure | Number of months since hiring date working in firm $f$ in $t-1$ (before the move) |
| Age | Age of the individual in years at $t-1$ (before the move) |
| Wage | Log wage of individual in $t-1$ (before the move) |
| Log (firm size) | Log of the firm size (number of employees) in $t-1$ (before the move) |
| Micro firm | Firms with fewer than 50 employees (in $t-1$ or $t$, depending on the model) |
| Small firm | Firms between 50 and 199 employees (in $t-1$ or $t$, depending on the model) |
| Medium firm | Firms between 200 and 499 employees (in $t-1$ or $t$, depending on the model) |
| Large firm | Firms with 500 or more employees (in $t-1$ or $t$, depending on the model) |
| Schooling dummies | 10 year dummies corresponding to different degrees of schooling (no schooling is dropped from the dummies list) |
| Year dummies | 28 year dummies: 1988 to 2021, excluding 1989, 1990, 1991, 2000, 2001, and 2002. 1987 is dropped from the dummies list |
| Sector dummies | 26 sector dummies corresponding to different firm industries. Sectors 1-4 are dropped from the dummies list. |

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