Worker Mobility in Production Networks

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Abstract

This paper documents that production networks play an essential role in the job search and matching process. We document five facts about worker mobility in production networks using employer-employee data matched with the universe of firm-to-firm transactions for the Dominican Republic: 1) workers move between buyers and suppliers almost twice as much as predicted by standard labor market characteristics, 2) movers between buyers and suppliers experience larger earnings increases than other movers, 3) incumbent workers earnings increase when their firm hires from its buyers or suppliers, 4) firm-to-firm trade increases following supply chain hires, and 5) hiring from buyers or suppliers is associated with stronger firm growth. Survey evidence points to supply chain-specific human capital and better information about job applicants as the main reasons for hiring within the supply chain. These results reveal a new channel through which factors affecting the supply chain, such as international outsourcing or contracting frictions, impact labor markets.

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1 Introduction

Search frictions in the labor market make it harder for workers to find good jobs (Haltiwanger, Hyatt, Kahn and McEntarfer, 2018), especially in developing economies (Donovan, Lu and Schoellman, 2023). The role of social networks, such as family or neighbors, in mitigating these frictions is well-documented (Topa, 2011). The role of firm production networks, in contrast, is largely unexplored. There are many reasons why buyer-supplier networks could matter for job-finding. Workers may be able to use business contacts to find job opportunities at buyers and suppliers, and may have skills and knowledge that are particularly valued within the supply chain.

This paper is the first to document the role of production networks as job-finding networks. Merging firm-to-firm transactions from the VAT registry with worker-level records from social security for the universe of formal firms in the Dominican Republic between 2012 and 2019, we construct a novel dataset tracking more than 1.2 million workers per year and 1.1 million job changes. We use this data to document ***five novel facts*** about worker mobility in the production network.

Fact 1: workers tend to move between buyers and suppliers. In our data, almost one-fifth of job-to-job transitions are to a buyer or supplier of a worker's original employer. We compare this to the share of job-to-job transitions to buyers and suppliers under counterfactuals in which worker moves are random. Standard worker and labor market characteristics, such as age, pre-move earnings, industry, location, and college degree, explain just over half of the observed mobility to buyers and suppliers in the data. This finding holds across industries, municipalities, and firm sizes, is similar for upstream and downstream moves, and is stronger for workers with higher earnings and tenure.

Fact 2: movers between buyers and suppliers experience larger earnings increases than other movers. We use an event-study specification to estimate the earnings dynamics of workers who move between buyers and suppliers relative to other movers. Workers moving between buyers and suppliers and those moving to other firms have similar pre-move trends in earnings, mitigating the concern that they are differentially selected based on pre-move trends in earnings. Controlling only for worker characteristics, we find that earnings are 6.7 percentage points higher after four years for movers to buyers or suppliers.[1] We re-estimate our specification including origin and destination firm-year fixed effects, which capture all firm-specific factors that impact workers' pre- and post-move earnings. We find that, of the 6.7 percentage points earnings gap four years after a move, 2.2 percentage points (one-third) is explained by an improvement in the worker-

[1]For comparison, the earnings premium paid by multinational firms is estimated to be 7 percentage points in the US (Setzler and Tintelnot, 2021) and 9 percentage points in Costa Rica (Alfaro-Ureña, Manelici and Vasquez, 2021).

firm match component of earnings. We document that this supply chain premium is present only for high-wage workers and only when the buyer and supplier continue to trade after the worker moves.

Fact 3: the earnings of incumbent workers increase when their firm hires from its buyers or suppliers. We document the earnings dynamics of incumbent workers before and after a new coworker is hired from a buyer or supplier. In line with the literature on coworker spillovers (Jarosch, Oberfield and Rossi-Hansberg, 2021; Herkenhoff, Lise, Menzio and Phillips, 2022), we find that the hiring of higher-wage coworkers is associated with higher earnings for incumbent workers. Our new finding is that incumbent worker earnings increase by almost 2% over three years when a new coworker is hired from a buyer or supplier compared to when a new coworker is hired from an unconnected firm, controlling for the average earnings of new hires.

Fact 4: firm-to-firm trade increases following supply chain hires. We use an event-study specification at the buyer-supplier level to estimate the dynamics of firm-to-firm trade following worker moves between the two firms. This allows us to test whether firms' purchasing and supplying decisions are independent of their hiring choices. Our main specification includes both buyer-year and supplier-year fixed effects, which deal with the concern that rapidly growing firms may both purchase more inputs and hire more workers from their suppliers. We do not find any evidence of pre-trends in firm-to-firm sales prior to a worker moving between the firms. Following a worker move, however, we find that firm-to-firm trade increases by almost 20% after four years, relative to other buyer-supplier pairs.

Fact 5: hiring from buyers or suppliers is associated with stronger firm growth. We document a positive cross-sectional relationship between firm sales growth over one and three-year horizons and the share of their new hires that are from buyers and suppliers. This relationship holds controlling for past sales growth, for the number of buyers and suppliers, and for total employment at buyers and suppliers. We find similar results for employment growth.

To shed further light on why firms hire workers from their buyers and suppliers, we examine the answers to two questions on hiring practices included in a representative survey of 200 Dominican manufacturing firms in December 2022. Over one-third of respondents stated that experience at one of the firm's buyers or suppliers is either a "*very important*" or "*the most important*" factor when hiring skilled workers, similar to the share of responses for experience at a competitor or referrals. The survey evidence also shows that the most common reason for hiring from buyers or suppliers is "*[...] specialized knowledge related to the firm's inputs and/or products*", followed by "*[...] received a referral for the worker*" and "*[...] good experience dealing with the worker while working for the previous employer*". The survey results indicate that both supply-chain related human capital ("specialized knowledge") and information (via referrals and past interactions) are key drivers of worker mobility in the production network.

We consider a wide variety of robustness checks for the facts documented in the paper. We show that neither the tendency of workers to move within the production network nor the supply chain earnings premium are explained by the presence of ex-coworkers at buyers and suppliers or by buyer-supplier pairs belonging to the same business group. Furthermore, we run a placebo test using future buyers and suppliers—i.e. firms that were not suppliers or buyers in the year the worker moved but became part of the production network in the two years after the move. We find that workers are less likely to move to future than current buyers and suppliers, and do not earn a premium when they move to future buyers and suppliers. This alleviates the concern that unobservable factors explain our results. Our results are also robust to alternative empirical frameworks, such as estimating the earnings premium using an AKM specification. Finally, while our results are limited to the Dominican Republic, we provide evidence that U.S. workers tend to move across more vertically integrated industries.

Job-finding through production networks may help explain some important macroeconomic patterns. A well-documented trend in recent decades is the dramatic increase in the globalization of supply chains (Antras and Chor, 2021). Our findings imply that, to the extent that this increase in foreign outsourcing led to fewer domestic supply linkages, it may have contributed to the declining labor market dynamism documented for the U.S. (Davis and Haltiwanger, 2014) and other advanced economies. Furthermore, contracting frictions are common in emerging market and developing economies, leading to sparser production networks (Oberfield and Boehm, 2020; Startz, 2021; Boehm, 2022). Our findings suggest that this sparseness exacerbates information frictions in developing country labor markets relative to advanced economies (Donovan et al., 2023). Policies that mitigate contracting frictions between firms—for instance by improving the court systems—could therefore ameliorate the functioning of the labor market. Our results also have implications for the debate regarding the use of 'no poaching' agreements (Starr, Prescott and Bishara, 2021; Krueger and Ashenfelter, 2022). While this debate focuses on agreements that prevent workers from moving to competitors, there is growing evidence that they also occur within supply chains.[2]

Related literature The use of social networks and personal referrals to find jobs is widespread and is the focus of an extensive literature (Topa, 2011). We contribute to this literature by showing that *firm* networks also play an important role in job finding. This paper

[2] See examples from Colombia (Battiston, Espinosa and Liu, 2021) and the U.S. (https://www.thefashionlaw.com/saks-louis-vuitton-gucci-prada-and-more-named-in-new-lawsuit-over-alleged-no-poaching-pact/). We thank Evan Starr for the pointer to the latter case.

also contributes to the recent literature on labor market boundaries and outside options (Caldwell and Harmon, 2019; Nimczik, 2023) by showing that buyers and suppliers are an important dimension of workers' labor markets.

A rapidly expanding literature highlights the importance of domestic production networks for firm performance (Bernard, Moxnes and Saito, 2019; Alfaro-Ureña, Manelici and Vásquez, 2022; Bernard, Dhyne, Magerman, Manova and Moxnes, 2022; Dhyne, Kikkawa, Komatsu, Tintelnot and Mogstad, 2022) and in particular for workers. In this latter strand, Alfaro-Ureña et al. (2021) estimate the impact of multinationals on workers, Huneeus, Kroft and Lim (2021b) and Adão, Carrillo, Costinot, Donaldson and Pomeranz (2022) combine employer-employee and production network data to analyze how production networks affect earnings inequality, and Demir, Fieler, Xu and Yang (2023) present evidence of assortative matching on worker wages between buyers and suppliers. Patault and Lenoir (2023) use French firm-to-firm trade and employer-employee data to examine how job-to-job transitions of sales managers lead to business stealing. Contributing to this literature, our paper is the first to document the importance of worker mobility between buyers and suppliers for workers' and firms' performance.

This paper also contributes to the literature on the importance of job-to-job transitions for wage growth and labor reallocation (Moscarini and Postel-Vinay, 2009, 2017; Haltiwanger et al., 2018; Bagger and Lentz, 2019; Albagli, Canales, Syverson, Tapia and Wlasiuk, 2020; Jarosch, 2021; Crane, Hyatt and Murray, 2022) and to the literature on the relevance of the fit between workers and jobs (Lachowska, Mas and Woodbury, 2020; Guvenen, Kuruscu, Tanaka and Wiczer, 2020; Lise and Postel-Vinay, 2020) by documenting the role of domestic production networks in these aspects.

The rest of the paper is structured as follows. Section 2 describes the data. Section 3 documents the five facts about worker mobility in production networks. Section 4 presents the survey-based evidence about firms' hiring practices. Section 5 presents a set of robustness tests and discusses the paper's limitations. Section 6 concludes.

2 Data

Our empirical setting is the Dominican Republic from 2012 to 2019. During this period the country experienced a period of sustained economic development and low and stable inflation. Real GDP growth averaged 5.6% per year—one of the fastest in Latin America—and average inflation was 2.8%, generally remaining within the central bank's target band.

In this paper we combine multiple datasets of anonymized administrative records.[3] The first dataset reports firm-level information for the universe of firms that file income

[3] section A2 reports additional details on the data sources and data collection.

taxes (i.e., assets, liabilities, revenue, expenditures, and the wage bill) and is compiled by the Directorate General of Internal Taxes. Moreover, the dataset includes the ownership structure of each firm, the ISIC 3 industry, and the municipality where firms are headquartered. The second dataset includes firm-to-firm transactions from the VAT registry, which allow us to identify each firm's domestic buyers and suppliers. The third dataset has wage and demographic information on employees from the Social Security Treasury. 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 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 make at least one transaction per year and have at least one permanent employee.[4]

We observe over 44,000 firms per year. The median firm employs seven workers and has an annual turnover of almost 30,000 USD, which grew at a rate of 8.9% per year. On average, firms employ more than 1.2 million workers, which represent 26.1% of the country's labor force.[5] The median worker's wage is 3,120 USD, which grew at an average annual rate of 5.6% over the period covered by the sample. The firm-to-firm transaction dataset includes almost 2.5 million transactions per year, of which about one-fourth occurs between firms of the same industry. The median firm, on average, has eight buyers and 28 suppliers.[6] A limitation of the dataset is that it does not cover the large informal economy of the Dominican Republic, which is typical for countries at this stage of development.

In addition to the previously described administrative data sources, we collaborated with the Central Bank of the Dominican Republic to incorporate questions about firms' hiring practices into the Business Opinion Survey of December 2022. The survey is run quarterly and targets 200 firms representative of the manufacturing sector to elicit their inflation expectations, among other indicators.

[4]We also apply some light data cleaning criteria to rule out likely erroneous records. These include dropping firms with annual sales below 10,000 Dominican pesos or a wagebill or purchases below 1,000 Dominican pesos (less than 200 US dollars and 20 US dollars at the 2019 exchange rate, respectively).

[5]According to the 2023 National Labor Force Survey, about 43% of the workforce was part of the formal sector and 70% of these employees worked in the private sector in 2022. Thus, the formal private sector accounted for 30% of the country's labor force, close to the 26% average we observe in our sample. The remaining difference is due to temporary contracts and formal self-employment.

[6]Many characteristics of the Dominican Republic's domestic production network are comparable to those of other emerging markets such as Chile and Costa Rica, as documented in section A1.

Measuring worker mobility We define a 'mover' as any worker whose highest-paying employer in year t is different from their highest-paying employer in year $t-1$.[7] We observe 1,152,279 worker moves between 2012 and 2019, implying that on average 13% of workers change employer from one year to the next. Movers tend to be younger and earn less, and are more likely to be male than non-movers.

We alternatively consider the subset of 'within-year movers'. We define a within-year mover in year t as a worker whose primary employer changed from year $t-1$ to $t+1$, with the worker receiving positive earnings from both firms in year t. The advantage of this definition is that it limits the duration of potential unemployment spells—or spells of work outside the formal sector—between jobs to at most ten months. This is useful as we do not have information on the reason for which workers stop working at a firm and extended unemployment spells can have a scarring effect on worker labor market outcomes. Under this definition, we observe 272,935 moves between 2012 and 2019.[8]

3 Five facts on worker mobility in production networks

3.1 Fact 1: workers tend to move between buyers and suppliers

Almost one-fifth of the workers who changed employer between 2012 and 2019 were hired by a buyer or supplier of their previous employer. The two network graphs in Figure 1 illustrate this pattern for a sub-sample of employers. In the left panel, we show the number of worker movements (blue edges) between 1,000 random firms (black nodes, scaled by total firm employment). In the right panel, we randomly draw 500 firms and for each of these we draw one of their buyers or suppliers at random, thereby oversampling firms with supply linkages. A striking pattern emerges: worker movements are considerably more frequent between buyers and suppliers than between firms drawn randomly.

Given that buyers and suppliers account for less than 0.1% of firm pairs in the economy, it is remarkable that 18.4% of worker moves happen between them.[9] However, since larger firms have more buyers and suppliers, the typical buyer or supplier tends to be

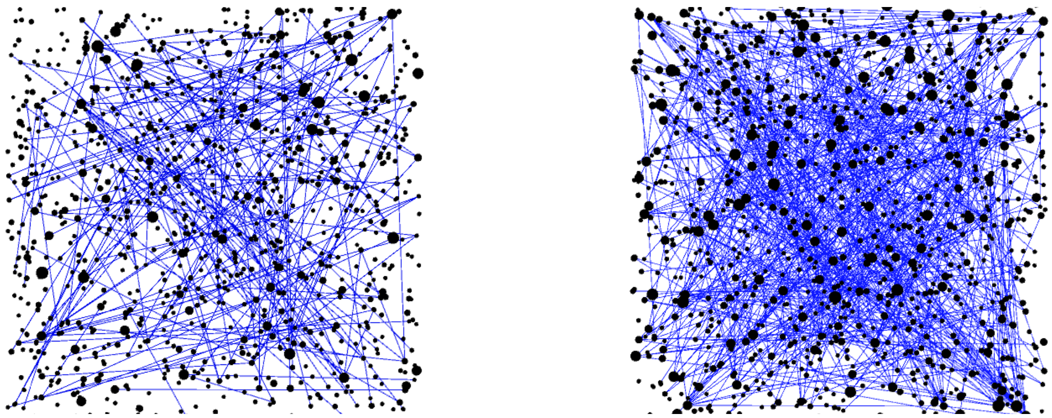
[7]This definition of a mover is consistent with annual data and the fact that we do not observe the start and end date of workers' jobs. 10% of workers in our database report income from multiple firms within the same year. Thus, we focus on the highest-paying employer (or main job), which is standard in the literature (Card, Heining and Kline, 2013). The results of the paper are robust to restricting the sample to workers with only one employer each year.

[8]Note that, under this alternative definition, a worker who leaves his employer in December and joins a new employer in January is not counted as a 'within-year' move. Also, a worker who changes jobs once a year for two consecutive years is dropped, as well as any worker moving at the end of our sample.

[9]As a benchmark, 43% of workers move to a firm within the same 2-digit industry, of which there are 42. The intra-industry share of movers we find for the Dominican Republic is similar to the one in Bjelland, Fallick, Haltiwanger and McEntarfer (2011) for U.S. NAICS super-sectors (i.e., 40%).

Figure 1: Worker flows between firms

(a) Random firms (b) Buyers and suppliers



Notes: The nodes denote firms, with their size proportional to the number of employees. Blue edges indicate that at least one worker is moving between the two firms. Panel (a) uses a sample of 1,000 randomly selected firms in 2019. Panel (b) uses a sample of firm pairs in 2019 that traded in 2018 and account for 1,000 unique firms. Both samples use firms with a number of employees ranging between 21 and 500. Figure A12 additionally shows the edges connecting buyers and suppliers.

larger than the typical firm. Therefore, buyers and suppliers are expected to account for a disproportionate share of worker flows. Moreover, the association between production networks and worker flows could be due to other factors. For example, the overlap between employees' labor markets and firms' product markets could result from supply chains being co-located and workers searching for jobs locally.

We therefore examine if workers tend to move between buyers and suppliers even after taking into account other factors that could explain this pattern. We construct the share of worker moves to buyers and suppliers under a counterfactual random allocation of workers to firms that are likely to be part of their labor market (Glitz and Vejlin, 2021; Bernard and Zi, 2022). We first define a firm as having N job openings if it hires N workers from other firms. We then randomly assign workers to job openings and measure the share of workers who move to buyers and suppliers. We repeat this randomization procedure 100 times and construct the average share of moves to buyers and suppliers across draws. By allocating workers to job openings rather than firms, this approach accounts for the fact that larger firms both have more buyers and suppliers and tend to hire more workers. Figure 2 compares the share of workers allocated to buyers and suppliers in the random allocation to the share in the data, along with the corresponding odds ratios.[10]

[10] Bootstrapped standard errors are negligibly small and thus unreported. With a sufficiently large number of conditioning variables, every worker would be assigned to the firm they actually moved to. To avoid mechanical overfitting, we restrict the sample of movers to those with a potential labor market of at least 50 job openings. The total sample size, therefore, shrinks as conditioning variables are added. Our results are not sensitive to using alternative values for the minimum number of job openings.

Figure 2: Share of workers moving to buyers or suppliers vs. random allocation
(Percent)

Notes: The blue bars denote the shares of movers to buyers or suppliers in the data, the red bars denote the same shares obtained from randomly allocating workers to firms controlling for different factors, and the black dots show the corresponding odds ratio. The first random allocation exercise shows results where movers are randomly allocated to any job opening (1,152,279 movers). The second exercise restricts the random allocation to job openings filled by workers from the same origin municipality and industry (1,143,023 movers). The third exercise additionally restricts the random allocation to job openings filled by workers in the same age quintile and of the same gender (1,111,083 movers). The fourth exercise additionally restricts the random allocation to job openings filled by workers in the same pre-move earnings quintile (1,019,242 movers). Finally, the fifth exercise additionally restricts the random allocation to job openings filled by workers with the same university degree (17,091 movers).

The first set of bars shows that, without any controls, we would expect 6.7% of workers to move between buyers and suppliers if moving randomly, just over one third of what we observe in the data. The corresponding odds ratio is 3.2. We then assign movers only to job openings filled by workers from the same origin municipality and industry. Consequently, the random share incorporates the likelihood that workers search for jobs locally and that suppliers and buyers tend to be co-located. We find that the random share increases to 10.9%, with a corresponding odds ratio of 1.9, still well above 1. We then additionally restrict movers to be randomly allocated to job openings filled by workers in the same age group, of the same gender, and in the same pre-move earnings quintile. This increases the random share only slightly to 11.4%, with the odds ratio remaining stable at 1.8. Lastly, we also restrict movers to be randomly allocated to job openings filled by workers with the same university degree.[11] While the share of workers moving between buyers and suppliers increases both in the random allocation and in the data, the odds ratio declines only marginally to 1.7. These results alleviate the concern that workers only move between buyers and suppliers because of occupational similarities, insofar as university degree is a strong predictor of occupation.

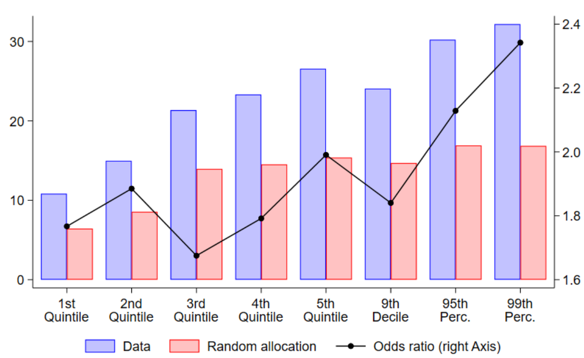
[11]Our data covers 66 degrees, which include industrial engineering, civil engineering, medicine, pharmacy, marketing, economics and finance, and others. The sample size shrinks considerably because the data on university education is limited to workers who graduated after 2007 (see Appendix A2).

In Appendix Table A7, we show that the tendency to move between buyers and suppliers holds for workers in all industries, for workers changing or staying in the same industry or municipality, for men and women, for white and non-white workers, and for workers in all age groups. Workers are no more likely to move to buyers than to suppliers, but are relatively more likely to move to their employers' top buyers and suppliers.

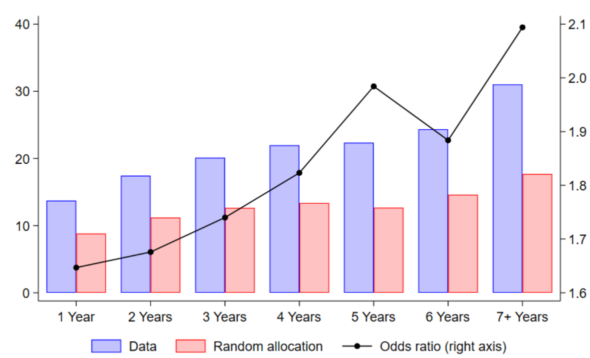
The ways in which workers find jobs vary considerably according to their skills and education (Lester, Rivers and Topa, 2021; Carrillo-Tudela, Kaas and Lochner, 2022). Figure 3 documents heterogeneity in the likelihood that workers move between buyers and suppliers along two dimensions of human capital: pre-move earnings and tenure at the original employer. The share of movers between buyers and suppliers increases from 10% to 27.5% between the bottom and top earnings quintile, with the corresponding odds ratios going from 1.8 to 2.1. Similarly, the share of movers between buyers and suppliers increases from 15.1% for workers with under two years of tenure to 29.2% for workers with at least six years of tenure, with the corresponding odds ratio rising from 1.7 to 2.[12] In summary, the production network plays a greater role in facilitating job finding for high-skilled workers.

Figure 3: Heterogeneity in the share of movers to buyers and suppliers
(Percent)

(a) By pre-move earnings



(b) By pre-move tenure



Notes: The left panel shows the share of movers to buyers or suppliers (blue bars) along with the random allocation share (red bars), by pre-move earnings group; the black dots show the odds ratio. The right panel shows the same series by tenure at the origin firm. To accurately measure tenure, the sample is restricted to workers that moved between 2018 and 2019 so that worker tenure at the origin firm can be identified for up to seven years.

[12] Furthermore, Table A7 reports that workers with tertiary degrees are relatively more likely to move to buyers and suppliers than workers without a college degree.

3.2 Fact 2: movers between buyers and suppliers experience larger earnings increases than other movers

Job-to-job movers tend to see higher earnings increases than job stayers (Hahn, Hyatt, Janicki and Tibbets, 2017; Moscarini and Postel-Vinay, 2017). This is also true in the Dominican Republic, as shown in Figure 4 which plots median earnings growth between $t-1$ and $t+1$ by earnings quintile separately for stayers and movers. Strikingly, the figure also shows that movers between buyers and suppliers tend to have higher earnings growth than other movers.

Movers between buyers and suppliers have different characteristics than other movers (subsection 3.1), and may be moving to different types of firms. To control for these factors, we estimate the differences between their respective earnings dynamics using the following event-study specification:

$$E_{i,o,d,t+k} = \alpha^k + \delta^k X_{i,t-1} + \beta^k SB_{o,d,t-1} + \phi^k_{o,t} + \phi^k_{d,t} + \gamma^k X_{o,d} + \eta_{i,d,o,t,k} \tag{1}$$

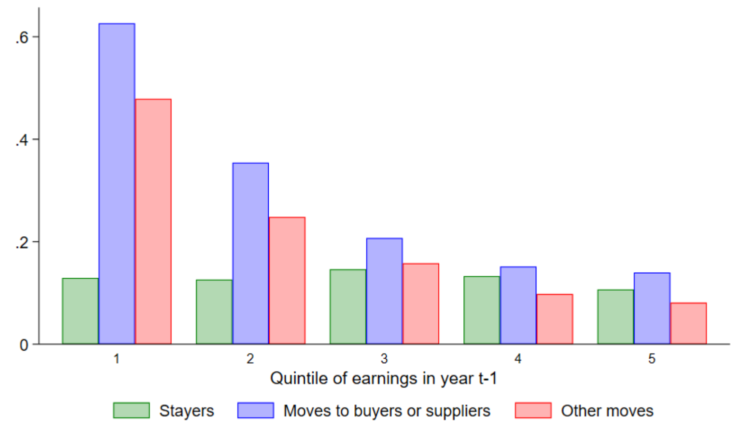
where i is a worker who moves from origin firm o to destination firm d in year t; $E_{i,o,d,t+k}$ is the (log) of average monthly earnings paid by i's main employer in year $t+k$; $SB_{o,d,t-1}$ is a dummy variable which equals one if firm o was a buyer or supplier of firm d in period $t-1$, and zero otherwise; $X_{i,t-1}$ is a set of worker-level controls which include the log of earnings in the year before the move, age deciles, and gender; and $X_{o,d}$ is a set of origin-destination firm-level controls to allow for different earnings dynamics depending on the joint characteristics of the two firms. These controls include fixed effects for the interaction of origin and destination firm size quintiles, municipalities, and industries, and for whether the two firms belong to the same business group.[13] We estimate the specification both including and excluding origin firm-year and destination firm-year fixed effects.

Since we are interested in earnings dynamics following job-to-job transitions, we restrict the sample to within-year movers (29% of which are to buyers or suppliers), which has the advantage of minimizing the duration of possible unemployment spells (see section 2). The sample includes workers that move in any year between 2012 and 2019. We estimate Equation 1 separately for each horizon $k = -3, \ldots, 4$ to test both for differences in pre-trends and to capture the persistence of the earnings differential following a move. This allows us to test whether workers who move along the supply chain are differentially selected based on pre-move trends in (or shocks to) earnings.[14]

[13] We define two firms as being in the same business group if either (a) one firm is a top 10 shareholder of the other or (b) they have at least one of their top 10 shareholders in common. We also check that results are robust to defining two firms as being in the same business group if we observe more than 20 moves between them in a year.

[14] This specification has the benefit of simplicity and flexibility regarding controls. It is also analogous to

Figure 4: Earnings growth of stayers and movers
(Earnings growth from year $t-1$ to $t+1$)



Notes: The figure reports the median earnings growth between year $t-1$ and $t+1$ for workers who stay at the same firms (green bars), for within-year movers to a buyer or supplier of their previous employer (blue bars), for within-year movers to other firms (red bars), by earnings quintile in year $t-1$.

The left panel of Figure 5 plots the earnings dynamics of supply chain movers relative to other movers controlling for worker characteristics but *excluding* firm fixed effects and firm-pair covariates. The results show that the earnings of workers moving between buyers and suppliers behave similarly to those of other movers up until the move, and that a large earnings gap opens up after the move. Supply chain movers have 7.7 pp higher earnings the year after the move than other movers, gradually declining to 6.7 pp four years after the move (see Table A8 for the regression results). This earnings gap could be due to supply chain movers sorting into higher-earnings firms and/or an increase in the match specific component of earnings.

We then control for sorting by including origin and destination firm-year fixed effects and firm-pair controls in the right panel of Figure 5 (we report the regression results in Table A9). These fixed effects allow us to isolate the change in the match-specific component of worker earnings for buyer-supplier movers relative to other movers. [15] The results in the right panel of Figure 5 continue to show no evidence of differential pre-trends. The

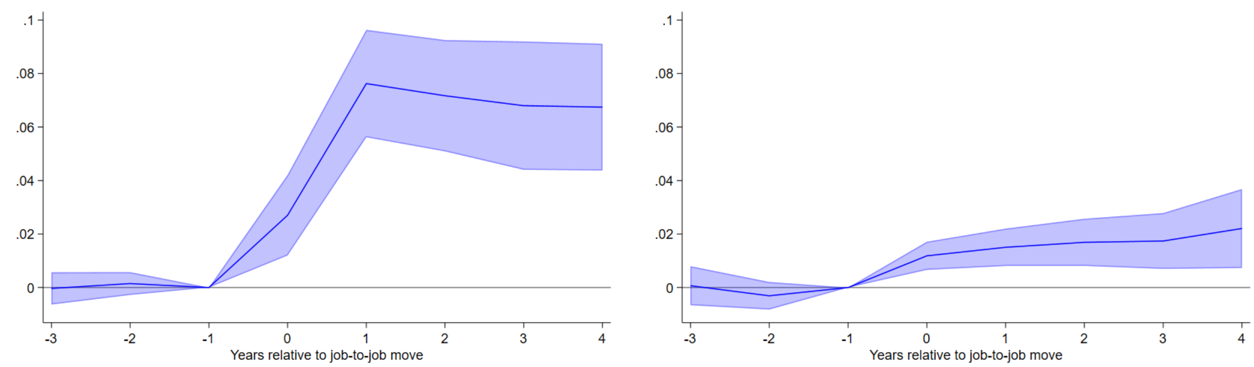
the local projection approach to difference-in-differences of Dube, Girardi, Jorda and Taylor (2023), which is robust to the econometric problems associated with the OLS estimation of two-way fixed effects highlighted by Goodman-Bacon (2021) and Callaway and Sant'Anna (2021). Dube et al. (2023) also exclude from the control group workers who are treated in period $t>0$. We show in Figure A13 that results are robust to imposing this restriction.

[15]The firm-year fixed effects also allow for the firm component of earnings to depend on whether a worker is joining or leaving the firm, as well as when the worker joined or left the firm. This empirical specification is therefore more flexible than the classical AKM decomposition (Abowd, Kramarz and Margolis, 1999)).

earnings premium for supply chain movers is 1.5 pp one year after the move, rising to 2.2 pp by the fourth year after the move. Of the 6.7 pp earnings gap four years after a move estimated in the left panel, 4.5 pp (two-thirds) is explained by supply chain movers sorting into higher-earnings firms and 2.2 pp (one-third) is explained by an improvement in the match-specific component of earnings, which we label the 'supply chain earnings premium'.

Figure 5: Earnings dynamics of movers, with controls
(Relative earnings of movers to buyers or suppliers)

(a) Without firm-year FE (b) With firm-year FE



Notes: The figure plots the coefficients β from Equation 1, along with the 95% confidence interval. Panel (a) includes year fixed effects and fixed effects for worker age deciles and gender, and a dummy for whether the origin and destination firm have any common ownership. Panel (b) additionally includes origin firm-year and destination firm-year fixed effects, as well as fixed effects for the interactions of origin and destination firm municipality, industry, and employment quintile. Standard errors are double clustered at the origin and destination firm level. The regression results are in Table A8 and Table A9.

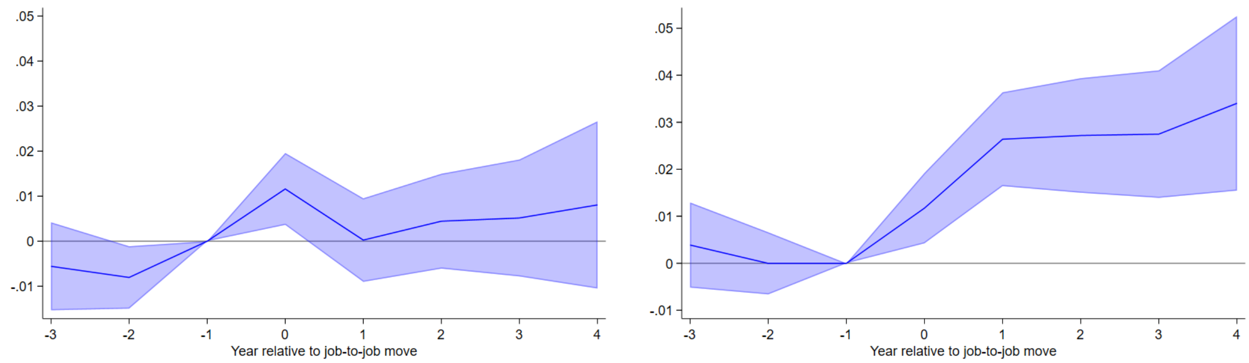
We examine the heterogeneous earnings dynamics of supply chain movers with respect to their pre-move earnings. We amend Equation 1 by interacting the variable identifying supply chain movers, SB, with a dummy variable for whether movers' earnings are above or below the median earnings of movers in the year before the move. As shown in Figure 6, we find a large earnings premium for high-earnings workers moving along the supply chain, reaching 2.6 pp one year after the move and 3.3 pp four years after the move. This is substantially higher than the estimate for the full sample of supply chain movers. On the other hand, we find a small and statistically insignificant earnings premium for low-earnings workers.[16] Finally, in another exercise (section A5), we find that workers moving along the supply chain not only benefit from an earnings premium, but also from lower separation rates with the new employer (and thus longer employer-employee match duration).

[16]We find quantitatively similar results when we run the regression in Equation 1 separately for workers with above and below median earnings.

Figure 6: Earnings dynamics of movers by pre-move earnings
(Relative earnings of movers to buyers or suppliers)

(a) Low earners
(With firm-year FE)

(b) High earners
(With firm-year FE)



Notes: The figure plots the coefficients from a version of Equation 1 that allows for earnings heterogeneity, along with the 95% confidence intervals. The panels include year fixed effects and fixed effects for worker age deciles and gender, and a dummy for whether the origin and destination firm have any common ownership, origin firm-year and destination firm-year fixed effects, as well as fixed effects for the interactions of origin and destination firm municipality, industry, and employment quintile. Standard errors are double clustered at the origin and destination firm level.

3.3 Fact 3: incumbent workers earnings increase when their firm hires from its buyers or suppliers

Incumbent workers may experience a change in earnings when a new coworker is hired from a buyer or supplier for various reasons, such as peer effects within the firm (Cornelissen, Dustmann and Schönberg, 2017; Jarosch et al., 2021; Herkenhoff et al., 2022) or through rent-sharing if firms that hire from their buyers and suppliers tend to perform better. We examine whether having a new coworker from a buyer or supplier is associated with future earnings gains by estimating the following specification, akin to that from Section 3.2:

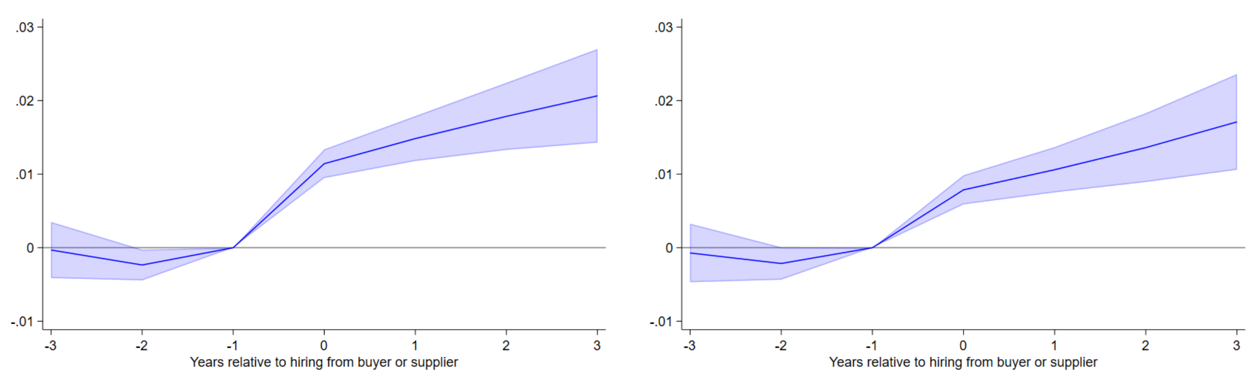
$$E_{i,d,t+k} = \alpha^k + \rho^k \cdot E_{i,t-1} + \phi^k \cdot \bar{E}_{-i,t} + \delta^k H_{d,t} + \beta^k SB_{d,t} + \gamma^k X_{i,t} + \omega^k X_{d,t} + \varepsilon_{i,d,t,k} \tag{2}$$

where $E_{i,d,t+k}$ is the (log) average monthly earnings of worker i in firm d at time $t+k$, with $-3 \leq k \leq 3$. $H_{d,t}$ is a dummy variable that takes value one if firm d hired a worker between period $t-1$ and t from another firm, and zero otherwise; and $SB_{d,t}$ is a dummy variable that takes value one if firm d hired a worker from any of its buyers or suppliers between period $t-1$ and t, and zero otherwise. We control for the log of worker earnings in period $t-1$, age deciles, and gender. Because rapidly growing firms may both be more likely to experience higher earnings growth and hire from buyers or suppliers, we control for employment and sales growth from $t-1$ to t. We also control for firm employment in period $t-1$ because small firms tend to have higher growth rates. Given the findings from Jarosch et al. (2021) and Herkenhoff et al. (2022), we control for the average earnings of worker i's coworkers in period $t-1$. Finally, we include industry-municipality-year fixed effects. We cluster standard errors at the firm level. The sample is restricted to workers i who are at the same firm d in every year from $t+k$ to $t+1$ for $-3 \leq k \leq 0$, and $t-1$ to $t+k$ for $1 \leq k \leq 3$. We restrict the sample to firms with at most 100 workers in all years. This restriction helps to identify workers more likely to interact with new hires.

Figure 7a presents the coefficients on the hiring from a buyer-supplier dummy β^k, along with 95% confidence intervals (see also Table A10). Workers' earnings increase by 1.1% in the year their firm hires from its buyers or suppliers. Earnings continue to grow in the following years, by an additional 0.4% after 1 year and an additional 1% after 3 years. Given that we documented in subsection 3.2 that high-earnings workers are more likely to move along the supply chain, Figure 7b restricts the sample to firms that are hiring at least one worker from another firm in period t and adds a control for the average salary of the firm's new hires.[17] Including these controls does not change the estimated higher earnings associated with being in a firm that hired a worker from a buyer or supplier.

Figure 7: Earnings dynamics of new coworkers of supply chain movers
(Earnings of coworkers)

(a) All firms (b) Only hiring firms



Notes: The figure plots the coefficients β^k from Equation 2, along with the 95% confidence interval. Panel (a) is based on a sample of workers who are at the same firm in every year from $t+k$ to $t+1$ for $-3 \leq k \leq 0$, and $t-1$ to $t+k$ for $1 \leq k \leq 3$. Additionally, we restrict the sample to workers in firms with at most 100 workers in all years. The specification includes worker-level controls (earnings in period $t-1$, age deciles, gender, and the average earnings of coworkers in period $t-1$), firm-level controls(employment and sales growth from $t-1$ to t, and employment in period $t-1$), and industry$\times$municipality$\times$ year fixed effects. Panel (b) is based on a sample of workers in firms that hired from another firm between years $t-1$ and t. The specification also controls for the average earnings of the new workers hired by the firm between year $t-1$ and t. The regression results are in Table A10 and Table A11.

[17] See also Table A11, which shows that, consistent with the literature, workers at firms whose new hires have higher earnings tend to experience higher future earnings growth.

3.4 Fact 4: firm-to-firm trade increases following supply chain hires

We examine the dynamics of sales between buyers and suppliers around workers moves. To do so, we estimate an event-study specification similar to the one adopted in subsection 3.2:

$$y_{b,s,t+k} = \phi_{b,t,k} + \phi_{s,t,k} + \beta_k FM_{b,s,t} + \varepsilon_{b,s,t,k} \tag{3}$$

where buyer b and supplier s are two firms trading in $t-1$, $y_{b,s,t+k}$ is the log of sales between b and s in year $t+k$, and $FM_{b,s,t}$ is a dummy equal to one if in year t we observe a worker moving between b and s for the first time. $\phi_{b,t,k}$ and $\phi_{s,t,k}$ are buyer-year and supplier-year fixed effects for each horizon k, which capture any firm-level time-varying shocks. As in Equation 1, we estimate the equation for each horizon $k = -3, \ldots, 4$. Thus, the parameters β_k trace the sales dynamics between suppliers and buyers for pairs that hire from each other in year t.

The challenge with identifying the relationship between firm-to-firm sales dynamics and worker movements is that the likelihood that workers move between buyers and suppliers depends on the the strength of the firm-to-firm sales (subsection 3.1), and firms that hire from their buyers or suppliers tend to experience higher subsequent sales growth (Fact 5). We therefore choose the control group from a comparison pool of firm-pairs with similar characteristics to treated firms, and using a matching procedure following Azoulay, Graff Zivin and Wang (2010) and Jäger and Heining (2022).

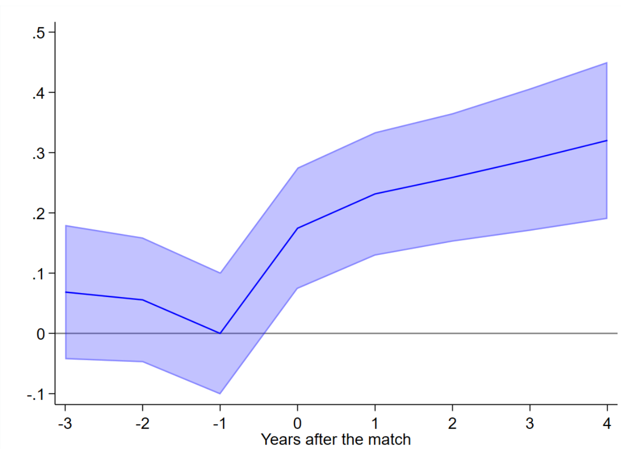
To construct the estimation sample, we first restrict our attention to firm-pairs that traded in $t-1$ and with no common ownership at any point between 2012 and 2019. We then define an event as the first time we see one or more workers moving between the buyer and supplier forming the firm-pair. We drop observations such that $t \leq 2014$ so that our event definition more accurately captures first-time moves. The treatment group consists of firm-pairs experiencing an event in period t. We use a matching procedure to select comparable firm-pairs for the control group. The pool of firm-pairs forming the control group satisfies the additional restrictions that 1) the firm-pair never experienced an event during the sample period, and 2) both firms in the firm-pair experienced an event with one of their buyers or suppliers in period t. The first restriction ensures that firm-pairs in the control group are not treated in a later or earlier period (Dube et al., 2023), while the second ensures that firms in the control group are similarly selected to firms in the treatment group. For each treatment firm pair, we then select one firm pair from the comparison group pool with similar firm-to-firm sales in $t-1$. This latter restriction ensures that the distribution of firm-to-firm sales for the treatment and control groups are similar. We provide more details on our approach in Appendix A3.

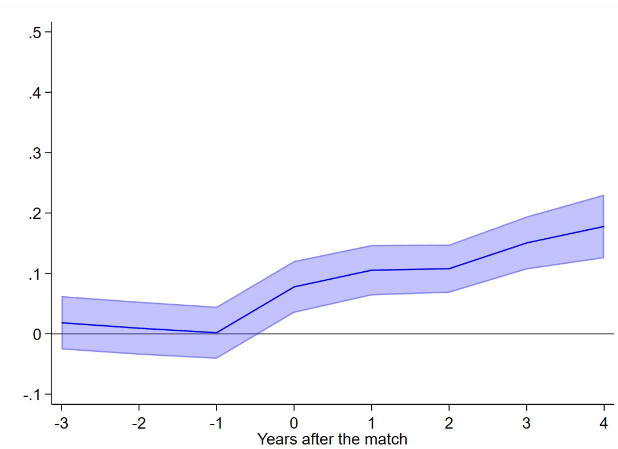
Figure 8 presents the results (see also Table A13). Buyer-supplier pairs with no worker move in year t display similar pre-event trends.[18] Following a worker move, the sales from the supplier to the buyer increase substantially. Sales are approximately 30% higher with respect to the control group after four years. The inclusion of buyer-year and supplier-year fixed effects reduces the estimate to close to 20%. Appendix A3 documents that these findings are similar for both upstream and downstream worker moves.

Figure 8: Firm-to-firm trade and worker moves
(Log of firm-to-firm sales)

(a) Year FE

(b) Buyer×year and supplier×year FE





Notes: The figure plots the coefficients β^k from Equation 3 along with 95% confidence intervals. Firms in the control group—a subset of the firm pairs that do not experience any worker move between them—are selected according to a coarsened exact matching so that the distribution of sales in year $t-1$ is the same for the control and treated group (see section A3). The left panel shows the results from the specification including only year fixed effects, while the right panel shows the results including buyer×year and supplier×year fixed effects. Standard errors are double clustered at the buyer and supplier level. Firm pairs are also excluded if either there is ever common ownership during the sample period or if there is a worker movement observed before 2015.

3.5 Fact 5: hiring from buyers and suppliers is associated with stronger firm growth

Fact 4 shows that bilateral firm-to-firm trade relationships strengthen following worker moves. However, this result does not directly connect hiring from buyers and suppliers to firm growth as firm-to-firm sales (purchases) could increase despite flat total sales (purchases) if other buyers (suppliers) get crowded out.

We therefore compare the performance of firms that hire from buyers or suppliers to that of firms that do not. Figure 9 plots the share of new hires coming from buyers and suppliers against firm-level sales growth over the following one (panel a) and three (panel

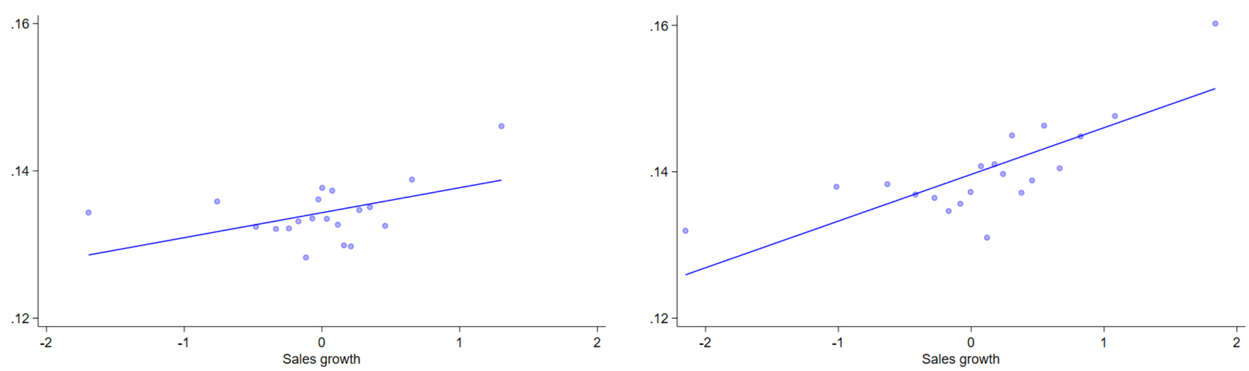
[18]While the matching procedure mechanically results in similar trade in $t-1$, it does not affect earlier years.

b) years (see also Table A14). Firms with more buyers and suppliers tend to have higher growth rates (Bernard et al., 2022) and will mechanically be more likely to hire from their buyers and suppliers. To account for this, we control for the (log) number of buyers and suppliers and for (log) total employment at buyers and suppliers. We also control for current and lagged (log) sales, as well as industry-municipality-year fixed effects. Figure 9 shows that firms hiring relatively more along the supply chain have higher average future sales growth, both over the short and medium term. In particular, firms at the top versus bottom 5% of the distribution of three-year sales growth hire a 2 pp higher share of workers along the supply chain.[19] We find similar results for employment growth instead of sales growth (Table A14).

Figure 9: Hiring from buyers and suppliers and firm growth
(Share of workers hired from buyers or suppliers)

(a) One-year horizon

(b) Three-year horizon



Notes: The figure shows binned scatterplots in which the vertical axes report the share of firms' new hires—among total new hires from other firms—from its buyers or suppliers (in the previous year) and the horizontal axes report the firms' sales growth over one year (from t to $t+1$) or three years (from t to $t+3$). Data is residualized with respect to industry$\times$municipality$\times$year fixed, log sales, lag of log sales, log number of buyers plus suppliers, log total employment at buyers and suppliers, and log average earnings of the new hires. The sample is restricted to firms that hire at least one worker. The average share of new hires coming from buyers and suppliers is 12% and the the median is zero.

4 Why do firms hire from their buyers and suppliers?

To shed light on the reasons for which firms hire from buyers and suppliers, we examine the answers to two questions about firms' hiring practices included in the Business Opinion Survey run by the Central Bank of the Dominican Republic in December 2022 (see section A2 for more details).

[19] We estimate a complementary specification that shows that firms hiring from buyers and suppliers for the first time grow more than firms that do not start hiring along the supply chain in the same year.

The first question inquired how much firms value the production network experience compared to other factors. Specifically, respondents were asked: *"How important are these factors when hiring skilled workers?"*, and possible factors included (i) *"Experience in the same or similar job position"*, (ii) *"Experience at competitor firms"*, (iii) *"Experience at the firms' buyers or suppliers"*, (iv) *"Academic studies the worker completed and the institution the worker graduated from"*, and (v) *"Referral from a personal contact or employee"*. For each factor, respondents could select one of the following: *"Not important"*, *"Somewhat important"*, *"Very important"*, and *"The most important"*.

We report the survey results for this question in Table 1. Experience in a similar job position and academic studies were the two factors most commonly deemed very important or the most important factors. Over one-third of respondents stated that experience at one of the firm's buyers or suppliers is either very important or the most important factor when hiring skilled workers, with this share being close to those for experience at a competitor and for referrals. These results confirm our findings in the administrative data that experience along the supply chain is an important factor that firms take into account when hiring.

Table 1: Relevant factors when hiring

Question: How important are these factors when hiring skilled workers?

Answer	Not important	Somewhat important	Very important	The most important factor	Share of firms	Employment-weighted share of firms
(i) Experience in the same or similar job positions	9	24	68	48	78%	83%
(ii) Experience in one of the company's competitors	31	58	53	7	40%	27%
(iii) Experience in one of the company's buyers or suppliers	48	47	43	9	35%	30%
(iv) Academic studies and the institution where the worker graduated	22	40	69	18	58%	75%
(v) A referral from a personal connection or current employee of the company	39	45	50	11	42%	31%

Notes: 149 firms responded to the survey question. Respondents could select multiple options. The shares of firms are calculated by summing responses "very important" and "the most important factor". The employment weights are calculated using information from survey responses.

The second question directly asked about the reasons for hiring along the supply chain. Respondents were asked: *"If you have hired any worker from a buyer or supplier in the last three years, what were the reasons for such hiring?"*, and could choose any number of options among the following: (i) *"We have not hired any worker from a buyer or supplier in the last three years"*, (ii) *"The worker had specialized knowledge related to the firm's inputs and/or products"*, (iii) *"We received a referral for the worker"*, (iv) *"We had good ex-*

perience dealing with the worker while working for the previous employer", (v) *"To create trust and improve the relationship with the buyer or supplier"*, and (vi) *"Other reasons"*.

Table 2 reports the share of firms selecting each option. We find that 30% of the respondents recall hiring a worker from a buyer or supplier in the last three years, very close to the 28% we observe in the administrative data. Among these firms, 67% of the respondents answered that specialized knowledge was a reason to hire along the supply chain, 59% answered that they received a referral for the worker, 41% answered that they had a positive experience dealing with the worker, and 20% answered that the goal was to improve the relationship with the supplier or buyer. Only 17% of respondents included "other reasons" as an answer, suggesting that the options provided were fairly comprehensive.

Table 2: Reasons for hiring along the supply chain

Question: If you have hired any worker from a buyer or supplier in the last three years, what were the reasons for such hiring?

Answer	Number of responses	Share of firms	Employment-weighted share of firms
(i) We have not hired any worker from a buyer or supplier in the last three years	98		
(ii) The worker had specialized knowledge related to the firm's inputs and/or products	27	67%	62%
(iii) We received a referral for the worker	23	59%	35%
(iv) We had good experience dealing with the worker while working for the previous employer	17	41%	28%
(v) To create trust and improve the relationship with the buyer or supplier	8	20%	8%
(vi) Other reasons	8	17%	22%

Notes: 136 firms responded to the survey questions. Respondents could select multiple options. The shares of firms are calculated with respect to firms that selected any option other than (i). All firms that selected (i) did not select any other option, except one firm that also selected (vi) (thus this respondent is not considered when calculating the shares). The employment weights are calculated using information from survey responses.

Both referrals and previous positive interactions with the worker can be grouped into information-based reasons for hiring, as the hiring firm is likely to have better information about the worker and vice-versa. Workers who are in touch with their counterparts at buyers and suppliers are also more likely to learn about job openings at those firms. We find that both human capital and information are roughly equally important reasons for hiring along the supply chain: 67% vs. 77% unweighted and 62% vs. 52% weighted by employment, respectively. In summary, the survey evidence shows that both lower information frictions within supply chains and workers' supply chain-specific skills and knowledge are the key reasons that workers move along the supply chain.

5 Robustness and limitations

In this section, we first summarize the results of a series of robustness tests, which we present in more detail in section A5. Then, we discuss the limitations of our study.

5.1 Robustness

Ex-coworker networks One alternative explanation for our results is that worker flows between unconnected firms could lead both to future worker flows, because individuals learn about job opportunities via coworker networks (Lester et al., 2021; Caldwell and Harmon, 2019), and to the formation of buyer-supplier linkages, because of information spillovers. We evaluate the importance of this mechanism by running the random matching exercise on a sample that excludes workers who moved to a firm in which one of their ex-coworkers was employed. Reassuringly, the results are broadly unchanged: the share of movers to buyers and suppliers remains significantly higher than that from randomly matching workers to firms, which suggests that networks of previous coworkers cannot account for worker mobility between buyers and suppliers. The results on the supply chain earning premium are also unaffected when controlling for the presence of former coworkers at the destination firm.

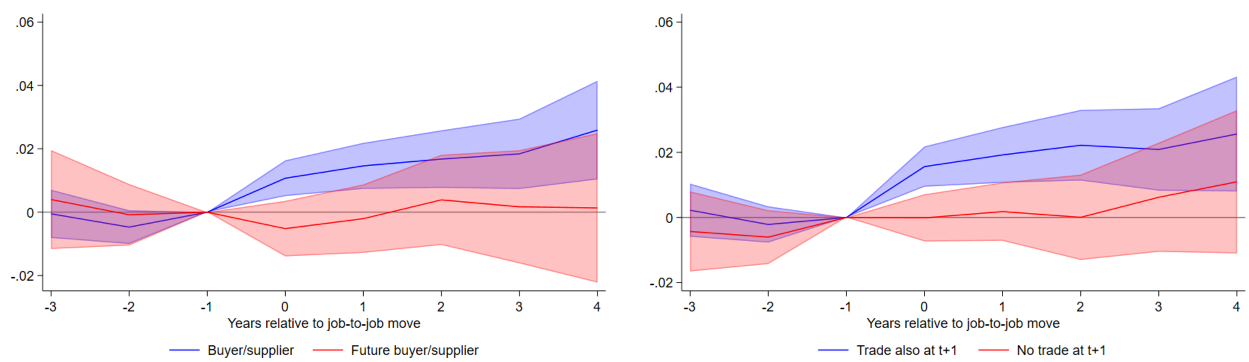
Business ownership networks Networks of ex-coworkers are not the only relevant network shaping worker flows. For example, workers have a higher propensity to move within the same business group (Cestone, Fumagalli, Kramarz and Pica, 2019; Huneeus, Larrain, Larrain and Prem, 2021a), which could overlap with firms' production networks. However, we find that the likelihood of workers moving along the supply chain is significantly higher than that from randomly matching workers to firms, even when we exclude workers moving between firms with common ownership. The earning regressions also explicitly account for common ownership between origin and destination firms.

A placebo test with future buyers and suppliers Another potential issue is that unobservable factors correlated with supply chain linkages could affect both worker and trade flows between firm pairs. For instance, buyer-supplier pairs with similar occupational compositions may have a relatively high share of workers moving between them and trade disproportionately more. We mitigate this concern by calculating the share of movers to firms that 1) have not traded in the past and 2) start trading in the two years following the workers' move—'future' buyers and suppliers—and compare it to the share obtained by randomly matching workers to firms. We find that the share of movers to future buyers and suppliers is higher in the data than in the random matching exercise, but to a lesser extent than for 'current' buyers and suppliers (the odds-ratio is 1.4 vs 1.8, see Table A2). Therefore, current supply chain linkages remain an important factor in explaining worker mobility.

The estimates of the earnings premium for workers who move to buyers and suppliers are robust to including or excluding a rich set of firm-pair level controls. Nonetheless, unobservable factors at the firm-pair level could similarly confound our results. To address this concern, we conduct a placebo test by augmenting Equation 1 with a dummy for workers that move to future buyers or suppliers. If factors other than supply chain linkages lead to the earnings premium, we should observe similar patterns for these movers. We do not find any earnings premium for movers to future buyers and suppliers (Figure 10 panel a). Similarly, we find no earnings premium for workers who move along the supply chain if the buyer-supplier relationship ends in the year after the move (Figure 10 panel b). These findings confirm that the supply chain premium is indeed due to the existence and the persistence of the buyer-supplier relationships.

Figure 10: Robustness of earnings dynamics
(Log of earnings)

(a) Future suppliers or buyers (b) Continue trade in $t+1$



Notes: Panel (a) plots the coefficients from a regression of movers' earnings k years after the move on a binary variable equal to one if the worker moves to a current buyer or supplier of the previous employer and on another binary variable equal to one if the worker moves to a future buyer or supplier of the previous employers, along with the 95% confidence interval. Panel (b) plots the coefficients from a regression of movers' earnings k years after the move on a binary variable equal to one if the worker move to a current buyer or supplier of the previous employer and this buyer-supplier relationship continues in the year after the move, and on another binary variable equal to one if the worker move to a current buyer or supplier of the previous employer and this buyer-supplier relationship does not continue in the year after the move, along with the 95% confidence interval. Both panels include year fixed effects, fixed effects for worker age deciles, gender, and a dummy for whether the origin and destination firm have any common ownership, origin firm-year and destination firm-year fixed effects, as well as fixed effects for the interactions of origin and destination firm municipality, industry, and employment quintile. Standard errors are double clustered at the origin and destination firm level. See section A5 for more details.

Alternative empirical frameworks We also test the robustness of our results to employing alternative empirical frameworks. We find that workers' excess likelihood of moving along the supply chain is even more striking when we estimate it using a regression-based approach following Kramarz and Thesmar (2013) and Kramarz and Skans (2014). Furthermore, we find that the supply chain earnings premium is similar if we estimate it using an alternative empirical framework based on the AKM decomposition of earnings into worker-, firm-, and match-specific components (Abowd et al., 1999).

Other robustness Appendix A5 reports some additional robustness tests. We document that the earnings premium is robust to focusing only on workers who remain at the destination firm for multiple years after moving, and to keeping workers whose monthly earnings are higher in their new job than their old job. The former result contrasts with the transitory earnings premium documented in Dustmann, Glitz, Schönberg and Brücker (2016) and Glitz and Vejlin (2021) for workers who find jobs through social networks. The latter result shows that our earnings premium is present among a subsample of workers whose moves are more likely to be voluntary. We also study mobility along the production networks for workers following mass layoffs—in order to isolate job separations due to firm-level shocks—and confirm that workers still disproportionately move to buyers and suppliers.

5.2 Limitations

Our data covers formal firms and workers formally employed with permanent contracts, thereby excluding job transitions into and out of the informal sector. As in other emerging economies, the share of informal employment is high in the Dominican Republic, at 57% according to the 2023 National Labor Force Survey. Firms operating in the informal sector are usually smaller, less productive, and exhibit lower growth rates than formal firms, and informal workers receive relatively lower earnings and benefits (La Porta and Shleifer, 2014). Small and less productive firms also have fewer buyers and suppliers (Bernard et al., 2022). Our results suggest that workers disproportionately move to buyers and suppliers in every industry, location, and firm size category. This pattern, however, is stronger for workers with higher earnings and hired from firms that grow faster. Additionally, the supply chain-specific earnings premium is present only for high earners. All in all, this suggests that while our findings are also likely to hold in the informal sector, it may be to a weaker degree than in the formal sector.

The data on the production network and labor market in this paper covers only the Dominican Republic. In section A4, we leverage publicly available industry-level data and document that U.S. workers tend to move across more vertically integrated industries. While we cannot directly test whether supply chain moves are similarly frequent, this provides suggestive evidence that the connection between production networks and worker mobility is likely a feature common to other economies.

We do not quantify the costs associated with worker turnover, such as hiring and training costs, which tend to be high for skilled workers (Blatter, Muehlemann and Schenker, 2012). While we document several positive outcomes associated with hiring along the supply chain, it may lead to higher turnover for some firms and thus entail costly efforts such as posting vacancies, interviewing applicants, and training incoming workers. This is particularly relevant for low-earnings firms in highly productive supply chains, which may suffer from high turnover as workers use them as springboards towards better paid jobs. On the other hand, these costs may be less relevant for worker-firm matches along the supply chain, as they tend to last longer than others (see Table A4).

Finally, our paper presents a set of key facts about worker mobility in the production network, but does not rationalize them within a theoretical model. A general equilibrium quantitative assessment of the impact of supply chain hiring on the economy is left for future research.

6 Conclusion

In this paper, we provide new insights into the job search and matching process by highlighting the essential role played by the firm-to-firm production network. Using administrative records for the Dominican Republic, we document five novel facts: 1) workers tend to move between buyers and suppliers, 2) movers between buyers and suppliers experience larger earnings increases than other movers, 3) incumbent workers earnings increase when their firm hires from its buyers or suppliers, 4) firm-to-firm trade increases following supply chain hires, 5) hiring from buyers and suppliers is associated with stronger firm growth. We also run a survey of Dominican manufacturing firms, which reveals that production networks are a source of information about job seekers (through referrals and direct contact), while also indicating the presence of a supply chain-specific component of human capital. These findings have implications for a wide range of policy-relevant questions, such as the connection between sparser production networks and weaker job ladders in developing economies, the reasons for declining labor market dynamism in advanced economies, and the economic impact of “no-poaching” clauses between buyers and suppliers.

Since our paper is the first to document the link between production networks and labor market flows, it opens up several avenues for future research. Firstly, it will be important to document whether production networks are similarly important for labor market flows in other countries at different levels of development. Secondly, our results suggest that the structure of production networks may have a large macroeconomic impact on worker earnings and aggregate productivity through labor market mobility. Macroeconomic general equilibrium models with firm-to-firm networks and worker mobility could be used to quantify these effects. Thirdly, future research can explore the importance of production networks for informal workers.

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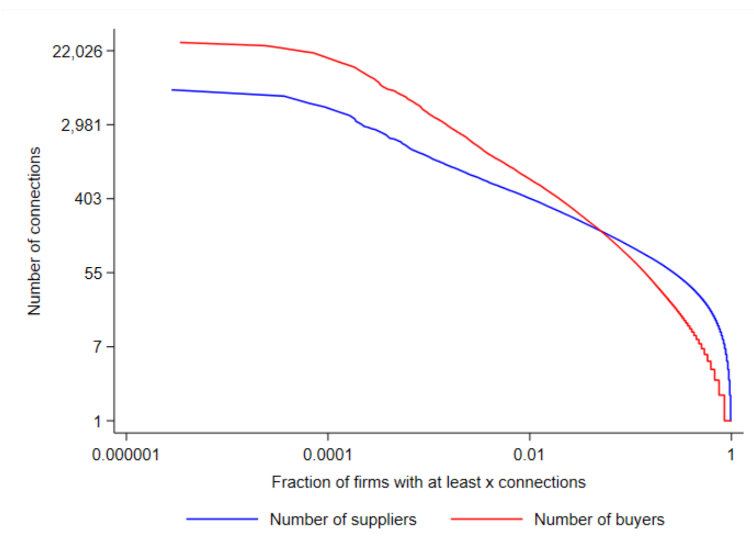
Online Appendix

A1 Workers in the buyer-supplier network

We examine some key aspects of the network of buyers and suppliers in the Dominican Republic and compare them to the evidence from other papers in the literature. The first feature we look at is the density of the network. We plot the inverse of the cumulative distribution of firms' in- and out-degrees for 2019—the latest year in our dataset—in Figure A1. The distributions are highly skewed, suggesting that both buyers and suppliers are connected with only a few counterparts, while a small number of firms are connected with many other firms in the production network. For example, 1% of firms have over 400 suppliers and 700 buyers. These distributions are well approximated with a Pareto distribution. The estimated parameters of per-firm suppliers and per-firm buyers are -0.30 and -0.45, respectively, which are in line with the evidence for other emerging markets: -0.58 and -0.73 in Costa Rica (Alfaro-Ureña, Fuentes, Manelici and Vásquez, 2018), -0.28 and -0.30 in Chile (Grigoli, Luttini and Sandri, 2022); but less negative than in advanced economies: -1.50 and -1.32 in Japan (Bernard et al., 2022).

Figure A1: Number of firms and number of connections



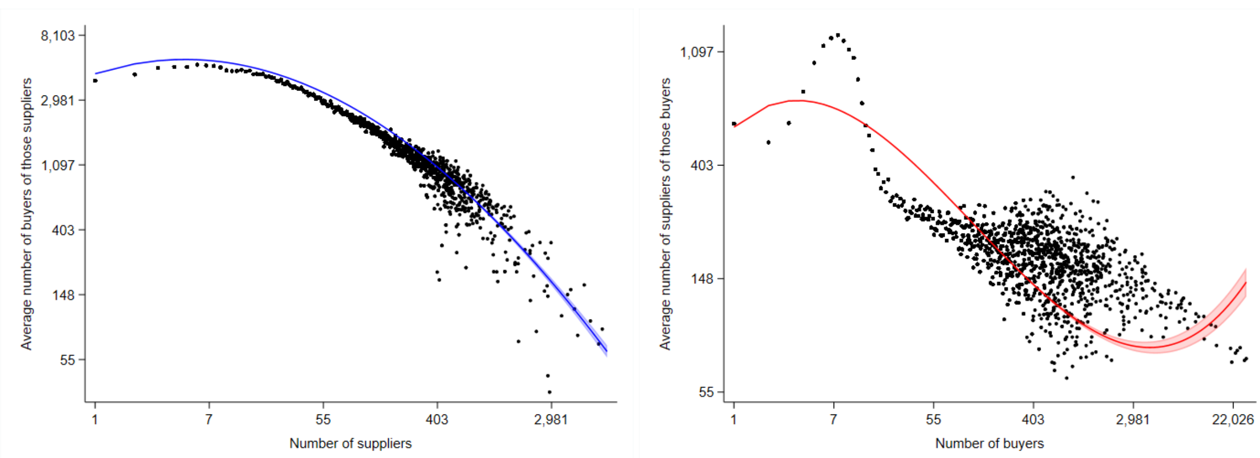
Notes: The figure shows the inverse of the cumulative distribution functions of the number of suppliers per buyer and of the number of buyers per supplier in 2019.

To explore if larger firms are generally connected to similar firms, we examine the degree of assortativity between buyers and suppliers. In the case of suppliers, we count the number of buyers for each supplier in 2019 and relate it to the average number of suppliers of those buyers. Figure A2a depicts a negative degree of assortativity. Hence, a supplier that has many buyers is in general connected with buyers that are buying only from a few suppliers, indicating a dependence of small buyers on large suppliers. The coefficient estimate from a linear regression suggests that an increase of 1% in the number of buyers is associated with a 2.2 reduction in the average number of suppliers. This estimate is in line with the one of Bernard et al. (2022) (-2 for Japan) and of Alfaro-Ureña et al. (2018) (-1.8 for Costa Rica).

Similarly, in Figure A2b we plot the degree of assortativity for buyers. The relationship for buyers is also negative, with a coefficient estimate from a linear regression suggesting that an increase of 10% in the buyer's number of suppliers is associated with a 0.7% reduction in the average number of buyers. We conclude that when firms have many suppliers, these suppliers sell to only a few buyers, pointing to a dependence of small suppliers on large buyers.

Figure A2: Assortative matching

(a) Suppliers per buyer and number of buyers (b) Buyers per supplier and number of suppliers



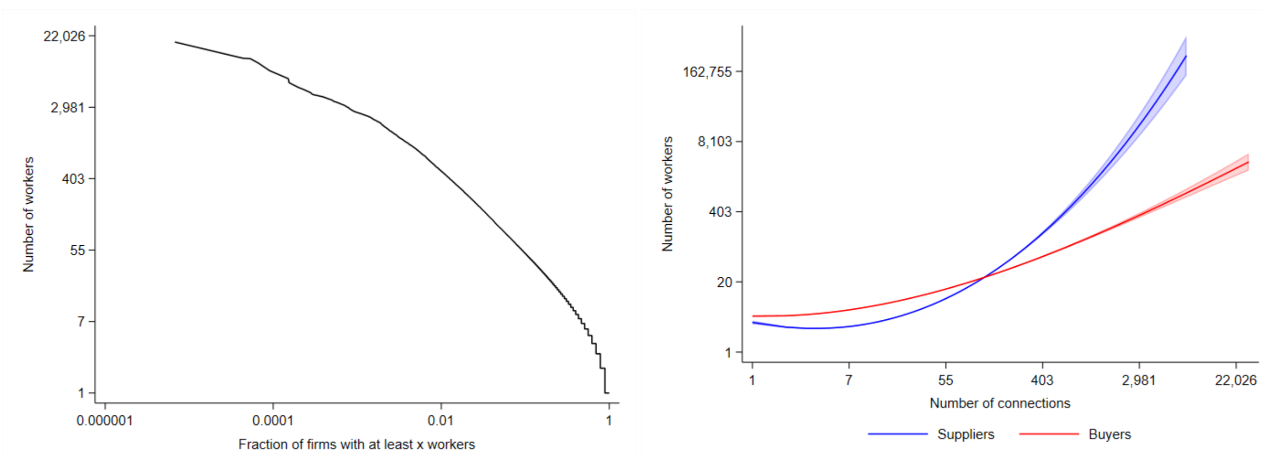
Notes: Panel (a) shows the predicted values of a third-degree polynomial regression of the log of the number of suppliers for each buyer on the log of the average number of buyers for those suppliers in 2019. Panel (b) shows the predicted values of a third-degree polynomial regression of the log of the number of buyers for each buyer on the log of the average number of suppliers for those buyers in 2019. The shaded areas denote the 95% confidence intervals.

We now turn to the distribution of workers in the production network. Figure A3a plots the inverse of the cumulative distribution function of the number of workers in 2019. This shows that a large portion of firms have only a few employees and that only a few firms employ a lot of workers. For example, about 10% of the firms had one single employee in 2019, compared with 1% with 470 employees and one hundredth of 1% with about 8,300 employees.

But do employees work in firms with more buyer and supplier linkages? In Figure A3b we plot the relationship between the number of connections of buyers and suppliers and the number of employees in 2019. Both in the case of suppliers and in the case of buyers, there is a positive relationship, suggesting that firms with more connections are also the ones with a bigger workforce. The coefficient estimates of linear regressions indicate that an increase of 10% in the number of connections is associated with a 4% increase in the number of employees at the firm for buyers and a 7% increase for suppliers. Both relationships are convex, with a steeper part of the polynomial for larger numbers of connections. This is especially true for the number of suppliers, which means that any additional connection is associated with a larger increase in the number of workers employed by these suppliers if the initial number of connections is already large.

Figure A3: Number of firms, connections, and workers

(a) Number of firms and workers (b) Number of connections and workers



Notes: Panel (a) shows the inverse of the cumulative distribution functions of the number of workers per firm in 2019. Panel (b) shows the predicted values of third degree polynomial regressions of the log of the number of workers on the log of the number of connections in 2019; the shaded areas denote the 95% confidence intervals.

A2 Additional information on data sources

The datasets for the empirical analysis combine administrative records from four entities: the Directorate General of Internal Taxes, the Directorate General of Customs, the Social Security Treasury, and the Ministry of the Economy, Planning, and Development. The administrative records come from several tax forms that all economically active entities must fill out. Of these, 92% submit the tax forms electronically, allowing for a broad spectrum of consistency checks. Moreover, the authorities crosscheck the data with information across different institutions, further ensuring the integrity of the information.

To maintain confidentiality, the information provided by the authorities assigns a random identifier for each taxpayer in the dataset.

The firm-level information for the entire universe of firms that file income tax at the Directorate General of Internal Taxes is collected from the following records: form IR1 (*Declaración Jurada de Impuestos sobre la Renta a las Personas Físicas*), form IR2 (*Declaración Jurada de Impuestos sobre la Renta a las Personas Jurídicas*), form IT1 (*Declaración Jurada de Impuesto a la Transferencia de Bienes y Servicios Industrializados*), and form IR3 (*Declaraciýón Pago de Retenciones de Asalariados*).

Information on firm-to-firm transactions is collected from VAT tax form 606 (*Formato de Envío de Compras de Bienes y Servicios*). When a firm in the formal sector buys from another firm that is not registered at the Directorate General of Internal Taxes, the transaction is recorded within the expenditures of the formal firm. Moreover, if the seller has an electoral identifier, that is used to record the bilateral transaction; if not, the transaction is reported as "other expenditures" of the firm in the formal sector.[20]

Figure A4 plots the geographical distribution of the average number of firms and workers over the national territory. Unsurprisingly, most firms and workers are headquartered in the provinces surrounding the capital Santo Domingo (Distrito Nacional, Santo Domingo, and San Cristóbal), the second largest city of the country Santiago de Los Caballeros (Santiago and La Vega), and the touristic provinces (Puerto Plata, La Romana, and Altagracia). The rest are primarily based in the areas connecting these three poles.

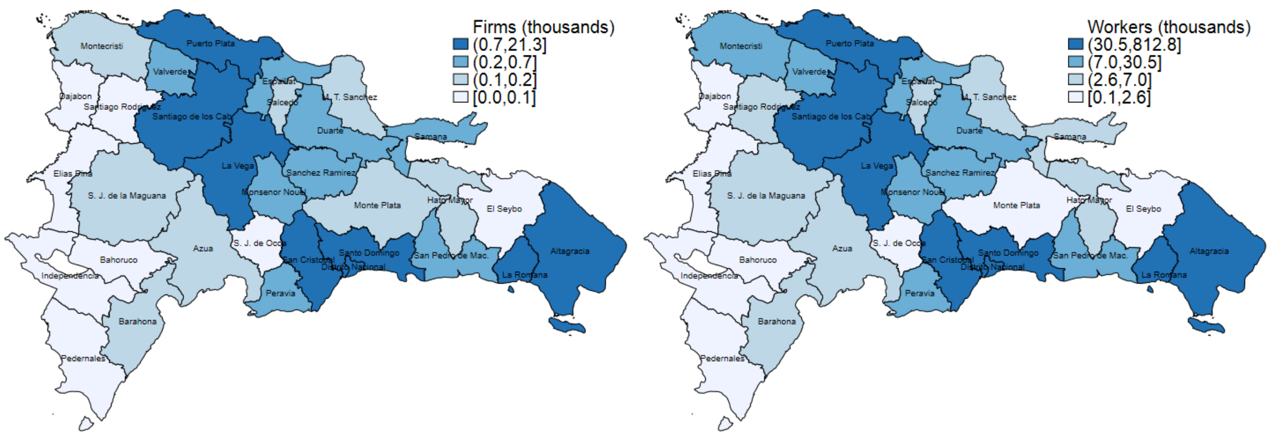
An additional dataset includes information on tertiary educational attainment for a restricted number of workers put together by the Ministry of the Economy, Planning, and Development. For workers who graduated with a college degree between 2007 and 2019, we observe the educational institution they graduated from, the degree they obtained, and the graduation year.

Survey data The last source of information used in the paper is the quarterly firm survey conducted by the Central Bank of the Dominican Republic (*Encuesta de Opinión Empresarial al Sector Manufacturero*). The survey includes 16 questions and targets managers in 200 firms in the manufacturing sector.[21] It is administered via face-to-face interviews, in which the interviewers collect information on the recent performance of the firm as

[20]To limit the impact of outliers and measurement error, firm- worker- and firm-pair-level variables are winsorized at the top 2% if their distribution is one-sided or top and bottom 1% otherwise. The only exception is the analysis of firm-to-firm trade where We do not winsorize nor trim sales because this would impact disproportionally more the firm-pairs with worker movements between them (as more observations would be close to the upper limit).

[21]State enterprises, sugar manufacturers, oil refineries, and firms in free trade zones are excluded from the survey.

Figure A4: Geographical distribution of firms and workers



(a) Firms (b) Workers

Notes: The figure displays the average number of firms and workers during 2012–2019.

well as the managers' views about what factors affected this. It also elicits managers' beliefs about the firm's performance in the near future and the economic outlook for the industry and country. Upon our request, the Central Bank of the Dominican Republic agreed to add two questions about firms' hiring practices in December 2022.

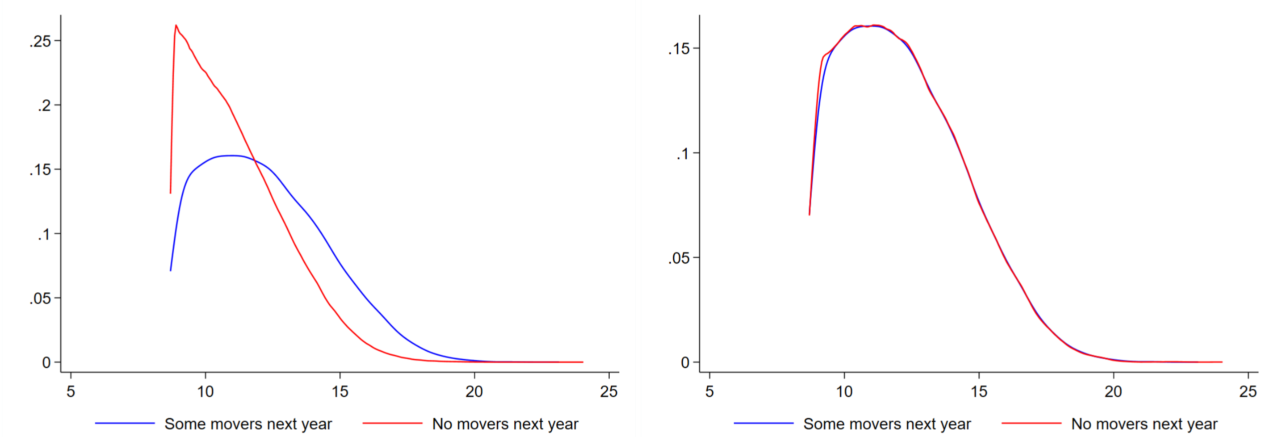
A3 Firm-to-firm trade: coarsened exact matching

This Appendix provides additional details on the matching procedure used in subsection 3.4. A key challenge in identifying the relationship between firm-to-firm sales dynamics and worker movements is that workers are more likely to move between buyer-supplier pairs with relatively higher pre-existing sales. In particular, Table A7 shows that workers are relatively more likely to move to a top buyer or supplier than to any buyer or supplier. This could affect the estimated sales dynamics in specification Equation 3 because firm-to-firm sales are likely to be persistent. Simply controlling for log sales in $t-1$ could fail to capture non-linearities in the relationship between firm-to-firm sales and worker mobility. This problem is likely to be important as illustrated by Figure A5a, which shows that the distributions of $t-1$ sales between firm-pairs that experienced workers move in period t versus those that did not are markedly different.

We therefore use use a coarsened exact matching procedure (Azoulay et al., 2010; Jäger and Heining, 2022) to ensure that the distribution of firm-to-firm sales in $t-1$ among firm-pairs in the control group is similar to that in the treatment group. To implement this, we divide firm-to-firm sales into 10,000 bins. For each firm-pair in the treatment group, we match it to a firm-pair in the comparison group pool that is in the same firm-to-firm sales bin (without replacement).[22] The resulting distributions of log firm-to-firm sales in $t-1$ for the treatment and control groups are virtually identical, as shown in Figure A5b. For the specifications with buyer-year and supplier-year fixed effects, we first residualize log firm-to-firm sales against both sets of fixed effects before running the matching procedure.

Figure A5: Distribution of log sales according to worker movements across pairs in the following year

(a) Full sample (b) After coarsened exact matching



Notes: Panel (a) shows the kernel density of the distribution of log sales between buyers and suppliers for the full sample, according to whether we observe a worker movement between the two firms or not in the following year. Panel (b) shows the kernel density of the distribution of log sales between buyers and suppliers after the coarse exact matching procedure, according to whether we observe a worker movement between the two firms or not in the following year. The sample is restricted to buyer-supplier pairs that trade in 2012, between which no workers move between 2012 and 2015, and that have no common ownership.

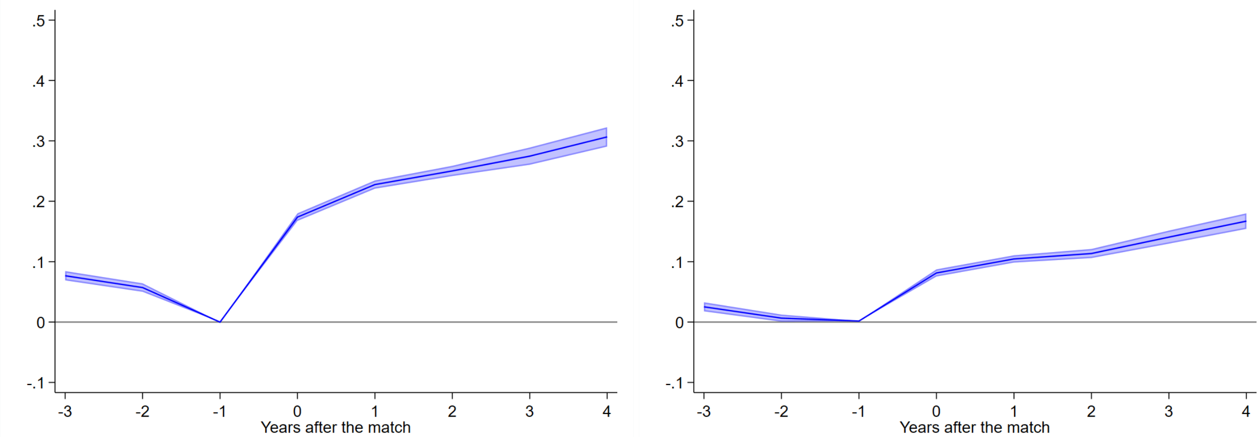
The standard errors in Figure 8 are double-clustered at the buyer and supplier level. One concern could be that the additional randomness implied by the matching procedure could invalidate our inference. To test if this is the case, we repeat the matching procedure 50 times and plot the median and median plus/minus one standard deviation of the coefficients in Figure A6. We find that such randomness is in fact negligible with respect to the estimated effects, therefore mitigating this concern.

[22]As described in the main text, the comparison group pool is constructed as follows. We first restrict our attention to firm-pairs that traded in $t-1$ and with no common ownership at any point between 2012 and 2019. We then restrict our attention to firm-pairs where both firms experienced an event with one of their buyers or suppliers in period t, where an event is defined as the first time we see one or more workers moving between a firm-pair. By construction, this last restriction does not affect the set of firm-pairs in the treatment group. We drop observations such that $t \leq 2014$ so that our event definition more accurately captures first-time moves.

Figure A6: Firm-to-firm trade and worker moves: variance introduced by matching algorithm

(a) Year FE

(b) Buyer×year and supplier×year FE



Notes: This figure shows the median of the coefficients β_k of Equation 3 obtained by estimating the coarsened exact matching algorithm 50 times, together with plus/minus one standard deviation confidence intervals. Panel (a) refers to the specification including only year fixed effects, while panel (b) refers to the specification including buyer×year and supplier×year fixed effects.

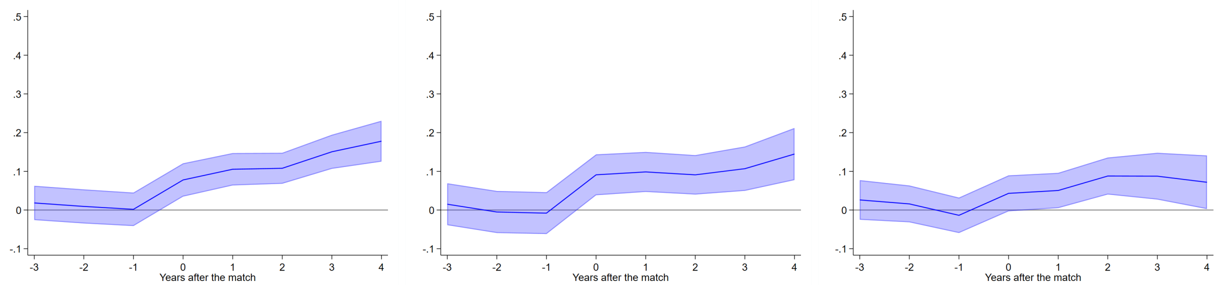
Finally, we examine whether the relationship between firm-to-firm sales and worker moves is different for downstream moves (from suppliers to buyers) versus upstream moves (from buyers to suppliers). These results allow us to speak to whether different mechanisms are relevant for upstream and downstream moves. For example, buyers may tend to poach workers from their suppliers in order to insource part of the production process. Conversely, when a worker moves upstream, the hiring supplier may insource some of the tasks previously performed by the buyer. This may increase the value-added produced upstream, and a given quantity of inputs sold may increase total sales to the buyer through higher prices. We find that worker moves in either direction are associated with similar increases in sales, with the point estimates being larger for downstream moves (Figure A7). This suggests that insourcing is unlikely to be a primary mechanism driving these results. Instead, we infer that the results are driven by the strengthening of the supply chain relationships.

A4 Mobility across industries

The availability of matched firm-to-firm trade and employer-employee data for research remains scarce, which makes it difficult to test the external validity of our findings. However, we compare how *industry*-level worker mobility patterns correlate with industry-level input-output connections in the Dominican Republic and in the United States.

Figure A7: Firm-to-firm trade and worker moves: upstream vs downstream moves

(a) Downstream or upstream (b) Downstream (c) Upstream



Notes: This figure shows the coefficients obtained from estimating Equation 3 when the dummy variable identifying worker moves takes value one, alternatively, if a worker moves between the two firms in year t for the first time (panel a), if a worker moves from the supplier to the buyer (panel b), and if a worker moves from the buyer to the supplier (panel c); together with 95% confidence intervals. Panel b (c) also includes a variable to control for first-time movements upstream (downstream). The control group—a subset of the firm pairs that do not experience any worker move between them—is selected according to a coarsened exact matching so that the distribution of sales in year $t-1$ is the same for the control and the treated group, see section A3. buyer×year and supplier×year FEs are included in all specifications. Standard errors are double clustered at the buyer and supplier level. Firm-pairs are excluded if there is common ownership during the sample period.

Given all pairs of industries (n, m) (with $m \neq n$), we estimate the following specification:

$$ShLeavers_{n \to m,t} = \phi_{m,t} + \phi_{n,t} + \gamma ShTrade_{n,m,t} + \eta_{n,m,t} \tag{4}$$

where $ShLeavers_{n \to m,t}$ is the share of the workers who leave industry n and move to industry m; and $ShTrade_{n,m,t}$ is either the share of industry n's sales purchased by industry m, or the share of industry n's purchases from industry m. For the Dominican Republic, we aggregate our worker and firm-level data to the 2-digit industry level. For the United States, we leverage the 1-digit industry-level data on job-to-job flows from the US Census Bureau and merge it with the input-output tables from the Bureau of Economic Analysis. We standardize all variables to compare coefficients across samples.[23]

Table A1 presents the regression results. As expected, the estimates in columns (1) and (2) indicate a positive and significant correlation between inter-industry worker flows and trade for the Dominican Republic.[24] Importantly, we find similar results for the U.S. The results in columns (3) and (4) suggest that workers move disproportionately between upstream and downstream industries. While we cannot directly test whether supply chain moves are common in other countries, these results suggest that our findings for the Dominican Republic are likely relevant to other economies.

[23] Our results are very similar without standardization.

[24] All findings are robust to the inclusion of fixed effects for the cross-products of the industries (and location) of both origin and destination industries, thus they also hold *within* industry pairs.

Table A1: Trade and worker flows between industry pairs

	Dominican Republic		United States	
	(1)	(2)	(3)	(4)
Share of sales	0.195***		0.121**	
	(0.0466)		(0.0508)	
Share of purchases		0.272***		0.213*
		(0.0538)		(0.0994)
Observations	12,642	12,642	728	728
R^2	0.630	0.637	0.542	0.553

Notes: Data for the Dominican Republic is at the 2-digit industry level, data for the U.S. is at the 1-digit industry level. The dependent variable is the share of all workers leaving an industry and moving to another relative to the total number of movers; for the US, the variables are constructed using job-to-job flows from the US Census based on the Longitudinal Employer-Household Dynamics (https://lehd.ces.census.gov/data/). The independent variable is either the share of sales of one industry to another (columns 1 and 3) or the share of purchases of one industry from another (columns 2 and 4). For the U.S., we rely on the input-output matrix from the Bureau of Economic Analysis (https://www.bea.gov/industry/input-output-accounts-data). The sample covers the period 2012–2015, as the U.S. data are available up to 2015. All regressions include origin industry-year and destination industry-year fixed effects. Standard errors are double-clustered at the level of the industries forming the pair. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

A5 Robustness exercises

This Appendix discusses several robustness tests for the findings documented in section 3.

A5.1 Social networks

People often learn about job opportunities via social networks (Dustmann et al., 2016; Lester et al., 2021) and in particular through former coworkers (Caldwell and Harmon, 2019). Personal networks may also matter for the creation of new supply chain linkages.[25] A worker moving between unconnected firms could therefore both lead to future labor mobility as well as the formation of buyer-supplier linkages, creating an identification concern. We evaluate the importance of this channel by running the random allocation exercise described in subsection 3.1 on a sample of workers who moved between 2018 and 2019, and excluding workers who moved to a firm in which one of their ex-coworkers was employed.[26] The results in column (3) of Table A2 indicate that the share of movers to buyers and suppliers remains significantly higher than that from randomly allocating workers to firms, with an odds ratio of 1.6. This suggests that networks of previous coworkers cannot account for worker mobility between buyers and suppliers.

[25]For example, Patault and Lenoir (2023) show that job-to-job changes of sales managers leads to new linkages between their new employer and their former employer's buyers.

[26]We define a worker's set of ex-coworkers as those workers employed at the same firm in the same year between 2012 and 2017, provided that the firm had fewer than 100 workers.

Table A2: Random allocation: robustness and heterogeneity

	Baseline (all movers)	Future buyers and suppliers	Excluding ex-coworkers	2nd degree connections	Within-year movers
	(1)	(2)	(3)	(4)	(5)
Data	18.7	2.8	17.5	1.2	30.5
Random allocation	11.4	2.0	11.5	0.9	14.7
Odds ratio	1.8	1.4	1.6	1.3	2.6
Number of movers	1,019,242	394,409	167,946	828,894	136,559

Notes: The table reports the share of movers who move to buyers or suppliers, along with the random allocation share, the corresponding odds ratio, and the number of movers. In all columns, we randomly allocate workers within groups of job openings conditioning on industry, municipality, age, gender and worker earnings quintile. The first column includes all movers. The second column focuses on movers to future suppliers and buyers. The third column drops workers who move to firms in which they have ex-coworkers. The fourth column reports the share of movers to indirect supply chain connections. The fifth column restricts the sample to within-year movers whose earnings increase during the move year. To avoid mechanical overfitting as the number of controls increases, workers in groups with less than 50 movers are dropped: this causes the baseline share of movers to buyers and suppliers to be 18.7% rather than 18.4% as in the full sample.

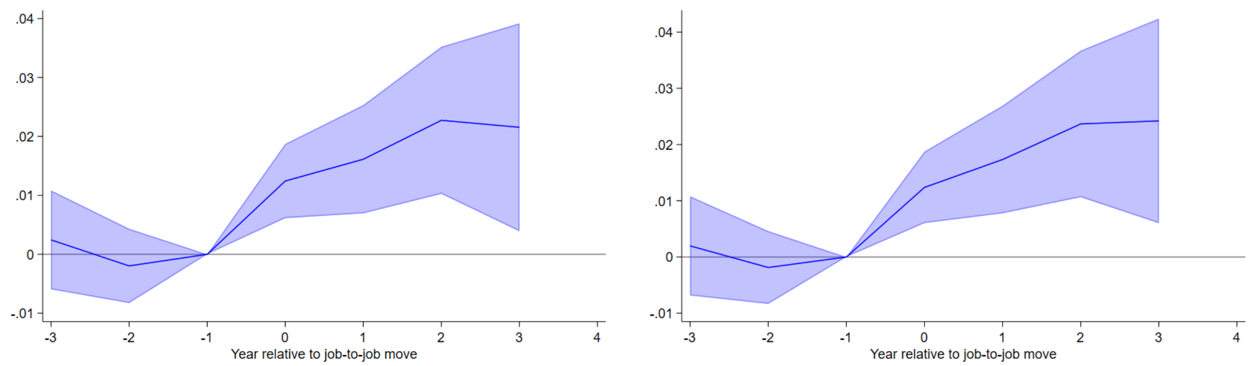
We also test if the network of previous coworkers can explain the earnings premium paid to workers moving to buyers and suppliers. First, we run the regression in Equation 1 controlling for a dummy taking value 1 when there is an ex-coworker in the destination firm (Figure A8a). Second, we restrict the sample to workers who move to firms in which they have no ex-coworkers (Figure A8b). In both cases, the results show that social networks do not explain the supply chain earnings premium.

A5.2 Common ownership

Networks of ex-coworkers are not the only relevant network shaping worker flows. Workers also have a higher propensity to move within the same business group (Cestone et al., 2019), which could overlap with firms' production networks. We address this possibility by repeating our random allocation procedure excluding workers who move between firms with common ownership. We find that the likelihood of workers moving along the supply chain remains significantly higher than in under random matching. As shown in Table A3, the odds ratio is 1.6. In the case of the earnings premium regressions, common ownership is captured by a dummy variable that equals one when the origin and destination firm have common ownership, and zero otherwise. We conclude that firm ownership networks are not a main drivers of our results.

Figure A8: Robustness to ex-coworker networks
(Relative earnings of movers to buyers or suppliers)

(a) Including ex-coworker dummies (b) Dropping moves to ex-coworkers



Notes: The figure plots the coefficient β^k from Equation 1, along with the 95% confidence interval. Panel (a) additionally includes an ex-coworker dummy variable. Panel (b) drops any moves to firms in which the worker had an ex-coworkers. We define a worker's set of ex-coworkers as any worker also employed at the same firm in the same year prior to the move year, provided that the firm had fewer than 100 workers. We therefore only include workers who move from 2016 on in the sample, which restricts our attention to horizons $k \leq 3$. Standard errors are twoway clustered at the origin and destination firm level.

A5.3 Unobservables

Another concern is that unobservable factors correlated with supply chain linkages could drive both worker and trade flows between firm pairs. For instance, some other underlying social networks may both facilitate the creation of supply chain relationships and provide information on workers and jobs. Or, employees at buyers and suppliers may share some occupational similarity, making workers at one firm more likely to be able to fill a vacancy at a buyer or supplier. To assess the relevance of this concern, we measure the share of workers who move to firms that have not traded in the past and start trading after workers move—i.e., future buyers and suppliers—and compare it to the share obtained with a random allocation of workers to these firms, using odds ratios.[27] If high mobility rates between suppliers and buyers were entirely explained by firm-pair characteristics other than supply chain connections, we should not observe differences in the odds ratios for moves to current vs. future suppliers and buyers. As shown in column (2) of Table A2, 2.8% of workers move to future buyers or supplies, which compares to a share of 2% under random matching, implying an odds ratio of 1.4. Thus, while the odds ratio for future buyers and suppliers is greater than one, it is smaller than that for current suppliers and buyers of 1.8 reported in column (1). This confirms that the existence of

[27] We define a future supplier or buyer as a firm that i) operates in the same year that the worker moves, ii) is not a supplier or a buyer in the year that the worker moves or any year prior to it, and iii) that becomes a supplier or a buyer within the two years following the worker moves. To observe a few years before and after the workers' moves, we restrict the sample to firm pairs that had workers moving in 2015, 2016, or 2017.

Table A3: Robustness exercises with the random allocation approach

	Data	Random allocation	Odds ratio	Number of movers
	(1)	(2)	(3)	(4)
Conditioning on:				
Origin industry and municipality	19	11	1.8	1,027,295
Firm size category	21	15	1.6	596,386
Firm average wage deciles	21	13	1.7	706,263
No common ownership	17	11	1.6	971,804
Mass layoffs	18	9	2.2	74,703

Notes: The table reports the share of movers who move to buyers or suppliers, along with the random allocation share, the corresponding odds ratio, and the number of movers. The random allocation share is estimated by randomly reshuffling movers across vacancies occupied by workers which are observationally similar in terms of destination industry and municipality, gender, age group, and previous salary quintile, as well as the conditioning factors reported in the table. We perform 100 simulations and report the average share of movers across simulations. The first row includes the destination industry and municipality of the mover as conditioning variables, rather than origin industry and municipality used in the baseline. The second row additionally includes destination firm size categories (≤ 20, 20-50, 50-100, 100-500, 500+) as a conditioning variable on top of the baseline set of conditioning variables. The third row additionally includes deciles of destination firm average wages as a conditioning variable on top of the baseline set of conditioning variables. The fourth row drops workers who move between pairs of firms that have the same owners. The fifth row includes only movers who leave a firm experiencing a mass layoff during the move year, where a mass layoff is defined as a situation where the firm's number of permanent employees falls by at least 30 workers *and* 25% of baseline employment.

the supply chain linkage is the key factor explaining worker mobility between buyers and suppliers.

Unobservable factors at the firm-pair level could also explain the supply chain earnings premium we document. We therefore conduct a placebo test to compare the earnings dynamics of movers to current buyers or suppliers and the earnings dynamics of movers to future buyers or suppliers. We estimate the following equation:

$$E_{i,o,d,t+k} = \alpha^k + \delta^k X_{i,t-1} + \beta^k SB_{o,d,t-1} + \lambda^k FutureSB_{o,d,t-1} + \phi^k_{o,t} + \phi^k_{d,t} + \gamma^k X_{o,d} + \eta_{i,d,o,t,k} \quad (5)$$

where $FutureSB_{o,d,t-1}$ is dummy variable equal to 1 if firms d and o start trading for the first time in the two years following the worker moves (i.e., between $T+1$ and $T+2$).[28] The results in panel (a) of Figure 10 show that workers moving to current buyers and suppliers experience a large increase in earnings compared to the control group, while workers moving to future buyers and suppliers do not. At the same time, neither group of movers displays pre-trends in earnings growth. These results mitigate concerns about unobservable confounders and support our findings that supply chain connections explain the

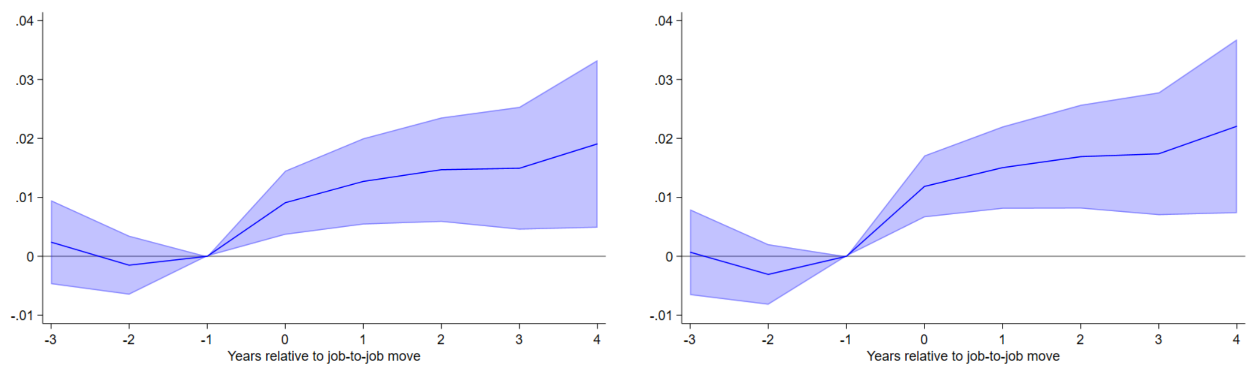
[28]We exclude from the sample workers moving between firms that started trading in the same year as the job change (as we do not observe whether the firms started trading before or after the worker move). Thus, the control group consists of firm pairs that never traded and firms that traded in the past but not in $t-1$.

earnings premium.[29]

Supply chain linkages may also be related to factors that make workers' labor markets and firms' output markets overlap. For instance, the geographic and industry categories may not be granular enough to capture key dimensions of workers' labor markets (Nimczik, 2023), especially because we do not observe workers' occupations. Reassuringly, the results in Figure A9 indicate that including firm-pair controls (i.e., fixed effects for the interactions of origin and destination firm municipality, industry, and employment quantile) in Equation 1 has virtually no impact on the earning dynamics of movers.

Figure A9: Earnings dynamics of movers, alternative specifications
(Relative earnings of movers to buyers or suppliers)

(a) Without firm-pair controls (b) With firm-pair controls



Notes: This figure plots the coefficient β^k from Equation 1, along with the 95% confidence interval. The left panel includes year fixed effects, fixed effects for worker age deciles ($\leq$25, 26-35, etc..), gender and a dummy for whether the origin and destination firm have any common ownership, and origin-firm x year and destination-firm x year fixed effects. The right panel additionally includes fixed effects for the interactions of origin and destination firm municipality, industry and employment quintile. Standard errors are twoway clustered at the origin and destination firm level.

In subsection 3.4, we document that trade between buyers and suppliers increases after a worker moves between the two firms. This could be related to movers' knowledge of the relationship-specific inputs, which complements the use or production of these inputs at the destination firm. That is, new hires from a supplier may know particularly well how to use the inputs produced by their previous employer (and vice versa for workers moving from a buyer to a supplier), thus increasing the gains from firm-to-firm trade.[30] The supply chain earnings premium could then be a return to the worker for the

[29]Our results are also robust to dropping firm pairs that only traded for one year, thereby focusing on relatively more stable supply linkages (unreported).

[30]The increase in trade could also be due to the resolution of hold-up problems through the personal connections of new hires at the origin firm. Yet, as both technical knowledge and social capital are forms of human capital, this is consistent with the human capital of movers strengthening the supply chain relationship. According to the survey results in section 4, improving supply chain relationships is not one of the main reasons firms hire along the supply chain, suggesting that social capital and personal connections may be less relevant in our setting.

increase in the destination firm's surplus. If this is the case, the earnings premium should be contingent on continuing the buyer-supplier relationship after the worker moves. In contrast, if the earnings premium is driven by suppliers and buyers having better information about idiosyncratic worker qualities unrelated to the supply chain, we would not expect the earnings premium to depend on the continuation of the buyer-supplier relationship after the worker moves.

We investigate the relationship between the earnings premium and the post-move dynamics of supplier-to-buyer sales by estimating the following specification

$$\begin{aligned} E_{i,o,d,t+k} =& \alpha^k + \delta^k X_{i,t-1} + \beta^k SB_{o,d,t-1} \times SB_{o,d,t+1} + \omega^k SB_{o,d,t-1} \times (1 - SB_{o,d,t+1}) \\ & + \phi^k_{o,t} + \phi^k_{d,t} + \gamma^k X_{o,d} + \eta_{i,d,o,t,k} \end{aligned} \tag{6}$$

which features the interaction between the buyer-supplier dummy variable, $SB_{o,d,t-1}$, and a dummy taking value one if the two firms also traded after the worker's move, $SB_{o,d,t+1}$. Panel (b) of Figure 10 shows that the supply chain premium is present when the buyer and supplier continue trading after the worker' move, while it vanishes when the supply chain link breaks after the move.[31]

A5.4 Mass layoffs

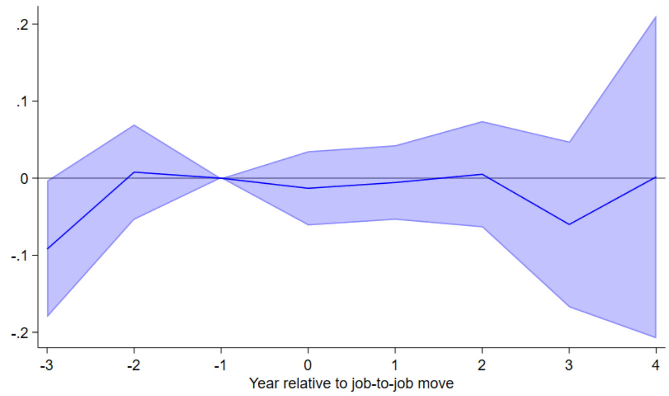
We investigate whether our results are similar when focusing on workers who leave the firm during a mass layoff, in order to isolate job separations due to firm-level shocks rather than worker-level ones (Gibbons and Katz, 1991). We define a mass layoff as a decline in a firm's labor force by at least 30% and a minimum of 25 workers. We restrict the sample to workers who are let go during these mass layoff events and find another job by the following year.

First, we find that workers tend to find jobs at buyers and suppliers after a mass layoff, as shown in Table A3. The share of workers hired by a buyer or a supplier following a mass layoff is 18%, similar to the share we see for all movers; this compares to a share of 9% when workers are randomly matched to firms. Secondly, we estimate the earnings premium using Equation 1 including only workers who move following a mass layoff and present the results in Figure A10. We find no evidence of a supply chain earnings premium for these movers.[32]

[31] One issue in the interpretation of these results is that supply chain relationships that break or shrink after the worker's move may be less important linkages to start with. We perform two robustness checks to ensure that this is not the case. Reassuringly, we find that these results are robust to controlling for premove log sales between buyer and supplier or dropping from the sample short-lived (one year only) supply chain relationship (unreported).

[32] As section 4 indicate that both information flow and supply chain-specific human capital are reasons to hire workers from buyers and suppliers, these results suggest that the mass layoff movers may still use

Figure A10: Supply chain earnings premium for mass layoff movers
(Relative earnings of movers to buyers or suppliers)



Notes: The figure plots the coefficients β^k from Equation 1, along with 95% confidence intervals estimated including mass layoff movers only. Workers are considered a mass layoff movers if they leave a firm which is decreasing permanent employment by at least 25 units and 30% of their workforce in the last year the workers have such firm as main employer. The within-year movers sample contains about 13,800 mass layoff movers, although the sample shrinks to about 3,800 movers for the longer horizons (4 years). The regressions include year fixed effects and fixed effects for worker age deciles ($\leq$25, 26-35, etc..), gender, a dummy for whether the origin and destination firm have any common ownership, origin-firm x year and destination-firm x year fixed effects, as well as fixed effects for the interactions of origin and destination firm municipality, industry and employment quintile. Standard errors are twoway clustered at the origin and destination firm level.

A5.5 Separation rates

A poor fit between an employer and an employee can lead to the employee rapidly quitting or being let go. At the same time, an excessively high turnover can be detrimental to both workers and firms. To assess whether matches formed along the supply chain involve a lower turnover rate, we focus on within-year movers and compare their separation rate to that of workers who move outside the firm's production network. We do so by estimating the following equation over the horizons $k = 2, \ldots, 6$

$$S_{i,o,d,t+k} = \alpha^k + \delta^k X_{i,t-1} + \beta^k SB_{o,d,t-1} + \phi^k_{o,t} + \phi^k_{d,t} + \gamma^k X_{o,d} + \eta_{i,d,o,t,k} \quad (7)$$

where i is a worker moving from origin firm o to destination firm d in year t.[33] This equation differs from Equation 1 in that the dependent variable $S_{i,o,d,t+k}$ is a dummy that equals one if the worker separated from the destination firm in year $t+k$, conditional on remaining at the destination firm up to year $t+k-1$.[34]

the supply chain connections to find a job but that their supply chain-specific human capital may be less valuable since the origin firm is experiencing a large negative shock. These results further highlight the connection between the supply chain relationship and the earning premium for supply chain movers.

[33]The separation rate in the year of the move is zero by construction given our definition of within-year moves.

[34]Separations are accounted for by workers dropping out of the employer-employee data and by those moving to other firms.

Table A4 presents the results of the estimation. The top panel shows the results controlling for year fixed effects and worker characteristics. We find that separation rates are 7.4 pp lower for workers who move to buyers or suppliers during the first year, with the gap shrinking to 3.2 pp in the sixth year. In the last column, we substitute the dependent variable with the duration of the match for workers who moved in 2013, which allows us to measure the post-move match duration up to six years after the move. We find that moves along the supply chain last 4.5 months longer than others. These results can in part be explained by workers who move to buyers or suppliers being hired by firms with more stable positions. As shown in the bottom panel, however, including both firm fixed effects and firm-pair controls confirms the longer tenure for workers moving to buyers and suppliers. In this case, average separation rates are 2 pp lower during the first post-move year, with no distinguishable differences from the fourth year. This leads to the match duration being almost 2 months longer. We conclude that there is a supply chain match duration premium alongside the earnings premium.

Table A4: Separation rates

	Without firm-year fixed effects					
Horizon	2	3	4	5	6	Match duration
Buyer or supplier	-0.074***	-0.059***	-0.041***	-0.041***	-0.032***	0.383***
	(0.007)	(0.007)	(0.006)	(0.008)	(0.011)	(0.051)
Observations	214,636	106,581	54,015	26,142	9,725	32,546
R^2	0.012	0.010	0.007	0.008	0.006	0.021
	With firm-year fixed effects					
Horizon	2	3	4	5	6	Match duration
Buyer or supplier	-0.020***	-0.013**	0.001	-0.013	-0.030	0.153***
	(0.005)	(0.007)	(0.009)	(0.013)	(0.026)	(0.053)
Observations	166,982	76,212	35,329	15,679	5,173	23,954
R^2	0.356	0.384	0.418	0.460	0.480	0.438

Notes: This table shows the results from the mover-level regression in Equation 7. The dependent variable (in all columns expect the last one) is a dummy variable equal to 1 if and only if a worker, who moved to a new firm in year t, separates from their firm in year $t+k$, conditional on being at the same firm from $t+1$ to $t+k-1$. In the last column, the dependent variable is the observed match duration, in number of years, for workers who move in 2013 (max six years). The top panel includes year fixed effects and fixed effects for worker age deciles ($\leq$25, 26-35, etc..), gender and a dummy for whether the origin and destination firm have any common ownership. The bottom panel additionally includes origin-firm x year and destination-firm x year fixed effects, as well as fixed effects for the interactions of origin and destination firm municipality, industry and employment quintile. Standard errors are twoway clustered at the origin and destination firm level.

A5.6 Empirical methodology

Kramarz and Thesmar (2013) We test the robustness of the results that supply chain linkages explain worker movements in subsection 3.1 using an alternative regression-based approach. We follow the approach used in Kramarz and Thesmar (2013), Kramarz and Skans (2014), and San (2022) who estimate the impact of connections between a worker and a potential employer on the probability of hiring. We estimate the following specification for the probability that mover i, who works for origin firm $o(i)$ in year $t-1$, moves to the destination firm d in year t:

$$P_{d,i,t} = \phi(d, t, X_i, X_{o(i)}) + \beta SB_{d,o(i),t-1} + u_{d,i,t} \tag{8}$$

where $P_{d,i,t}$ equals one if worker i moved to firm d in period t and $SB_{d,o(i),t-1}$ takes value one if firm d is a buyer and/or supplier of o during year t. The specification also includes a set of controls $\phi(d, t, X_i, X_{o(i)})$.

The key advantage of this approach is that it is extremely flexible in controlling for assortative matching on observable worker (and origin firm) characteristics, as the function ϕ can be different for each employer and year. That is, each firm can have a unique propensity to hire workers with certain characteristics (e.g., working in a specific industry and location) and this propensity may change over time.

For characteristics X_i and $X_{o(i)}$, we can then define a 'class' of movers c as those that share these same characteristics, except for SB. The probability model can be re-written as:

$$P_{d,i,t} = \phi(d, t, c(i)) + \beta SB_{d,o(i),t-1} + u_{d,i,t} \tag{9}$$

where $\phi(d, t, c(i))$ is a set of employer $\times$ class $\times$ year fixed effects. In our case, we define a class as the combination of workers' origin industry, destination industry, earning quintile, gender, age category, decile of firm size, and average earnings (to further control for the patterns of assortative matching between firms' skills usage documented by Demir et al. (2023)), and a dummy for whether the origin firm and the hiring firm have any business group relationship.

Given that we observe more than 1,000,000 moves and that we have on average about 16,000 hiring firms per year, estimating Equation 8 is computationally challenging. However, we follow Kramarz and Thesmar (2013) and estimate the parameter of interest β by collapsing groups of workers along the dimensions defined by the classes as per Equation 9. As reported in Table A5, we find that workers are more likely to move between buyers and suppliers. The odds ratios are larger than using the random allocation approach. Our preferred empirical method remains the latter because it does not impose the additive structure of Equation 8, which can be consequential when dealing with very small baseline probabilities.

Table A5: Probability of moving to a firm, regressions à la Kramarz and Thesmar (2013)

	(1)	(2)	(3)	(4)
Buyers or suppliers	0.014***			
	(0.000)			
Buyers		0.022***		
		(0.001)		
Suppliers			0.084***	
			(0.006)	
Top 5 buyers or suppliers				0.145***
				(0.002)
Odds ratio	4.1	6.7	10.9	54.2
Observations	316,772	254,582	203,105	128,673

Notes: Firm-Class fixed effects are included. A class is defined by the combination of a worker's origin industry, destination, earning quintile, gender, age category, decile of firm size and average wage. Coefficients and standard errors are multiplied by 100. Standard errors are double clustered at the industry and municipality level. The sample size changes in every specification because the observations are included in the procedure only when, for a given hiring firm-class combination, there are both connected and non-connected workers. Thus, the effective sample size depends on the initial sample size, controls, and independent variables of interest.

AKM decomposition We also test the robustness of our results on the earnings dynamics around worker moves using the AKM decomposition of Abowd et al. (1999). Following this approach, the log of earnings (or earnings rate) of employee i at employer $d(i, t)$ at time t can be written as

$$E_{i,t} = \alpha_i + \phi_{d(i,t)} + \gamma X_{i,t} + e_{i,t}$$

where α_i and $\phi_{d(i,t)}$ are employee and firm fixed effects, respectively; and $X_{i,t}$ is a set of time-varying controls, including worker age and year fixed effects. The error term $e_{i,t}$ can be decomposed as a sum of a match-specific component, $\eta_{i,d(i,t)}$, and a time-varying error term (Card et al., 2013), leading to the augmented model

$$E_{i,,t} = \alpha_i + \phi_{d(i,t)} + \gamma X_{i,t} + \eta_{i,d(i,t)} + \tilde{e}_{i,t}$$

While the goal of the literature relying on the AKM decomposition is typically to assess the contribution of each element in explaining the dispersion of earnings across workers, we use this approach to re-examine the findings of subsection 3.2. For this specification, we also include "stayers" (i.e., workers who do not change employers during years $t-1$ to $t+1$), given that this helps identify the coefficients on $X_{i,t}$.[35]

Let $PostMove_{i,t}$ be a dummy variable equal to one if worker i transitions from a job to another in year t or before, and zero otherwise. Thus, $PostMove_{i,t} = 0$ before the observed job-to-job move and for all the stayers. Then, let parameter c be the expected value of $\eta_{i,d(i,t)}$ across all observations such that $PostMove_{i,t} = 0$ (i.e., $E[\eta_{i,d(i,t)}|PostMove_{i,t} = 0] = c$, where expectations are conditional on the set of worker and firm fixed effects). When a worker moves ($PostMove_{i,t} = 1$), we allow the match-specific term to be different from c and the characteristics of the move to have an impact on its value. In fact, Figure 4 reveals large increases in earnings for movers. The increase in earnings is especially large for workers who move along the supply chain and those who have low earnings before the move. Therefore, we allow our empirical specification to detect changes in match quality by modeling the expected value of $\eta_{i,d(i,t)}$ as $E[\eta_{i,d(i,t)}|PostMove_{i,t} = 1] = c + \delta_q + \beta SB_{i,t}$ where δ_q is a fixed effect for the quintile of pre-move earnings of worker i and $SB_{i,t}$ is a dummy equal to one if worker i moved along the supply chain (i.e. firm $d(i,t)$ was a buyer or supplier of i's previous employer before the move). This yields the following equation:

$$E_{i,t} = \alpha_i + \phi_{d(i,t)} + \gamma X_{i,t} + PostMove_{i,t}(\beta SB_{i,t} + \delta_q) + \epsilon_{i,t} \tag{10}$$

The parameter of interest, β, captures how the match-specific earnings component differs for workers who move along the supply chain versus other workers, given the quintile of their initial earnings. While this specification is derived from the same earnings equation as AKM, we do *not* perform an AKM decomposition, as we are not interested in estimating the worker and firm fixed effects which, in our setting, are merely controls. Therefore, we circumvent the identification and estimation challenges involved in the estimation of the distribution of α_i and $\phi_{d(i,t)}$ (Kline, Saggio and Sølvsten, 2020).

In our robustness test, we first estimate the more parsimonious equation

$$E_{i,t} = \alpha_i + \delta \cdot PostMove_{i,t} + \beta \cdot PostMove_{i,t} \cdot SB_{i,t} + \gamma X_{i,t} + \epsilon_{i,t} \tag{11}$$

which is a restricted version of Equation 10 as firm fixed effects are excluded and the parameter δ—which captures how earnings change after a worker moves to a new firm relative to workers who stay at the same firm—is the same for all workers. The total change in earnings following a move to a buyer or supplier relative to stayers is then given by $\beta + \delta$. Because the firm fixed effects are excluded, the parameters β and δ capture changes in earnings due to both moves to different firms and changes in the match-specific fit. The

[35] For ease of interpretation, we drop workers that moved more than once during our sample period and we exclude the year in which the worker moves (as the main employer could be either the origin or the destination firm).

results in column (1) of Table A6 show a positive and statistically significant δ, suggesting that job-to-job transitions are important for workers to earn higher earnings. The average gain is 6.7 percentage points. β is also positive and statistically significant, confirming that moves to buyers and suppliers lead to larger earnings gains relative to moves to other firms.

We then move on to disentangle the change in earnings due to movements across different types of firms versus match-specific components. To do that, we then include firm fixed effects. As both worker and firm fixed characteristics are absorbed, the parameter δ now captures the difference in match-specific components between pre- and post-move matches for workers who move between firms. The parameter β captures the additional change in the match-specific component for workers moving along the supply chain. Column (2) of Table A6 reports the estimates of δ and β when the employer fixed effects are included. The estimate of δ is positive and statistically significant, although about half as large as in the specification without firm fixed effects. This suggests that workers in general move to firms that both pay higher earnings on average and that are also a better fit for them. β is also positive and significant, indicating that moves to buyers and suppliers lead to better matches relative to other moves. We also repeat the exercise including firm-year fixed effects ($\phi_{d(i,t),t}$), to control for the fact that workers might move to firms that are experiencing positive shocks. The results are robust to this augmentation, see column (3).

The estimate of the additional earnings premium from moving to buyers or suppliers is 0.8 pp in the most saturated specification including firm-year fixed effects. These estimates are smaller than the ones presented in subsection 3.2. One explanation is that job changes may be followed by larger earnings increases for workers starting from a lower base earnings and that workers moving to buyers or suppliers are more likely to be high earners.

We therefore augment our specification by allowing the coefficient δ to be heterogeneous according to the pre-move earnings quintile of the worker, estimating the specification in Equation 10. This specification allows for the possibility that workers with lower earnings are more likely to move to firms that are a better fit for them as they have more room to climb the job ladder. The results in columns (4) to (6) show that when we account for the heterogeneity in pre-move earnings, the additional impact of moving to buyers and suppliers is 8.6 pp, falling to 2.3 pp when we control for firm-year fixed effects. These estimates are close in magnitude to the estimates presented in subsection 3.2. We conclude that the results are quantitatively and qualitatively similar to those from estimating Equation 1 for the changes in earnings, and in particular the match-specific component of earnings following a worker moving along the supply chain.

Table A6: Worker earnings and job-to-job changes, two-way fixed effects specification

	(1)	(2)	(3)	(4)	(5)	(6)
Move to buyer/supplier	0.045***	0.023***	0.008***	0.086***	0.037***	0.023***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Move	0.067***	0.035***	0.029***			
	(0.001)	(0.001)	(0.001)			
Observations	8,355,445	8,349,762	8,278,923	8,355,445	8,349,762	8,278,923
R^2	0.902	0.928	0.940	0.903	0.929	0.940
Firm FE	-	✓	✓	-	✓	✓
Firm×year FE	-	-	✓	-	-	✓
Move×pre-move quintile of earnings FE	-	-	-	✓	✓	✓

Notes: Estimates of Equation 11 (columns 1 and 4) and Equation 10 (columns 2-3 and 5-6). Worker and year fixed effects are included in all specifications. Standard errors are clustered at the worker level.

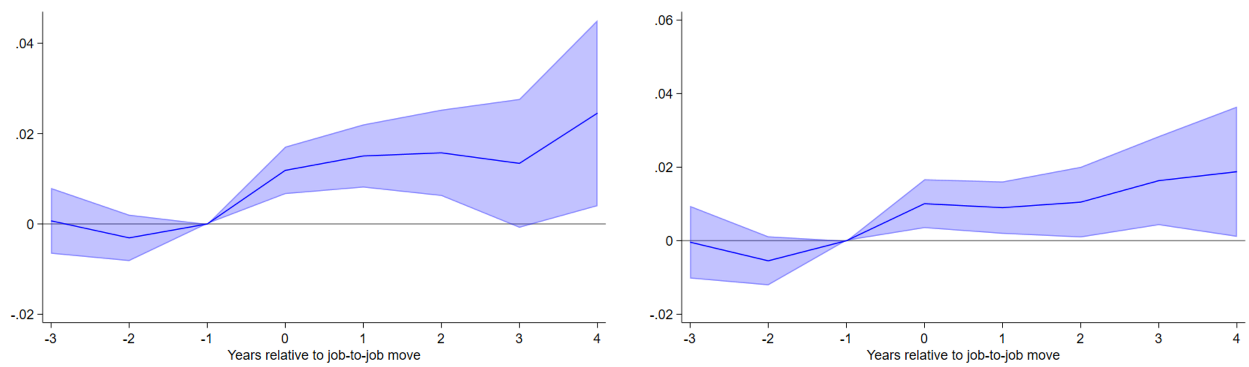
A5.7 Additional sample restrictions

Some workers repeatedly change firms in consecutive years. Our baseline specification in Equation 1 does not differentiate between workers that move only once (i.e, that do not move again until $t = k$) and those that move multiple times (i.e., workers changing firms again in $t \geq 2$). We test the robustness of the results by restricting the sample to those workers who stay at the destination firm after the move. The results in panel (a) of Figure A11 show that this additional restriction has no material effect on the earnings dynamics of movers.

We finally examine whether the supply chain earnings premium can be explained by the fact that workers moving along the supply chain have a higher probability of experiencing an increase in earnings—for instance because they find jobs quickly and shorten unemployment spells—or larger earning gains conditional on having higher earnings at the new employer. Panel (b) of Figure A11 shows a significant supply chain earnings premium for workers whose average earnings in the year of the move at the destination firm are higher than at the origin firm.

Figure A11: Earnings dynamics of movers, additional sample restrictions
(Relative earnings of movers to buyers or suppliers)

(a) Stayers at destination firm (b) Earnings increase in year of the move

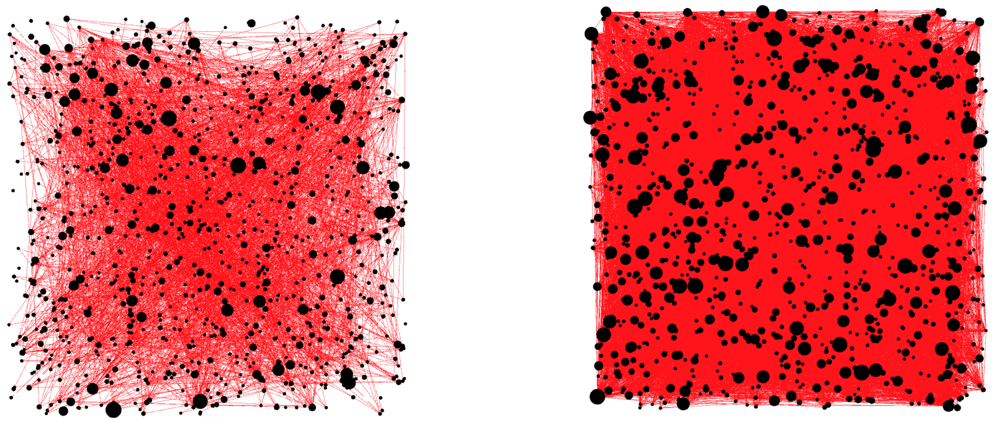


Notes: The figure plots the coefficient β^k from Equation 1, along with the 95% confidence interval. In panel (a) we condition, for k$\geq$2, on workers not separating from the destination firm. In panel (b) we restrict the sample to movers whose average earnings in the year of the move at the destination firm are higher than their average earnings in the year of the move at the origin firm. Both panels include origin-firm x year and destination-firm x year fixed effects, as well as fixed effects for the interactions of origin and destination firm municipality, industry and employment quintile. Standard errors are twoway clustered at the origin and destination firm level.

A6 Additional Appendix Figures and Tables

Figure A12: Trade flows between firms

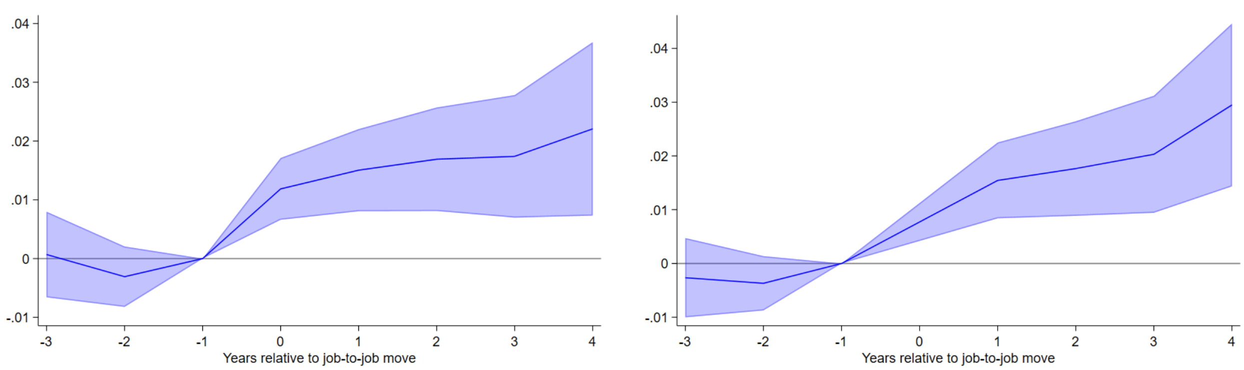
(a) Trade flows between random firms (b) Trade flows between trading firms



Notes: The nodes denote firms, with their size proportional to the number of employees. Red edges denote the firms that traded. Panels (a) uses a sample of 1,000 randomly selected firms in 2019. Panels (b) uses a sample of firm pairs that traded in 2018 and account for 1,000 unique firms. Both samples use firms with a number of employees ranging between 21 and 500. The figure is used for illustrative purposes: randomly selecting edges of a network and then studying the properties of the resulting sub-networks might lead to biased estimates of the network properties (Chandrasekhar and Lewis, 2011).

Figure A13: Earnings dynamics of movers, clean controls following Dube et al. (2023)
(Relative earnings of movers to buyers or suppliers)

(a) Baseline (b) With Dube et al. (2023) restrictions



Notes: The left figure plots the coefficient β^k from Equation 1, along with the 95% confidence interval. The specification includes year fixed effects and fixed effects for worker age deciles ($\leq$25, 26-35, etc..) and gender, a dummy for whether the origin and destination firm have any common ownership, origin firm-year and destination firm-year fixed effects, as well as fixed effects for the interactions of origin and destination firm municipality, industry, and employment quintile. The right panel additionally restricts the control group in the sample (workers who moved outside the production network at t=0) to workers who don't later move within the supply chain between t=1 and t=4. Standard errors are double clustered at the origin and destination firm level.

Table A7: Heterogeneity in share of supply chain moves

	Data	Random allocation	Odds ratio	Number of movers
	(1)	(2)	(3)	(4)
Panel A: By feature of supplier-buyer relationship				
Moves from supplier to buyer	13.0	7.3	1.9	1,019,242
Moves from buyer to supplier	11.5	6.9	1.8	1,019,242
Move to top 5 supplier or buyer	7.8	2.9	2.8	828,894
Panel B: By industry				
Agriculture	13	6	2.2	10,499
Construction	18	6	3.6	39,319
Education	7	3	2.1	3,038
Finance and insurance	29	23	1.3	17,747
Health	16	10	1.6	6,391
Hotels and hospitality	22	13	1.9	96,844
Manufacturing	17	14	1.3	126,267
Other	13	5	2.9	131,000
Real estate	17	7	2.6	9,153
Transportation	18	11	1.8	57,770
Wholesale and retail trade	27	18	1.7	148,056
Panel C: By geography				
Excluding National District and Santo Domingo	16	11	1.5	216,970
Only National District and Santo Domingo	22	13	1.9	429,114
Panel D: Switchers vs. stayers				
Switching industry	18	11	1.7	362,264
Same industry	21	13	1.9	283,820
Switching municipality	16	12	1.4	278,875
Same municipality	23	12	2.1	367,209
Switching industry and municipality	14	11	1.3	176,935
Same industry and municipality	23	12	2.1	181,880
Panel E: By gender				
Men	20	13	1.8	463,853
Women	18	10	1.9	182,231
Panel F: By age				
Younger than 25	18	13	1.5	178,184
Older than 25	20	13	1.7	274,902
Older than 35	20	10	2.2	192,998
Panel G: By ethnicity				
White	22	12	2.0	48,022
Other	19	12	1.8	576,697
Panel H: By education level				
No tertiary education & Born after 1984	18	12	1.6	512,914
Any tertiary degree & Born after 1984	24	15	1.7	38,666
Any tertiary degree	24	15	1.8	56,456

Notes: The table reports the share of movers who move to buyers or suppliers, along with the random allocation share, the corresponding odds ratio, and the number of movers for selected groups. The random allocation share is estimated by randomly reshuffling movers across vacancies occupied by workers which are observationally similar in terms of destination industry and municipality, gender, age group, and previous salary quintile. We perform 100 simulations and report the average share of movers across simulations.

Table A8: Earnings results, main specification without firm-year FE

Log earnings in $t =$	-3	-2	-1	0	1	2	3	4
Buyer/supplier	0.000	0.001	-	0.027***	0.077***	0.072***	0.068***	0.067***
	(0.003)	(0.002)	-	(0.008)	(0.010)	(0.012)	(0.012)	(0.012)
Observations	138,313	191,705	-	273,003	273,003	190,408	134,593	87,821
R^2	0.733	0.834	-	0.740	0.529	0.510	0.483	0.462
Year FE	✓	✓	-	✓	✓	✓	✓	✓
Worker controls	✓	✓	-	✓	✓	✓	✓	✓

Notes: This table plots the results from the regression in Equation 1 for each horizon k. The specification includes year fixed effects and fixed effects for worker age deciles ($\leq$25, 26-35, etc..), gender and a dummy for whether the origin and destination firm have any common ownership. Standard errors are twoway clustered at the origin and destination firm level.

Table A9: Earnings results, main specification with firm-year FE

Log earnings in $t =$	-3	-2	-1	0	1	2	3	4
Buyer/supplier	0.001	-0.003	-	0.012***	0.015***	0.017***	0.017***	0.022***
	(0.004)	(0.003)	-	(0.003)	(0.004)	(0.004)	(0.005)	(0.007)
Observations	102,865	145,822	-	213,379	213,379	145,448	100,974	64,161
R^2	0.841	0.898	-	0.888	0.829	0.793	0.768	0.754
Year FE	✓	✓	-	✓	✓	✓	✓	✓
Worker controls	✓	✓	-	✓	✓	✓	✓	✓
Origin & destination firm FE	✓	✓	-	✓	✓	✓	✓	✓
Firm-pair controls	✓	✓	-	✓	✓	✓	✓	✓

Notes: This table plots the results from the regression in Equation 1 for each horizon k. The specification includes year fixed effects and fixed effects for worker age deciles ($\leq$25, 26-35, etc..), gender and a dummy for whether the origin and destination firm have any common ownership, origin-firm x year and destination-firm x year fixed effects, as well as fixed effects for the interactions of origin and destination firm municipality, industry and employment quintile. Standard errors are twoway clustered at the origin and destination firm level.

Table A10: Hiring and earnings of coworkers, all firms

Log earnings in $t =$	-3	-2	-1	0	1	2	3
New hire	-0.009***	-0.005***	-	0.010***	0.017***	0.024***	0.029***
	(0.002)	(0.001)	-	(0.001)	(0.001)	(0.002)	(0.003)
New hire from buyer or supplier	-0.000	-0.002**	-	0.011***	0.015***	0.018***	0.021***
	(0.002)	(0.001)	-	(0.001)	(0.002)	(0.002)	(0.003)
Average coworker earnings	-0.012***	-0.009***	-	0.047***	0.072***	0.094***	0.110***
	(0.002)	(0.001)	-	(0.001)	(0.002)	(0.003)	(0.004)
Observations	452,345	702,373	-	1,085,791	1,085,791	704,876	455,515
R^2	0.916	0.957	-	0.954	0.900	0.866	0.838

Notes: This table shows the results from the worker-level regression in Equation 2 for different horizons -3≤k≤3. The samples are restricted to workers i who are at the same firm d in every year from $t+k$ to $t+1$ for $-3 \leq k \leq 0$, and $t-1$ to $t+k$ for $1 \leq k \leq 3$. We restrict the sample to workers in firms with at most 100 workers in all years. The specification includes the following worker-level controls: log(earnings) in period $t-1$, age deciles, gender and the average earnings of worker i's coworkers in period $t-1$. We also include the following firm-level controls: employment and sales growth from $t-1$ to t, and employment in period $t-1$. We include industry×municipality× year fixed effects. Standard errors are clustered at the firm level.

Table A11: Hiring and earnings of coworkers, hiring firms only

Log earnings in $t =$	-3	-2	-1	0	1	2	3
New hire from buyer or supplier	-0.000	-0.002*	-	0.008***	0.011***	0.014***	0.017***
	(0.002)	(0.001)	-	(0.001)	(0.002)	(0.002)	(0.003)
Average coworker earnings	-0.006	-0.001	-	0.005**	0.014***	0.034***	0.046***
	(0.004)	(0.002)	-	(0.002)	(0.003)	(0.005)	(0.006)
Average log(earnings) of new hires	-0.001	-0.006***	-	0.061***	0.082***	0.082***	0.083***
	(0.003)	(0.002)	-	(0.002)	(0.003)	(0.004)	(0.005)
Observations	291,467	452,837	-	712,894	712,894	451,282	284,329
R^2	0.915	0.955	-	0.951	0.895	0.863	0.836

Notes: This table shows the results from the worker-level regression in Equation 2 for different horizons -3≤k≤3. The samples are restricted to workers i who are at the same firm d in every year from $t+k$ to $t+1$ for $-3 \leq k \leq 0$, and $t-1$ to $t+k$ for $1 \leq k \leq 3$. We restrict the sample to workers in firms with at most 100 workers in all years and that hire a worker from another firm between year $t-1$ and t. The specification includes the following worker-level controls: log(earnings) in period $t-1$, age deciles, gender, and the average earnings of worker i's coworkers in period $t-1$. We also include the following firm-level controls: employment and sales growth from $t-1$ to t, employment in period $t-1$, and the average log(earnings) of new job-to-job hires at the firm in year t. We include industry×municipality× year fixed effects. Standard errors are clustered at the firm level.

Table A12: Heterogeneity in earnings event study results, with firm-year FE

	Tenure $\geq$ 4y	Age < 30		Women		Stayers	
	k = 1	k=1	k=4	k=1	k=4	k=1	k=4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Buyer or supplier	0.014***	0.013***	0.026**	0.012***	0.018**	0.015***	0.017*
	(0.005)	(0.005)	(0.010)	(0.004)	(0.008)	(0.004)	(0.009)
Tenure/young/female/stayer	-0.028***	0.423***	-0.149	0.004	0.048***	-	-
	(0.004)	(0.064)	(0.091)	(0.003)	(0.006)	-	-
Interaction	0.011*	0.003	-0.006	0.012*	0.017	-0.001	0.011
	(0.006)	(0.005)	(0.010)	(0.006)	(0.011)	(0.006)	(0.013)
Observations	127,863	213,323	64,097	213,323	64,097	213,323	64,097
R^2	0.824	0.830	0.754	0.830	0.755	0.830	0.754
Share	0.24	0.51	0.50	0.32	0.32	0.44	0.44

Notes: This table plots the results from the regression in Equation 1 for horizons $k = 1$ and $k = 4$, interacting the dummy for whether a worker moves to a buyer or supplier with a dummy variable for: (1) workers being under the age of 30, (2) female worker, (3) workers who stay within the same industry. The specification includes year fixed effects and fixed effects for worker age deciles ($\leq$25, 26-35, etc..), gender and a dummy for whether the origin and destination firm have any common ownership, origin-firm x year and destination-firm x year fixed effects, as well as fixed effects for the interactions of origin and destination firm municipality, industry and employment quintile. Standard errors are twoway clustered at the origin and destination firm level.

Table A13: Supplier to buyer sales and worker moves

	Year FE						
Horizon	-3	-2	0	1	2	3	4
First worker move	0.0556	0.175***	0.232***	0.259***	0.288***	0.320***	
	(0.0569)	(0.0529)	(0.0514)	(0.0523)	(0.0544)	(0.0603)	(0.0665)
Observations	75,405	86,352	102,227	95,908	71,604	50,777	31,614
	Buyer$\times$year and supplier$\times$year FE						
Horizon	-3	-2	0	1	2	3	4
First worker move	0.0183	0.00929	0.0777***	0.105***	0.108***	0.151***	0.178***
	(0.0226)	(0.0224)	(0.0219)	(0.0213)	(0.0204)	(0.0224)	(0.0269)
Observations	72,837	83,541	98,961	92,806	69,483	49,322	30,679

Notes: This table shows the results from the firm-pair regressions in Equation 3. The dependent variable is the log of supplier's sales to the buyer in year $t + k$ where $k = -3, ..4$ is the horizon. The independent variable is a binary variable equal to one iff in year t it is observed for the first time that at least one worker move between the supplier to the buyer or viceversa. Treatment and control groups are matched through a coarsened exact matching procedure. See subsection 3.4 and section A3 for more details. Standard errors are twoway clustered at the buyer and supplier level.

Table A14: Firm growth and hiring from buyers and suppliers

	Sales growth				Employment growth			
Horizon	1 year	3 years	1 year	3 years	1 year	3 years	1 year	3 years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of new hires	0.031***	0.111***			0.014***	0.035***		
from buyers and suppliers	(0.008)	(0.020)			(0.004)	(0.013)		
First time hiring			0.112***	0.242***			0.039***	0.051***
from buyers or suppliers			(0.008)	(0.017)			(0.005)	(0.011)
Observations	160,365	96,489	86,756	48,674	155,734	93,147	83,572	46,550
R^2	0.089	0.094	0.098	0.121	0.081	0.071	0.069	0.067

Notes: Columns (1) and (2) report the coefficient of a regression of firm sales growth over one year (delta log, from t to $t+1$) or three years (delta log, from t to $t+3$) on the share of new hires–among the new hires that worked at another firm in the previous year–that in the previous year worked at a firm which was a buyer or supplier of the hiring firm. Columns (3) and (4) report the coefficient of a regression of firm sales growth over one year (delta log, from t to $t+1$) or three years (delta log, from t to $t+3$) on a binary variable equal to one iff the firm hires for the first time (within the sample period) in year t at least one worker from a buyer or supplier. In all regressions controls include industry$\times$municipality$\times$year fixed, log sales, lag of log sales, log number of buyers plus suppliers, log total employment at buyers and suppliers, and log average wages of the new hires. Firms are included in the sample only if they hire at least one worker are included. Moreover, in columns (3) and (4) firms are excluded if the first year the firm hires a worker from a buyer or a supplier is before 2015 or if the first year the firm hires a worker from a buyer or a supplier is after year t (Dube et al., 2023). Columns (5) to (8) repeats the same exercise as columns (1) to (4) substituting employment growth (headcount of permanent workers in the balance sheet) to sales growth as dependent variable. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.