Learning and Talent Allocation along the Supply Chain*

Paula Beltran
IMF

Francesco Grigoli
IMF

Nicola Pierri
IMF

Marvin Cardoza
DGII

June 1, 2026

Abstract

We document that human capital accumulates through knowledge spillovers between workers connected via supply chain relationships. Using employer–employee data matched with firm-to-firm transactions from the Dominican Republic, we show that workers learn from the employees of their employers' buyers and suppliers. These learning spillovers are quantitatively large, portable across industries, and more pronounced among high-wage and highly educated workers. We also find that firms become more likely to begin exporting a product after hiring a worker from a supplier of a firm that already exports that product. We complement our empirical findings with a model in which equilibrium wages reflect learning spillovers. An estimated version of the model predicts that human capital would be 18 percent lower in the absence of learning along the supply chain. Our findings further carry implications for talent allocation: the sorting of high-human-capital workers into more central firms amplifies knowledge diffusion and boosts aggregate wage growth.

Keywords: human capital, knowledge spillovers, learning, networks, supply chain

JEL Codes: J24, J62, L14, O33

*Paula Beltran, International Monetary Fund, pbeltransaavedra2@imf.org; Francesco Grigoli, International Monetary Fund, fgrigoli@imf.org; Nicola Pierri, International Monetary Fund, npierri@imf.org; Marvin Cardoza, General Directorate of Domestic Revenues of the Dominican Republic, mcardoza@dgii.gov.do. The views expressed in this paper are those of the authors and do not necessarily represent those of the International Monetary Fund, its Executive Board, or its Management, nor the views of the General Directorate of Domestic Revenues of the Dominican Republic. We thank Jaime Arellano-Bover, Paco Buera, Kevin Donovan, Luca Mazzone, and Jonathan Vogel for their insightful comments.

1 Introduction

Learning from other workers is a key channel of on-the-job human capital accumulation (Cornelissen, Dustmann and Schönberg, 2017; Jarosch, Oberfield and Rossi-Hansberg, 2021; Herkenhoff et al., 2024). Yet our understanding of how such learning occurs remains limited. Progress on this front is particularly important for developing economies, where workers experience slower upward mobility (Donovan, Lu and Schoellman, 2023) and tend to accumulate human capital at a lower rate over the life cycle (Lagakos et al., 2018; Ma, Nakab and Vidart, 2024).

In this paper, we leverage employer-employee data matched with firm-to-firm transactions from the Dominican Republic—a rapidly growing developing economy—to document that workers learn from the employees of their employer's buyers and suppliers. The potential for knowledge diffusion along the supply chain is large. Since firms with more buyers and suppliers tend to be more productive (Bernard et al., 2022) and pay higher wages, the average worker is typically connected—through their employer—to trading partners that employ higher-wage workers than their own coworkers. Insofar as wage gaps capture differences in human capital, this fact suggests considerable scope for learning from employees at buyers and suppliers. Practically, workers could learn from the employees of buyers and suppliers in a variety of ways. For example, learning can occur through direct interaction—such as conversations or joint projects—or indirectly, through exposure to more efficient work practices, higher-quality inputs, or superior documentation and production processes.

To rationalize our empirical findings, we develop a theoretical model of human capital accumulation in production networks. The model features heterogeneous firms connected through buyer-supplier relationships and workers that move up in the skill ladder through stochastic upgrading. The key innovation is that the rate of skill upgrading depends on two channels: learning from coworkers within the firm and, importantly, learning from the employees at trading partners. Firms operate in a frictional labor market and set wages through Nash bargaining over joint surplus, which incorporates the option value of future learning. This framework allows us to formally characterize how spillover intensity and network connectivity shape aggregate human capital.

We employ five different empirical approaches to isolate this novel source of knowledge diffusion. The first two build on Herkenhoff et al. (2024) and Jarosch, Oberfield and Rossi-Hansberg (2021)—who study knowledge spillover among same-employer coworkers. We augment their empirical frameworks to test for knowledge spillovers along the supply chain, while controlling for learning spillovers among coworkers. Both frame-

works infer learning by documenting that workers experience stronger future wage growth when they work with higher paid coworkers. However, they rely on different specifications and different sample selections, which are micro-founded in different models: Herkenhoff et al. (2024) emphasize the role of labor market search frictions and focus on workers who move to a new employer after an unemployment spell; Jarosch, Oberfield and Rossi-Hansberg (2021) present a theory of learning within a competitive labor market and study the long-term wage growth of a broader set of workers.

Results from both empirical frameworks indicate that learning spillovers occur not only among workers within the same firm, but also among workers employed by their employer's buyers and suppliers. The magnitude of spillovers from buyers and suppliers varies across specifications, but it generally exceeds that of within-firm spillovers. We find evidence of spillovers from both suppliers and buyers, with the latter being marginally stronger. The estimated coefficients are only modestly affected by the inclusion of controls for the size, productivity, and production network's size of the worker's employer, as well as that of its buyers and suppliers. This suggests that wage dynamics are unlikely to merely reflect firm-level characteristics unrelated to human capital. Importantly, our results are not driven by workers transitioning to better-paid buyers or suppliers (Cardoza et al., 2024), and remain robust to the inclusion of destination firm-by-year fixed effects. Because we rely on wage dynamics to infer changes in human capital, it is reassuring that the results are consistent across empirical frameworks derived from models with markedly different assumptions about labor markets and wage-setting mechanisms. Furthermore, the results hold when measuring workers' human capital using worker fixed effects estimated from an AKM decomposition (Abowd, Kramarz and Margolis, 1999).

We corroborate these findings using two additional approaches based on the wage dynamics of workers before and after a job change. The first is an event study design that focuses on workers displaced by large-scale downsizing at their employer, allowing us to isolate job changes driven by firm-level shocks rather than individual decisions (Jacobson, LaLonde and Sullivan, 1993; Bertheau et al., 2023; Acabbi, Alati and Mazzone, 2024). Within this group of workers, we find that those previously employed at firms whose buyers and suppliers paid higher wages tend to earn more at their subsequent employers, controlling for their pre-move wages and coworkers' wages. These results remain consistent even when we include destination firm-by-year fixed effects. The second approach focuses on firms that, for the first time, start a new—and sizable, in terms of sales—supply chain relationship with a firm paying relatively high wages, having had no prior supply chain relationships with high-wage buyers or suppliers. We find that work-

ers who leave the firm after the formation of this high-wage connection earn more than other employees at the same destination firm, whereas workers who leave before the connection is formed do not. This pattern is consistent with workers acquiring knowledge through their employer's new high-wage link, which is then reflected in their wages at the time of a job transition.

These four empirical approaches rely on wages to infer human capital and learning; we therefore complement our findings with a fifth approach that leverages product-level export data.[1] Specifically, we establish a novel empirical fact: firms are more likely to begin exporting a specific product after hiring, for the first time, a worker from a firm that already exports that product. A natural interpretation is that the worker's human capital serves as a valuable input into the production and/or export of that product. We observe a similar pattern when firms hire workers from suppliers of exporters of a given product. This suggests that the relevant human capital is not confined to employees of exporting firms, but is also present among workers at their suppliers—consistent with learning along the supply chain.

Although we find that workers learn from both the employees of buyers and suppliers and from coworkers, the distribution of these gains differs across worker characteristics. Spillovers from buyers and suppliers are stronger for higher-wage, more educated, and older workers, whereas coworker spillovers are more pronounced among lower-wage workers. Moreover, learning from coworkers is more important for workers staying within the same industry, while learning from buyers and suppliers is equally valuable for industry switchers.

Selection biases are the most important threat to the learning interpretation of our findings. Specifically, workers with greater wage growth potential may sort into firms whose production networks are composed of higher-paying partners. To address this concern, we follow the approach of Herkenhoff et al. (2024), measuring the extent to which higher-wage workers sort into firms with higher buyer and supplier wages. Reassuringly, we find no evidence of such sorting. This suggests that while learning from employees at buyers and suppliers is an important source of human capital accumulation, job seekers may not have the information to assess its potential. This may reflect the fact that it is generally easier to acquire information on the quality of a prospective employer and coworkers than to assess the characteristics of its buyers and suppliers.

[1] Previous literature examining knowledge spillovers among workers at the aggregate level has primarily relied on wage dynamics as an indirect measure of human capital accumulation and learning. A related strand of research estimates peer effects in the workplace (Mas and Moretti, 2009) and in educational settings (De Giorgi, Pellizzari and Redaelli, 2010) using more granular data on performance or productivity, though typically focusing on a single—or a small number of—firms, establishments, or schools.

Similarly, workers displaced from firms with higher-paying buyers and suppliers do not exhibit differential pre-displacement trends, suggesting they are comparable to other displaced workers. This is also the case for workers moving before and after their origin firm establishes a high-wage connection. Two additional identification threats, commonly discussed in the peer-effects literature, are correlated unobservable shocks and the reflection problem (i.e., reverse causality). Correlated shocks are unlikely to drive our results, as our empirical specifications link future worker wages to current wages of coworkers and employees at buyers and suppliers. We find limited scope for reflection as well: the relationship between future wage growth and current buyer and supplier wages holds even for workers who have just joined a new employer, and thus could not have influenced the wages of their employers' partners.

A key implication of our findings is that the allocation of high human capital workers to firms with more buyers and suppliers can foster learning spillovers in the economy.[2] Building on this intuition, we present a back-of-the-envelope calculation to quantify the impact of the tendency of high-wage workers to work for central firms: we find that absent this tendency, average real wage growth would be 11% lower.

We establish theoretically that strengthening either spillover channel raises aggregate human capital. The mechanism operates through two reinforcing forces: a direct effect, whereby workers upgrade skills faster when exposed to higher-quality peers and trading partners, and an indirect effect, whereby the resulting increase in the option value of future learning induces firms to post more vacancies and expand employment. In equilibrium, wages incorporate this option value, providing a theoretical foundation for our empirical specifications. We show that a positive reduced-form coefficient on network-partner wages in the EUE regression identifies the presence of network spillovers, and that the structural spillover parameter is identified from the estimated elasticity of individual wages to those of trade partners. We further show that network connectivity shapes aggregate human capital,as disconnecting firms from the supply chain reduces the economy's human capital stock.

We complement these findings by calibrating the general equilibrium model to the Dominican Republic. The estimation targets the EUE regression coefficients from the empirical analysis alongside moments of the wage distribution and the correlation between wages and network position. The calibrated model allows us to move beyond the

[2]This reasoning assumes that the knowledge spillovers from highly skilled workers do not diminish as the size of the networks of their employers increases, for instance because these workers have to divide their time dealing with more numerous suppliers and buyers. We therefore test whether learning spillovers are smaller when the size of the networks of the buyers and suppliers is larger. We find this is the case, but the magnitudes are small enough that can be ignored.

reduced-form evidence in two ways. First, we quantify the aggregate effects of network spillovers on human capital and output, accounting for equilibrium responses in hiring, wages, and the endogenous distribution of workers across firms. Second, we conduct counterfactual experiments that would be difficult to study empirically, such as selectively disconnecting groups of firms from the production network or shutting down the network learning channel entirely.

Our counterfactuals indicate that network learning spillovers account for 18% of the aggregate human capital stock. Without this channel, between-firm wage dispersion widens as workers at less connected firms can no longer accumulate human capital through their employer's supply chain relationships. Our results indicate that the allocation of talent across the network matters, as reversing the assortativity of productivity and connectivity costs about one-sixth of the total network learning effect, and this sorting channel operates almost entirely through network spillovers. Selectively disconnecting firms from the network shows that the aggregate effect depends critically on which firms are removed: excluding the top productivity decile from the supply chain reduces aggregate human capital by 11%, more than an order of magnitude larger than the effect of excluding the bottom decile. Disruptions to the supply chain relationships of large, productive firms can therefore have aggregate consequences well beyond the directly affected parties.

Our findings about workers' learning on the supply chain can help explain some macroeconomic patterns. The slower rate of on-the-job human capital accumulation in emerging markets and developing economies (Lagakos et al., 2018; Ma, Nakab and Vidart, 2024) can be attributed in part to the less dense production networks in these countries due to the stronger prevalence of contracting frictions (Oberfield and Boehm, 2020; Startz, 2025). The same frictions may also slow down the rate of technology diffusion within the economy by limiting the positive spillovers coming from firms with high human capital, helping to explain the lack of productivity convergence between countries (Johnson and Papageorgiou, 2020). Our novel findings have also implications for local productivity spillovers and agglomeration externalities. Previous literature shows that worker turnover is an important factor for knowledge diffusion (Stoyanov and Zubanov, 2012), especially within a local labor market (Serafinelli, 2019). Our results indicate that workers with high human capital provide knowledge not only to the firm they work at, but also to the firm's supply chain, thus accelerating knowledge diffusion even without leaving their current firm. Insofar supply chains are locally clustered, these spillovers further amplify agglomeration externalities. Similarly, our findings also help explain the presence of external economies of scale at the sector level (Bartelme et al., 2025), whose

magnitude are a major determinant of optimal trade policy (Cuñat and Zymek, 2025): firms tend to trade more within their own sector, thus allowing the knowledge of high human capital individuals to spread rapidly within a sector. To the extent that supply chains are locally clustered, the network learning spillovers documented in this paper provide a micro-foundation for agglomeration externalities.

Related literature Our paper is related to the studies highlighting the importance of interactions between workers as a source of human capital accumulation (Cornelissen, Dustmann and Schönberg, 2017; Jarosch, Oberfield and Rossi-Hansberg, 2021; Herkenhoff et al., 2024; Nix, 2020), and more broadly, to the papers showing how certain firm characteristics—such as size (Arellano-Bover, 2024; Gregory, 2020; Arellano-Bover and Saltiel, 2026), productivity (Acabbi, Alati and Mazzone, 2024), or multinational status (Alfaro-Ureña, Manelici and Vasquez, 2021; Dhyne et al., 2021)—are associated with stronger accumulation of employees' human capital. With respect to these studies, we document the importance of workers' learning from employees of their employers' buyers and suppliers as a source of human capital diffusion.

The paper is also related to the growing literature that examines the importance of supply chains for workers. Studies in this area find that supply chains can facilitate labor mobility (Cardoza et al., 2024; Komatsua and Dhyneb, 2023; Ma, 2025), and have a role in explaining wage inequality (Huneeus, Kroft and Lim, 2021), exposure to external shocks (Dhyne et al., 2025), and the incidence of distortions (Arkolakis, Huneeus and Miyauchi, 2025). We contribute by documenting the role of supply chains for on-the-job learning.

Finally, our paper contributes to the literature documenting the importance of supply chain relationships for firm performance (Bernard, Moxnes and Saito, 2019; Bernard et al., 2022)—with a particular focus on multinational enterprises (Alfaro-Ureña, Manelici and Vásquez, 2022), superstar firms (Amiti et al., 2024), or technology adoption (Criscuolo et al., 2025). We contribute by documenting the importance of supply chain relationships for workers' career progressions.

The rest of the paper is organized as follows. Section 2 describes the data sources and the variable construction. Section 3 discusses three facts motivating the empirical analysis. Section 4 presents the empirical results on learning spillovers from buyers and suppliers from a range of empirical approaches. Section 5 discusses the implications of our results for talent allocation along the supply chain. Section 6 presents the theoretical model. Section 7 illustrates the quantitative results from an estimated version of the model. Section 8 concludes.

2 Data

Our empirical analysis leverages micro-level datasets for the Dominican Republic over the period 2012–2023. During this period, the Dominican Republic was among the fastest growing countries in the world, averaging 4.8% real GDP growth per year. Growth remained stable until 2019. In 2020, the COVID-19 pandemic led to an output contraction of almost 8%, followed by a rapid recovery in 2021. Inflation was also stable, averaging 4% per year, and generally remained within the central bank's target band.

2.1 Sources

For our empirical exercises, we merge the following administrative datasets:[3]

- Firm-level financial information for the universe of firms in the country (i.e., assets, liabilities, revenues, expenditures, and the wage bill) from a dataset compiled by the General Directorate of Domestic Revenues based on income tax declaration forms. The dataset also includes the ownership structure of each firm, the ISIC Revision 3 industry, and the municipality where firms are headquartered.

- Annual data on firm-to-firm transactions from the value added tax (VAT) registry, which allow us to identify each firm's domestic buyers and suppliers.

- Records of the Social Security Treasury providing wage and demographic information on firms' employees. Each month employers report payments to employees (including bonuses, overtime work, etc.) to calculate social security contributions and withholding taxes. We observe the wage data at an annual frequency, where the value reported is the average worker earnings for the months in which the employee had social security obligations. Employees are classified as permanent or temporary based on whether they have social security obligations. In the analysis, we restrict the sample to firms in the private formal sector that engage in at least one transaction per year and have at least one permanent employee.[4]

[3]The administrative records come from several tax forms that all economically active entities are required to submit. Of these, 92% submit the tax forms electronically, allowing for extensive internal consistency checks. Moreover, the authorities cross-validate the data with information across different institutions, further ensuring the integrity of the information. To maintain confidentiality, the information provided by the authorities assigns anonymized identifiers to all taxpayers in the dataset.

[4]Following Cardoza et al. (2024), we apply light data cleaning procedures to rule out likely erroneous records. We drop firms with annual sales below 10,000 Dominican pesos or a wagebill or purchases below 1,000 Dominican pesos (approximately 200 US dollars and 20 US dollars at the 2019 exchange rate, respectively).

- Information on tertiary educational attainment for a subset of workers from the Ministry of the Economy, Planning, and Development. Specifically, for workers who graduated with a college degree between 2007 and 2023, we observe the educational institution they graduated from, the degree they obtained, and the graduation year.
- HS 4-digit product-year level exports for the universe of firms from the General Directorate of Customs.

2.2 Sample and metrics of workers' human capital

The final sample consists of approximately 2.8 million workers employed by 91,490 firms. The average firm sells to 42 buyers, sources inputs from 37 suppliers, and employs 20 workers. However, the distribution is heavily skewed due to large and central firms, such that the median firm has 5 buyers, 20 suppliers, and 5 employees.

Our baseline metric of workers' human capital is based on the wages that firms pay to their employees. In each year, a worker may have more than one job, earning wages from more than a single employer.[5] To measure human capital at firms' buyers and suppliers, we proceed in two steps. For each firm we first weight buyer wages by sales shares and supplier wages by purchase shares. We then compute the simple average of these two weighted measures. We consider only suppliers for firms that do not report VAT sales ('B-to-C' firms). We also construct a number of alternative measures, focusing exclusively on the main buyers and suppliers of each firm according to the sales and purchase shares (e.g., the top three buyers and suppliers, etc.) and computing the simple average across these firms. Similarly, our measure of human capital among coworkers is based on the average wages earned by employees at the same firm. Following Herkenhoff et al. (2024), for each worker and year we compute the average wage of stable coworkers, which are those that remain at the same firm since the year before through the year after.

We also employ an alternative measure of workers' human capital based on the decomposition approach of Abowd, Kramarz and Margolis (1999) (AKM, hereafter). This procedure aims to net out firm-specific wage components to better isolate the variation attributable to worker-specific human capital (Cornelissen, Dustmann and Schönberg, 2017; Hong and Lattanzio, 2025). Specifically, we regress the log wage of a worker i at a firm $f(i)$ in year t on worker, firm, and year variables, and extract the estimated worker fixed effects. This estimation is performed "backward-looking"; that is, for each year y we estimate the worker fixed effects $\theta_{i,y}$ using only data $t \leq y$, so that the human capital

[5] Following the literature (Card, Heining and Kline, 2013), for each employee and year we consider only the wages earned at the main employer—the firm paying the highest wages.

measure is not affected by future shocks.

3 Some motivating facts

This section documents three data patterns that motivate the regression analysis in the next section. We show that firms paying higher wages tend to be more connected in the production network, that workers at buyers and suppliers earn higher wages than those at their own firm, and that there is positive assortative matching both within firms and across buyer–supplier links, with the former being stronger.

Firms that pay higher wages tend to have more numerous buyers and suppliers. More central firms in the production network are connected to a larger set of trading partners and therefore have the potential to generate spillovers to more firms. It is therefore important to establish the empirical relationship between network centrality and firms' human capital.

Figure 1 illustrates the relationship between firm-level wages and network connectivity by plotting the average decile of the number of buyers and suppliers across deciles of firms' wage distribution. Firms in the first wage decile fall between the fourth and fifth deciles in terms of buyer and supplier counts, whereas firms in the tenth wage decile lie between the seventh and eighth deciles.[6] This relationship, however, is likely influenced by firm size. We find that even after residualizing the number of buyers and suppliers with respect to firm employment, a positive association remains, as indicated by the dashed lines.[7] The positive relationship also holds when measuring worker-level human capital by the worker fixed effects from an AKM decomposition except for the non-monotonicity at the top two deciles (Figure A.1).

From a worker's perspective, wages at buyers and suppliers tend to be higher than those at their own firm. To explore the potential for human capital diffusion through buyer–supplier relationships, we compare workers' own wages to those earned by employees at their employer's buyers and suppliers, as well as to wages of stable coworkers within the same firm.

Figure 2 overlays the distributions of log wages across these groups. Workers' own wages—winsorized at the 0.5th and 99.5th percentiles—are similar in both average (9.7)

[6] A regression of log wages on the log number of buyers (suppliers) using 2023 data—the final year in the sample—yields coefficients of 0.08 (0.14) and R^2 values of 7% (11%). These correlations are robust across all years in the sample.

[7] Specifically, we orthogonalize the log number of buyers and suppliers with respect to a third-degree polynomial in the log number of employees. In this specification, the coefficients from regressing log wages on the residualized log number of buyers and suppliers are 0.05 and 0.11, respectively.

Figure 1: Firms' wages and number of buyers and suppliers

(Average decile)



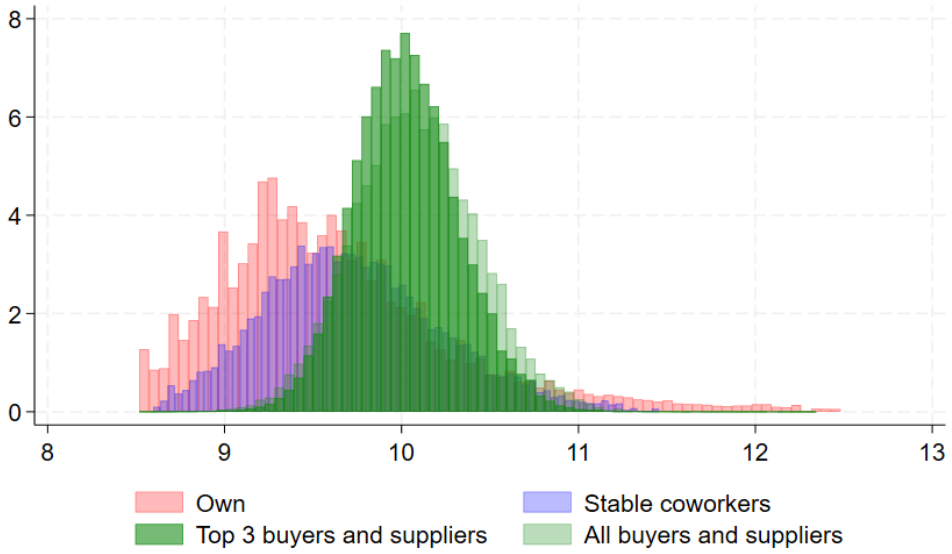
Notes: The figure shows the relationship between the decile of firms' wages and the average decile of the number of buyers and suppliers. The figure also shows the relationships where the number of buyers and suppliers is residualized with respect to a third-degree order polynomial of the size of the firm, measured with the firm employment.

and median (9.5) to those of stable coworkers (9.6 and 9.7, respectively). The standard deviation of coworkers' wages (0.50) is notably lower than that of workers' own wages (0.67), reflecting aggregation across multiple individuals. By contrast, the wage distributions of buyers and suppliers lie to the right of both workers' own wages and those of their coworkers, and exhibit significantly lower dispersion. We present two measures: (i) the average of the sales-weighted log wages of buyers and suppliers, and (ii) the simple average of log wages among the top three buyers and top three suppliers. Both distributions have higher means and medians (10.0 and 10.1, respectively), consistent with our earlier finding that firms paying higher wages tend to be more embedded in buyer–supplier networks. These distributions are also narrower (with standard deviations of 0.30 and 0.35, respectively), reflecting the fact that they are averages across firm-level wage distributions.

There is positive assortative matching among coworkers, as well as among employees at buyers and suppliers; however, the former is quantitatively more significant. Labor markets exhibit substantial and increasing sorting: workers with higher human capital tend to be employed at firms with similarly skilled coworkers (Card, Heining and Kline, 2013). Moreover, firms producing higher-quality goods are more likely to hire high human capital workers and to transact with other high-quality firms, leading to a

Figure 2: Wage distributions

(Percent)



Notes: The figure shows the distribution of log wages among workers, across stable coworkers, at buyers and suppliers, and at top 3 buyers and suppliers. Stable coworkers are those that remain at the same firm since the year before until the year after.

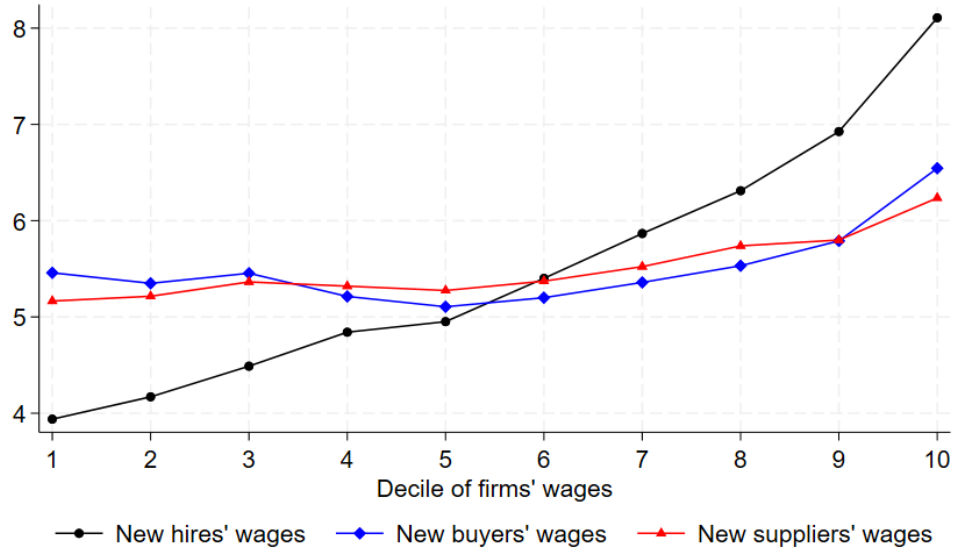
positive correlation in wages across buyer–supplier links (Demir et al., 2024*a*). We assess the extent of sorting in our data by examining the correlation between a firm's average log wage of stable employees and (i) the average log wage of its new hires, and (ii) the average log wage of the employees at its new buyers and suppliers. To mitigate potential spillover effects among coworkers and trading partners, we lag all wage measures.[8]

Figure 3 illustrates the degree of sorting by plotting the average wage decile of new hires, new buyers, and new suppliers—conditional on firms having at least one of each in a given year—against the decile of the firm's own wage distribution. The correlation between incumbent workers' wages and those of new hires is strong and positive: the average decile of new hires' wages rises from below 4 to above 8 as we move from the lowest to the highest wage firms. The correlation with the wages of new buyers and suppliers is also positive, but notably weaker. The average decile of new buyers' and suppliers' wages increases from approximately 5.5 to 6.5, exhibits a non-monotonic pattern, and it is visible only among firms above the median of the wage distribution. Regression results confirm this pattern: the coefficient on new hires' wages is roughly four times larger than those on new buyers' and suppliers' wages (Table A.1). Similar, though slightly attenu-

[8]We include only new hires who remain at the firm for at least three years, and restrict buyer–supplier relationships to those lasting at least three years. The sample is limited to post-2015 data to ensure that we capture genuine new hires and relationships, rather than reactivations of prior links.

ated, results emerge when measuring human capital using worker fixed effects from an AKM decomposition (Figure A.2).

Figure 3: Assortative matching with coworkers' and buyers and suppliers' wages
(Average decile)



Notes: The figure shows the relationship between the decile of lagged firms' wages and the average decile of lagged wages of new hires, new buyers, and new suppliers.

4 Learning from employees of buyers and suppliers

This section estimates learning spillovers along the supply chain using a variety of different empirical strategies.

4.1 Learning spillovers around EUE transitions

We start by examining learning spillovers by adapting the empirical strategy of Herkenhoff et al. (2024), who examine human capital diffusion among employees working in teams within a framework of learning spillovers and labor market search. Their empirical analysis focuses on employment-unemployment-employment (EUE) transitions–defined as cases where individuals move from stable employment at one firm to stable employment at another, with an intervening spell of unemployment. This focus is motivated by the fact that individuals hired by new firms must renegotiate their wages, whereas those who remain with the same firm tend to negotiate wages less frequently. As such, the new wage is more likely to reflect the human capital accumulated up to that point.

We restrict our sample to EUE transitions and modify their baseline specification as[9]

$$w_{i,t+2} = \alpha + \rho w_{i,t} + \phi_1 w^*_{f(i),t} + \phi_2 w^{B\&S}_{f(i),t} + \Phi X_{i,f(i),t} + \epsilon_{i,t}, \tag{1}$$

where $w_{i,t+2}$ and $w_{i,t}$ denote the log wages of worker i in years $t+2$ (post-unemployment) and t (pre-unemployment), respectively; $w_{f(i),t}$ is the average log wage of i's stable coworkers at firm $f(i)$ in year t—defined as those employed at the same firm in both $t-1$ and $t+1$; and $w^{B\&S}_{f(i),t}$ is the average log wage of stable workers at the buyers and suppliers of firm $f(i)$. The vector $X_{i,f(i),t}$ includes controls for worker characteristics (gender and age), firm-level variables (log sales, log employment, labor productivity, share of VAT sales, and log number of suppliers), the average of these firm-level variables among buyers and suppliers, and industry-municipality-year fixed effects.

Our parameter of interest is ϕ_2, which captures learning spillovers from buyers and suppliers, conditional on the worker's own wage and spillovers from coworkers (captured by ϕ_1). Following Herkenhoff et al. (2024), we focus on employees of firms with at most 100 workers in year t, to ensure meaningful coworker interactions. A key difference relative to their specification is the inclusion of a richer set of controls.[10] This addresses the concern that firms that pay higher wages may also be different in other aspects (e.g., size, productivity, growth, among others). Not controlling for firms' characteristics may pose identification challenges. For example, productive investment at one firm may spill over to its buyers and suppliers, indirectly affecting its employees' wages (Bernard, Moxnes and Saito, 2019; Alfaro-Ureña, Manelici and Vásquez, 2022; Amiti et al., 2024; Arellano-Bover, 2024; Acabbi, Alati and Mazzone, 2024). These controls may, however, partially absorb the variation in human capital heterogeneity that we aim to capture through firm wages, potentially attenuating our estimates.

Table 1 presents the regression results. The upper panel reports coefficients for coworkers' wages and those of buyers and suppliers using non-standardized variables. As shown in Section 3, the distribution of buyers' and suppliers' wages is more compressed than that of coworkers' wages. Therefore, the lower panel reports coefficients after standardizing these variables to have zero mean and unit variance.

Column (1) presents the most parsimonious specification, controlling only for year fixed effects. We find evidence that workers learn not only from coworkers but also

[9] We construct the EUE sample using annual data. Specifically, an individual must be employed at a firm in year $t-1$, absent from the employer-employee data in year t, and employed at a different firm in year $t+1$. Since we do not observe informal employment, we cannot distinguish between EUE transitions and transitions involving informal employment between formal jobs. Also, unlike Herkenhoff et al. (2024), we cannot exclude multi-establishment firms due to data limitations.

[10] Herkenhoff et al. (2024) only include year, sector, state, race, and gender fixed effects.

Table 1: Regressions *à la* Herkenhoff et al. (2024)

	(1)	(2)	(3)	(4)	(5)	(6)
Own wages	0.374***	0.374***	0.544***	0.0457***	0.369***	0.303***
	(0.007)	(0.007)	(0.012)	(0.012)	(0.008)	(0.011)
Coworkers' wages	0.045***	0.019***	0.015	0.040***	0.013*	-0.027***
	(0.005)	(0.006)	(0.009)	(0.007)	(0.007)	(0.008)
Buyers' and suppliers' wages	0.085***	0.075***	0.094***	0.026**		0.035***
	(0.007)	(0.009)	(0.015)	(0.011)		(0.012)
Suppliers' wages					0.044***	
					(0.008)	
Buyers' wages					0.044***	
					(0.006)	
Results with standardized variables						
Coworkers' wages	0.020***	0.008***	0.007	0.017***	0.006*	-0.012***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Buyers' and suppliers' wages	0.023***	0.021***	0.026***	0.007**		0.010***
	(0.002)	(0.003)	(0.004)	(0.003)		(0.003)
Suppliers' wages					0.013***	
					(0.002)	
Buyers' wages					0.019***	
					(0.003)	
Sample	All	All	> B&S	≤ B&S	All	All
Controls	No	Yes	Yes	Yes	Yes	Yes
Destination firm × year FEs	No	No	No	No	No	Yes
Observations	76,008	72,527	33,966	37,494	63,869	38,873
R^2	0.263	0.313	0.344	0.273	0.311	0.725

Notes: The table reports estimates of learning spillovers from cowokers and from buyers and suppliers. The sample consists of workers that experience an EUE transition between year t and year $t+2$, employed at firms with less than 100 employees in year t. The dependent variable is workers' wages in year $t+2$, while the independent variables are at time t. Controls include worker characteristics (gender and age), firm-level variables (log sales, log employment, labor productivity, share of VAT sales, and log number of suppliers), the average of firm-level variables among buyers and suppliers, and industry-municipality-year fixed effects. Standard errors are clustered at the firm level. Columns (3) uses a subsample of individuals whose wage is higher than the average wage of their buyers and suppliers, and column (4) uses a subsample of individuals whose wage is lower or equal than the average wage of their buyers and suppliers. ***, **,* denote statistical significance at 1, 5, and 10% levels.

from buyers and suppliers. Specifically, individuals earn higher wages if they previously worked at firms whose buyers and suppliers paid higher wages.[11] After standardizing the independent variables, we find that the magnitudes of spillovers from coworkers and from buyers and suppliers are comparable.[12]

Starting in Column (2), we incorporate controls for worker and firm characteristics, as well as industry-municipality-year fixed effects. Our core finding remains robust: workers earn higher wages if, prior to an unemployment spell, their previous employers' buyers and suppliers paid higher wages, pointing to learning spillovers along the supply chain. We also continue to find evidence of learning from coworkers; however, the inclusion of controls reduces the magnitude of the coworker wage coefficient by more than half. This suggests that spillovers from buyers and suppliers may be less affected by confounding factors than those from coworkers. After standardizing the key independent variables, we find that learning spillovers from the supply chain are quantitatively stronger than those from within the firm. Specifically, a one standard deviation increase in the wages of buyers and suppliers is associated with a future wage increase for workers that is approximately twice as large as the effect of a one standard deviation increase in coworker wages.

Herkenhoff et al. (2024) and Jarosch, Oberfield and Rossi-Hansberg (2021) find that workers with relatively lower wages are the ones that benefit the most from learning from coworkers. We test this hypothesis in our setting, extending it to learning from buyers and suppliers. In Columns (3) and (4), we split the sample according to whether the wage of the worker in year t is above or below the average wages of its employer's buyers and suppliers, respectively. We find that the coefficient on coworkers' wages is positive and significant only for lower wage workers. In contrast, learning from buyers and suppliers is a significant source of spillovers primarily for high-wage workers, even though the coefficient remains positive and significant also for lower wage ones. For the latter, however, learning spillovers from buyers and suppliers are less important than spillovers from coworkers. A possible explanation for these findings is that the average wages of buyers and suppliers is much higher than workers' own wages, as documented in Section 3; hence, some workers may simply be too far away in the "knowledge space" to learn from workers at buyers and suppliers. This latter result is also consistent with Cardoza et al. (2024), who show that supply chain human capital specificity is more important for

[11] As shown in Table B.1, these results are robust to using the average of the top three buyers and suppliers, rather than the average across all.

[12] We estimate a smaller coefficient on own wages than Herkenhoff et al. (2024) (0.374 vs. 0.513—0.773), likely due to greater measurement error in the Dominican Republic data and our restriction to workers unemployed for a full year rather than a quarter. The coefficient on coworker wages is also smaller.

high-wage workers.

In Column (5), we investigate whether learning spillovers along the supply chain differ depending on direction—specifically, whether they are stronger downstream (from buyers) or upstream (from suppliers). The results suggest that knowledge diffusion occurs in both directions, but is more pronounced when spillovers originate from buyers.

Finally, Column (6) introduces destination employer-year fixed effects, allowing us to effectively compare workers hired by the same firm.[13] These results underscore a key distinction between learning from coworkers and learning from buyers and suppliers. Learning from coworkers appears to influence wages primarily through access to higher-paying employers. In contrast, learning from buyers and suppliers generates a wage premium even after conditioning on the hiring employer.

Heterogeneity We now turn to examine a few dimensions along which learning spillovers could be heterogeneous. First, employees with a higher level of education might be better equipped to take advantage of the learning occurring through their relationships with buyers and suppliers (as well as with their coworkers) compared to employees with lower levels of education. To test this hypothesis, we estimate

$$w_{i,t+2} = \alpha + \rho w_{i,t} + \phi_1 w^*_{f(i),t} + \phi_2 w^{B\&S}_{f(i),t} + Z_{i,t} \times \left(\overline{\rho} w_{i,t} + \overline{\phi_1} w^*_{f(i),t} + \overline{\phi_2} w^{B\&S}_{f(i),t} \right) + \Phi X_{i,f(i),t} + \epsilon_{i,t}, \quad (2)$$

where $Z_{i,t}$ is a dummy for whether worker i attained tertiary education prior to year t. Hence, coefficients $\overline{\phi_1}$ and $\overline{\phi_2}$ capture differential learning spillovers for workers with tertiary education from coworkers and from buyers and suppliers, respectively. The results in Table B.2 indicate that spillovers from buyers and suppliers are at least twice as large for workers with tertiary education. When we condition on workers being hired by the same firm (by including destination firm-year fixed effects), however, we do not find statistically significant differential effects for workers with tertiary education, likely because of sorting of highly educated workers into the same firms. Interestingly, we do not find any evidence of differential effects of learning from coworkers for workers with tertiary education.

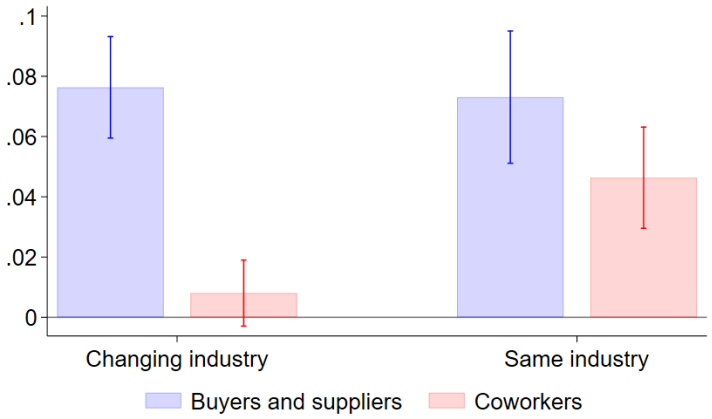
We also examine whether our results are heterogeneous depending on whether workers remain in the same industry after the EUE transition. One may argue that learning spillovers from buyers and suppliers are industry-specific, and therefore yield a return only if the worker continues to be employed in the same industry in which human capital was accumulated. We explore this by estimating a specification analogous to Equation 2,

[13] Previous literature emphasizes the increasing importance of employers in determining workers' wages (Card, Heining and Kline, 2013; Song et al., 2019).

replacing $Z_{i,t}$ with a dummy for whether the industry before and after the unemployment spell is the same. Figure 4 shows that knowledge spillovers from buyers and suppliers are robust to industry switching: workers benefit from these external connections regardless of whether they remain in the same industry after an unemployment spell. In contrast, coworker spillovers are only present when workers move within the same industry, suggesting that peer learning is more dependent on shared industry-specific knowledge. This distinction underscores the broader applicability of external network learning.

Figure 4: Learning spillovers and industry switching

(Percent)



Notes: The figure shows learning spillovers from cowokers and from buyers and suppliers, conditioning on whether workers switch industry or remain within the same industry after the EUE transition. The sample consists of workers that experience an EUE transition between year t and year $t+2$, employed at firms with less than 100 employees in year t. The dependent variable is workers' wages in year $t+2$, while the independent variables are at time t. Controls include worker characteristics (gender and age), firm-level variables (log sales, log employment, labor productivity, share of VAT sales, and log number of suppliers), the average of firm-level variables among buyers and suppliers, and industry-municipality-year fixed effects. The bars denote the point estimates and the whiskers denote the 90% confidence intervals, obtained from standard errors clustered at the firm level.

Robustness Our findings hold across a range of robustness checks. The results remain stable when we vary the method of aggregating wages across buyers and suppliers, alter the set of buyers and suppliers considered (e.g., the top 10 or those accounting for a large share of sales and purchases), or residualize wages of employees at buyers and suppliers with respect to firm characteristics. Measuring workers' human capital using worker fixed effects from a standard AKM decomposition (Cornelissen, Dustmann and Schönberg, 2017) yields similar conclusions, although the magnitudes of spillovers from coworkers and from buyers and suppliers become more comparable.[14] The results are

[14]The use of AKM worker fixed effects also allows us to confirm that the results are robust to controlling nonparametrically for all firm-specific factors.

also robust to evaluating spillovers over a longer horizon ($t+4$ or $t+6$ instead of $t+2$), excluding workers who move along the supply chain—ensuring that our findings are not driven by the wage premium documented for such moves in Cardoza et al. (2024)—and including in the sample firms with more than 100 employees. Table B.3 reports the results of these robustness tests.

A potential concern is that unobserved occupational differences—rather than learning—may drive the estimated spillovers, given the strong correlation between occupation and wages. Because occupation is not directly observed, we proxy for it using detailed information on workers' tertiary education, interacting degree major with industry fixed effects. This approach captures systematic differences in task content and skill requirements across fields of study and sectors, while allowing for flexible occupation–industry sorting. For workers born after 1985 who do not appear in the tertiary education records, we assume no tertiary attainment and group them accordingly. The estimates reported in **??** remain stable with the inclusion of these controls, suggesting that our results are unlikely to be driven by occupational composition or measurement error in occupational assignment. Excluding workers without tertiary education weakens the estimates, which is expected given the resulting loss of sample size and variation rather than a change in the underlying relationship.

4.2 Learning spillovers in the short- and long run

We now turn to the empirical approach of Jarosch, Oberfield and Rossi-Hansberg (2021), which is based on a model of competitive labor market. In this case, the sample is broadened to all workers (instead of focusing on those experiencing an EUE transition) and the specification aims to estimate the elasticity of workers' wages to coworkers' wages (which include all coworkers rather than only stable ones) both in the short- and long-term.

We adapt the authors' specification to estimate the magnitude of spillovers along the supply chain as follows

$$w_{i,t+h} = \alpha^h + \rho^h w_{i,t} + \phi_1^h \overline{w}_{-i,f(i),t} + \phi_2^h w_{f(i),t}^{B\&S} + \Phi^h X_{i,f(i),t} + u_{i,t}^h, \tag{3}$$

where $w_{i,t+h}$ is the wage of worker i in year $t+h$, with $h = 1,\ldots,10$; $\overline{w}_{-i,f(i),t}$ denotes the average wages of all coworkers; $w_{f(i),t}^{B\&S}$ is the average wages of employees of buyers and suppliers of worker i's firm $f(i)$; and $X_{i,f(i),t}$ is a set of controls including gender, year, age, and tenure fixed effects.[15] As in the previous exercise, the sample consists of workers

[15] We define coworkers as workers at the same firm in year t, because we do not have establishment-level information. We thus drop from the sample workers at employers with more than 100 employees

employed at firms with less than 100 employees in year t.

Table 2 presents the estimation results. As in Jarosch, Oberfield and Rossi-Hansberg (2021), workers with higher paid coworkers experience stronger wage growth over the following decade. The coefficient on coworkers' wages nearly doubles over the first three years and then stabilizes thereafter. This is consistent with wages slowly adapting to human capital accumulation through merit compensation and/or worker mobility across firms. Turning to our variable of interest, we find evidence of learning spillovers from buyers and suppliers. Specifically, we observe a similar but slightly slower dynamic pattern: the coefficient increases over the first four years before stabilizing.[16] This delayed response is consistent with learning from contacts external to the firm, which likely occurs less frequently and therefore requires sustained exposure to fully materialize, in contrast to more immediate peer learning within the firm. Importantly, the stabilization of coefficients at longer horizons suggests that the estimated effects reflect persistent gains in human capital rather than transitory wage shocks.

Robustness The results are robust to a wide battery of tests. Learning spillovers from buyers and suppliers are broadly consistent if we focus on the top three buyers and suppliers only (Table B.7) or use AKM worker fixed effects to measure human capital (Table B.8). Examining separately learning spillovers from buyers and learning spillovers from suppliers indicates that these have similar magnitudes (Table B.9). Moreover, we do not find major asymmetries between spillovers to low- or high-wage workers (Table B.10).

We also estimate Equation 3 augmented with degree-major-industry fixed effects to proxy for workers' occupation. An advantage of using this specification is that it can be estimated on a considerably larger sample of workers with tertiary education compared to the sample restricted to workers going through EUE transitions. Table B.11 reports the results for the sample including all employees as well as the subsample of workers with tertiary education, controlling for degree-major-industry fixed effects. The results are remarkably robust.

as these firms are most likely to be multi-establishment firms. We are also unable to control for workers' occupations.

[16] The magnitude of the coefficients on wages of buyers and suppliers is substantially smaller than that on workers' own wages. However, when we add a rich set of firm controls at the employer- and buyer and supplier-level as described in Subsection 4.1, the coefficients on buyers' and suppliers' wages are larger than the ones on workers' own wages (Table B.5). This larger magnitude disappears if we standardize the regressors to take into account differences in dispersion (Table B.6).

Table 2: Regressions *à la* Jarosch, Oberfield and Rossi-Hansberg (2021)

	$h=1$ (1)	$h=2$ (2)	$h=3$ (3)	$h=4$ (4)	$h=5$ (5)
Own wages	0.904***	0.845***	0.809***	0.790***	0.773***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Coworkers' wages	0.040***	0.056***	0.063***	0.060***	0.061***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Buyers' and suppliers' wages	0.022***	0.038***	0.046***	0.051***	0.054***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)
Observations	3,636,837	2,860,575	2,306,188	1,847,631	1,453,246
R^2	0.846	0.742	0.670	0.619	0.573

	$h=6$ (6)	$h=7$ (7)	$h=8$ (8)	$h=9$ (9)	$h=10$ (10)
Own wages	0.756***	0.740***	0.727***	0.712***	0.700***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Coworkers' wages	0.062***	0.062***	0.069***	0.069***	0.069***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Buyers' and suppliers' wages	0.055***	0.056***	0.054***	0.056***	0.052***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.009)
Observations	1,114,896	822,704	570,805	355,637	166,133
R^2	0.535	0.503	0.475	0.446	0.422

Notes: The table reports estimates of learning spillovers from cowokers and from buyers and suppliers. The sample consists of workers employed at firms with less than 100 employees in year t. The dependent variable is workers' wages in year $t+h$, while the independent variables are at time t. All regressions control for gender, age, tenure, and year fixed effects. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

4.3 Movers around mass layoffs and high-wage connections

To further investigate how high-wage buyers and suppliers influence workers' future earnings, we conduct an event study focusing on "displaced workers"—individuals who lose their jobs due to mass layoffs.[17] This approach allows us to examine wage dynamics following a shock that is plausibly exogenous to individual workers' human capital and performance, in the spirit of Jacobson, LaLonde and Sullivan (1993).

Following recent literature (Bertheau et al., 2023; Acabbi, Alati and Mazzone, 2024), we define displaced workers as individuals who (i) are at most 50 years old, (ii) have been employed by the same firm for at least three consecutive years, (iii) leave that firm during a mass layoff, and (iv) do not return to the same firm for at least three years. We then estimate the following local projections (Dube et al., 2025)

$$w_{i,t+h} = \rho^h w_{i,t} + \phi_1^h w_{-i,f(i),t} + \phi_2^h w_{f(i),t}^{B\&S} + \Phi^h X_{i,f(i),t} + u_{i,t}^h, \tag{4}$$

where $w_{i,t+h}$ is the log wage of worker i displaced in year t; $w_{i,t}$ is the wage at the firm from which the worker is displaced; $w_{-i,f(i),t}$ and $w_{f(i),t}^{B\&S}$ denote the average wages of stable coworkers and the average wages of buyers and suppliers at worker i's pre-displacement firm $f(i)$, respectively; and $X_{i,f(i),t}$ is a set of controls including firm-level variables and the average of these firm-level variables among buyers and suppliers as described in Subsection 4.1, along with industry, municipality, and year fixed effects.

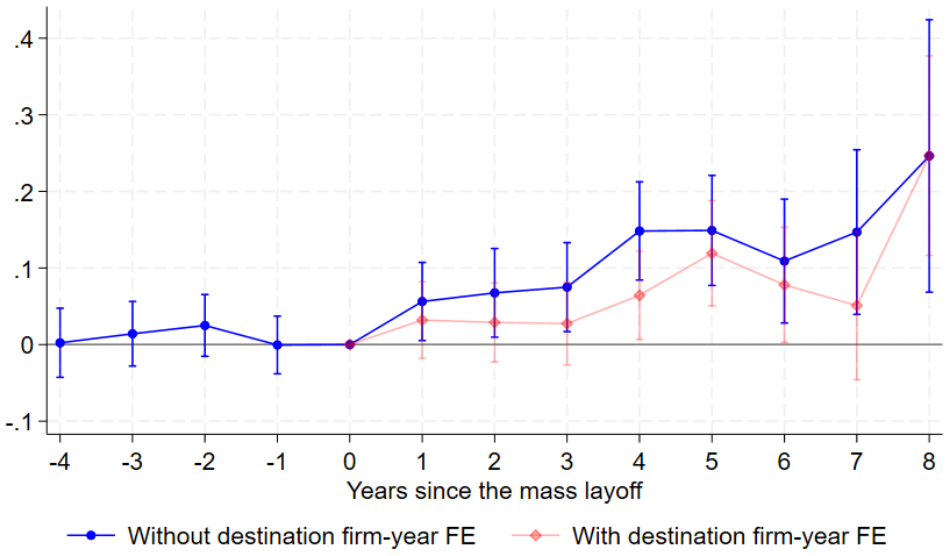
Figure 5 plots the estimated coefficients ϕ_2^h for $h = -4, \ldots, 8$. We find that workers displaced from firms with higher-wage buyers and suppliers tend to earn higher wages after displacement, even after controlling for pre-displacement wages. Crucially, these workers do not exhibit different wage trajectories prior to displacement, suggesting that they are not positively selected on unobservables. The wage premium increases gradually over time, consistent with human capital acquired prior to displacement being progressively reflected in wages as workers reenter employment and renegotiate compensation. This dynamic pattern closely mirrors the gradual adjustment documented in the previous section using the competitive labor market framework of Jarosch (2021), reinforcing the interpretation that learning spillovers—rather than transitory wage effects—drive the results. This pattern persists—albeit to a lesser extent—when we include destination firm-year fixed effects. That is, displaced workers earn higher wages even when comparing individuals hired by the same firm.[18] These findings further reinforce the evidence that

[17] A mass layoff is defined as a year in which a firm with a minimum of 50 employees reduces its employment by at least 30%.

[18] Table B.13 reports the results of the estimations. Pre-displacement trends cannot be estimated when destination firm-by-year fixed effects are included, as these absorb variation in buyers' and suppliers' wages

workers learn from employees at buyers and suppliers.

Figure 5: Displaced workers' wages and pre-displacement suppliers and buyers' wages
(Percent)



Notes: The figure shows the relationship between buyers' and suppliers' wages and displaced workers' wages around mass layoffs. All regressions control for firm-level variables (log sales, log employment, labor productivity, share of VAT sales, and log number of suppliers), the average of firm-level variables among buyers and suppliers, and industry, municipality, and year fixed effects. The dots denote the point estimates and the whiskers denote the 90% confidence intervals, obtained from standard errors clustered at the firm level.

We also explore learning spillovers for workers whose employers establish new trading relationships with firms that pay relatively high wages. The hypothesis is that workers learn from the employees of the new high-wage buyer or supplier and, as a result, the associated accumulation of human capital is reflected in their wages when they move on to a new employer and renegotiate their compensation. Hence, for this exercise we focus on a subset of movers who remain at the origin firm for at least two years before the move and do not return to the origin firm until the end of the sample period.

We identify new supply-chain relationships with firms that pay substantially higher wages than a given firm's existing buyers or suppliers, and that are economically meaningful in terms of trade value. Specifically, we define a high-wage connection as the first instance in which a firm: (i) acquires a new buyer or supplier that belongs to the top decile of the average log-wage distribution across all firms; (ii) this new partner ranks among the firm's top five suppliers (buyers) in terms of purchases (sales); and (iii) the firm's highest-wage buyer or supplier in the previous two years was at most in the sev-

prior to displacement.

enth decile of the average log-wage distribution across all firms. Applying these criteria, we identify 1,160 high-wage connections among more than 90,000 firms in the sample.

We then test whether workers who move after their employer establishes a high-wage connection experience larger wage gains than workers moving before such an event using the following specification

$$w_{i,t+h} = \delta^h_{t+h,f(i,t+h)} + \rho^h w_{i,t} + \gamma^h M_{i,t} \times PostHW_{i,t} + \beta^h M_{i,t} \times PreHW_{i,t} + \Phi^h X_{i,f(i,t),t} + u^h_{i,t}, \quad (5)$$

where $M_{i,t}$ is an indicator variable indicating whether worker i changes employer in year $t+1$; $PostHW_{i,t}$ and $PreHW_{i,t}$ are dummy variables for whether worker i changes employer after or before the employer establishes a high-wage connection; and $\delta^h_{t+h,f(i,t+h)}$ is a destination firm-year fixed effect to capture all shocks affecting i's destination firm. The set of controls includes age, gender, tenure, industry, municipality, and the mover indicator. The parameters β^h and γ^h describe the evolution of movers' wages for workers moving before or after an high-wage connection event, respectively, relative to other workers employed by the same firm. The control group consists of all workers who remain with the same employer in years t and $t+1$ (i.e., $PreHW_{i,t} = PostHW_{i,t} = 0$).

Figure 6 shows that workers moving after their employers establish a high-wage connection earn significantly more than other employees of the same firm who do not move, up to 9% more after five years. Reassuringly, their wages do not show differential pre-move trends prior to the high-wage connection. Conversely, the wages of workers moving to a new employer before a high-wage connection are statistically the same as the wages of workers that remain at the same employer.[19] These results show that high-wage connections lead to significant knowledge spillovers that are fully reflected in wages when workers find new employers, corroborating the idea that workers learn along the supply chain.[20]

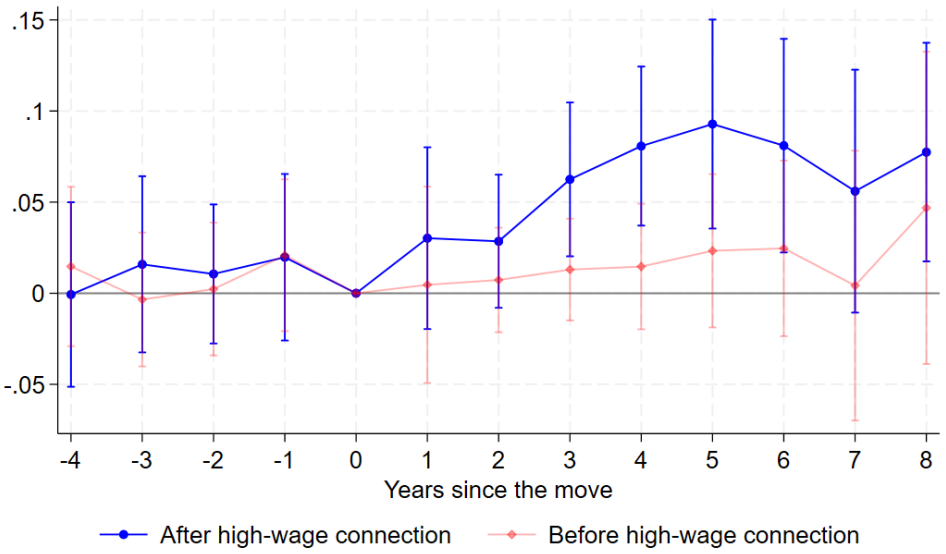
4.4 Sorting, reflection, and correlated shocks

What other factors besides learning spillovers could be captured by the elasticity of future wages to current buyers' and suppliers' wages? The literature has emphasized different identification challenges, including sorting, the reflection problem, and correlated shocks. In this section, we discuss the evidence suggesting that in our setting these issues appear to be negligible.

[19] A Wald test rejects the null hypothesis that $\gamma^h = \beta^h$ at the 5% confidence level for $3 \leq h \leq 5$.

[20] Table B.14 reports the results of the estimations. These findings are robust to focusing on the top ten—rather than five—buyers or suppliers. Estimates, however, become noisy when focusing on the top three buyers or suppliers or when excluding the control group of stayers.

Figure 6: Wages of workers moving before and after a high-wage connection
(Relative wages of movers)



Notes: The figure shows wage dynamics for workers who change employer before and after their origin employer establishes a high-wage connection. A high-wage connection is defined as the first occurrence in which the origin firm trades with a firm in the top decile of the average log wage distribution across all firms, the new buyer or supplier is among the top five buyers or suppliers in terms of sales, and the highest wage connection in the previous two years was at most in the seventh decile of the average log wage distribution. The treatment groups consist of workers who remained at the origin firm at least two years and do not return to the origin firm for at least two years, the control group consists of all workers who remain with the same employer in years t and $t+1$. All regressions control for worker-level variables (age, gender, tenure) and industry, municipality, and firm-year fixed effects. The dots denote the point estimates and the whiskers denote the 90% confidence intervals, obtained from standard errors clustered at the firm level.

We start with sorting. Workers with higher-wage coworkers may experience faster wage growth not because of peer-effects, but because they were more capable to begin with—for example, due to greater learning potential—which led them to be hired by higher-paying firms. Quantitative models studying learning from coworkers explicitly account for this type of sorting, and often discipline the model by estimating the extent of assortative matching. This concern is less pronounced when analyzing learning along the supply chain, given the weaker assortative matching of firms based on the wage margin. However, it may still be present.[21]

[21] Previous literature proposes to estimate peer effects by exploiting exogenous shocks to non-overlapping peer groups (De Giorgi, Pellizzari and Redaelli, 2010; De Giorgi, Frederiksen and Pistaferri, 2020). In our setting, this would imply using a shifter of human capital for firms that are buyers and/or suppliers of the buyers and/or suppliers of a worker's firm, and that do not directly trade with the employer. We do not follow this strategy because firm-level shocks travel along the supply chain, thereby affecting a firms' suppliers of their suppliers or firms' buyers of their buyers (Dhyne et al., 2021; Demir et al., 2024*b*).

We run a battery of tests to examine how sorting may be affecting the results presented so far. We start with the results using the specification of Herkenhoff et al. (2024). Following their approach, we estimate the degree of sorting by examining the extent to which workers who have higher wages join firms with higher paid coworkers and/or higher paid buyers and suppliers as follows

$$w^*_{d(i),t+2} = \alpha + \upsilon_1 w_{i,t} + \upsilon_2 w^*_{f(t),t} + \upsilon_3 w^{B\&S}_{f(i),t} + \Upsilon X_{i,f(i),t} + \epsilon_{i,t}, \tag{6}$$

where $w^*_{d(i),t+2}$ is the average log wage of stable coworkers of worker i in the destination firm $d(i)$ in year $t+2$. Note that we also include the wages of buyers and suppliers in year t as an additional regressor. In this setting, υ_1 measures the strength of sorting on observables. Then, to measure the extent of sorting towards firms with higher-wage buyers and suppliers, we replace the dependent variable in Equation 6 with the average wage of stable buyers and suppliers of the destination firm, $w^{B\&S}_{d(i),t+2}$.

Table 3: Sorting of high-wage workers

	Coworkers' X at $t+2$				Buyers' and suppliers' X at $t+2$			
	X =Wages		X =AKM workers' FE		X =Wages		X =AKM workers' FE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Own wages	0.152***	0.144***	0.143***	0.134***	0.010***	-0.004	0.016***	0.007***
	(0.006)	0.006)	(0.005)	(0.005)	(0.003)	(0.003)	(0.002)	(0.002)
Coworkers' X	0.082***	0.076***	0.057***	0.053***	0.017***	0.003	0.011***	0.004
	(0.006)	(0.006)	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
B&S' X	0.062***	0.035***	0.060***	0.040***	0.077***	0.065***	0.079***	0.067***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.006)	(0.006)	(0.006)	(0.006)
B&S' X at t+2		0.355***		0.292***				
		(0.008)		(0.010)				
Coworkers' X at t+2						0.121***		0.094***
						(0.003)		(0.003)
Observations	55,957	54,442	62,318	54,442	62,318	54,442	56,274	43,423
R^2	0.227	0.262	0.300	0.337	0.300	0.337	0.121	0.150

Notes: The table reports estimates of learning spillovers from cowokers and from buyers and suppliers. The sample consists of workers that experience an EUE transition between year t and year $t+2$, employed at firms with less than 100 employees in year t. The dependent variable, which is always taken in year $t+2$, is coworkers' wages in columns (1) and (2), coworkers' fixed effects from an AKM decomposition in columns (3) and (4), buyers' and suppliers' wages in columns (5) and (6), and workers' fixed effects from an AKM decomposition for employees at buyers' and suppliers in columns (7) and (8); the independent variables are at time t, unless otherwise indicated. All regressions include controls for worker characteristics (gender and age), firm-level variables (log sales, log employment, labor productivity, share of VAT sales, and log number of suppliers), the average of firm-level variables among buyers and suppliers, and industry-municipality-year fixed effects. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

Table 3 presents the results of the estimations, and its first row presents estimates of

Moreover, any shock that would lead a firm to hire workers with higher human capital may also affect the firm in other ways.

the sorting coefficient υ_1. We detect a significant degree of sorting. As shown in Column (1) and Column (2), workers with higher wages move to other firms with higher paid coworkers after an EUE transition, with the degree of sorting being barely impacted by the inclusion of the buyers and suppliers wages in $t+2$. Columns (5) shows that higher-wage workers also tend to go to firms that have higher-paying buyers and suppliers. However, once we condition on the wages of coworkers in year $t+2$ in column (6), we do not observe any sorting with respect to buyers' and suppliers' wages. Similar regressions using worker fixed effects from an AKM decomposition instead of wages to measure workers' human capital suggest that there is some degree of positive sorting between workers and buyers and suppliers, as shown in columns (7) and (8). However, the coefficient υ_1 in Column (4), which captures sorting with respect to coworkers' AKM fixed effects, is almost twenty times larger than the same coefficient in Column (8), which captures sorting with respect to buyers and suppliers' workers' AKM fixed effects. Thus, when we measure human capital with AKM fixed effects, sorting with respect to the buyers and suppliers' human capital is quantitatively negligible once own-firm human capital is taken into account.

Finally, in the event-study approach assessing learning spillovers from buyers and suppliers around mass layoffs, the presence of sorting can be detected by violations of parallel pre-trends. Our results in Figure 5 clearly point to the absence of differential pre-displacement trends, even though workers displaced from firms with high-wage buyers and suppliers have higher earnings post-displacement. Similarly, Figure 6 shows that the group of post-high wage connection movers has no differential pre-move wage dynamics relative to stayers and to pre-high wage connection movers, suggesting that these groups are comparable.

In sum, the evidence presented here consistently supports the notion that sorting does not represent a major source of concern to identify the effects of learning along the supply chain. In fact, the lack of sorting of workers with respect to buyers' and suppliers' wages is unsurprising. While workers may be able to collect information about the firm they are considering joining (for instance, by talking with other employees, visiting the job location, or interviewing with the managers), acquiring the same type of information about firms in the supply chain is likely to be more substantially more challenging.

We also consider two additional sources of bias prominently discussed in the peer-effect literature (Manski, 2000; De Giorgi, Pellizzari and Redaelli, 2010; De Giorgi, Frederiksen and Pistaferri, 2020), namely the reflection problem and correlated shocks. The reflection problem could bias our estimates if buyers' and suppliers' wages were higher because of the higher human capital of the worker (i.e., reverse causality). To mitigate

this concern, we re-estimate Equation 3 restricting the sample to workers who changed firm between year $t-1$ and year t and remain at the destination firm for at least three years. Since these workers joined their new employer in year t, they are unlikely to have had the chance to affect the wages of their coworkers or of the employees at the origin firm's buyers and suppliers. The results in Table B.12 confirm our baseline findings.

Correlated shocks are also unlikely to drive our results. If the estimated relationship reflected common firm-level or network-level shocks, the effect should be strongest contemporaneously and attenuate over time, and should largely disappear once workers leave the affected firm. In Subsection 4.1 and Subsection 4.3, we focus on workers who move to new employers, effectively breaking the link between firm-level shocks and workers' future wages. And in Subsection 4.2 and Subsection 4.3 we find that the impact of exposure to high-wage buyers and suppliers persists—and in fact grows—with the time horizon; this dynamic pattern is difficult to reconcile with transitory or correlated shocks, but is consistent with gradual human capital accumulation after workers change employers.

4.5 Evidence from product exports

We now depart from wages as a metric of human capital and instead rely on product-export data to identify knowledge diffusion. Building on the literature showing that worker mobility facilitates knowledge diffusion across firms (Stoyanov and Zubanov, 2012)—which is a key driver of economic growth (Perla, Tonetti and Waugh, 2021)—we examine whether firms are more likely to begin exporting a new product after hiring workers from firms that already export that specific product or from firms that supply those exporters.[22]

The underlying intuition is that hiring workers with product-specific human capital may enable firms to enter new product markets, for example by leveraging the workers' expertise directly or by recognizing new opportunities based on their knowledge. If this mechanism is at play, we should observe a correlation between the hiring of such workers and the firm's export activity in the same product. Moreover, if workers acquire knowledge through interactions with buyers and suppliers—as documented in other subsections of Section 4 using wage data—then hiring workers from the main suppliers of firms already exporting a product may also facilitate entry into that product's export market.

To test these hypotheses, we focus on firms that exported at least one product in any

[22] While this mechanism could be equally relevant for domestic sales, our analysis focuses on exports due to the lack of product-level data for domestic transactions.

year and estimate the following specification

$$NewE_{f,p,t+h} = \alpha^{h}_{c(p),f,t} + \lambda^{h}_{p,t} + \beta^{h} NewH_{p,f,t+h} + \gamma^{h} NewHS_{p,f,t+h} + \epsilon^{h}_{p,f,t}, \tag{7}$$

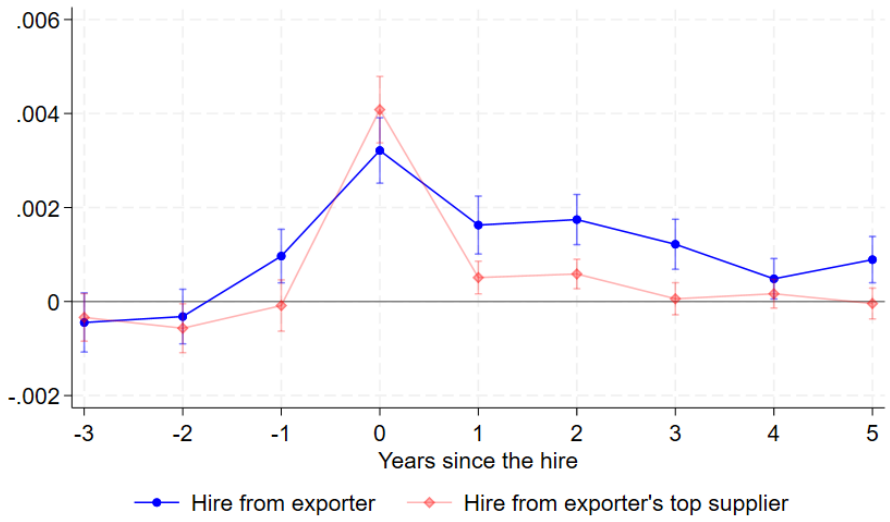
where $NewE_{f,p,t+h}$ is a binary indicator for whether firm f exported product p (defined at the HS 4-digit level) for the first time in year $t+h$, with $h = -3, \ldots, 5$; $NewH_{p,f,t+h}$ indicates whether firm f hired, for the first time in year $t+h$, a worker from a firm that was already exporting product p; similarly, $NewHS_{p,f,t+h}$ captures whether firm f hired a worker from a firm that was one of the top three suppliers of a firm exporting product p.[23] The specification includes firm-year-product class fixed effects ($\alpha^{h}_{c(p),f,t}$) and product-year fixed effects ($\lambda^{h}_{p,t}$), which control for firm-level and product-level shocks—such as productivity changes or demand fluctuations—that could simultaneously affect hiring and export decisions. The interaction of firm-year fixed effects with product class accounts for multi-product firms expanding specific segments of their business rather than targeting individual products. The coefficients of interest, β^{h} and γ^{h}, trace the probability of export entry before and after the hiring of workers from exporters or their suppliers. The regression sample includes only observations from 2016 onward, as we use data from 2012 to 2015 to identify whether firms had previously exported a given product or hired workers from relevant firms.[24]

Figure 7 shows that the probability of a firm starting to export a certain product (relative to other products in the same category) is 0.003 percentage points higher in the year it hires for the first time a worker from a firm that exports the same product.[25] Given that the mean of the dependent variable is approximately 0.3%, this represents a 10–15% increase relative to the baseline probability. The probability of starting to export the product remains 0.001 to 0.002 percentage points higher for up to five years. This pattern suggests that employees of exporting firms possess product-specific skills that are transferable to new employers when they change jobs, thereby facilitating the production and export of the product. Moreover, the probability of starting to export is also about 0.001 percentage points higher for other products, perhaps reflecting an increased firm demand for such skills after beginning to export a product.

The probability of starting to export a product is 0.004 percentage points higher in the year a firm hires for the first time a worker from a firm that is a top supplier to an exporter of that product. This elevated probability remains close to 0.001 percentage points higher for the two years following the hire, but is not significantly different be-

[23] Supplier firms are flagged only if they do not directly export product p themselves.
[24] Subsection B.4 report additional descriptive evidence.
[25] Appendix Table B.15 reports the results of the estimations.

Figure 7: Product exports and hiring from exporting firms or their suppliers (Percentage points)



Notes: The figure shows the relationship between the probability of exporting a product and hiring from an exporter of that product or one of its main suppliers. The sample consists of observations post-2016 to identify whether firms had previously exported a given product or hired workers from relevant firms. All regressions control for firm-year-product class fixed effects and product-year fixed effects. The dots denote the point estimates and the whiskers denote the 90% confidence intervals, obtained from standard errors clustered at the firm level.

fore the hire or beyond three years afterward. These findings suggest that workers at major suppliers of exporting firms carry valuable product-specific expertise, consistent with the idea that workers benefit from learning spillovers along the supply chain. The additional evidence in Subsection B.4 suggests that these effects are stronger for more complex products (Hausmann et al., 2014) and when the mover has been employed at the origin exporter (or supplier) firm for at least a couple of years prior to the move.

5 Allocation of talent along the supply chain

The evidence of learning spillovers from buyers and suppliers has implications for the allocation of talent along the supply chain. Specifically, they imply that placing high human capital workers at firms with a larger number of buyers and suppliers may favor economy-wide knowledge diffusion. This is because workers at more central firms in the production network can potentially "spill their human capital" to a broader set of workers, thereby amplifying the knowledge diffusion. On the other hand, spillovers may diminish as the number of recipients increases if knowledge is at least partially transmitted through direct interactions between workers. This is because the time and attention

that a worker can devote to each contact is limited. That is, as the number of buyers and suppliers grows, the intensity of each individual connection may weaken, potentially reducing the spillover effects.

To test this hypothesis, we restrict the sample to individuals that experience EUE transitions and examine whether the estimated spillovers along the supply chain decline as the number of connected firms increases. Importantly, the relevant network is not that of the worker's employer, but rather the network of the employer's buyers and suppliers—that is, the number of buyers of its suppliers and the number of suppliers of its buyers. These firms represent the actual source of the knowledge spillovers. Hence, for each worker's employer, we measure the size of its buyers' and suppliers' production networks by taking the weighted average of the log number of buyers' suppliers and of suppliers' buyers with weights equal to the purchases and sales. Then, we compute the average between the two. To estimate the spillover elasticity with respect to the size of buyers' and suppliers' network, we augment Equation 1 with this variable and its interaction with buyers' and suppliers' wages.

Table 4 presents the regression results for all buyers and suppliers or alternatively the top three buyers and suppliers, as well as using wages or the worker fixed effects from the AKM decomposition as measures of human capital. The coefficient on the interaction term of the measure of human capital with the network size is not statistically significant when we consider all buyers and suppliers, as shown in columns (1) and (2). It is also not statistically significant when we use wages and focus on the top three buyers and suppliers in columns (3). It is instead statistically different from zero when in column (4), suggesting that larger buyers and suppliers' networks are associated with weaker knowledge spillovers.[26] Even in this case, however, the magnitude of this effect in economic terms is economically small: a one standard deviation increase in the network size—which corresponds to an increase in the average log number of connected firms of 0.97, or 264%—is associated with a decline in the size of the learning spillovers by less than 15%. We conclude that the "per-capita" knowledge spillovers from high-skilled employees at buyers and suppliers may diminish when these workers are connected to more firms, however the magnitude of the diminishing returns is negligible.

These findings imply that human capital diffusion is stronger when high-human-capital workers are employed by firms with a larger number of buyers and suppliers—as documented in Section 3—as this increases the number of potential recipients of knowl-

[26]The network size variable is demeaned, so that the coefficient on the buyers' and suppliers' wages captures learning spillovers at the average level of network size. We do not report the coefficient on the size of the network as it is highly correlated with the controls, which already include the average log number of suppliers of the buyers and suppliers.

Table 4: Learning spillovers from buyers and suppliers and network size

	All buyers and suppliers		Top three buyers and suppliers	
	X = wages (1)	X =AKM fixed effects (2)	X = wages (3)	X=AKM fixed effects (4)
Own wages	0.373***	0.364***	0.373***	0.363***
	(0.007)	(0.007)	(0.007)	(0.007)
Coworkers' X	0.019***	0.128***	0.015***	0.124***
	(0.006)	(0.008)	(0.006)	(0.008)
Buyers' and suppliers' X	0.059***	0.092***	0.075***	0.127***
	(0.009)	(0.014)	(0.010)	(0.015)
Buyers' and suppliers' $X \times$ network size	-0.010	-0.003	-0.001	-0.018**
	(0.008)	(0.013)	(0.009)	(0.015)
SD of network size	0.74	0.74	0.65	0.97
SD/coefficient (percent)	-13	-2	-9	-14
Observations	72,488	72,506	72,527	72,532
R^2	0.313	0.317	0.313	0.318

Notes: The table reports estimates of learning spillovers from cowokers and from buyers and suppliers, conditioning on the size of the network. The sample consists of workers that experience an EUE transition between year t and year $t+2$, employed at firms with less than 100 employees in year t. The dependent variable is workers' wages in year $t+2$, while the independent variables are at time t. The network size is measured by the average log number of buyers' suppliers and suppliers' buyers. SD/coefficient refers to the ratio between the interaction coefficient multiplied by the standard deviation of the network size, over the coefficient of buyers' and suppliers' wages. Controls include worker characteristics (gender and age), firm-level variables (log sales, log employment, labor productivity, share of VAT sales, and log number of suppliers), the average of firm-level variables among buyers and suppliers, and industry-municipality-year fixed effects. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

edge spillovers. To quantify the contribution of this mechanism to wage growth, we perform a back-of-the-envelope calculation of the change in annual wage growth that would result from weaker spillovers–under a counterfactual scenario in which all firms had the same average log wage (and thus the same average worker human capital). The calculation is illustrated by the following

$$\Delta w = \frac{\phi_2}{\overline{Tenure}} \times (\overline{w}_{B\&S} - \overline{w}) = \frac{0.035}{3.59} \times (10.03 - 9.63) = 0.0039. \tag{8}$$

We start from the average real wage growth in our sample Δw (defined as the change in log wages minus the inflation rate), which is 3.6%. Then, to estimate the annual spillover effect, we use the coefficient ϕ_2 from the most saturated specification in Table 1, which is 0.035. We interpret this coefficient conservatively, assuming that wages reflect human capital only at the time of the EUE transition, hence all learning from buyers and suppliers is reflected in the post-transition wage. Given that the average job tenure $\overline{Tenure}$ in our sample is 3.59 years (measured in 2023 to minimize truncation bias), the annual spillover is calculated as 0.035/3.59. We then compute the counterfactual change in wage growth as the product of the annual spillover and the difference between the average log wage of buyers and suppliers and the overall average log wage in the sample. This yields an estimated reduction in annual wage growth of 0.39 percentage points, or approximately 11% of the observed real wage growth. In other words, if high-wage workers were not employed at highly connected firms, the average real wage growth would be 11% lower.

This calculation relies on simplifying assumptions and abstracts from general equilibrium effects, Jensen's inequality, and the "missing intercept problem" (Wolf, 2023). Nonetheless, it highlights the broader economic relevance of our findings for aggregate wage growth through enhanced knowledge diffusion along the supply chain.

6 A model of human capital accumulation in production networks

This section develops a model to formalize the mechanisms through which coworker and network spillovers shape human capital accumulation and wages. The model provides theoretical foundations for the empirical specifications by showing how the spillover parameters map to coefficients on coworker and network-partner wage proxies—in particular, the coefficient ϕ_2 in equation Equation 1, which captures learning spillovers from

buyers and suppliers for workers experiencing employment-unemployment-employment transitions.

Environment The economy operates in continuous time, $t \geq 0$, and is populated by a finite set of firms, indexed $i \in \Omega = \{1, \ldots, N\}$, and a unit mass of workers, indexed j. All agents are risk-neutral and discount future payoffs at a common rate $\rho > 0$.

Workers are characterized by their human capital level, $h \in \mathcal{H} = \{h_1, h_2, \ldots, h_H\}$, where $h_1 < h_2 < \cdots < h_H$. This discrete ladder structure follows the literature on human capital accumulation and job ladders (Pissarides, 2000; Postel-Vinay and Robin, 2002). Workers can move upward on this ladder through a stochastic Poisson process governed by endogenous learning spillovers experienced at their workplace. Workers at the top of the ladder (h_H) cannot upgrade further.

Firms are heterogeneous along several dimensions. Each firm i is characterized by its intrinsic productivity $A_i > 0$ and its position within the production network. The network is defined by buyer-supplier relationships: firm i maintains a set of suppliers $\mathcal{S}(i) \subseteq \Omega$ from whom it purchases intermediate inputs, and a set of buyers $\mathcal{B}(i) \subseteq \Omega$ to whom it sells its output. We denote by $\mathcal{P}(i) = \mathcal{S}(i) \cup \mathcal{B}(i)$ the set of firm i's trading partners. These network links influence both production possibilities and, crucially, exposure to learning spillovers.

The complete state of a firm is summarized by a vector $\boldsymbol{z}_i$, which encompasses its network connections $(\mathcal{S}(i), \mathcal{B}(i))$, its workforce composition $\boldsymbol{n}(i) = (n_1(i), \ldots, n_H(i))$ where $n_\ell(i)$ denotes the mass of workers with skill h_ℓ, and its productivity A_i. Total employment at firm i is $n(i) = \sum_{\ell=1}^{H} n_\ell(i)$.

Production technology Firm i produces a differentiated intermediate good $q(i)$ using a combination of labor $L(i)$ and intermediate inputs $X(i)$. The labor input is formed by aggregating workers of different skill types via a Constant Elasticity of Substitution (CES) function

$$L(i) = \left(\sum_{\ell=1}^{H} a_\ell \, n_\ell(i)^{\frac{\sigma_L - 1}{\sigma_L}} \right)^{\frac{\sigma_L}{\sigma_L - 1}}, \tag{9}$$

where $a_\ell > 0$ represents the productivity weight of type-ℓ workers, and $\sigma_L > 0$ is the elasticity of substitution between worker types. We assume that $a_{\ell+1} > a_\ell$ for all ℓ, so that higher-skilled workers are more productive.

Intermediate inputs sourced from supplier firms $\omega \in \mathcal{S}(i)$ are aggregated using an-

other CES function

$$X(i) = \left(\sum_{\omega \in \mathcal{S}(i)} b_{i\omega} \, x_{\omega i}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{10}$$

where $x_{\omega i}$ is the quantity of input purchased from supplier ω, $b_{i\omega} > 0$ is a relationship-specific weight capturing the importance of supplier ω to firm i, and $\sigma \geq 1$ is the elasticity of substitution across suppliers. Higher values of σ imply greater substitutability within the supply chain.

Final output at the firm level combines the labor and intermediate input aggregates via Cobb-Douglas technology

$$q(i) = A_i \, L(i)^{\alpha} \, X(i)^{1-\alpha}, \tag{11}$$

where $\alpha \in (0,1)$ is the labor share in production. Individual firm outputs are aggregated into a final consumption good Y using a CES function over all firms. Market clearing for each intermediate good requires that its production equals the sum of intermediate demand from downstream firms and final demand.

Learning and human capital accumulation Motivated by our empirical findings, we incorporate two distinct channels: learning from coworkers within the firm and learning from the workforce of network partners. The coworker channel builds on evidence that workers' productivity and wages respond to the composition of their peers (Mas and Moretti, 2009; Cornelissen, Dustmann and Schönberg, 2017; Herkenhoff et al., 2024; Nix, 2020). The network channel captures the novel source of knowledge diffusion documented in this paper—that workers learn from employees at their employer's buyers and suppliers.[27]

A worker at skill level h_ℓ employed by firm i upgrades to $h_{\ell+1}$ at a Poisson rate

$$\lambda_\ell(i) = \gamma_c \underbrace{\sum_{\ell'=1}^{H} \frac{n_{\ell'}(i)}{n(i)} \times \frac{h_{\ell'}}{h_\ell}}_{\equiv \mathrm{CSP}_\ell(i)} + \gamma_n \underbrace{|\mathcal{P}(i)|^{-\eta} \sum_{i' \in \mathcal{P}(i)} \sum_{\ell'=1}^{H} \frac{n_{\ell'}(i')}{n(i')} \times \frac{h_{\ell'}}{h_\ell}}_{\equiv \mathrm{NSP}_\ell(i)}, \tag{12}$$

where $\gamma_c, \gamma_n \geq 0$ are the parameters governing the intensity of coworker and network spillovers, respectively.

[27] This channel relates to findings on knowledge diffusion through supply chains (Bernard, Moxnes and Saito, 2019; Bernard et al., 2022) and the role of buyer-supplier relationships for firm performance and technology adoption (Javorcik, 2004; Alfaro-Ureña, Manelici and Vasquez, 2021).

The first term—the *Coworker Spillover Potential* (CSP)—captures within-firm learning. It is a weighted average of the skill ratios $h_{\ell'}/h_\ell$ across all coworkers, where the weights are employment shares. The ratio $h_{\ell'}/h_\ell$ implies that higher-skilled colleagues provide a stronger impetus for upgrading: a worker surrounded by peers at the same level ($h_{\ell'} = h_\ell$) experiences limited learning, while one surrounded by much higher-skilled colleagues learns more rapidly. This formulation captures mentoring relationships, knowledge transfer through observation and collaboration, and competitive pressures that motivate skill acquisition.

The second term—the *Network Spillover Potential* (NSP)—captures between-firm learning mediated by production linkages. It depends on the skill composition of the workforce at all of firm i's trading partners. The term $|\mathcal{P}(i)|^{-\eta}$ parameterizes how the network spillover scales with the number of trading partners. When $\eta = 0$, each additional partner provides an independent learning channel, so the network spillover is proportional to the total number of partners. When $\eta = 1$, the sum is normalized by the number of partners, so additional links dilute rather than augment spillovers. Intermediate values capture partial congestion: some information from each partner is redundant with what other partners provide. This channel reflects knowledge diffusion through supply-chain interactions: direct interaction with employees at buyers and suppliers, or indirect learning by observing more efficient work practices, working with higher quality inputs, or following better instruction manuals and reports. [28]

When $\gamma_n = 0$, the model reduces to a standard on-the-job learning framework with only internal spillovers, as in Herkenhoff et al. (2024). When $\eta = 1$, the network term reduces to the mean skill ratio across partners, and additional connections do not increase the total learning rate. The general case $\gamma_c, \gamma_n > 0$ with $\eta \in (0, 1)$ nests both channels and allows us to assess their relative importance as well as the returns to network size.

Search and matching The labor market features search frictions, following the Diamond-Mortensen-Pissarides framework (Pissarides, 2000). We extend this canonical structure to accommodate heterogeneous workers and firms, building on Postel-Vinay and Robin (2002) and Cahuc, Postel-Vinay and Robin (2006).

The market is segmented by skill type. For each skill level h_ℓ, let N_ℓ denote the measure of unemployed job seekers and V_ℓ denote aggregate vacancies posted by all firms. A constant-returns-to-scale matching function $m(N_\ell, V_\ell)$ determines the aggregate flow of new matches. We assume that m is increasing, concave, and satisfies $m(0, V) = m(N, 0) = 0$.

[28] The $|\mathcal{P}|^{-\eta}$ term arises from a contact technology governing the rate of learning encounters with partner employees. We provide a microfoundation in Appendix E.

We further define labor market tightness as $\theta_\ell \equiv V_\ell / N_\ell$. The vacancy-filling rate—the Poisson rate at which a firm's type-ℓ vacancy is filled—is $q_\ell(\theta_\ell) \equiv m(N_\ell, V_\ell)/V_\ell = m(1/\theta_\ell, 1)$, which is decreasing in θ_ℓ. The job-finding rate—the Poisson rate at which a type-ℓ unemployed worker finds a job—is $p_\ell(\theta_\ell) \equiv \theta_\ell\, q_\ell(\theta_\ell) = m(1, \theta_\ell)$, which is increasing in θ_ℓ.

Firms choose how many vacancies $v_\ell(i)$ to post for each skill type. Vacancy posting is costly, with total cost

$$C(i) = \sum_{\ell=1}^{H} c\left(\frac{v_\ell(i)}{n_\ell(i)}\right) n_\ell(i), \tag{13}$$

where $c(\cdot)$ is strictly increasing and strictly convex, satisfying $c(0) = 0$, $c'(0) = 0$, and $\lim_{x\to\infty} c'(x) = \infty$. The specification of costs as a function of the vacancy-to-employment ratio $v_\ell(i)/n_\ell(i)$ captures congestion in recruitment.

Employment relationships dissolve exogenously at a skill-specific separation rate $s_\ell > 0$. The stock of workers of skill ℓ at firm i evolves according to the flow equation

$$\dot{n}_\ell(i) = \underbrace{q_\ell(\theta_\ell)\, v_\ell(i)}_{\text{Hiring inflow}} + \underbrace{\lambda_{\ell-1}(i)\, n_{\ell-1}(i)}_{\text{Upgrading from } \ell-1} - \underbrace{\lambda_\ell(i)\, n_\ell(i)}_{\text{Upgrading to } \ell+1} - \underbrace{s_\ell\, n_\ell(i)}_{\text{Separations}}, \tag{14}$$

with the conventions $\lambda_0(i) \equiv 0$ (i.e., no upgrading into the lowest level from below) and $\lambda_H(i) \equiv 0$ (i.e., no upgrading out of the highest level). In steady state, $\dot{n}_\ell(i) = 0$ for all ℓ and i.

Value functions Let $J(\boldsymbol{z}_i)$ denote the joint present value of firm i and its workforce, where $\boldsymbol{z}_i$ summarizes the firm's state. This joint value represents the expected discounted sum of output minus vacancy costs, accounting for all future worker transitions. We define the *marginal joint value* of a type-ℓ worker as

$$\Psi_\ell(\boldsymbol{z}_i) \equiv J(\boldsymbol{z}_i + \boldsymbol{e}_\ell) - J(\boldsymbol{z}_i), \tag{15}$$

where $\boldsymbol{e}_\ell$ is the unit vector with a one in position ℓ and zeros elsewhere. This object captures the increment to joint surplus from adding one worker of skill ℓ to firm i's workforce.

The value function J satisfies the Hamilton-Jacobi-Bellman (HJB) equation

$$\rho J(\boldsymbol{z}_i) = \pi(\boldsymbol{z}_i) - C(i) + \sum_{\ell=1}^{H} q_\ell(\theta_\ell)\, v_\ell(i)\, \mathbb{E}\Big[\Psi_\ell(\boldsymbol{z}_i)\Big] + \sum_{\ell=2}^{H} \lambda_{\ell-1}(i)\, n_{\ell-1}(i)\Big[\Psi_\ell(\boldsymbol{z}_i) - \Psi_{\ell-1}(\boldsymbol{z}_i)\Big] + \Sigma_i - \sum_{\ell=1}^{H} s_\ell\, n_\ell(i)\, \Psi_\ell(\boldsymbol{z}_i), \tag{16}$$

where $\pi(\boldsymbol{z}_i)$ denotes flow profit (output minus intermediate input costs and wages) and the terms on the right-hand side have the following interpretation:

- $\pi(\boldsymbol{z}_i) - C(i)$: Net flow payoff from current production minus vacancy costs.
- $\sum_\ell q_\ell v_\ell \mathbb{E}[\Psi_\ell]$: Expected value from new hires, where each filled vacancy adds a worker worth Ψ_ℓ in expectation.
- $\sum_{\ell \geq 2} \lambda_{\ell-1} n_{\ell-1} [\Psi_\ell - \Psi_{\ell-1}]$: Capital gains from internal skill upgrading. When a worker transitions from $\ell - 1$ to ℓ, the firm experiences a value change of $\Psi_\ell - \Psi_{\ell-1}$.
- Σ_i: Network spillover value, capturing the benefits accruing to firm i from human capital accumulation occurring at its trading partners.
- $\sum_\ell s_\ell, n_\ell, \Psi_\ell$: Expected loss in joint value due to exogenous separations of workers of each skill type

The term Σ_i embodies the network externalities central to our analysis. Human capital upgrading at partner firms $i' \in \mathcal{P}(i)$ raises their average skill $\bar{h}_{i'}$, which in turn improves the NSP and hence the learning rates $\lambda_\ell(i)$ at firm i. Following the logic of input-output multipliers (Acemoglu et al., 2012), these effects propagate through the network. Let $\boldsymbol{G}$ be the $N \times N$ matrix where $G_{ii'}$ represents the direct influence of firm i''s human capital on firm i's value. The total spillover value can be expressed as $\Sigma_i = [(\boldsymbol{I} - \boldsymbol{G})^{-1}\mathcal{H}]_i$, where $\mathcal{H}$ is the vector of direct learning-induced value increments across firms.[29]

Bargaining protocol and wage determination Wages are determined through Nash bargaining over the joint surplus, following the canonical approach in search models (Pissarides, 2000). We extend the standard bilateral bargaining framework to incorporate the multi-worker, multi-skill structure of the model, drawing on Cahuc, Postel-Vinay and Robin (2006) and Postel-Vinay and Robin (2002).

Consider a type-ℓ worker. The relevant surplus to be divided is the marginal joint value $\Psi_\ell(\boldsymbol{z}_i)$—the increment to the firm-worker coalition's value from the match. Let

[29] The matrix G is the $N \times N$ network adjacency (or spillover influence) matrix, where $G_{ii'}$ represents the normalized strength of the network externality from firm i' to firm i (e.g., $G_{ii'} = 1/|\mathcal{P}(i)|$ if $i' \in \mathcal{P}(i)$ and zero otherwise). The vector $\mathcal{H}$ stacks the direct learning-induced value increments across firms, with the i-th element given by

$$\mathcal{H}_i = \sum_{\ell=2}^{H} \lambda_{\ell-1}(i)\, n_{\ell-1}(i) [\Psi_\ell(\boldsymbol{z}_i) - \Psi_{\ell-1}(\boldsymbol{z}_i)].$$

The term $[(\boldsymbol{I} - G)^{-1}\mathcal{H}]_i$ captures the geometric series $\mathcal{H} + G\mathcal{H} + G^2\mathcal{H} + \cdots$, representing direct, second-order, and all higher-order spillover benefits from learning events throughout the network.

$\beta \in (0,1)$ denote the worker's bargaining power. The wage is set to give the worker a fraction β of the surplus above their outside option.

For a worker hired from unemployment, the outside option is the value of unemployment U_ℓ. The Nash bargaining solution yields

$$w_\ell(\boldsymbol{z}_i, U) = (1-\beta)U_\ell + \beta\,\Psi_\ell(\boldsymbol{z}_i). \tag{17}$$

Hence, these workers receive their outside option plus a share β of the surplus $\Psi_\ell(\boldsymbol{z}_i) - U_\ell$. For job-to-job transitions, the structure follows Cahuc, Postel-Vinay and Robin (2006) and Postel-Vinay and Robin (2002). When a worker currently employed at firm i receives an offer from firm j, bargaining occurs with the current match value as the relevant outside option. If firm j offers a higher surplus, the worker moves and the new wage satisfies

$$w_\ell(\boldsymbol{z}_j, \boldsymbol{z}_i) = (1-\beta)\Psi_\ell(\boldsymbol{z}_i) + \beta\,\Psi_\ell(\boldsymbol{z}_j). \tag{18}$$

In this case, the worker captures a share β of the surplus gain from moving, $\Psi_\ell(\boldsymbol{z}_j) - \Psi_\ell(\boldsymbol{z}_i)$, on top of their value at the origin firm.

The value of unemployment U_ℓ is determined by the Bellman equation:

$$\rho\, U_\ell = b_\ell + p_\ell(\theta_\ell)\,\mathbb{E}_j\Big[\max\{W_\ell(\boldsymbol{z}_j, U) - U_\ell, 0\}\Big], \tag{19}$$

where b_ℓ is the flow value of unemployment (e.g., home production or unemployment benefits) and the expectation is over the distribution of firms posting type-ℓ vacancies. The unemployed worker receives flow payoff b_ℓ plus the expected capital gain from finding a job, where W is the expected value of finding a job.

Remark 1 (Wages and learning value). A key implication of the bargaining structure is that wages incorporate the option value of learning. The marginal joint value $\Psi_\ell(\boldsymbol{z}_i)$ includes not only the worker's current marginal product, but also the expected future value from potential skill upgrading. Firms with higher CSP or NSP—and hence higher learning rates—offer workers a more valuable learning growth option. Through bargaining, workers capture a share of this value, generating a wage premium for employment at high-spillover firms. This mechanism provides the theoretical foundation for our empirical identification strategy.

Optimal vacancy posting Firms choose vacancy postings to maximize the joint value.[30] The first-order condition for optimal $v_\ell(i)$ equates the marginal cost of posting a vacancy

[30] This is equivalent to assuming efficient bargaining.

to the expected marginal benefit

$$c'\left(\frac{v_\ell(i)}{n_\ell(i)}\right) = q_\ell(\theta_\ell)\,\mathbb{E}\Big[\Psi_\ell(\boldsymbol{z}_i)\Big]. \tag{20}$$

The left-hand side is the marginal cost of an additional vacancy. The right-hand side is the expected value of filling that vacancy: the probability q_ℓ of finding a worker times the expected surplus $\mathbb{E}[\Psi_\ell]$ from hiring. In equilibrium, firms expand hiring until these margins are equal.

This condition reveals how learning spillovers affect hiring decisions. Higher γ_c or γ_n increase learning rates λ_ℓ, which in turn increases Ψ_ℓ through the capital gains term in the HJB equation. Firms respond by posting more vacancies, generating the indirect hiring effect that reinforces the direct impact of faster learning on aggregate human capital.

Equilibrium definition A *stationary Markov equilibrium* consists of:

1. Value functions $J(\boldsymbol{z}_i)$ and marginal values $\Psi_\ell(\boldsymbol{z}_i)$ for all firms and skill types;
2. Policy functions: vacancy postings $v_\ell(i)$ and wages $w_\ell(\boldsymbol{z}_i, \cdot)$;
3. Workforce distributions $\boldsymbol{n}(i) = (n_1(i), \ldots, n_H(i))$ for all firms;
4. Market tightnesses θ_ℓ for all skill types;
5. Prices for intermediate goods and the final good;

such that:

(i) *Firm optimization*: Vacancy postings satisfy the first-order condition in Equation 20, taking market tightness as given.

(ii) *Wage determination*: Wages satisfy the Nash bargaining solutions of Equation 17 and Equation 18.

(iii) *Labor market clearing*: For each skill type ℓ, aggregate vacancies equal the sum of firm-level postings, $V_\ell = \sum_{i\in\Omega} v_\ell(i)$, and aggregate unemployment N_ℓ is consistent with steady-state flows.

(iv) *Product market clearing*: Supply equals demand for each intermediate good and the final good.

(v) *Stationarity*: The workforce distribution is stationary, $\dot{n}_\ell(i) = 0$ for all ℓ, i.

(vi) *Rational expectations*: Agents' expectations are consistent with the equilibrium stochastic process.

6.1 Learning spillovers and transmission in the network

We now present the main theoretical findings regarding the impact of learning spillovers and network structure. We derive three key propositions characterizing the system's response to these learning mechanisms: Proposition 1 and Proposition 2 analyze the determinants of aggregate human capital, focusing on spillover intensity and network connectivity, and Proposition 3 links these mechanisms to observable wages and outlines an empirical identification strategy.[31]

Our analysis rests on the economically intuitive premise that higher skills are more valuable. The following lemma confirms that this property holds within the model's equilibrium.

Assumption 1 (Monotonicity of primitives)**.**

(i) The labor aggregator weights satisfy $a_{\ell+1} > a_\ell$ for all $\ell < H$.

(ii) The human capital levels satisfy $h_1 < h_2 < \cdots < h_H$.

These assumptions ensure that higher skill is associated with higher marginal product and a greater scope for providing learning spillovers to others.

Lemma 1 (Monotonicity of worker value)**.** *Under Assumption 1, the marginal joint value is strictly increasing in skill*

$$\Psi_{\ell+1}(\boldsymbol{z}) > \Psi_\ell(\boldsymbol{z}) \quad \textit{for all } \ell < H \textit{ and all states } \boldsymbol{z}.$$

The lemma states that skill progression represents a capital gain: adding a higher-skilled worker to the firm generates more surplus. This property reflects not only the direct productivity advantage of higher-skilled workers but also their dynamic contribution to the learning environment. Higher-skilled workers raise the CSP for their coworkers, generating positive externalities within the firm. [32] This complementarity between individual and aggregate human capital echoes findings in Cornelissen, Dustmann and Schönberg (2017) and Herkenhoff et al. (2024) on the importance of peer quality for wage dynamics.

[31] The proofs for all results are provided in Appendix C.

[32] A countervailing force exists: from Equation 12, higher-skilled workers have lower own upgrade rates since h_ℓ appears in the denominator. This second-order effect is dominated by the first-order gains from higher marginal product and spillovers to coworkers.

6.1.1 Spillover intensity and aggregate human capital

We define *aggregate human capital* as the employment-weighted sum of skills in the economy

$$H_{\text{agg}} \equiv \sum_{i \in \Omega} \sum_{\ell=1}^{H} h_\ell \, n_\ell(i).$$

This object summarizes the economy's stock of productive knowledge. The first main result establishes how this stock responds to the intensity of learning spillovers.

Proposition 1 (Effect of spillover intensity)**.** *In a stable stationary equilibrium, an increase in either spillover parameter raises aggregate human capital*

$$\frac{dH_{agg}}{d\gamma_c} > 0 \quad \textit{and} \quad \frac{dH_{agg}}{d\gamma_n} > 0,$$

provided the respective spillover channel is active ($\gamma_c > 0$ or $\gamma_n > 0$).

Proposition 1 demonstrates that enhancing knowledge diffusion—whether through workers' peer effects or external network linkages—unambiguously raises the economy's aggregate skill base. This result holds robustly, even after accounting for general equilibrium adjustments in firm hiring behavior.

The mechanism operates through two reinforcing channels: the *direct* transition effect and the *indirect* hiring effect. Regarding the former channel, a higher spillover intensity raises learning rates $\lambda_\ell(i)$ for all workers at all firms. Incumbent workers upgrade their skills faster, mechanically increasing the stock of human capital. This channel is analogous to an increase in the efficiency of on-the-job training. As for the latter channel, faster learning raises the option value embedded in $\Psi_\ell(z_i)$: workers hired today will be more productive tomorrow. Firms respond by posting more vacancies (as implied by the FOC in Equation 20, which shows that higher Ψ_ℓ induces more hiring). The resulting expansion in employment further raises H_{agg}.

Proposition 1 provides theoretical grounding for empirical findings on the aggregate importance of peer effects. For example, Moretti (2004) documents large social returns to education operating through local human capital spillovers. Our model formalizes a related mechanism at the firm level: individual learning generates externalities that cumulate into substantial aggregate effects.

The preceding result establishes that strengthening spillover intensity raises aggregate human capital for all connected firms. A natural follow-up question is whether the structure of the production network itself matters for aggregate outcomes. We now show

that network participation is the relevant margin: disconnecting a firm from the supply chain reduces aggregate human capital, and the magnitude depends on the firm's employment share.

Proposition 2 (Network participation and aggregate human capital)**.** *In a stable stationary equilibrium with $\gamma_n > 0$, disconnecting firm i from the production network (setting $\mathcal{P}(i) = \emptyset$) strictly reduces aggregate human capital.*

This result clarifies the role of the production network for aggregate human capital. In our framework, each connected firm's learning rate depends on the average skill of its partners' workers, and hence disconnecting a firm eliminates this channel entirely for its workers, producing a first-order loss. The proposition also provides a theoretical foundation for the counterfactual experiments.

6.1.2 Wages and empirical identification

Consider a worker employed at origin firm i with initial skill h_ℓ. During employment, the worker's skill evolves stochastically, with upgrade rates depending on the spillover environment

$$\lambda_m(i) = \gamma_c \frac{\bar{h}(i)}{h_m} + \gamma_n \frac{\bar{h}^{net}(i)}{h_m}.$$

After separating and being hired by destination firm j, the worker's wage reflects accumulated human capital. The following proposition formalizes how the coefficient on network-partner wages relates to the structural parameter γ_n.

Proposition 3 (Network spillovers and destination wages)**.** *Under regularity conditions stated in Subsection D.1 of Appendix D, consider a worker with initial skill h_ℓ employed at origin firm i who separates, experiences unemployment, and is hired by destination firm j. Let $\tilde{w} \equiv \log w$ denote log wages and $\tilde{w}^{net}_{i,t}$ denote the average log wages at the network partners of the origin firm. Then:*

(i) ***Sign identification.*** *The expected log destination wage is increasing in network-partner wages at the origin firm if and only if $\gamma_n > 0$*

$$\frac{\partial \mathbb{E}[\tilde{w}_{i,t+2}]}{\partial \tilde{w}^{net}_{i,t}} > 0 \iff \gamma_n > 0.$$

(ii) ***Coefficient decomposition.*** *The reduced-form coefficient in the empirical specification*

$$\tilde{w}_{i,t+2} = \delta_{j,t+2} + \rho \tilde{w}_{i,t} + \phi\, \tilde{w}^{net}_{i,t} + X'_{i,t}\Phi + \epsilon_{i,t} \tag{21}$$

satisfies $\phi = \gamma_n \cdot \bar{\Lambda}$, where $\bar{\Lambda} > 0$ depends on the skill ladder structure, separation rate, and the equilibrium skill distribution.

(iii) ***Role of network connectivity.*** *The scaling factor $\bar{\Lambda}$ depends on equilibrium objects shaped by network connectivity, implying that economies with denser production networks may exhibit larger reduced-form coefficients even at identical γ_n.*

This proposition delivers a robust qualitative result: $\phi > 0$ implies $\gamma_n > 0$, establishing that workers accumulate human capital from network partners. The magnitude of ϕ reflects both the primitive spillover intensity γ_n and an economy-specific amplification factor $\bar{\Lambda}$ that captures how network structure translates spillovers into wage gains. Controlling for the worker's own wage $\tilde{w}_{i,t}$ absorbs initial skill and origin-firm wage premia, ensuring that ϕ captures variation in network-partner skill composition. Destination firm-year fixed effects $\delta_{j,t+2}$ absorb all destination-side heterogeneity, so identification comes from comparing workers hired by the same firm who came from origins with different network environments.

This identification strategy builds on two influential empirical frameworks. Herkenhoff et al. (2024) estimate peer effects using job-to-job movers by exploiting variation in coworker quality across employers. Jarosch, Oberfield and Rossi-Hansberg (2021) use within-firm variation in coworker composition over time. Our framework extends both approaches to network spillovers, providing theoretical justification for including network-partner wages alongside coworker wages in the regression specification. The decomposition $\phi = \gamma_n \bar{\Lambda}$ clarifies that the sign of γ_n is identified without additional assumptions, while the magnitude depends on equilibrium objects.

Remark 2 (Asymmetric identification). The sign identification in part (i) is asymmetric across the two spillover channels. The result $\phi_2 > 0 \Leftrightarrow \gamma_n > 0$ is robust: network-partner wages do not respond to individual worker skill, so their variation conditional on coworker wages is exogenous. The converse does not hold for coworker spillovers: $\phi_1 > 0$ does not imply $\gamma_c > 0$. Network spillovers endogenously raise average coworker skill, generating a positive ϕ_1 even when $\gamma_c = 0$. This effect is amplified by the non-linear effects of the upgrading probability, which prevents the linear regression from fully absorbing the network channel through $\tilde{w}^{net}$.

7 Quantitative analysis

This section provides a quantitative assessment of network learning spillovers in general equilibrium. We calibrate the model to the Dominican Republic and conduct counterfac-

tual experiments that vary the intensity of network learning and the allocation of talent across the production network.

7.1 Calibration

We calibrate the model to the Dominican Republic using matched employer-employee administrative data linked to firm-to-firm transaction records. External parameters are set from data and the literature, the network structure is taken directly from VAT records, and the remaining structural parameters are estimated by matching model-generated moments to their empirical counterparts.

7.1.1 External parameters

Separation rate We compute the separation rate directly from the matched employer-employee data. The annual separation probability—the fraction of workers employed at a firm in year t who are no longer at the same firm in year $t+1$—is 28%. This measure includes transitions to other firms as well as exits from formal employment, with a right-censoring correction for the final panel year. Converting to a continuous-time hazard yields $s = -\log(1-0.28) \approx 0.329$.

Job-finding rate We do not directly observe the job-finding rate in the data, which records only formal employment spells. We derive it from the steady-state flow balance condition $f \cdot u = s \cdot (1-u)$, using the unemployment rate of 5 percent as indicated by macro data for the Dominican Republic, giving $f = s(1-u)/u \approx 6.24$ per year. This is consistent with high turnover but rapid reabsorption in steady state.

Remaining parameters The discount rate is $\rho = 0.05$, the worker's bargaining power is $\beta = 0.5$ (symmetric Nash bargaining), and the matching function elasticity is $\xi = 0.5$, following Pissarides (2000) and Petrongolo and Pissarides (2001). Table 5 summarizes these choices.

Skill ladder We capture worker heterogeneity with a discrete skill ladder with $H = 7$ rungs, following Herkenhoff et al. (2024). We normalize the lowest level to $h_1 = 1$ and set the spacing between adjacent rungs to one-quarter of the interquartile range of log wages in the data, ensuring that the interquartile range of the empirical wage distribution spans approximately four rungs of the skill ladder.

Network structure and firm productivity For each simulated economy, firm productivity and network positions are drawn jointly using a Gaussian copula. Correlated draws are transformed into their respective marginals: productivity follows a Pareto distribution with shape governed by κ_A, and network degree is set to match the average number of trading partners observed in the VAT transaction data. The copula parameter ρ_{AC} controls the correlation between productivity and connectivity. A random network is then generated to match the target degrees.

Table 5: External parameters

Parameter	Description	Value	Source
s	Separation rate	0.329	DR employer-employee data
f	Job-finding rate	6.24	$s(1-u)/u$, $u = 0.05$
ρ	Discount rate	0.05	Pissarides (2000)
β	Bargaining power	0.5	Symmetric Nash
ξ	Matching elasticity	0.5	Petrongolo and Pissarides (2001)
H	Skill rungs	7	Herkenhoff et al. (2024)
Δ_h	Skill spacing	0.173	IQR($\log w$)/4 from data

7.1.2 Estimated parameters and model fit

We estimate six structural parameters by minimizing the distance between model-generated moments and their empirical counterparts via grid search. The identification exploits approximate block-diagonality: the Pareto shape κ_A primarily governs between-firm wage dispersion, while ρ_{AC} primarily governs the wage-connectivity correlation. These firm-level moments are largely independent of the spillover parameters γ_n and η, which are instead identified by the standardized EUE regression coefficients and their interaction with connectivity from Table 1. The vacancy cost c_0 is identified by the job-finding rate through the free-entry condition.

Table 6 reports the estimated parameter values and Table 7 compares model-generated moments to data. All six moments fall within one standard deviation of their data targets.

The estimated $\gamma_n = 0.80$ implies substantial network learning. The large value required to match even a modest standardized coefficient reflects the high turnover rate in the Dominican Republic's formal sector. With an annual separation probability of 28%, workers have relatively short employment spells during which to absorb network spillovers, necessitating a high per-period learning rate. This is consistent with Herkenhoff et al. (2024), who also find that large learning parameters are needed to match

reduced-form spillover coefficients in the presence of high worker turnover.[33]

The returns-to-size parameter $\eta = 0.70$ indicates moderate diminishing returns to the number of trading partners. A firm with twice as many partners receives approximately $2^{1-0.70} \approx 1.23$ times the network spillover. The parameter is identified from the interaction between the B&S spillover coefficient and the employer's own network size in the EUE regression (Table B.16 in the appendix): a one-standard-deviation increase in the number of buyers and suppliers raises the B&S wage elasticity by approximately 16%, consistent with an aggregation that lies between the sum ($\eta = 0$) and the mean ($\eta = 1$). The estimated value implies that additional trading partners provide learning opportunities with moderate congestion.

The Pareto shape, $\kappa_A = 0.80$, generates a fat-tailed productivity distribution, and $\rho_{AC} = 0.65$ implies a strong positive correlation between firm productivity and network centrality. These two parameters are identified by firm-level wage moments that are largely orthogonal to the learning parameters.

Table 6: Parameter estimates

Parameter	Description	Estimate	Primary identifying moment
γ_n	Network spillover intensity	0.80	ϕ_2^{std} (EUE regression)
η	Returns to network size	0.70	$\phi_2 \times C$ interaction ratio
κ_A	Pareto shape (productivity)	0.80	$\text{Var}(\log \bar{w}_j)$
ρ_{AC}	Productivity–connectivity corr.	0.65	$\text{Corr}(\log \bar{w}_j, \log C_j)$
γ_c	Coworker spillover intensity	0.001	ϕ_1^{std} (EUE regression)
c_0	Vacancy posting cost	0.50	Job-finding rate f

Notes: Parameter values from grid search over 2,400 cells. Each evaluation uses 200 firms, 8,000 workers, and 50 time periods, averaged over 5 simulation seeds.

7.2 The effect of network learning spillovers

We use the calibrated model to quantify the aggregate effects of network learning spillovers and the role of talent allocation across the production network. We compare the calibrated baseline economy to counterfactual economies in which we shut down the network learning channel, remove the correlation between firm productivity and network position, or both. Table 8 reports the results and Table 9 decomposes the contributions of each channel.

[33] The estimated coworker parameter matches well the elasticity of wages to coworkers' wages.

Table 7: Targeted moments

Moment	Data	Model	Difference	Identifies
ϕ_1^{std} (coworkers' wages)	0.008	0.011 ± 0.015	+0.003	γ_c
ϕ_2^{std} (B&S wages)	0.021	0.025 ± 0.010	+0.004	γ_n
$\phi_2 \times C$ interaction ratio	0.160	0.166 ± 0.040	+0.006	η
$\text{Var}(\log \bar{w}_j)$	0.240	0.238 ± 0.030	−0.002	κ_A
$\text{Corr}(\log \bar{w}_j, \log C_j)$	0.336	0.306 ± 0.070	−0.030	ρ_{AC}
Job-finding rate f	6.24	6.20 ± 0.22	−0.04	c_0

Notes: Data targets: ϕ_1^{std} and ϕ_2^{std} from Table 1 (Column 2, standardized coefficients);$\phi_2 \times C$ interaction ratio from Table B.16, defined as the percentage change in the B&S wage elasticity for a one standard deviation increase in own network size; $\text{Var}(\log \bar{w}_j)$ from Social Security records; $\text{Corr}(\log \bar{w}_j, \log C_j)$ from merged Social Security and VAT data; $f = s(1-u)/u$ with $s = 0.329$ and $u = 0.05$. Model moments: mean ± standard deviation across simulation seeds. Each seed uses 200 firms, 8,000 workers, and 50 time periods.

Table 8: Counterfactual experiments

Scenario	$\Delta\bar{h}$ (%)	$\text{Corr}(\bar{h}_j, A_j)$	$\bar{h}_{A^{90}}/\bar{h}_{A^{10}}$
Baseline	—	+0.55	1.05
No network ($\gamma_n = 0$)	−18.4	+0.59	1.14
No sorting ($\rho_{AC} = 0$)	−1.5	+0.26	1.03
Negative sorting ($\rho_{AC} = -0.65$)	−3.1	—	—
No network + no sorting	−18.4	+0.59	1.14

Notes: Each scenario modifies one or more parameters from the estimated baseline while holding the rest fixed. $\Delta\bar{h}$: percentage change in employment-weighted average human capital relative to baseline. $\text{Corr}(\bar{h}_j, A_j)$: correlation between firm-level average human capital and productivity. $\bar{h}_{A^{90}}/\bar{h}_{A^{10}}$: ratio of average human capital at top-decile versus bottom-decile productivity firms. All moments computed from the steady-state equilibrium with 200 firms.

Network learning. Removing the network learning channel ($\gamma_n = 0$) reduces average human capital by 18.4%, confirming that inter-firm knowledge diffusion through production linkages is a quantitatively important source of on-the-job skill accumulation. The effect operates through two reinforcing channels. First, a direct upgrading channel: workers lose access to skill upgrading through exposure to employees at their employer's trading partners, so the flow of workers from lower to higher skill rungs slows. Second, an indirect hiring channel: the reduction in workers' expected skill growth lowers the surplus from employment relationships, reducing vacancy posting and tightening the labor market.

The magnitude is broadly consistent with estimates from the peer effects literature. Herkenhoff et al. (2024) find that coworker learning accounts for roughly two-thirds of on-the-job human capital accumulation, while Jarosch (2021) estimate that learning accounts for 4 to 9% of lifetime compensation. Our estimate lies above these benchmarks, reflecting the additional network channel that is absent from models with only within-firm spillovers.

Without network spillovers, between-firm wage dispersion rises, as the skill-upgrading channel that partially compresses wages across firms is removed. Workers at less productive firms can no longer acquire human capital through their employer's supply chain connections, so wages more closely reflect the underlying productivity distribution and between-firm inequality widens.

Talent allocation. One-sixth of the network learning effect is attributable to the allocation of talent across the production network. Reversing the correlation between firm productivity and network centrality, that is, moving productive firms from the center to the periphery of the network ($\rho_{AC} = +0.65 \to -0.65$), reduces aggregate human capital by 3.1%, compared to the 18.4% total effect of shutting down network learning entirely. Removing the correlation altogether ($\rho_{AC} = 0$) accounts for half of this, reducing human capital by 1.5%.

The mechanism is that productive firms attract more skilled workers, and when these firms occupy central network positions, their skilled workforces enter the network spillover potential of a larger number of trading partners. Workers at those partners upgrade faster because they are exposed to higher-skill workforces. When productive firms instead occupy peripheral positions, their skilled workforces benefit fewer partners, and the aggregate rate of skill upgrading falls. The equilibrium correlation between average human capital and firm productivity reflects these forces. In the baseline, the correlation between firm-level human capital and productivity is 0.55, whereas no assortativity of the

network, ie., setting $\rho_{AC} = 0$, reduces it to 0.26, roughly half of the total in the baseline. In addition, the sorting effect operates entirely through the network learning channel. Without network spillovers ($\gamma_n = 0$), removing or reversing the productivity-connectivity correlation has no effect on aggregate human capital.

Table 9: Decomposition: network spillovers and talent allocation

	With sorting ($\rho_{AC} = 0.65$)	Without sorting ($\rho_{AC} = 0$)
Effect of network spillovers on $\bar{h}$		
$\Delta\bar{h}$ when $\gamma_n \to 0$	−18.4%	−16.6%
Amplification from sorting	**1.8 pp**	
Effect of sorting on $\bar{h}$		
With network spillovers ($\gamma_n = 0.8$)	+1.5%	
Without network spillovers ($\gamma_n = 0$)	0.0%	
Positive versus negative sorting		
$\Delta\bar{h}$: $\rho_{AC} = +0.65$ vs. -0.65	+3.1%	
Amplification (pos. vs. neg.)	+3.6 pp	

Notes: The amplification measures the difference in the network spillover effect with versus without sorting: (−18.4%)−(−16.6%) = 1.8 pp. Sorting has zero effect on aggregate human capital without network spillovers ($\gamma_n = 0$).

Table 9 decomposes the aggregate effect. Reversing the correlation between productivity and network position reduces aggregate human capital by 3.1%, roughly one-sixth of the total network learning effect. Moving productive firms to the periphery of the network is costly because these firms employ the most skilled workers, and their trading partners lose a valuable source of spillovers. This sorting channel operates entirely through network learning. Without network spillovers, removing or reversing the productivity-connectivity correlation has no effect on aggregate human capital. With network spillovers active, sorting contributes 1.5% to aggregate human capital and amplifies the network effect by 1.8 percentage points.

These results suggest that the structure of supply chain relationships has consequences for aggregate human capital and the allocation of talent. Specifically, the extent of learning from buyers and suppliers depends on which firms are well connected. Through the lens of the model, productive firms attract more skilled workers, and when these firms occupy central network positions, workers at their partners upgrade faster because they are exposed to higher-skill workforces. Altogether, the results imply that trade liberalization, FDI entry, industrial policy, and supply chain disruptions have the potential to

reshape the production network and thereby affect human capital accumulation. When a productive firm gains new trading partners—for instance, through trade openness that connects exporters to local suppliers, through FDI linkages, or through industrial policies that promote upstream-downstream integration—workers at those partners gain a source of network spillovers that increases wuth the skill level of the new partner's workforce. The sorting results indicate that the human capital gains from policies that reshape the network are larger when the targeted firms are more productive, since it is the skill composition of the connected workforce that determines the magnitude of the spillover.

Table 10: Heterogeneous effects of network disruptions

Scenario	$\Delta\bar{h}$ (%)	Corr$(\bar{h}_j, A_j)$
By productivity decile		
Bottom decile disconnected	−0.6	+0.42
Top decile disconnected	−10.9	−0.38
By connectivity decile		
Least connected disconnected	−0.5	—
Most connected disconnected	−6.9	—

Notes: Each row removes all trading links for the specified group of firms and recomputes the steady-state equilibrium while holding all other parameters at their estimated values. $\Delta\bar{h}$: percentage change in employment-weighted average human capital relative to the fully connected baseline. Corr$(\bar{h}_j, A_j)$: correlation between firm-level average human capital and productivity. Firms are ranked by their baseline productivity draw (A_i) or by their number of trading partners $(|\mathcal{P}(i)|)$.

Heterogeneous effects of network disruptions The aggregate effects of network learning depend on which firms participate in the production network. We quantify this by selectively removing all trading links for specific groups of firms defined by their productivity or connectivity. Table 10 reports the results.

Disconnecting the top productivity decile from the network reduces aggregate human capital by about 11%, more than half as much as shutting down the network channel entirely. The correlation between human capital and productivity at the firm level reverses when the top decile is disconnected, indicating that the remaining firms' human capital no longer tracks productivity. In contrast, disconnecting the bottom productivity decile costs only 0.6%. Similar patterns emerge when firms are ranked by connectivity: disconnecting the most connected decile costs 6.9%, against 0.5% for the least connected. These results have implications for the welfare consequences of supply chain

disruptions. Shocks that sever the trading relationships of large, productive, or highly connected firms, such as trade sanctions, natural disasters, or pandemic-induced disruptions, can reduce aggregate human capital well beyond the directly affected workers, through reduced knowledge diffusion to all trading partners.

8 Conclusions

This paper is the first to document that workers learn from other workers employed at the buyers and suppliers of their employers. These knowledge spillovers are identified using five different empirical strategies, are quantitatively large, and are distinct from the spillovers between coworkers of the same firm documented by previous literature. We show that they explain a meaningful share of aggregate wage growth and have implications for several policy-relevant debates.

To rationalize the empirical results, we develop a theory of human capital accumulation that integrates both learning spillovers from coworkers and from the workforce of trading partners within a frictional labor market. We calibrate the model to the Dominican Republic and find that shutting down network learning reduces aggregate human capital by 18%. The effect is dominated by high-productivity firms: we show that disconnecting the top productivity decile from the supply chain costs eighteen times as much as disconnecting the bottom decile. Assortativity of productivity and connectivity amplifies knowledge diffusion, explainin: this channel explains 1/6 of the network effects.

References

Abowd, John M, Francis Kramarz, and David N Margolis. 1999. "High wage workers and high wage firms." *Econometrica*, 67(2): 251–333.

Acabbi, Edoardo Maria, Andrea Alati, and Luca Mazzone. 2024. "Human capital ladders, cyclical sorting, and hysteresis." Bank of England Working Paper No. 1,077.

Acemoglu, Daron, Vasco M Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2012. "The Network Origins of Aggregate Fluctuations." *Econometrica*, 80(5): 1977–2016.

Alfaro-Ureña, Alonso, Isabela Manelici, and Jose P Vasquez. 2021. "The effects of multinationals on workers: Evidence from Costa Rican microdata." Princeton University, Department of Economics, Center for Economic Policy Studies. Working Papers, 285.

Alfaro-Ureña, Alonso, Isabela Manelici, and José P Vásquez. 2022. "The effects of joining multinational supply chains: New Evidence from firm-to-firm linkages." *Quarterly Journal of Economics*, 137(3): 1495–1552.

Amiti, Mary, Cédric Duprez, Jozef Konings, and John Van Reenen. 2024. "FDI and superstar spillovers: Evidence from firm-to-firm transactions." *Journal of International Economics*, 152: 103972.

Arellano-Bover, Jaime. 2024. "Career consequences of firm heterogeneity for young workers: First job and firm size." *Journal of Labor Economics*, 42(2): 549–589.

Arellano-Bover, Jaime, and Fernando Saltiel. 2026. "Differences in on-the-job learning across firms." *Journal of Labor Economics*, 44(1): 149–188.

Arkolakis, Costas, Federico Huneeus, and Yuhei Miyauchi. 2025. "Production Network Formation, Trade, and Welfare." CESifo Working Paper No. 11833.

Bartelme, Dominick, Arnaud Costinot, Dave Donaldson, and Andres Rodriguez-Clare. 2025. "The textbook case for industrial policy: Theory meets data." *Journal of Political Economy*, 133(5): 1527–1573.

Bernard, Andrew B, Andreas Moxnes, and Yukiko U Saito. 2019. "Production networks, geography, and firm performance." *Journal of Political Economy*, 127(2): 639–688.

Bernard, Andrew B, Emmanuel Dhyne, Glenn Magerman, Kalina Manova, and Andreas Moxnes. 2022. "The origins of firm heterogeneity: A production network approach." *Journal of Political Economy*, 130(7).

Bertheau, Antoine, Edoardo Maria Acabbi, Cristina Barceló, Andreas Gulyas, Stefano Lombardi, and Raffaele Saggio. 2023. "The unequal consequences of job loss across countries." *American Economic Review: Insights*, 5(3): 393–408.

Buera, Francisco J., and Ezra Oberfield. 2020. "The Global Diffusion of Ideas." *Econometrica*, 88(5): 1657–1698.

Cahuc, Pierre, Fabien Postel-Vinay, and Jean-Marc Robin. 2006. "Wage Bargaining with On-the-Job Search: Theory and Evidence." *Econometrica*, 74(2): 323–364.

Cai, Jie, Nan Li, and Ana Maria Santacreu. 2022. "Knowledge Diffusion, Trade, and Innovation across Countries and Sectors." *American Economic Journal: Macroeconomics*, 14(1): 104–145.

Card, David, Jörg Heining, and Patrick Kline. 2013. "Workplace heterogeneity and the rise of West German wage inequality." *Quarterly Journal of Economics*, 128(3): 967–1015.

Cardoza, Marvin, Francesco Grigoli, Nicola Pierri, and Cian Ruane. 2024. "Worker mobility in production networks." *Review of Economic Studies*, rdae114.

Cornelissen, Thomas, Christian Dustmann, and Uta Schönberg. 2017. "Peer Effects in the Workplace." *American Economic Review*, 107(2): 425–56.

Criscuolo, Chiara, Antoine Dechezleprêtre, Louise Guillouet, Guy Lalanne, and Francesco Manaresi. 2025. "Digital and green spillovers across firm-level production networks in Estonia." OECD Science, Technology and Industry Working Papers 2025.11.

Cuñat, Alejandro, and Robert Zymek. 2025. "Unbalanced Trade 2.0." IMF Working Paper 25/191.

De Giorgi, Giacomo, Anders Frederiksen, and Luigi Pistaferri. 2020. "Consumption network effects." *Review of Economic Studies*, 87(1): 130–163.

De Giorgi, Giacomo, Michele Pellizzari, and Silvia Redaelli. 2010. "Identification of social interactions through partially overlapping peer groups." *American Economic Journal: Applied Economics*, 2(2): 241–275.

Demir, Banu, Ana Cecilia Fieler, Daniel Yi Xu, and Kelly Kaili Yang. 2024*a*. "O-ring production networks." *Journal of Political Economy*, 132(1): 200–247.

Demir, Banu, Beata Javorcik, Tomasz K Michalski, and Evren Ors. 2024*b*. "Financial constraints and propagation of shocks in production networks." *Review of Economics and Statistics*, 106(2): 437–454.

Dhyne, Emmanuel, Ayumu Ken Kikkawa, Magne Mogstad, and Felix Tintelnot. 2021. "Trade and domestic production networks." *The Review of Economic Studies*, 88(2): 643–668.

Dhyne, Emmanuel, Ayumu Ken Kikkawa, Toshiaki Komatsu, Magne Mogstad, and Felix Tintelnot. 2025. "Firm responses and wage effects of foreign demand shocks with fixed labor costs and monopsony." *American Economic Review*, 115(12): 4328–4368.

Donovan, Kevin, Will Jianyu Lu, and Todd Schoellman. 2023. "Labor market dynamics and development." *Quarterly Journal of Economics*, 138(4): 2287–2325.

Dube, Arindrajit, Daniele Girardi, Oscar Jorda, and Alan M Taylor. 2025. "A Local Projections Approach to Difference-in-Differences." *Journal of Applied Econometrics*.

Gregory, Victoria. 2020. "Firms as learning environments: Implications for earnings dynamics and job search." *FRB St. Louis Working Paper*, , (2020-036).

Hausmann, Ricardo, César A Hidalgo, Sebastián Bustos, Michele Coscia, and Alexander Simoes. 2014. *The atlas of economic complexity: Mapping paths to prosperity*. MIT Press.

Herkenhoff, Kyle, Jeremy Lise, Guido Menzio, and Gordon M Phillips. 2024. "Production and learning in teams." *Econometrica*, 92(2): 467–504.

Hong, Long, and Salvatore Lattanzio. 2025. "The peer effect on future wages in the workplace." *Journal of Applied Econometrics*, 40(5): 521–539.

Huneeus, Federico, Kory Kroft, and Kevin Lim. 2021. "Earnings inequality in production networks." NBER Working Paper 28424.

Jacobson, Louis S, Robert J LaLonde, and Daniel G Sullivan. 1993. "Earnings losses of displaced workers." *American Economic Review*, 83(4): 685–709.

Jarosch, Gregor. 2021. "Searching for job security and the consequences of job loss." NBER Working Paper No. 28481.

Jarosch, Gregor, Ezra Oberfield, and Esteban Rossi-Hansberg. 2021. "Learning from coworkers." *Econometrica*, 89(2): 647–676.

Javorcik, Beata Smarzynska. 2004. "Does foreign direct investment increase the productivity of domestic firms? In search of spillovers through backward linkages." *American Economic Review*, 94(3): 605–627.

Johnson, Paul, and Chris Papageorgiou. 2020. "What remains of cross-country convergence?" *Journal of Economic Literature*, 58(1): 129–175.

Komatsua, Toshiaki, and Emmanuel Dhyneb. 2023. "Job Ladder over Production Networks." Unpublished manuscript.

Lagakos, David, Benjamin Moll, Tommaso Porzio, Nancy Qian, and Todd Schoellman. 2018. "Life cycle wage growth across countries." *Journal of Political Economy*, 126(2): 797–849.

Manski, Charles F. 2000. "Economic analysis of social interactions." *Journal of Economic Perspectives*, 14(3): 115–136.

Mas, Alexandre, and Enrico Moretti. 2009. "Peers at work." *American Economic Review*, 99(1): 112–145.

Ma, Xiao, Alejandro Nakab, and Daniela Vidart. 2024. "Human capital investment and development: The role of on-the-job training." *Journal of Political Economy Macroeconomics*, 2(1): 107–148.

Ma, Xiaonan. 2025. "A simple search model with employer network." Unpublished Manuscript.

Moretti, Enrico. 2004. "Workers' education, spillovers, and productivity: Evidence from plant-level production functions." *American Economic Review*, 94(3): 656–690.

Nix, Emily. 2020. "Learning Spillovers in the Firm." Unpublished manuscript.

Oberfield, Ezra, and Johannes Boehm. 2020. "Misallocation in the market for inputs: Enforcement and the organization of production." *Quarterly Journal of Economics*, 135(4): 2007–20058.

Perla, Jesse, Christopher Tonetti, and Michael E Waugh. 2021. "Equilibrium technology diffusion, trade, and growth." *American Economic Review*, 111(1): 73–128.

Petrongolo, Barbara, and Christopher A Pissarides. 2001. "Looking into the black box: A survey of the matching function." *Journal of Economic literature*, 39(2): 390–431.

Pissarides, Christopher A. 2000. *Equilibrium Unemployment Theory.* . 2nd ed., Cambridge, MA:MIT Press.

Postel-Vinay, Fabien, and Jean-Marc Robin. 2002. "Equilibrium wage dispersion with worker and employer heterogeneity." *Econometrica*, 70(6): 2295–2350.

Serafinelli, Michel. 2019. ""Good" firms, worker flows, and local productivity." *Journal of Labor Economics*, 37(3): 747–792.

Song, Jae, David J Price, Fatih Guvenen, Nicholas Bloom, and Till Von Wachter. 2019. "Firming up inequality." *Quarterly journal of economics*, 134(1): 1–50.

Startz, Meredith. 2025. "The value of face-to-face: Search and contracting problems in Nigerian trade." Unpublished manuscript.

Stoyanov, Andrey, and Nikolay Zubanov. 2012. "Productivity Spillovers Across Firms Through Worker Mobility." *American Economic Journal: Applied Economics*, 4(2): 168–98.

Wolf, Christian K. 2023. "The missing intercept: A demand equivalence approach." *American Economic Review*, 113(8): 2232–2269.

Online appendix

A Motivating facts

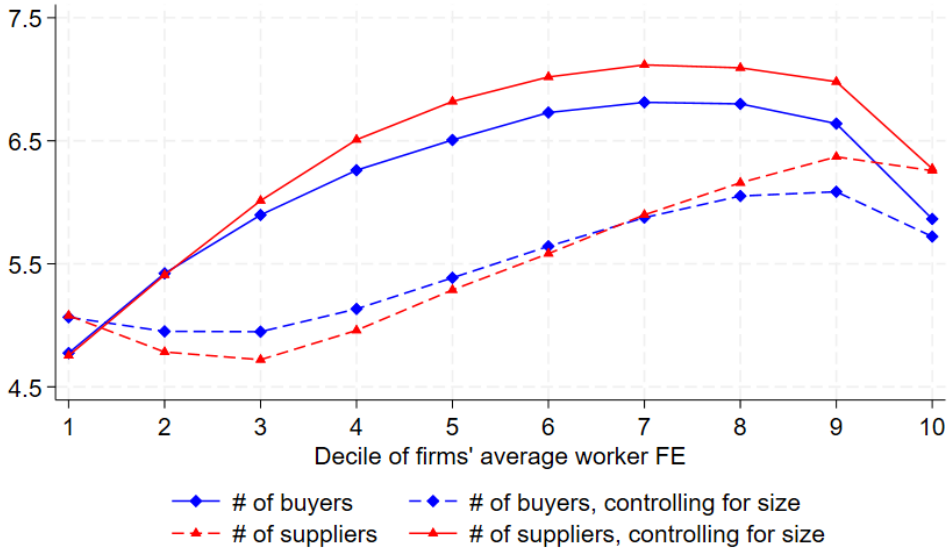
Figure A.1 shows the relationship between the metric of human capital obtained from worker fixed effects obtained from an AKM deocomposition and the number of buyers and suppliers.

Table A.1 reports the regression results quantifying the degree of sorting of high-wage workers into firms with high-wage coworkers and high-wage buyers and suppliers. The results indicate that the former is substantially higher than the latter.

Figure A.2 illustrates the assortative matching among coworkers and across buyers and suppliers, using AKM worker fixed effects.

Figure A.1: Firms' human capital and number of buyers and suppliers

(Average decile)



Notes: The figure shows the relationship between the quintile of firms' wages—measured by the worker fixed effects from an AKM decomposition—and the average quintile of the number of buyers and suppliers. The figure also shows the relationships where the number of buyers and suppliers is residualized with respect to a third-degree order polynomial of the size of the firm, measured with the firm employment.

Table A.1: Sorting of firms along different margins

	(1)	(2)	(3)	(4)
New hires' wages	0.468***			0.431***
	(0.008)			(0.010)
New suppliers' wages		0.132***		0.097***
		(0.004)		(0.007)
New buyers' wages			0.103***	0.066***
			(0.006)	(0.008)
Observations	56,066	116,228	69,185	27,777
R^2	0.193	0.025	0.025	0.193

Notes: The sample consists of post-2015 observations as the data prior to that is used to identify new buyer-supplier relationships. All regressions control for year fixed effects. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

Figure A.2: Assortative matching with coworkers' and buyers' and suppliers' wages, AKM decomposition



Notes: The figure shows the relationship between the decile of lagged firms' wages—measured by the worker fixed effects from an AKM decomposition—and the average decile of lagged wages of new hires, new buyers, and new suppliers.

B Heterogeneity and robustness

B.1 Empirical framework *à la* Herkenhoff et al. (2024)

Table B.1 presents the results when using the average of the top three buyers and suppliers instead of the average across all of them. The results are similar to the baseline.

Table B.2 reports the results on heterogeneity along the tertiary education margin. Spillovers from buyers and suppliers are significantly larger for workers with tertiary education. When we include destination firm-year fixed effects, however, we do not find differential effects for workers with tertiary education, possibly reflecting the fact that highly educated workers sort into the same firms.

Table B.3 presents a set of robustness exercises. Column (2) shows that the results are not driven by the focus on firms with at most 100 employees. Column (3) shows that the results are robust to excluding workers who in year $t+2$ work for a buyer or supplier of the firm they work for in year t.[34] Columns (4) and (5) document that the coefficients of interest are even larger than at $t+2$, suggesting that the gains from having higher-wages coworkers and buyers and suppliers are not short-lived, consistent with such gains being related to human capital accumulation. Column (6) shows that focusing on stable coworkers only is not necessary for the results. Column (7) uses backward-looking AKM worker fixed effects instead of wages to measure human capital.[35] Results are very similar to baseline when using different methods of aggregating buyers and suppliers' wages: in column (8), we report the results using the average log wages of the top 10 buyers and top 10 suppliers, and in column (9) we use the weighted average log wages of the buyers and suppliers responsible for the firms' top 25% of sales or purchase. Finally, column (10) presents a specification where rather than controlling for buyers' and suppliers' firms characteristics by including the average of those variables in the regression, we first regress firm-level average wages on the controls, then take the regression residual, and finally average the firm residualized wages across buyers and suppliers. This alternative procedure leads to qualitatively similar estimates, although the coefficient for buyers' and suppliers' wages is smaller and the coefficient for own-firm workers' wages becomes larger (but still smaller than the coefficient for buyers' and suppliers' wages).

In Table B.2, we first group employees without tertiary education with those born

[34] Cardoza et al. (2024) show that workers tend to move along the supply chain and that these movements are associated with higher wages. This result addresses the concern that the wages of buyers and suppliers' workers are a measure of better outside option rather than spillovers.

[35] The results are similar to those obtained when focusing on wages—except that the own-firm coworkers' wages coefficient and buyers and suppliers workers' wages coefficients have very similar magnitude when we use AKM fixed effects as a measure of human capital.

after 1985 who do not appear in the tertiary education data, assuming that the latter did not attain tertiary education. Then, we include degree-major times industry fixed effects to proxy for occupation. The estimates in columns (1) to (3) indicate that our results are robust to the inclusion of degree-major times industry fixed effects. In columns (4) and (5), we exclude workers with no tertiary education. In this case, the results are weaker, but this is unsurprising given the small sample size.

Table B.1: Top buyers and suppliers

	(1)	(2)	(3)	(4)	(5)	(6)
Own wages	0.374***	0.374***	0.544***	0.0457***	0.369***	0.303***
	(0.007)	(0.007)	(0.012)	(0.012)	(0.008)	(0.011)
Coworkers' wages at t	0.045***	0.019***	0.016*	0.040***	0.013**	-0.026***
	(0.005)	(0.006)	(0.009)	(0.007)	(0.007)	(0.008)
Top 3 buyers' and suppliers' wages	0.075***	0.055***	0.063***	0.022**		0.030***
	(0.006)	(0.008)	(0.012)	(0.009)		(0.011)
Top 3 suppliers' wages					0.028***	
					(0.007)	
Top 3 buyers' wages					0.034***	
					(0.006)	
Regressions with standardized variables						
Coworkers' wages	0.020***	0.008***	0.007*	0.018***	0.006**	-0.012***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Top 3 buyers' and suppliers' wages	0.025***	0.018***	0.021***	0.007**		0.010***
	(0.002)	(0.003)	(0.004)	(0.003)		(0.004)
Top 3 suppliers' wages					0.011***	
					(0.003)	
Top 3 buyers' wages					0.016***	
					(0.003)	
Sample	All	All	> B&S	≤ B&S	All	All
Controls	No	Yes	Yes	Yes	Yes	Yes
Destination firm × year FEs	No	No	No	No	No	Yes
Observations	76,008	72,527	33,966	37,494	63,869	38,873
R^2	0.263	0.313	0.344	0.273	0.311	0.725

Notes: The table reports estimates of learning spillovers from cowokers and from the top three buyers and suppliers. The sample consists of workers that experience an EUE transition between year t and year $t+2$, employed at firms with less than 100 employees in year t. The dependent variable is workers' wages in year $t+2$, while the independent variables are at time t. Controls include worker characteristics (gender and age), firm-level variables (log sales, log employment, labor productivity, share of VAT sales, and log number of suppliers), the average of firm-level variables among buyers and suppliers, and industry-municipality-year fixed effects. Columns (3) uses a subsample of individuals whose wage is higher than the average wage of their buyers and suppliers, and column (4) uses a subsample of individuals whose wage is lower or equal than the average wage of their buyers and suppliers. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

Table B.2: Heterogeneity with respect to tertiary educational attainment

	(1)	(2)	(3)	(4)	(5)	(6)
Own wages	0.269***	0.266***	0.184***	0.239***	0.234***	0.149***
	(0.009)	(0.009)	(0.012)	(0.009)	(0.009)	(0.013)
Coworkers' wages	0.070***	0.043***	0.001	0.071***	0.043***	0.004
	(0.006)	(0.007)	(0.010)	(0.006)	(0.007)	(0.010)
Buyers' and suppliers' wages	0.071***	0.049***	0.026*	0.076***	0.055***	0.031**
	(0.007)	(0.011)	(0.015)	(0.007)	(0.011)	(0.015)
Buyers' and suppliers' wages × tertiary education	0.176***	0.183***	0.218***	0.076**	0.080**	0.086
	(0.035)	(0.037)	(0.064)	(0.035)	(0.038)	(0.064)
Own-wages × tertiary education				0.142***	0.148***	0.224***
				(0.024)	(0.026)	(0.040)
Coworkers' wages × tertiary education				0.026	0.020	-0.013
				(0.024)	(0.026)	(0.043)
Controls	No	Yes	Yes	No	Yes	Yes
Industry x municipality x year FE	No	Yes	Yes	No	Yes	Yes
Firm x year FE	No	No	Yes	No	No	Yes
Observations	49,873	47,073	22,460	49,873	47,073	22,460
R^2	0.287	0.340	0.746	0.289	0.342	0.748

Notes: The table reports estimates of learning spillovers from cowokers and from buyers and suppliers, conditioning on workers having attained tertiary education. The sample consists of workers that experience an EUE transition between year t and year $t+2$, employed at firms with less than 100 employees in year t. The dependent variable is workers' wages in year $t+2$, while the independent variables are at time t. Controls include worker characteristics (gender and age), firm-level variables (log sales, log employment, labor productivity, share of VAT sales, and log number of suppliers), the average of firm-level variables among buyers and suppliers, and industry-municipality-year fixed effects. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

Table B.3: Robustness to changes in sample, horizons, and measures of human capital

	Baseline	Include large firms	No B&S moves	$t+4$ horizon	$t+6$ horizon
	(1)	(2)	(3)	(4)	(5)
Own wages	0.374***	0.378***	0.365***	0.418***	0.428***
	(0.007)	(0.006)	(0.008)	(0.011)	(0.014)
Coworkers' wages	0.019***	0.021***	0.018***	0.020**	0.031**
	(0.006)	(0.006)	(0.006)	(0.009)	(0.012)
Buyers' and suppliers' wages	0.075***	0.060***	0.064***	0.083***	0.076***
	(0.009)	(0.008)	(0.010)	(0.015)	(0.020)
Observations	72,527	228,819	66,898	33,293	20,020
R^2	0.313	0.328	0.310	0.288	0.272

	All coworkers	AKM FEs	Top 10 B&S	Top 25% B&S	B&S wages residualized
	(6)	(7)	(8)	(9)	(10)
Own wages	0.374***	0.365***	0.374***	0.374***	0.374***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Coworkers' wages	0.018**	0.127***	0.017***	0.020***	0.022***
	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)
Buyers' and suppliers' wages	0.067***	0.124***	0.083***	0.066***	0.041***
	(0.008)	(0.014)	(0.010)	(0.008)	(0.009)
Observations	84,841	72,532	72,527	72,448	72,526
R^2	0.306	0.318	0.313	0.313	0.312

Notes: The table reports estimates of learning spillovers from cowokers and from buyers and suppliers. The sample consists of workers that experience an EUE transition between year t and year $t+2$. The dependent variable is workers' wages in year $t+2$, while the independent variables are at time t, unless reported otherwise. Column (1) reports the baseline; column (2) relaxes the restriction of firms with less than 100 employees; column (3) excludes EUE transitions to buyers and suppliers; column (4) and column (5) uses workers' own wages at time $t+4$ and $t+6$, respectively; column (6) uses the average of all coworkers' wages instead of stable ones; column (7) replaces coworkers' wages and buyers' and suppliers' wages with worker fixed effects from an AKM decomposition; column (8) and column (9) take the average of buyers' and suppliers' wages considering only the average of the top 10 buyers and suppliers and the top 25% buyers and suppliers, respectively; column (10) uses the average of the residualized buyers' and suppliers' wages with respect to the firm-level controls for buyers and suppliers. All regressions include controls for worker characteristics (gender and age), firm-level variables (log sales, log employment, labor productivity, share of VAT sales, and log number of suppliers), the average of firm-level variables among buyers and suppliers, and industry-municipality-year fixed effects. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

Table B.4: Robustness to the inclusion of proxies of occupation

	All employees			Only employees with tertiary education	
	(1)	(2)	(3)	(4)	(5)
Own wages	0.250***	0.249***	0.171***	0.323***	0.337***
	(0.009)	(0.009)	(0.012)	(0.025)	(0.033)
Coworkers' wages	0.063***	0.045***	-0.000	0.089***	0.074**
	(0.006)	(0.007)	(0.010)	(0.026)	(0.036)
Buyers' and suppliers' wages	0.056***	0.056***	0.031**	0.106**	0.101
	(0.007)	(0.011)	(0.015)	(0.042)	(0.062)
Controls	No	Yes	Yes	No	Yes
Industry x municipality x year FE	No	Yes	Yes	No	Yes
Firm x year FE	No	No	Yes	No	No
Degree x major x industry FE	Yes	Yes	Yes	Yes	Yes
Observations	49,463	46,695	22,131	3,289	2,695
R^2	0.308	0.354	0.751	0.379	0.459

Notes: The table reports estimates of learning spillovers from coworkers and from buyers and suppliers, controlling for degree-major-industry fixed effects. The sample consists of workers that experience an EUE transition between year t and year $t+2$, employed at firms with less than 100 employees in year t. The dependent variable is workers' wages in year $t+2$, while the independent variables are at time t. Controls include worker characteristics (gender and age), firm-level variables (log sales, log employment, labor productivity, share of VAT sales, and log number of suppliers), the average of firm-level variables among buyers and suppliers, and industry-municipality-year fixed effects. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

B.2 Empirical framework *à la* Jarosch, Oberfield and Rossi-Hansberg (2021)

Table B.5 reports the estimates when we add a rich set of firm controls at the employer- and buyer and supplier-level. In Table B.6, we standardize the regressors to account for differences in dispersion. Table B.7 reports the results when we focus on the top three buyers and suppliers only, while Table B.8 uses AKM worker fixed effects to measure human capital. Results are very similar to those reported in the main text. Table B.9 compares learning spillovers from buyers and learning spillovers from suppliers, and in Table B.10 we examine asymmetries between spillovers to low- or high-wage workers. We do not find evidence of differential effects for upstream or downstream spillovers, nor of asymmetries. In Table B.11, we report the results for all employees as well as for the sample of workers with tertiary education, controlling for degree-major-industry fixed effects. Results are again robust. Finally, Table B.12 reports the results obtained by restricting the sample to workers who changed firm between year $t-1$ and year t and remained at the destination firm for at least three years, with results comparable to the baseline.

Table B.5: Robustness to additional controls

	$h=1$ (1)	$h=2$ (2)	$h=3$ (3)	$h=4$ (4)	$h=5$ (5)
Own wages	0.903***	0.844***	0.807***	0.788***	0.770***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Coworkers' wages	0.019***	0.023***	0.023***	0.021***	0.019***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Buyers' and suppliers' wages	0.025***	0.044***	0.054***	0.059***	0.063***
	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)
Observations	3,636,708	2,860,336	2,305,904	1,847,330	1,452,960
R^2	0.849	0.748	0.678	0.627	0.582
	$h=6$ (6)	$h=7$ (7)	$h=8$ (8)	$h=9$ (9)	$h=10$ (10)
Own wages	0.753***	0.736***	0.723***	0.708***	0.695***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Coworkers' wages	0.018***	0.016***	0.016***	0.015***	0.013**
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)
Buyers' and suppliers' wages	0.064***	0.068***	0.073***	0.074***	0.069***
	(0.006)	(0.007)	(0.008)	(0.009)	(0.011)
Observations	1,114,656	822,494	570,654	355,530	166,074
R^2	0.545	0.514	0.486	0.457	0.434

Notes: The table reports estimates of learning spillovers from cowokers and from buyers and suppliers. The sample consists of workers employed at firms with less than 100 employees in year t. The dependent variable is workers' wages in year $t+h$, while the independent variables are at time t. All regressions control for workers' characteristics (gender, age, and tenure), firm-level variables (log sales, log employment, log number of suppliers, labor productivity, share of VAT sales, and log number of suppliers), the average of firm-level variables among buyers and suppliers, and industry-municipality-year fixed effects. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

Table B.6: Standardized regressors

	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$
	(1)	(2)	(3)	(4)	(5)
Own wages	0.903***	0.844***	0.807***	0.788***	0.770***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Coworkers' wages	0.010***	0.012***	0.012***	0.012***	0.010***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Buyers' and suppliers' wages	0.008***	0.014***	0.017***	0.018***	0.020***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Observations	3,636,708	2,860,336	2,305,904	1,847,330	1,452,960
R^2	0.849	0.748	0.678	0.627	0.582
	$h=6$	$h=7$	$h=8$	$h=9$	$h=10$
	(6)	(7)	(8)	(9)	(10)
Own wages	0.753***	0.736***	0.723***	0.708***	0.695***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Coworkers' wages	0.010***	0.008***	0.009***	0.008***	0.007**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Buyers' and suppliers' wages	0.020***	0.021***	0.023***	0.023***	0.021***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Observations	1,114,656	822,494	570,654	355,530	166,074
R^2	0.545	0.514	0.486	0.457	0.434

Notes: The table reports standardized estimates of learning spillovers from cowokers and from buyers and suppliers. The sample consists of workers employed at firms with less than 100 employees in year t. The dependent variable is workers' wages in year $t+h$, while the independent variables are at time t. All regressions control for workers' characteristics (gender, age, and tenure), firm-level variables (log sales, log employment, log number of suppliers, labor productivity, share of VAT sales, and log number of suppliers), the average of firm-level variables among buyers and suppliers, and industry-municipality-year fixed effects. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

Table B.7: Top buyers and suppliers

	$h=1$ (1)	$h=2$ (2)	$h=3$ (3)	$h=4$ (4)	$h=5$ (5)
Own wages	0.904***	0.845***	0.809***	0.790***	0.773***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Coworkers' wages	0.039***	0.056***	0.062***	0.059***	0.060***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
Buyers' and suppliers' wages	0.021***	0.036***	0.043***	0.047***	0.052***
	(0.001)	(0.002)	(0.003)	(0.003)	(0.004)
Observations	3,635,107	2,859,118	2,305,066	1,846,774	1,452,587
R^2	0.846	0.742	0.670	0.619	0.573
	$h=6$ (6)	$h=7$ (7)	$h=8$ (8)	$h=9$ (9)	$h=10$ (10)
Own wages	0.756***	0.740***	0.727***	0.712***	0.700***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Coworkers' wages	0.061***	0.060***	0.066***	0.067***	0.066***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Buyers' and suppliers' wages	0.056***	0.057***	0.058***	0.060***	0.059***
	(0.004)	(0.005)	(0.006)	(0.007)	(0.008)
Observations	1,114,399	822,358	570,530	355,510	166,106
R^2	0.536	0.503	0.475	0.446	0.422

Notes: The table reports estimates of learning spillovers from cowokers and from the top three buyers and suppliers. The sample consists of workers employed at firms with less than 100 employees in year t. The dependent variable is workers' wages in year $t+h$, while the independent variables are at time t. All regressions control for gender, age, tenure, and year fixed effects. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

Table B.8: Measuring human capital with AKM worker fixed effects

	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$
	(1)	(2)	(3)	(4)	(5)
AKM worker FEs	0.931***	0.899***	0.872***	0.849***	0.830***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Coworkers' AKM FEs	0.148***	0.150***	0.149***	0.142***	0.130***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Buyers' and suppliers' AKM worker FEs	0.328***	0.327***	0.324***	0.314***	0.304***
	(0.012)	(0.013)	(0.013)	(0.014)	(0.014)
Observations	2,954,289	2,341,939	1,875,816	1,488,978	1,166,231
R^2	0.611	0.569	0.533	0.501	0.475
	$h=6$	$h=7$	$h=8$	$h=9$	$h=10$
	(6)	(7)	(8)	(9)	(10)
AKM worker FEs	0.812***	0.793***	0.778***	0.757***	0.742***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
Coworkers' AKM FEs	0.113***	0.091***	0.075***	0.049***	0.018*
	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)
Buyers' and suppliers' AKM worker FEs	0.293***	0.283***	0.275***	0.259***	0.225***
	(0.015)	(0.015)	(0.016)	(0.017)	(0.018)
Observations	891,064	652,876	449,660	277,849	127,735
R^2	0.452	0.431	0.412	0.392	0.379

Notes: The table reports estimates of learning spillovers from cowokers and from buyers and suppliers. The sample consists of workers employed at firms with less than 100 employees in year t. The dependent variable is workers' AKM fixed effects in year $t+h$, while the independent variables are at time t. All regressions control for gender, age, tenure, and year fixed effects. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

Table B.9: Upstream versus downstream learning spillovers

	$h=1$ (1)	$h=2$ (2)	$h=3$ (3)	$h=4$ (4)	$h=5$ (5)
Own wages	0.905***	0.847***	0.810***	0.793***	0.775***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Coworkers' wages	0.036***	0.052***	0.057***	0.053***	0.054***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Buyers' wages	0.013***	0.022***	0.027***	0.029***	0.030***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
Suppliers' wages	0.012***	0.019***	0.024***	0.027***	0.029***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)
Observations	3,162,952	2,499,709	2,019,263	1,623,433	1,280,769
R^2	0.842	0.738	0.666	0.615	0.568

	$h=6$ (6)	$h=7$ (7)	$h=8$ (8)	$h=9$ (9)	$h=10$ (10)
Own wages	0.759***	0.743***	0.731***	0.715***	0.701***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)
Coworkers' wages	0.055***	0.055***	0.061***	0.062***	0.065***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)
Buyers' wages	0.029***	0.026***	0.025***	0.029***	0.026***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)
Suppliers' wages	0.033***	0.037***	0.036***	0.034***	0.037***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)
Observations	984,640	727,910	506,579	315,559	147,474
R^2	0.531	0.500	0.473	0.443	0.419

Notes: The table reports estimates of learning spillovers from cowokers and from buyers and suppliers separately. The sample consists of workers employed at firms with less than 100 employees in year t. The dependent variable is workers' wages in year $t+h$, while the independent variables are at time t. All regressions control for gender, age, tenure, and year fixed effects. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

Table B.10: Asymmetric effects

	$h=1$ (1)	$h=2$ (2)	$h=3$ (3)	$h=4$ (4)	$h=5$ (5)
Own wages	0.884***	0.819***	0.779***	0.756***	0.740***
	(0.001)	(0.002)	(0.003)	(0.003)	(0.004)
Coworkers' wages > own wages	0.034***	0.046***	0.051***	0.050***	0.051***
	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
Coworkers' wages < own wages	0.032***	0.044***	0.049***	0.048***	0.049***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
B&S' wages > own wages	0.037***	0.059***	0.070***	0.075***	0.077***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)
B&S' wages < own wages	0.042***	0.067***	0.079***	0.084***	0.086***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)
Observations	3,636,837	2,860,575	2,306,188	1,847,631	1,453,246
R^2	0.846	0.742	0.670	0.619	0.573

	$h=6$ (6)	$h=7$ (7)	$h=8$ (8)	$h=9$ (9)	$h=10$ (10)
Own wages	0.727***	0.715***	0.705***	0.689***	0.679***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)
Coworkers' wages > own wages	0.054***	0.052***	0.058***	0.060***	0.059***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
Coworkers' wages < own wages	0.051***	0.050***	0.055***	0.057***	0.057***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
B&S' wages > own wages	0.076***	0.075***	0.072***	0.074***	0.068***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.009)
B&S' wages < own wages	0.084***	0.083***	0.080***	0.082***	0.075***
	(0.005)	(0.006)	(0.007)	(0.008)	(0.009)
Observations	1,114,896	822,704	570,805	355,637	1661,33
R^2	0.535	0.503	0.475	0.446	0.422

Notes: The table reports estimates of learning spillovers from cowokers and from buyers and suppliers, both for workers with wages above and below the average of buyers' and suppliers' wages. The sample consists of workers employed at firms with less than 100 employees in year t. The dependent variable is workers' wages in year $t+h$, while the independent variables are at time t. All regressions control for gender, age, tenure, and year fixed effects. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

Table B.11: Robustness to the inclusion of proxies of occupation

	All employees				
	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$
	(1)	(2)	(3)	(4)	(5)
Own wages	0.817***	0.712***	0.650***	0.624***	0.595***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)
Log avg wages of coworkers	0.080***	0.112***	0.125***	0.119***	0.123***
	(0.001)	(0.002)	(0.003)	(0.003)	(0.004)
Buyers' and suppliers' wages	0.028***	0.049***	0.059***	0.067***	0.073***
	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)
Observations	1,689,496	1,294,073	1,024,823	804,924	617,332
R^2	0.795	0.670	0.591	0.538	0.493
	$h=6$	$h=7$	$h=8$	$h=9$	$h=10$
	(6)	(7)	(8)	(9)	(10)
Own wages	0.572***	0.554***	0.541***	0.524***	0.506***
	(0.005)	(0.006)	(0.007)	(0.008)	(0.010)
Log avg wages of coworkers	0.126***	0.124***	0.126***	0.123***	0.122***
	(0.004)	(0.005)	(0.006)	(0.007)	(0.008)
Buyers' and suppliers' wages	0.078***	0.084***	0.087***	0.095***	0.094***
	(0.006)	(0.007)	(0.008)	(0.009)	(0.012)
Observations	460,237	329,413	220,997	133,066	59,434
R^2	0.460	0.431	0.402	0.372	0.347
	Only employees with tertiary education				
	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$
	(1)	(2)	(3)	(4)	(5)
Own wages	0.876***	0.779***	0.713***	0.670***	0.627***
	(0.002)	(0.003)	(0.005)	(0.006)	(0.007)
Coworkers' wages	0.063***	0.106***	0.131***	0.142***	0.156***
	(0.002)	(0.004)	(0.005)	(0.006)	(0.007)
Buyers' and suppliers' wages	0.024***	0.045***	0.057***	0.070***	0.079***
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)
Observations	264,448	218,643	182,491	151,155	123,589
R^2	0.854	0.744	0.662	0.602	0.547
	$h=6$	$h=7$	$h=8$	$h=9$	$h=10$
	(6)	(7)	(8)	(9)	(10)
Own wages	0.592***	0.563***	0.543***	0.517***	0.496***
	(0.008)	(0.009)	(0.011)	(0.012)	(0.015)
Coworkers' wages	0.167***	0.171***	0.174***	0.174***	0.181***
	(0.008)	(0.010)	(0.011)	(0.013)	(0.016)
Buyers' and suppliers' wages	0.086***	0.097***	0.114***	0.134***	0.113***
	(0.012)	(0.014)	(0.016)	(0.020)	(0.025)
Observations	98,057	73,961	51,784	32,408	14,843
R^2	0.503	0.468	0.437	0.406	0.374

Notes: The table reports estimates of learning spillovers from cowokers and from buyers and suppliers, controlling for degree-major-industry fixed effects. The sample consists of workers employed at firms with less than 100 employees in year t., and it is restricted to be the one including five lags of workers' own wages. The dependent variable is workers' wages in year $t+h$, while the independent variables are at time t. All regressions control for gender, age, tenure, and year fixed effects. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

Table B.12: Workers moving in t

	$h=1$ (1)	$h=2$ (2)	$h=3$ (3)	$h=4$ (4)	$h=5$ (5)
Own wages	0.927***	0.885***	0.834***	0.802***	0.779***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)
Coworkers' wages	0.078***	0.107***	0.108***	0.107***	0.103***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)
Buyers' and suppliers' wages	0.006*	0.012***	0.035***	0.046***	0.055***
	(0.003)	(0.004)	(0.006)	(0.008)	(0.010)
Observations	144,463	144,463	110,575	88,455	67,170
R^2	0.907	0.836	0.731	0.660	0.601

	$h=6$ (6)	$h=7$ (7)	$h=8$ (8)	$h=9$ (9)	$h=10$ (10)
Own wages	0.763***	0.755***	0.735***	0.732***	0.721***
	(0.006)	(0.008)	(0.010)	(0.013)	(0.018)
Coworkers' wages	0.096***	0.094***	0.093***	0.103***	0.108***
	(0.007)	(0.008)	(0.009)	(0.012)	(0.017)
Buyers' and suppliers' wages	0.056***	0.056***	0.052***	0.033*	0.017
	(0.011)	(0.014)	(0.016)	(0.020)	(0.028)
Observations	50,624	36,634	25,120	15,000	6,953
R^2	0.555	0.529	0.493	0.474	0.466

Notes: The table reports estimates of learning spillovers from cowokers and from buyers and suppliers. The sample consists of workers who changed firm between year $t-1$ and year t and remain at the destination firm for at least three years, and that were employed at firms with less than 100 employees in year t. The dependent variable is workers' wages in year $t+h$, while the independent variables are at time t. All regressions control for gender, age, tenure, and year fixed effects. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

B.3 Event studies of movers

Table B.13 reports the results of the event study regressions for displaced workers who change employer after a mass layoff. Table B.14 presents the regression results for workers moving before and after their origin firm establishes a high-wage connection.

Table B.13: Displaced workers' wages around mass layoffs

	$h=-4$	$h=-3$	$h=-2$	$h=-1$	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$	$h=7$	$h=8$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Own wages	0.680***	0.737***	0.791***	0.838***	0.725***	0.688***	0.673***	0.678***	0.679***	0.678***	0.653***	0.628***
	(0.014)	(0.013)	(0.011)	(0.011)	(0.016)	(0.018)	(0.017)	(0.021)	(0.019)	(0.022)	(0.025)	(0.024)
Coworkers' wages	0.022	0.019	0.052***	0.065***	-0.067***	-0.051***	-0.052***	-0.079***	-0.046**	-0.063***	-0.053*	-0.055
	(0.016)	(0.016)	(0.012)	(0.014)	(0.015)	(0.017)	(0.016)	(0.019)	(0.021)	(0.023)	(0.028)	(0.036)
Buyers' and suppliers' wages	0.002	0.014	0.025	-0.000	0.056*	0.068*	0.075**	0.148***	0.149***	0.109**	0.147**	0.246**
	(0.028)	(0.026)	(0.025)	(0.023)	(0.031)	(0.035)	(0.035)	(0.039)	(0.044)	(0.049)	(0.066)	(0.108)
Observations	50,022	64,573	86,737	86,737	48,041	44,386	40,070	32,984	19,980	14,500	9,721	6,362
R^2	0.623	0.698	0.798	0.856	0.584	0.528	0.489	0.479	0.494	0.498	0.440	0.416
Destination firm-year FE	No	No	No	No	No	No	No	No	No	No	No	No
					(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Own wages					0.726***	0.703***	0.678***	0.689***	0.703***	0.702***	0.693***	0.686***
					(0.024)	(0.022)	(0.024)	(0.024)	(0.023)	(0.023)	(0.033)	(0.031)
Coworkers' wages					-0.153***	-0.153***	-0.144***	-0.159***	-0.125***	-0.123***	-0.073**	-0.078**
					(0.016)	(0.016)	(0.018)	(0.019)	(0.020)	(0.023)	(0.029)	(0.037)
Buyers' and suppliers' wages					0.032	0.029	0.027	0.064*	0.119***	0.078*	0.051	0.247***
					(0.030)	(0.032)	(0.033)	(0.035)	(0.042)	(0.046)	(0.059)	(0.079)
Observations					37,015	33,601	30,075	24,347	13,814	9,765	6,323	4,082
R^2					0.813	0.791	0.768	0.769	0.798	0.797	0.774	0.766
Destination firm-year FE					Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports estimates of learning spillovers from buyers and suppliers for displaced workers around mass layoffs. The sample consists of workers aged at most 50 years old, employed by the same large firm (50 employees or more) for at least three consecutive years, that leave that firm during a year in which it reduces its workforce by at least 30%, and do not return to the same firm for at least three years. All regressions control for firm-level variables (log sales, log employment, labor productivity, share of VAT sales, and log number of suppliers), the average of firm-level variables among buyers and suppliers, and industry, municipality, and year fixed effects. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

Table B.14: Wages of workers moving before and after a high-wage connection

	$h=-4$ (1)	$h=-3$ (2)	$h=-2$ (3)	$h=-1$ (4)	$h=1$ (5)	$h=2$ (6)	$h=3$ (7)	$h=4$ (8)	$h=5$ (9)	$h=6$ (10)	$h=7$ (11)	$h=8$ (12)
Own wages	0.788***	0.827***	0.858***	0.902***	0.923***	0.874***	0.841***	0.809***	0.777***	0.757***	0.746***	0.726***
	(0.034)	(0.028)	(0.023)	(0.015)	(0.015)	(0.020)	(0.021)	(0.025)	(0.031)	(0.027)	(0.033)	(0.040)
Moving after high-wage connection	-0.001	0.016	0.011	0.020	0.030	0.029	0.063**	0.081***	0.093***	0.081**	0.056	0.077**
	(0.031)	(0.029)	(0.023)	(0.028)	(0.030)	(0.022)	(0.026)	(0.027)	(0.035)	(0.036)	(0.041)	(0.037)
Moving before high-wage connection	0.015	-0.003	0.002	0.021	0.005	0.007	0.013	0.015	0.023	0.025	0.004	0.047
	(0.027)	(0.022)	(0.022)	(0.025)	(0.033)	(0.017)	(0.017)	(0.021)	(0.026)	(0.029)	(0.045)	(0.052)
p-value of Wald test (after = before)	0.407	0.173	0.486	0.880	0.579	0.273	0.010	0.002	0.009	0.078	0.177	0.477
Observations	67,112	83,713	100,009	129,511	130,595	101,888	82,374	65,156	49,918	37,676	28,105	20,648
R^2	0.827	0.854	0.882	0.923	0.922	0.882	0.853	0.829	0.809	0.795	0.782	0.778

Notes: The table reports estimates of learning spillovers from buyers and suppliers for workers who change employer before and after their origin employer establishes a high-wage connection. A high-wage connection is defined as the first occurrence in which the origin firm trades with a firm in the top decile of the average log wage distribution across all firms, the new buyer or supplier is among the top five buyers or suppliers in terms of sales, and the highest wage connection in the previous two years was at most in the seventh decile of the average log wage distribution. The treatment groups consist of workers who remained at the origin firm at least two years and do not return to the origin firm for at least two years, the control group consists of all workers who remain with the same employer in years t and $t+1$. All regressions control for worker-level variables (age, gender, tenure) and industry, municipality, and firm-year fixed effects. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

B.4 Product exports: Sample information and heterogeneity

The sample used in the analysis in Subsection 4.5 comprises approximately 7,000 firms that exported at least one product for the first time, and around 52,000 firm-product instances of first-time exports. In 17% of cases, the exporting firm had hired a worker whose previous employer was already exporting that product (14% for products in the bottom quartile of the product complexity distribution, and 20% for those in the top quartile). In 28% of cases, the firm had hired a worker from one of the top three suppliers of a firm exporting the same product (20% for products in the bottom quartile of the product complexity distribution, and 32% for those in the top quartile). The unconditional probabilities of hiring from an exporter or a top supplier are 4 and 10%, respectively.

Previous literature documents that countries exporting more complex products tend to experience faster income growth (Hausmann et al., 2014), suggesting that the technological content of exported goods reflects firms' capabilities—and, more broadly, the human capital of their employees.[36]

Given the importance of product complexity, we examine whether the relationship between hiring and export entry varies across products of different complexity levels. Specifically, we allow the coefficients β^h and γ^h to vary by quartile of product complexity. The results, shown in Figure B.1, indicate that the link between hiring from suppliers of exporting firms and subsequent export entry is stronger for highly complex products.[37]

We conclude by examining whether the tenure of workers at their origin firm influences the estimated effects. To do so, we split the sample of job-to-job transitions based on whether workers had been employed at their previous firm for less than or more than three years.[38] Figure B.2 shows that the patterns documented thus far are primarily driven by workers with longer tenure at exporting firms or their suppliers. This finding is consistent with the idea that product-specific human capital takes time to accumulate.

[36] During the sample period, the average product complexity of Dominican exports—measured using the Product Complexity Index (PCI) from Hausmann et al. (2014)—increased significantly, as shown in Figure B.3.

[37] As an alternative approach, we augment the specification in Equation 7 by interacting product complexity with the variables $NewH_{p,f,t+h}$ and $NewHS_{p,f,t+h}$. The interaction between product complexity and $NewHS_{p,f,t+h}$ is positive and statistically significant for $h = 0, 1, 2$.

[38] When multiple workers move in the same year from a firm exporting a given product or from its suppliers, we use the average tenure. The median tenure among movers is two years, and only about one-third had been at their previous firm for three years or longer.

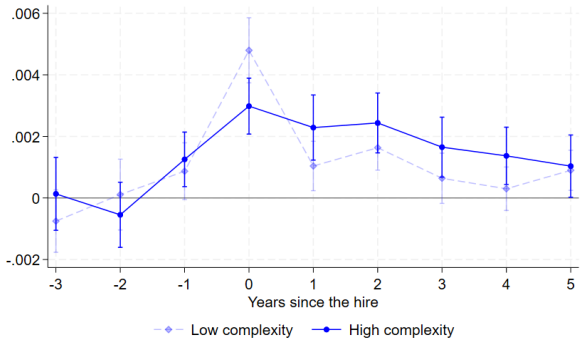
Table B.15: Product exports and hiring from exporting firms or their suppliers

	$h=-3$	$h=-2$	$h=-1$	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Hire from exporter	-0.000	-0.000	0.001***	0.003***	0.002***	0.002***	0.001***	0.000*	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hire from exporter's top supplier	-0.000	-0.001*	-0.000	0.004***	0.001**	0.001***	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	5,880,419	7,654,435	9,984,767	16,736,162	9,980,351	7,649,091	5,876,539	4,347,099	3,019,156
R^2	0.245	0.243	0.241	0.228	0.227	0.222	0.216	0.212	0.212

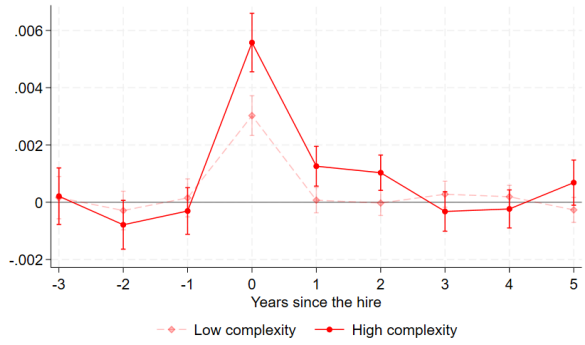
Notes: The table reports estimates of the probability of exporting a product and hiring from an exporter of that product or one of its main suppliers. The sample consists of observations post-2016 to identify whether firms had previously exported a given product or hired workers from relevant firms. All regressions control for firm-year-product class fixed effects and product-year fixed effects. Standard errors are clustered at the firm level. ***, **,* denote statistical significance at 1, 5, and 10% levels.

Figure B.1: Probability of exporting a new product, conditional on product complexity
(Percentage points)

(a) Hire from exporter



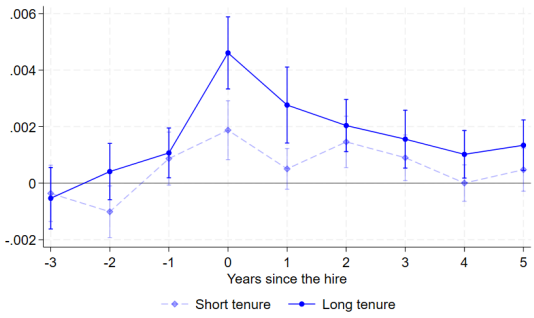
(b) Hire from exporter's top supplier



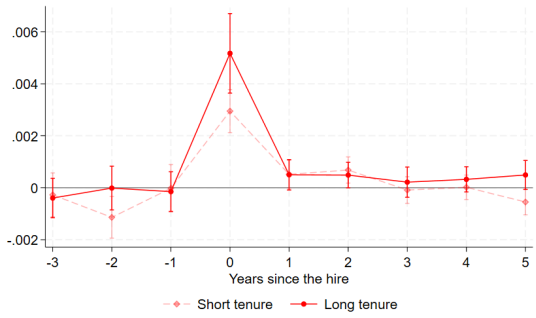
Notes: The figure shows the relationship between the probability of exporting a product and hiring from an exporter of that product or one of its main suppliers, by the level of product complexity. High (low) complexity products are those in the top (bottom) quartile of the product complexity distribution. The sample consists of observations post-2016 to identify whether firms had previously exported a given product or hired workers from relevant firms. All regressions control for firm-year-product class fixed effects and product-year fixed effects. The dots denote the point estimates and the whiskers denote the 90% confidence intervals, obtained from standard errors clustered at the firm level.

Figure B.2: Probability of exporting a new product, conditional on tenure at origin firm
(Percentage points)

(a) Hire from exporter

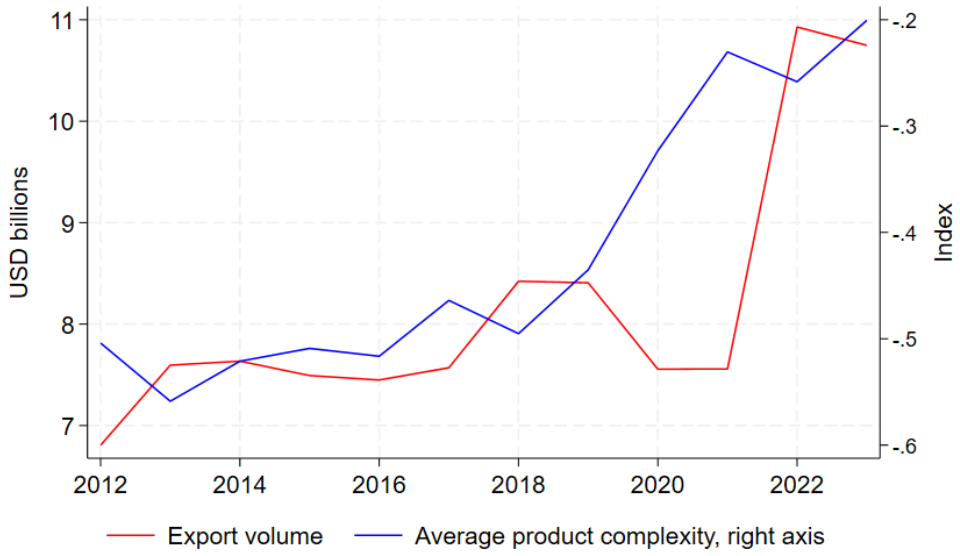


(b) Hire from exporter's top supplier



Notes: The figure shows the relationship between the probability of exporting a product and hiring from an exporter of that product or one of its main suppliers, by tenure at origin firm. Long (short) tenure corresponds to more (less) than three years at the origin firm. The sample consists of observations post-2016 to identify whether firms had previously exported a given product or hired workers from relevant firms. All regressions control for firm-year-product class fixed effects and product-year fixed effects. The dots denote the point estimates and the whiskers denote the 90% confidence intervals, obtained from standard errors clustered at the firm level.

Figure B.3: Export volume and product complexity



Notes: The figure shows the time series of export volume and the average of product complexity across exported Dominican products.

B.5 Returns to network size in the EUE regression

Table B.16 reports estimates from augmenting the baseline EUE specification in Equation 1 with two interaction terms: buyers' and suppliers' wages interacted with the network size of the employer's buyers and suppliers (as in Table 4), and buyers' and suppliers' wages interacted with the employer's own network size, measured as the log number of buyers and suppliers at the origin firm. Column (1) uses wages and Column (2) uses worker fixed effects from an AKM decomposition as the measure of human capital.

The coefficient on the own-network interaction is positive and statistically significant. A one standard deviation increase in the number of buyers and suppliers is associated with a 12–17% increase in the elasticity of wages to buyers' and suppliers' wages. This indicates that workers at more connected firms experience stronger learning spillovers from the supply chain, consistent with a network aggregation that lies between the sum ($\eta = 0$) and the mean ($\eta = 1$).

Table B.16: Returns to own network size in the EUE regression

	(1) Wages	(2) AKM FEs
Log wages at t	0.373***	0.363***
	(0.007)	(0.007)
Coworkers' wages at t	0.015**	
	(0.006)	
B&S wages at t	0.087***	
	(0.012)	
Coworkers' AKM FEs at t		0.124***
		(0.008)
B&S workers' AKM FEs at t		0.158***
		(0.020)
B&S wages × B&S network size	−0.005	−0.015
	(0.006)	(0.009)
B&S wages × own network size	0.010*	0.023**
	(0.005)	(0.009)
1 SD own network / B&S coeff. (%)	12	17
R^2	0.313	0.318
Observations	72,527	72,532

Notes: The dependent variable is the worker's log wage at $t+2$. The sample consists of workers experiencing EUE transitions, employed at firms with at most 100 employees in year t. Own network size is the log number of buyers and suppliers of the employer at t. B&S network size is the weighted average of the log number of buyers' suppliers and suppliers' buyers. Both interaction variables are demeaned. The row "1 SD own network / B&S coeff." reports the percentage change in the B&S wage elasticity associated with a one standard deviation increase in own network size. Controls include worker characteristics, firm-level variables, the average of firm-level variables among buyers and suppliers, and industry-municipality-year fixed effects. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C Proofs

This appendix provides detailed proofs of all lemmas and propositions.

C.1 Proof of Lemma 1 (monotonicity of worker value)

Proof. We establish that the joint marginal value of a worker is strictly increasing in skill, that is $\Psi_{\ell+1}(\boldsymbol{z}) > \Psi_\ell(\boldsymbol{z})$, using backward induction on the skill level ℓ.

Base case ($\ell = H-1$). Workers at the top of the skill ladder (h_H) cannot upgrade further, so $\lambda_H = 0$. The marginal value Ψ_H satisfies

$$\rho\Psi_H = \mathrm{MP}_H - s_H\Psi_H,$$

where $\mathrm{MP}_\ell \equiv \partial\pi/\partial n_\ell$ denotes the marginal product of a type-ℓ worker. Solving this expression yields $\Psi_H = \mathrm{MP}_H/(\rho + s_H)$. For a type-$(H-1)$ worker, the marginal value satisfies

$$\rho\Psi_{H-1} = \mathrm{MP}_{H-1} + \lambda_{H-1}\Big[\Psi_H - \Psi_{H-1}\Big] - s_{H-1}\Psi_{H-1},$$

which can be rearranged as $\Psi_{H-1} = (\mathrm{MP}_{H-1} + \lambda_{H-1}\Psi_H)/(\rho + s_{H-1} + \lambda_{H-1})$. By Assumption 1, $a_H > a_{H-1}$ implies $\mathrm{MP}_H > \mathrm{MP}_{H-1}$. Since $\Psi_H > \Psi_{H-1}$ requires

$$\frac{\mathrm{MP}_H}{\rho + s_H} > \frac{\mathrm{MP}_{H-1} + \lambda_{H-1}\Psi_H}{\rho + s_{H-1} + \lambda_{H-1}},$$

rearranging and using $\mathrm{MP}_H > \mathrm{MP}_{H-1}$ confirms $\Psi_H > \Psi_{H-1}$.

Inductive step. Suppose $\Psi_{k+1}(\boldsymbol{z}) > \Psi_k(\boldsymbol{z})$ for all $k \geq \ell$. We now consider a type-$(\ell-1)$ worker, whose marginal value satisfies

$$\Psi_{\ell-1} = \frac{\mathrm{MP}_{\ell-1} + \lambda_{\ell-1}\Psi_\ell}{\rho + s_{\ell-1} + \lambda_{\ell-1}}.$$

Comparing this expression with that of a type-Ψ_ℓ worker,

$$\Psi_\ell = \frac{\mathrm{MP}_\ell + \lambda_\ell\Psi_{\ell+1}}{\rho + s_\ell + \lambda_\ell}.$$

reveals two forces that ensure $\Psi_\ell > \Psi_{\ell-1}$. First, $\mathrm{MP}_\ell > \mathrm{MP}_{\ell-1}$ by Assumption 1. Second, the option value of upgrading is higher for type-ℓ workers: by the inductive hypothesis, $\Psi_{\ell+1} - \Psi_\ell > 0$, and type-$\ell$ workers are closer to capturing this gain. Both effects reinforce monotonicity, completing the induction. □

C.2 Proof of Proposition 1 (effect of spillover intensity)

Proof. We aim to sign the derivative of aggregate human capital with respect to the spillover parameter, $dH_{\text{agg}}/d\gamma$, for $\gamma \in \{\gamma_c, \gamma_n\}$. Since $\partial\lambda_\ell(i)/\partial\gamma > 0$, it suffices to determine the sign of $dH_{\text{agg}}/d\lambda_\ell(i)$.

The steady-state workforce distribution solves the system of flow-balance equations $\mathcal{F}(\boldsymbol{n}, \boldsymbol{\lambda}) = \mathbf{0}$ in Equation 14, which corresponds to the workforce dynamics in the main text. By the implicit function theorem,

$$\frac{d\boldsymbol{n}}{d\lambda_\ell} = -\boldsymbol{\mathcal{J}}^{-1}\frac{\partial\mathcal{F}}{\partial\lambda_\ell},$$

where $\boldsymbol{\mathcal{J}} = \partial\mathcal{F}/\partial\boldsymbol{n}$ is the Jacobian matrix of the system. Stability of the stready state requires that $-\mathbf{J}$ is a non-singular M-matrix, which implies $-\mathbf{J}^{-1} \geq 0$ element-wise.[39]

The perturbation vector $\partial\mathcal{F}/\partial\lambda_\ell$ has two components:

- *Direct effect*: $\partial\boldsymbol{A}/\partial\lambda_\ell \cdot \boldsymbol{n} = n_\ell(\boldsymbol{e}_{\ell+1} - \boldsymbol{e}_\ell)$, representing the direct flow of workers from skill level ℓ to $\ell + 1$.
- *Hiring response*: $\partial\boldsymbol{f}/\partial\lambda_\ell \geq \mathbf{0}$, where $\boldsymbol{f}$ captures vacancy-driven inflows. This is non-negative because higher learning rates raise Ψ_ℓ, inducing more hiring.

The change in aggregate human capital is

$$\frac{dH_{\text{agg}}}{d\lambda_\ell} = \boldsymbol{h}^T\frac{d\boldsymbol{n}}{d\lambda_\ell} = \boldsymbol{h}^T\left(-\boldsymbol{\mathcal{J}}^{-1}\right)\frac{\partial\mathcal{F}}{\partial\lambda_\ell}.$$

Since $-\boldsymbol{\mathcal{J}}^{-1} \geq 0$ and the perturbation vector induces net upward movement in the skill distribution, $dH_{\text{agg}}/d\lambda_\ell > 0$. Applying the chain rule the implies $dH_{\text{agg}}/d\gamma > 0$ for both spillover parameters. □

D Identification: Assumptions and proofs

This appendix provides the theoretical foundation for the identification result stated in Proposition 3, clarifying the assumptions under which network-partner wages can be used as proxies for learning spillovers.

[39] A sufficient condition is that separation rates $\{s_\ell\}$ are large relative to learning rates and network spillover intensities, ensuring $-\mathbf{J}$ is strictly diagonally dominant.

D.1 Assumptions

Assumption 2 (Wage monotonicity)**.** Equilibrium wages are strictly increasing in worker skill: $w_k(f) < w_{k'}(f)$ for $h_k < h_{k'}$.

Assumption 3 (Separable wage structure)**.** The wage function satisfies $w_k(f) = \omega(h_k) \cdot \Gamma(f) + \kappa$, where $\omega(\cdot)$ is strictly increasing in worker skill.

Assumption 4 (Log-linear wages)**.** Log wages are approximately linear in log skill: $\log w_k(f) \approx \mu(f) + \sigma \log h_k$.

Assumption 5 (Network heterogeneity)**.** Conditional on coworker wages and controls, network-partner wages exhibit residual variation: $\mathrm{Var}(\tilde{w}^{net}_{i,t} | \tilde{w}^{cw}_{i,t}, X_{i,t}) > 0$.

Assumption 2 follows from model primitives (Lemma 1). Assumption 3 is satisfied when production is linear in efficiency units or when CES substitutability is sufficiently high. Assumption 4 is a local approximation that when the skill ladder is approximately log-linearly spaced. Assumption 5 requires that firms' positions in production networks are not perfectly aligned with their internal wage structures. This condition is satisfied whenever firms with similar coworker wages differ in the wage levels of their buyers and suppliers, as is the case in empirically observed production networks.

D.2 Supporting lemmas

Lemma 2 (Labor market conditions and skill)**.** *Under Assumption 1:*

(i) Labor market tightness is weakly increasing in skill: $\theta_{\ell+1} \geq \theta_\ell$.

(ii) The job-finding rate is weakly increasing in skill: $p_{\ell+1} \geq p_\ell$.

(iii) The value of unemployment is strictly increasing in skill: $U_{\ell+1} > U_\ell$.

Proof. Part (i). The first-order condition for vacancies implies $c'(v_\ell/n_\ell) = q_\ell(\theta_\ell)\mathbb{E}[\Psi_\ell]$. The cost of a successful hire is $c'(\cdot)/q_\ell(\theta_\ell)$, which is increasing in θ_ℓ. Since $\mathbb{E}[\Psi_{\ell+1}] > \mathbb{E}[\Psi_\ell]$ by Lemma 1, equilibrium requires firms to post relatively more vacancies for higher-skill workers, implying $\theta_{\ell+1} \geq \theta_\ell$.

Part (ii). The job-finding rate $p_\ell = \theta_\ell q_\ell(\theta_\ell)$ is increasing in θ_ℓ for standard matching functions. Hence, higher labor market tightness for skilled workers translates directly into higher job-finding rates, so $p_{\ell+1} \geq p_\ell$.

Part (iii). The value of unemployment satisfies $\rho U_\ell = b_\ell + p_\ell \mathbb{E}[\max(\beta(\Psi_\ell - U_\ell), 0)]$. Since $p_{\ell+1} \geq p_\ell$ and $\mathbb{E}[\Psi_{\ell+1}] > \mathbb{E}[\Psi_\ell]$, the right-hand side is larger for $\ell + 1$, implying $U_{\ell+1} > U_\ell$.[40] □

This lemma establishes that climbing the skill ladder—facilitated by learning spillovers—systematically improves workers' labor market prospects. Higher-skilled workers enjoy faster re-employment rates and stronger outside options. This monotonicity property ensures that skill acquisition translates into improved labor market outcomes.

D.3 Proof of Proposition 3 (identification)

Proof. We establish each part through a sequence of intermediate results as follows.

Step 1: Equilibrium wages are strictly increasing in skill.

We show $w_{\ell+1}(i) > w_\ell(i)$ for all $\ell < H$ and all firms i. From the Nash bargaining solution in Equation 17

$$w_\ell(i) = (1 - \beta)U_\ell + \beta\Psi_\ell(i). \tag{22}$$

By Lemma 1, $\Psi_{\ell+1}(i) > \Psi_\ell(i)$. It therefore remains to show that $U_{\ell+1} \geq U_\ell$.

The value of unemployment satisfies

$$\rho U_\ell = b_\ell + p_\ell(\theta_\ell)\, \mathbb{E}_j \left[\beta(\Psi_\ell(j) - U_\ell)^+\right],$$

where $(x)^+ = \max\{x, 0\}$ and the expectation is over firms j posting vacancies for type-ℓ workers. In equilibrium, if all matches generate positive surplus (which holds when b_ℓ is not too large), workers accept all offers and

$$U_\ell = \frac{b_\ell + p_\ell \beta\, \mathbb{E}_j[\Psi_\ell(j)]}{\rho + p_\ell \beta}.$$

Since $\mathbb{E}_j[\Psi_{\ell+1}(j)] > \mathbb{E}_j[\Psi_\ell(j)]$ (by Lemma 1), and assuming the flow value of employment exceeds unemployment benefits ($\rho \mathbb{E}_j[\Psi_\ell(j)] > b_\ell$ for all ℓ, which holds when b_ℓ is not too large), we have $U_{\ell+1} \geq U_\ell$.

Combining with $\Psi_{\ell+1}(i) > \Psi_\ell(i)$ in Equation 22:

$$w_{\ell+1}(i) > w_\ell(i) \quad \text{for all } \ell < H. \tag{23}$$

[40] Formally, define $T_\ell(U) = [b_\ell + p_\ell \mathbb{E}[\max\{\beta(\Psi_\ell - U), 0\}]]/\rho$. Since T_ℓ is strictly decreasing in U and $T_{\ell+1}(U) > T_\ell(U)$ for all U, the fixed point shifts right: $U_{\ell+1} > U_\ell$.

Step 2: Coworker wages proxy for coworker skill; network wages proxy for network skill.

We show that $\tilde{w}_{i,t}^{cw}$ is a valid proxy for $\text{CSP}_\ell(i)$ and that $\tilde{w}_{i,t}^{net}$ is a valid proxy for $\text{NSP}_\ell(i)$.

Recall that

$$\text{CSP}_\ell(i) = \frac{\bar{h}(i)}{h_\ell} = \frac{1}{h_\ell} \sum_{m=1}^{H} \frac{n_m(i)}{n(i)} h_m, \qquad \text{NSP}_\ell(i) = \frac{1}{h_\ell} \cdot |\mathcal{P}(i)|^{-\eta} \sum_{j \in \mathcal{P}(i)} \bar{h}(j).$$

For a worker at skill level ℓ, both objects are proportional to average skill—within the firm or across network partners—scaled by $1/h_\ell$.

By Step 1, wages are strictly increasing in skill. Therefore, within any firm or set of firms:

- Higher average coworker wages $\tilde{w}_{i,t}^{cw}$ indicate higher average coworker skill $\bar{h}(i)$
- Higher average network-partner wages $\tilde{w}_{i,t}^{net}$ indicate higher average network skill $\bar{h}^{net}(i)$

Conditional on firm-specific wage premia $\mu(i)$, absorbed by firm fixed effects in the regression, $\tilde{w}_{i,t}^{cw}$ is strictly increasing in $\bar{h}(i)$, and $\tilde{w}_{i,t}^{net}$ is strictly increasing in $\bar{h}^{net}(i)$. Hence there exist strictly increasing functions such that

$$\bar{h}(i) = f_c(\tilde{w}_{i,t}^{cw}; \mu(i)), \qquad \bar{h}^{net}(i) = f_n(\tilde{w}_{i,t}^{net}; \mu^{net}(i)). \tag{24}$$

Step 3: Skill distribution at separation.

Consider a worker who enters firm i at skill level h_ℓ. While employed, the worker:

- Upgrades from skill m to $m+1$ at Poisson rate $\lambda_m(i)$ for $m < H$
- Separates from the firm at Poisson rate s_m when at skill level m

Let $P_k(\ell, i)$ denote the probability that such a worker separates at skill level k. By standard results on competing Poisson processes:

Case $k = \ell$ (separates without upgrading):

$$P_\ell(\ell, i) = \frac{s_\ell}{s_\ell + \lambda_\ell(i)}. \tag{25}$$

Case $\ell < k < H$ (upgrades to k, then separates):

$$P_k(\ell, i) = \left[\prod_{m=\ell}^{k-1} \frac{\lambda_m(i)}{s_m + \lambda_m(i)} \right] \cdot \frac{s_k}{s_k + \lambda_k(i)}. \tag{26}$$

Case $k = H$ (reaches top of ladder):

$$P_H(\ell, i) = \prod_{m=\ell}^{H-1} \frac{\lambda_m(i)}{s_m + \lambda_m(i)}. \tag{27}$$

Verification: Define $\pi_m \equiv \lambda_m/(s_m + \lambda_m)$ (probability of upgrading before separating at level m). Then

$$P_\ell = 1 - \pi_\ell, \quad P_k = (1 - \pi_k) \prod_{m=\ell}^{k-1} \pi_m \text{ for } \ell < k < H, \quad P_H = \prod_{m=\ell}^{H-1} \pi_m.$$

Summing: $\sum_{k=\ell}^{H} P_k = (1 - \pi_\ell) + \pi_\ell(1 - \pi_{\ell+1}) + \pi_\ell\pi_{\ell+1}(1 - \pi_{\ell+2}) + \cdots = 1$ by telescoping.

Step 4: Higher spillovers shift the separation distribution toward higher skills.

We show that increasing any $\lambda_m(i)$ for $m \geq \ell$ shifts the distribution $\{P_k(\ell, i)\}_{k=\ell}^{H}$ in the sense of first-order stochastic dominance (FOSD).

Claim: For any $m \in \{\ell, \ldots, H-1\}$, increasing λ_m decreases $F_k \equiv \sum_{j=\ell}^{k} P_j$ for all $k \geq m$, which is the definition of FOSD.

Proof of Claim: We compute $\partial P_j/\partial \lambda_m$ for each j:

- For $j < m$: P_j does not depend on λ_m, so $\partial P_j/\partial \lambda_m = 0$.
- For $j = m$: $P_m = (1 - \pi_m)\prod_{r=\ell}^{m-1} \pi_r$ where $\pi_m = \lambda_m/(s_m + \lambda_m)$. Thus

$$\frac{\partial P_m}{\partial \lambda_m} = -\frac{s_m}{(s_m + \lambda_m)^2} \prod_{r=\ell}^{m-1} \pi_r < 0.$$

- For $j > m$: P_j contains factor π_m, so $P_j = \pi_m \cdot Q_j$ for some $Q_j > 0$ independent of λ_m. Thus

$$\frac{\partial P_j}{\partial \lambda_m} = Q_j \frac{s_m}{(s_m + \lambda_m)^2} > 0.$$

Since $\sum_j P_j = 1$, we have $\sum_j \partial P_j/\partial \lambda_m = 0$. The mass lost at $j = m$ equals the mass gained at $j > m$. For any $k \geq m$

$$\frac{\partial F_k}{\partial \lambda_m} = \sum_{j=\ell}^{k} \frac{\partial P_j}{\partial \lambda_m} = \frac{\partial P_m}{\partial \lambda_m} + \sum_{j=m+1}^{k} \frac{\partial P_j}{\partial \lambda_m}.$$

Since $\partial P_m/\partial \lambda_m < 0$ and the positive mass shifts to $j > m$ (some of which is beyond k when $k < H$), we have $\partial F_k/\partial \lambda_m \leq 0$ with strict inequality for $k < H$. This establishes FOSD. □

Now, since $\lambda_m(i) = \gamma_c \cdot \text{CSP}_m(i) + \gamma_n \cdot \text{NSP}_m(i)$, where $\text{CSP}_m(i) = \bar{h}(i)/h_m$ and $\text{NSP}_m(i) = \bar{h}^{net}(i)/h_m$:

- When $\gamma_c > 0$: higher $\bar{h}(i)$ raises $\text{CSP}_m(i)$ for all m, hence raises $\lambda_m(i)$ for all m, inducing a FOSD shift toward higher k
- When $\gamma_n > 0$: higher $\bar{h}^{net}(i)$ raises $\text{NSP}_m(i)$ for all m, hence raises $\lambda_m(i)$ for all m, inducing a FOSD shift toward higher k

Step 5: Expected destination wages and sign identification.

A worker who separates at skill k and is hired from unemployment by firm j receives wage $w_k(j)$. The expected log destination wage, conditional on starting at skill ℓ in firm i, is

$$\mathbb{E}[\tilde{w}_{j,t+2}|\ell, i] = \sum_{k=\ell}^{H} P_k(\ell, i) \cdot \mathbb{E}_j[\tilde{w}_k(j)], \tag{28}$$

where $\mathbb{E}_j[\tilde{w}_k(j)]$ is the expected log wage at the destination firm for a worker of skill k, averaging over hiring firms.

By Step 1, $\mathbb{E}_j[\tilde{w}_k(j)]$ is strictly increasing in k.

By Step 4, when $\gamma_c > 0$, increasing $\bar{h}(i)$ raises all learning rates $\lambda_m(i)$, inducing a FOSD shift in $\{P_k\}$ toward higher k. Similarly, when $\gamma_n > 0$, increasing $\bar{h}^{net}(i)$ induces a FOSD shift toward higher k.

By a standard property of FOSD: if distribution P' first-order stochastically dominates P, and $u(k)$ is strictly increasing, then $\mathbb{E}_{P'}[u(k)] > \mathbb{E}_P[u(k)]$.

Applying this with $u(k) = \mathbb{E}_j[\tilde{w}_k(j)]$: higher $\bar{h}(i)$ or $\bar{h}^{net}(i)$ raises expected destination wages when the corresponding spillover parameter is positive. Formally,

$$\frac{\partial \mathbb{E}[\tilde{w}_{j,t+2}|\ell, i]}{\partial \bar{h}(i)} > 0 \iff \gamma_c > 0, \qquad \frac{\partial \mathbb{E}[\tilde{w}_{j,t+2}|\ell, i]}{\partial \bar{h}^{net}(i)} > 0 \iff \gamma_n > 0. \tag{29}$$

By Step 2, $\bar{h}(i)$ is monotonically related to $\tilde{w}^{cw}_{i,t}$ and $\bar{h}^{net}(i)$ is monotonically related to $\tilde{w}^{net}_{i,t}$, conditional on firm-specific premia. Hence,

$$\frac{\partial \mathbb{E}[\tilde{w}_{j,t+2}]}{\partial \tilde{w}^{cw}_{i,t}} > 0 \iff \gamma_c > 0, \qquad \frac{\partial \mathbb{E}[\tilde{w}_{j,t+2}]}{\partial \tilde{w}^{net}_{i,t}} > 0 \iff \gamma_n > 0. \tag{30}$$

This establishes part (i). □

Step 6: Coefficient identification.

We derive the relationship between OLS coefficients and structural parameters.

For a worker at skill ℓ in firm i, the effect of network-partner wages on expected destination wages operates through all learning rates $\{\lambda_m(i)\}_{m=\ell}^{H-1}$

$$\frac{\partial \mathbb{E}[\tilde{w}_{j,t+2}|\ell,i]}{\partial \tilde{w}_{i,t}^{net}} = \sum_{m=\ell}^{H-1} \frac{\partial \mathbb{E}[\tilde{w}_{j,t+2}|\ell,i]}{\partial \lambda_m(i)} \cdot \frac{\partial \lambda_m(i)}{\partial \text{NSP}_m(i)} \cdot \frac{\partial \text{NSP}_m(i)}{\partial \tilde{w}_{i,t}^{net}}. \tag{31}$$

Since $\text{NSP}_m(i) = \bar{h}^{net}(i)/h_m$, an increase in $\tilde{w}_{i,t}^{net}$ raises $\bar{h}^{net}(i)$ and hence raises $\text{NSP}_m(i)$ for all m. Moreover, $\partial\lambda_m/\partial\text{NSP}_m = \gamma_n$ for all m.

Define

$$\Delta_\ell(i) \equiv \sum_{m=\ell}^{H-1} \frac{\partial \mathbb{E}[\tilde{w}_{j,t+2}|\ell,i]}{\partial \lambda_m(i)} \cdot \frac{1}{h_m} > 0,$$

which captures how faster learning across all levels raises expected destination wages. This is positive by Step 4.

Define

$$\xi(i) \equiv \frac{\partial \bar{h}^{net}(i)}{\partial \tilde{w}_{i,t}^{net}} > 0,$$

which captures how network wages map to network skill. This is positive by Step 2.

Then,

$$\frac{\partial \mathbb{E}[\tilde{w}_{j,t+2}|\ell,i]}{\partial \tilde{w}_{i,t}^{net}} = \gamma_n \cdot \Delta_\ell(i) \cdot \xi(i). \tag{32}$$

The OLS coefficient ϕ_2 identifies the average marginal effect

$$\phi_2 = \mathbb{E}\left[\frac{\partial \mathbb{E}[\tilde{w}_{j,t+2}|\ell,i]}{\partial \tilde{w}_{i,t}^{net}}\right] = \gamma_n \cdot \underbrace{\mathbb{E}[\Delta_\ell(i) \cdot \xi(i)]}_{\equiv \bar{\Lambda}_n > 0}. \tag{33}$$

Since $\Delta_\ell(i) > 0$ and $\xi(i) > 0$ for all workers, $\bar{\Lambda}_n > 0$.

By an identical argument,

$$\phi_1 = \gamma_c \cdot \bar{\Lambda}_c, \qquad \bar{\Lambda}_c \equiv \mathbb{E}[\Delta_\ell(i) \cdot \zeta(i)] > 0, \tag{34}$$

where $\zeta(i) = \partial\bar{h}(i)/\partial\tilde{w}_{i,t}^{cw} > 0$.

Separate identification: Assumption 5 ensures $\text{Var}(\tilde{w}_{i,t}^{net}|\tilde{w}_{i,t}^{cw}, X_{i,t}) > 0$. This residual variation identifies ϕ_2 separately from ϕ_1.

This establishes part (ii). □

Step 7: Structural recovery.

From Equation 33 and Equation 34

$$\gamma_c = \frac{\phi_1}{\bar{\Lambda}_c}, \qquad \gamma_n = \frac{\phi_2}{\bar{\Lambda}_n}. \tag{35}$$

The scaling factors $\bar{\Lambda}_c$ and $\bar{\Lambda}_n$ depend on:

- The skill ladder $\{h_\ell\}_{\ell=1}^H$
- The separation rates $\{s_\ell\}_{\ell=1}^H$
- The equilibrium distribution of workers across skill levels and firms

These objects are either directly observable or can be calibrated from data moments, allowing recovery of γ_c and γ_n.

This establishes part (iii). □ □

D.4 Proof of Proposition 2 (network participation)

Proof. We establish the result in two steps: first, we show that disconnecting firm i reduces aggregate human capital; second, we show that the reduction is increasing in the employment share of firm i.

Step 1: Disconnection reduces aggregate human capital.

When firm i is disconnected, $\mathcal{P}(i) = \emptyset$ and hence $\text{NSP}_\ell(i) = 0$ for all ℓ. The learning rate at firm i falls from

$$\lambda_\ell(i) = \gamma_c \text{CSP}_\ell(i) + \gamma_n \text{NSP}_\ell(i)$$

to $\lambda_\ell^0(i) = \gamma_c \text{CSP}_\ell(i)$. Since $\gamma_n > 0$ and $\text{NSP}_\ell(i) > 0$ prior to disconnection, $\lambda_\ell^0(i) < \lambda_\ell(i)$ for all $\ell < H$.

The steady-state workforce distribution at firm i solves the flow-balance system $\mathcal{F}(\boldsymbol{n}(i), \boldsymbol{\lambda}(i)) = \mathbf{0}$ from Equation 14. By the implicit function theorem,

$$\frac{d\boldsymbol{n}(i)}{d\lambda_\ell(i)} = -\mathcal{J}_i^{-1} \frac{\partial \mathcal{F}_i}{\partial \lambda_\ell(i)},$$

where $\mathcal{J}_i = \partial \mathcal{F}_i / \partial \boldsymbol{n}(i)$. As in the proof of Proposition 1, stability of the steady state implies that $-\mathcal{J}_i$ is a non-singular M-matrix, so $-\mathcal{J}_i^{-1} \geq 0$ element-wise.

The perturbation from reducing $\lambda_\ell(i)$ shifts workers from skill level $\ell+1$ back toward ℓ. Specifically, the direct effect is $\partial \mathcal{F}_i / \partial \lambda_\ell(i) = n_\ell(i)(\boldsymbol{e}_{\ell+1} - \boldsymbol{e}_\ell)$, which represents a reduction in the flow of workers upgrading from ℓ to $\ell+1$. Since $-\mathcal{J}_i^{-1} \geq 0$ and the perturbation induces net downward movement in the skill distribution, the change in aggregate human

capital at firm i satisfies

$$\Delta H_i = \boldsymbol{h}^T \frac{d\boldsymbol{n}(i)}{d\lambda_\ell(i)} \cdot \underbrace{(\lambda_\ell^0(i) - \lambda_\ell(i))}_{<0} < 0.$$

Summing over all skill levels $\ell = 1, \ldots, H-1$, the total reduction in human capital at firm i from setting all $\text{NSP}_\ell(i) = 0$ is strictly negative.

For firms $i' \neq i$ that previously traded with i, disconnection removes firm i from the set $\mathcal{P}(i')$. When $\eta = 1$, the NSP is a simple average over partners, so removing one partner leaves the average approximately unchanged provided $|\mathcal{P}(i')| \geq 2$; the effect on $\text{NSP}_\ell(i')$ is second-order. When $\eta < 1$, the NSP is a weighted sum where each additional partner contributes independently. Removing a partner eliminates its contribution from the sum, and the $|\mathcal{P}|^{-\eta}$ adjustment only partially compensates, so the effect on $\text{NSP}_\ell(i')$ is first-order and strictly negative. Combining the direct effect at firm i (strictly negative for all η) with the effects at its partners (second-order when $\eta = 1$, first-order when $\eta < 1$), the total change $\Delta H_{\text{agg}} < 0$.

Step 2: The reduction is increasing in employment.

The first-order effect derived in Step 1 is proportional to $n(i) = \sum_\ell n_\ell(i)$: a larger workforce at the disconnected firm means more workers experience the reduction in learning rates from $\lambda_\ell(i)$ to $\lambda_\ell^0(i)$.

To see this formally, note that the total reduction in aggregate human capital from disconnecting firm i can be written as

$$|\Delta H_{\text{agg}}| \approx \sum_{\ell=1}^{H-1} n_\ell(i) \cdot \gamma_n \, \text{NSP}_\ell(i) \cdot \underbrace{\left| \boldsymbol{h}^T (-\boldsymbol{\mathcal{J}}_i^{-1})(\boldsymbol{e}_{\ell+1} - \boldsymbol{e}_\ell) \right|}_{\equiv \delta_\ell > 0},$$

where δ_ℓ captures the steady-state human capital loss per unit reduction in the upgrading flow at level ℓ, and $\delta_\ell > 0$ by the M-matrix property established in Step 1.

Cross-firm variation in $|\Delta H_{\text{agg}}|$ is driven by variation in both $n_\ell(i)$ and $\text{NSP}_\ell(i)$. Firms with larger total employment $n(i)$ contribute more terms to the sum, producing a larger reduction. When $\eta < 1$, firms with more trading partners also have higher $\text{NSP}_\ell(i)$, so disconnecting them produces an additional loss per worker. Both forces favor high-productivity firms, as established below.

It remains to establish that high-productivity firms are larger in equilibrium. From the first-order condition for vacancy posting in Equation 20, $c'(v_\ell(i)/n_\ell(i)) = q_\ell(\theta_\ell)\,\mathbb{E}[\Psi_\ell(\boldsymbol{z}_i)]$. Since $\Psi_\ell(\boldsymbol{z}_i)$ is increasing in A_i (higher productivity raises the marginal product of work-

ers of all skill types), firms with higher A_i face a higher right-hand side and therefore post more vacancies per worker. In steady state, higher vacancy posting rates translate into larger workforces, establishing that $n(i)$ is increasing in A_i. Combined with the proportionality result above, this implies that disconnecting a higher-productivity firm produces a larger reduction in aggregate human capital. □

E Microfoundation for the network learning aggregation

This appendix provides a microfoundation for the network spillover term in equation (12). The derivation involves two building blocks: a contact technology governing the rate of learning interactions, and a Poisson upgrading process governing how interactions translate into skill gains.

E.1 Contact technology

A worker at firm i interacts with employees at each of the firm's $|\mathcal{P}(i)|$ trading partners through the normal course of business: coordination over orders and deliveries, site visits, joint problem-solving, quality inspections, and technical documentation. The total rate of learning interactions scales with the number of partners according to a contact technology:

$$\Lambda(i) = \mu \cdot |\mathcal{P}(i)|^{1-\eta}, \qquad \eta \in [0, 1], \tag{36}$$

where $\mu > 0$ is a base interaction rate and η governs the returns to network size. This formulation has a natural interpretation as a matching function between the worker's attention capacity (normalized to 1) and the pool of potential learning sources ($|\mathcal{P}(i)|$ partner firms): $\Lambda = m(1, |\mathcal{P}|) = \mu \cdot |\mathcal{P}|^{1-\eta}$. The structure parallels the matching function in the search literature. In the DMP framework, the flow of matches between workers and vacancies is $m(u, v) = m_0 u^{\xi} v^{1-\xi}$, where ξ governs the elasticity. Here, the worker is searching for learning opportunities across trading partners, and η governs the elasticity of the contact rate with respect to network size.

The per-partner contact rate is:

$$\mu_j = \frac{\Lambda(i)}{|\mathcal{P}(i)|} = \mu \cdot |\mathcal{P}(i)|^{-\eta}. \tag{37}$$

When $\eta = 0$, each trading relationship generates interactions at the fixed rate μ, independent of how many other relationships the firm maintains. The total contact rate scales linearly with $|\mathcal{P}|$. This is the natural specification when interactions are initiated by the

partner—incoming orders, deliveries, technical queries—and the worker is exposed to all of them without capacity constraints. Each trading relationship generates its own independent stream of business interactions, and these streams do not crowd each other out. When $\eta = 1$, the total contact rate is μ regardless of $|\mathcal{P}|$: the worker has a fixed attention budget that must be divided across all connections. Adding a new partner displaces time from existing ones, and the per-partner rate is $\mu/|\mathcal{P}|$. This is the implicit assumption behind the mean specification. Values $\eta \in (0,1)$ capture partial congestion: more partners bring more interactions, but at a decreasing rate. This nests a Cobb-Douglas matching function between attention and partners.

E.2 Poisson upgrading

Each interaction with partner j exposes the worker to a random employee at that firm. Following Jarosch, Oberfield and Rossi-Hansberg (2021) and Herkenhoff et al. (2024), the worker upgrades to $h_{\ell+1}$ if the encountered employee has skill above h_ℓ. The probability of this event is proportional to $\bar{h}(j)/h_\ell$, where $\bar{h}(j)$ is the average skill at partner j. Since interactions with each partner arrive as an independent Poisson process at rate μ_j, the upgrading rate from partner j is

$$\lambda_{\ell,j}(i) = \mu_j \cdot \frac{\bar{h}(j)}{h_\ell} = \mu \cdot |\mathcal{P}(i)|^{-\eta} \cdot \frac{\bar{h}(j)}{h_\ell}. \tag{38}$$

By the superposition property of independent Poisson processes, the total upgrading rate from all partners is the sum of the individual rates:

$$\lambda_\ell^{\text{net}}(i) = \sum_{j \in \mathcal{P}(i)} \lambda_{\ell,j}(i) = \mu \cdot |\mathcal{P}(i)|^{-\eta} \sum_{j \in \mathcal{P}(i)} \frac{\bar{h}(j)}{h_\ell}. \tag{39}$$

Setting $\gamma_n \equiv \mu$ yields the network term in equation (12). The additive structure across partners is not an assumption but a consequence of the independence of the Poisson interaction streams: each trading relationship generates its own flow of learning encounters, and these flows do not interfere with each other conditional on the contact rate. The only source of congestion operates through the contact technology ($\eta > 0$), which reduces the per-partner meeting rate as the number of relationships grows.

E.3 Connection to the idea diffusion literature

The Poisson superposition derivation above is the special case $\theta = 1$ of a more general framework grounded in the idea diffusion literature (Buera and Oberfield, 2020; Cai, Li and Santacreu, 2022). In those models, each interaction yields a signal whose quality is the product of a source component and an i.i.d. Fréchet noise term:

$$q_j = \bar{h}(j) \cdot \nu_j, \qquad \Pr(\nu_j \leq x) = \exp(-x^{-\theta}), \tag{40}$$

where $\theta > 0$ governs the dispersion of signal quality. The worker upgrades if the best signal across all partners exceeds h_ℓ. By the max-stability property of the Fréchet distribution, the maximum of independent draws is itself Fréchet with scale parameter $T(i) = \sum_j \bar{h}(j)^\theta$, so the upgrade rate is

$$\lambda_\ell^{\text{net}}(i) = \gamma_n \cdot |\mathcal{P}(i)|^{-\eta} \cdot \frac{1}{h_\ell} \left(\sum_{j \in \mathcal{P}(i)} \bar{h}(j)^\theta \right)^{1/\theta}. \tag{41}$$

This is a CES aggregator over partner qualities with elasticity parameter θ, combined with the contact technology from Section E.1. When $\theta = 1$, the CES aggregator reduces to the linear sum and equation (41) collapses to the Poisson specification derived above. When $\theta > 1$, signal noise is lower and the best partner contributes disproportionately; in the limit $\theta \to \infty$, only the best partner matters. The mapping to Buera and Oberfield (2020) is direct: each trading partner corresponds to a source of ideas, the Fréchet noise captures idiosyncratic variation in the quality of each encounter, and the additive structure of the scale parameter $T(i)$ reflects the independence of learning opportunities across partners.

The specification adopted in this paper sets $\theta = 1$, under which the Poisson and Fréchet derivations coincide. This choice is consistent with the empirical evidence: the standardized EUE coefficients for all B&S ($\phi_2^{\text{std}} = 0.021$) and for top-3 B&S ($\phi_2^{\text{std}} = 0.018$) are statistically indistinguishable, suggesting that learning opportunities are not concentrated at the best partners. Under $\theta = 1$, each partner contributes independently and the arrangement of partner qualities does not matter conditional on their sum. The general CES framework with $\theta \neq 1$ is available for extensions that require richer substitution patterns across partners.