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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. Employer-employee data, matched with the universe of firm-to-firm transactions for the Dominican Republic, reveals that one-fifth of workers who change firm move to a buyer or supplier of their original employer—significantly more than predicted by standard labor market characteristics. Supply chain moves are a major contributor to mobility up the job ladder. An event study shows that moving to a buyer or supplier is associated with a persistent 2 percent earnings premium relative to other workers hired by the same firm. Survey evidence shows that the main reasons for hiring within the supply chain are a supply chain-specific component of human capital and better information about job applicants. Worker mobility along the supply chain is also associated with an increase in firm-to-firm trade, which points to human capital as the most likely explanation for the supply chain earnings premium. These results reveal a new channel through which factors affecting the supply chain, such as international outsourcing or contracting frictions, affect labor market dynamism.

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1 Introduction

Changing employers is a common way workers find better jobs over time, and such transitions are important drivers of reallocation to high productivity firms (Haltiwanger, Hyatt, Kahn and McEntarfer, 2018). Search frictions impede this process, making it harder for workers to find good jobs, especially in developing economies (Donovan, Lu and Schoellman, 2023). Production networks could be important for labor market flows, as workers may be able to overcome search frictions by using business contacts to find job opportunities at buyers and suppliers, and may also have skills and knowledge that are particularly valued within the supply chain.

In this paper we provide the first evidence of how and why the production network matters for labor market flows. While the role of social connections—such as family or neighbors—for job-finding is well-documented (Topa, 2011), the role of firm networks has been largely unexplored. We overcome previous data limitations by using novel data linking transactions between firms (from the VAT registry) to worker-level records (from social security) for the universe of formal firms in the Dominican Republic.

We show that the firm production network is also a job-finding network for workers. One fifth of job-to-job transitions are to a buyer or supplier of a worker's original employer. These high mobility rates are only partly explained by observable factors (such as industry and location). We document that moves along the supply chain are associated with a 7 percentage point larger increase in earnings than other job changes.[1] Using an event-study specification, we estimate that two thirds of this is accounted for by supply chain movers being more likely to move to higher wage firms. The remaining third is explained by supply chain movers earning more even after accounting for the firm component of earnings. We name this the "supply chain earnings premium". Furthermore, we document that moves along the supply chain are associated with an increase in supplier-to-buyer sales.

What explains these findings? We survey managers in Dominican manufacturing firms to provide insights into the mechanisms. The survey results reveal the two main reasons why firms hire within the supply chain. The first reason is that these workers have specialized knowledge of the inputs and products of the firm. The second reason is that the firm has better information about these workers (via referrals or direct contact), thereby lowering search and matching frictions. We then investigate the causes of the supply chain earnings premium. In particular, we consider several implications of human capital and information-based explanations. We find that supply chain-specific knowledge

[1] For comparison, the wage 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).

of the firm's inputs and products is the most likely explanation for both the premium and the increase in firm-to-firm trade.

Another important feature of supply chain moves is that supply chain moves account for the majority of net hiring at high-wage and high-productivity firms. A well-known property of production networks—the fact that more productive firms have more suppliers and buyers (Bernard, Dhyne, Magerman, Manova and Moxnes, 2022)—can fully explain the tendency of supply chain movers to move up the firm wage ladder. Job search in the production network is therefore inherently more likely to lead to matches with higher-wage firms than random search. A key implication of these findings is that countries with sparser production networks should have weaker job ladders.

This new channel of job-finding through production networks can 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 in the U.S. (Davis and Haltiwanger, 2014) and other advanced economies.[2] Furthermore, contracting frictions are prevalent in emerging markets 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 the labor market and contributes to the weakness of the job ladder 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 as well.

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 such arrangements also occur within supply chains.[3] Our findings indicate that these clauses could be harmful to workers and labor market efficiency.

Our data covers all formal firms in the Dominican Republic between 2012 and 2019, containing information on more than 1,220,000 workers per year.[4] We observe 1,150,000 job changes over consecutive years, 19% of which are between buyers and suppliers. Standard worker and labor market characteristics, such as age, pre-move earnings, in-

[2]While merged employer-employee and firm-to-firm trade data are unavailable in the U.S., we use industry-level data to assess the external validity of our results. We show that workers exhibit a strong tendency to move to more vertically integrated sectors both in the U.S. and in the Dominican Republic.

[3]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.

[4]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 A4.

dustry, location, and college degree, can explain only half of this share. This tendency of workers to move along the supply chain is also not explained by observable assortative matching between firms, by firms' rank (in terms of size or average wages), nor by local labor markets or business groups overlapping with buyer-supplier networks. To evaluate the importance of unobservable factors that could drive both worker flows and trade between firms, we compare mobility rates between current and future suppliers and buyers. If high mobility rates between current suppliers and buyers are entirely explained by firm-pair characteristics other than the supply chain connection, then we expect workers to be equally likely to move between current and future suppliers and buyers. However, we find significantly higher mobility rates between current suppliers and buyers. We also show that the tendency to move between suppliers and buyers is not explained by ex-coworker networks, and holds to a lesser extent for indirect suppliers and buyers (buyers of buyers and suppliers of suppliers) where direct social contacts are less likely to be common. We infer that the production network is also a job-finding network for workers. This finding holds broadly across industries, municipalities, and firm sizes, is of similar relevance for upstream and downstream moves, and is stronger for workers with higher earnings and tenure.

Our second main finding is that movers along the supply chain are 5 percentage points more likely than other movers to move to higher-wage firms (up the firm wage ladder) and to higher-productivity firms (up the firm productivity ladder). This is entirely explained by the fact that high wage firms have more suppliers and buyers and are therefore over-represented in the production network. (For instance, firms in the top 20% of the wage distribution represent more than 50% of the suppliers of the average worker.) This highlights an important distinction between the production network and social networks for job search, given that the former is inherently more likely to lead to matches with higher-wage firms. Consistent with this, we find that workers at firms with fewer buyers and suppliers are less likely to move up the firm wage ladder. To quantify how important supply chain moves are for the job ladder, we follow Haltiwanger et al. (2018) and aggregate net job flows (defined as hires from other firms minus separations to other firms) across firms in the top vs. bottom quartiles of wages and labor productivity. We then decompose net job flows into two terms: (i) net job flows from buyers or suppliers and (ii) net job flows from other firms. We find that net job flows from buyers or suppliers account for over three-quarters of net job flows at high-wage firms.

These first two findings suggest that job changes along the supply chain have a large impact on workers' labor market outcomes. We therefore use an event-study approach to document the earnings dynamics of workers who move along the supply chain relative to those of other similar movers. Other movers have similar pre-move trends in earnings, mitigating the concern that they are differentially selected based on pre-move trends in (or shocks to) earnings. Controlling only for worker characteristics, we find that earnings are 6.7 percentage points higher after four years for supply chain movers, while separation rates are also lower.

This increase in earnings could be explained both by the higher frequency of moves to firms with higher wages, and also by these moves being associated with a larger increase in the match-specific component of earnings. To disentangle these two sources, we re-estimate our specification including origin and destination firm-year fixed effects. These fixed effects control for any firm-specific (and time-varying) factors that can impact workers' pre- and post-move earnings. This specification effectively compares similar workers moving to the same firm in the same year, controlling for worker characteristics and origin firm fixed effects. Our third main finding is that, of the 6.7 percentage points earnings gap four years after a move, 2.2 percentage points (one-third) is explained by supply chain movers earning more even after accounting for the firm component of earnings. This supply chain premium is persistent and is only for high-wage workers. We quantify the aggregate earnings gains to workers via supply chain moves using a back-of-the-envelope exercise and find that average worker earnings would be 1.4% lower in the absence of this premium.

A concern with our empirical specification is that supply chains may be correlated with confounding factors that make workers' labor markets and firms' output markets overlap. However, the inclusion of firm-pair controls, such as the cross-product of industries and locations of the origin and destination firms, does not materially impact the results, mitigating this concern. It is still possible that unobserved confounding factors affect our results, such as buyers and suppliers having similar occupational compositions. Similarly, social networks could both help firms find suppliers or buyers and workers obtain jobs. We first show that the estimated premium is very similar when controlling for the presence of an ex-coworker in the destination firm. We then assess the importance of unobservable factors by looking at workers who move to firms that are not current buyers or suppliers, but that become buyers or suppliers at a later date. We find that these moves are not followed by increases in earnings, confirming that our results are driven by the existence of current supply chain connection between firms.

Our fourth set of findings is to document two new facts about changes in *firm*-level outcomes around worker moves, specifically changes in firm-to-firm trade and coworker earnings. While firms' purchase and supply decisions are often considered independent from hiring decisions, hiring workers from within the supply chain may diminish firm-to-firm trade if the movers possess knowledge that allows the firm to insource some previously outsourced tasks. On the other hand, worker moves may lead to an increase in firm-to-firm trade if they help build trust between the firms, or if workers possess knowledge which complements the use of relationship-specific inputs in production. We show that, following a worker transition between a buyer and supplier, the likelihood of the relationship lasting increases by 6.3 percentage points and supplier-to-buyer sales increase by 4.4%. Hiring along the supply chain is therefore more likely motivated by the acquisition of the human and social capital of the worker rather than insourcing. We additionally follow Jarosch, Oberfield and Rossi-Hansberg (2021) to check for the presence of knowledge spillovers from new supply chain hires to new coworkers. We find a larger increase in coworker earnings when a new worker is hired from a buyer or supplier than from an unconnected firm, consistent with greater spillovers from hiring along the supply chain.

To shed light on the mechanisms underpinning why workers move along the supply chain and the causes of the supply chain earnings premium, we collaborated with the Central Bank of the Dominican Republic to add questions about hiring to a representative survey of 200 manufacturing firms implemented in December 2022. Over one-third of companies responded that experience in a buyer or supplier was either a "very important" or "the most important" factor when hiring skilled workers, similar to the share of responses about experience at a competitor or having a referral for the worker. The most commonly cited reason for hiring from suppliers or buyers was "specialized knowledge related to the firm's inputs and/or products", which was roughly as important as the number of firms either answering "received a referral" and/or "previous positive experience dealing with the worker" combined. The survey results indicate that information (about the worker or firm) and human capital are the main reasons for supply chain hiring.

Given that the most common survey response is that workers are hired because of their specialized knowledge, a natural explanation for the earnings premium is that it is a return on this supply chain component of workers' human capital. Consistent with this explanation, the earnings premium is larger for workers with more pre-move human capital, as measured by tenure or earnings. The finding that firm-to-firm trade increases following worker moves also suggests that these worker-firm matches generate a particularly large surplus precisely because they enhance the productive use of intermediate inputs, and hence the gains from trade. In particular, new hires from a supplier may be particularly knowledgeable about how to use the inputs produced by their previous employer (and vice versa for workers moving from a buyer to a supplier). However, given that the survey responses showed that referrals and direct contact are also important reasons for hiring within the supply chain, the supply chain earnings premium could instead result from firms having better information about workers in their buyers and suppliers (and vice versa). Hiring from within the supply chain may thereby reduce the uncertainty firms have about the goodness of fit of job applicants and enable them to screen more effectively. Workers selected in this way would be a better match with the hiring firm and therefore receive higher wages. Better information may also impact earnings through the wage bargaining process: workers hired from within the supply chain may also have better information about the firm, including performance and the distribution of wages. This additional information may enable them to bargain more aggressively.

To determine whether the supply chain earnings premium is mainly driven by the supply chain-specific component of human capital or by the more abundant information available to firms and workers, we test three implications of human capital that should not be present in the information-based explanation. We first show that the earnings premium does not shrink over time even for workers who stay at the destination firm, contrary to predictions of the workhorse models of hiring under uncertainty about match quality (Jovanovic, 1979; Dustmann, Glitz, Schönberg and Brücker, 2016). Secondly, we find that the supply chain earnings premium is absent when the supplier and buyer stop trading with each other after the worker moves. This would not be the case if the earnings premium was driven solely by an ex-ante informational advantage. Thirdly, we focus on workers moving following a mass layoff. For these workers supply chain-specific knowledge should be less valuable because the origin firm is experiencing a major negative shock. We show that these workers tend to disproportionately find jobs along the supply chain , but do not receive a premium when they do. Lastly, we consider alternative explanations for the supply chain earnings premium, including that supply chain movers suffer less from unemployment scarring, or face lower moral hazard, finding no evidence in favor of such explanations. We therefore argue that this evidence overall points to a human capital-based explanation for the supply chain earnings premium.

We formalize the mechanism of job search in production networks in a parsimonious model of on- the-job search, in the spirit of Postel-Vinay and Robin (2002) and Cahuc, Postel-Vinay and Robin (2006). Workers are more likely to learn about job opportunities within their employer's supply chain, thus reducing search frictions similar to the role of social connections in Calvo-Armengol and Jackson (2004). The model implies that economies with denser production networks have higher average wages and labor productivity. This is because high-productivity firms face lower search frictions when hiring, and are more likely to form productive matches through supply chain hires. This is a new channel through which factors affecting the production network, such as international outsourcing or contracting frictions, affect labor market dynamism.

Related Literature This paper 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). This literature, largely based on job ladder models, highlights that worker flows from low- to high-wage and productivity firms play an important role in workers' career trajectories and firm growth. We document the importance of domestic production networks in this process.

Another strand of the literature highlights the importance of the fit between workers and jobs. For instance, Lachowska, Mas and Woodbury (2020) find that most of the negative impact of a job displacement is due to the loss of the employer-employee specific component of earnings, while other papers estimate significant costs from the mismatch between workers' skills and either the job they occupy (Guvenen, Kuruscu, Tanaka and Wiczer, 2020; Lise and Postel-Vinay, 2020) or the available set of vacancies (Shimer, 2007; Şahin, Song, Topa and Violante, 2014).[5] We contribute by documenting that production networks are an important factor mitigating such human capital mismatch.

The use of social networks and personal referrals to find jobs is extremely 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 for job finding. In contrast to the literature on social networks, we emphasize the role of human capital within production networks as being an additional driver of worker mobility. We also highlight how the disproportionate share of high-productivity firms in production networks facilitates worker transitions up the job ladder. This paper also contributes to the recent literature on labor market boundaries and outside options (Caldwell and Harmon, 2019; Nimczik, 2020) by showing that supply chains are an important dimension of workers' labor markets.

A growing literature highlights the importance of domestic production networks for firm performance (Bernard, Moxnes and Saito, 2019; Alfaro-Ureña, Manelici and Vásquez, 2022; Bernard et al., 2022; Dhyne, Kikkawa, Komatsu, Tintelnot and Mogstad, 2022) and in particular for workers. In this latter category, Alfaro-Ureña et al. (2021) and Balsvik, Fitzgerald and Haller (2023) estimate the impact of multinationals on workers in Costa Rica and Norway respectively, and Demir, Fieler, Xu and Yang (2023); Huneeus, Kroft and Lim (2021b); Adão, Carrillo, Costinot, Donaldson and Pomeranz (2022) all combine employer-employee and production network matched data to analyze how production networks affect earnings inequality. 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.

The rest of the paper is structured as follows. Section 2 describes the data. Section 3 shows that the production network is also a job-finding network. Section 4 documents that these transitions are an important driver of moves up the firm wage ladder. Section 5 documents the existence of a supply chain earnings premium using an event study. Section 6 documents new evidence on firm outcomes around worker moves, specifically

[5]Studies of earnings inequality find that the match-specific component of earnings has only limited explanatory power for earnings dispersion (Card, Heining and Kline, 2013). The results of our paper indicate that moves along the supply chain lead to an increase in average earnings due to better worker-firm matches but we are silent on the implications for earnings dispersion.

firm-to-firm trade, and spillovers to coworkers. Section 7 discusses the possible explanations for our findings. Section 8 concludes.

2 Data

Our empirical setting is the Dominican Republic between the years 2012 and 2019. During the sample period, the country experienced a period of sustained economic development with an average real GDP growth of 5.6% per year, placing it among the fastest growing countries in Latin America. Inflation generally remained within the central bank's target band, at 2.8% on average. We combine several datasets that draw anonymized administrative records from the Directorate General of Internal Taxes and other public administrations. Additional details on the data sources and data collection are reported in Appendix A1.

The first dataset contains firm-level information for the entire universe of firms that file income taxes at the Directorate General of Internal Taxes. Specifically, the dataset includes annual data on assets, liabilities, revenue, expenditures, as well as the wage bill. Moreover, we observe the ownership structure of each firm with details about the size of the shareholders' participation in the firms' capital. The main industry (based on ISIC 3) and the municipality where the firm is headquartered are also reported.

The second dataset contains information on firm-to-firm transactions from the VAT registry. This allows us to identify all the domestic buyers and suppliers of each firm. Purchases by firms in the formal sector from suppliers in the informal sector (i.e., not registered at the Directorate General of Internal Taxes) get recorded in the accounts of the former. In the analysis, we restrict the sample to formal sector firms that make at least one transaction per year.

The third dataset contains information on employees from the Social Security Treasury. Each month all employers must report payments to all employees (including bonuses, overtime work, etc.) to calculate social security contributions and withholding taxes. We observe the data at annual frequency, where the value reported is the average worker earnings for the months in which the employee had social security obligations. For example, if an employee only worked for three months of the year, the annual earnings reported in the dataset correspond to the average of the three months. Employees are classified as permanent or temporary workers based on whether they have social security obligations. We restrict the sample to firms that have at least one permanent employee. We also observe all employees' age, gender, and ethnicity.

Table 1 provides a 'helicopter view' of the datasets we use in the subsequent analysis. We observe over 44,000 firms per year. The median firm in the sample 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, these firms employ more than 1.2 million workers, which represent 26.1% of the country's labor force. 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 25.9% take place between firms of the same industry. The median firm, on average, has eight buyers and 28 suppliers. More details about the production network are reported in Appendix A4. An obvious 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 level of development. Appendix A3 presents a discussion of how this limitation may affect the internal and external validity of our results.

In addition to the previously described administrative data sources, we collaborated with the Central Bank of the Dominican Republic to incorporate questions about firm hiring practices into a firm-level survey in December 2022. The quarterly survey of 200 firms is representative of the manufacturing sector and is typically run to ask firms about their inflation expectations. More details are presented in section A2.

Table 1: Dataset Overview

a. *Firm-level data*	Number of firms	Employees per firm (median)	Sales per firm (median, USD)	Sales growth (median, percent)
	44,476	7	29,628	8.9
b. *Worker-level data*	Number of workers	Share of labor force (percent)	Wages (median, USD)	Wage growth (median, percent)
	1,228,879	26.1	3,120	5.6
c. *Transaction-level data*	Number of transactions	Share of transactions within same industry (percent)	Number of buyers (median)	Number of suppliers (median)
	2,468,583	25.9	8	28

Notes: The table report annual averages over 2012–2019.

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 $t-1$.[6] We observe 1,152,279 worker moves between 2012 and 2019 implying that on average 13% of

[6]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 et al., 2013). The main results of the paper are robust to restricting the sample to workers with only one employer in each year.

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 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.[7]

3 Job-Finding Along the Supply Chain

In this section, we use administrative and survey data to document that the supplier-buyer network is also a job-finding network for workers. We first show that a disproportionate share of job changers move to suppliers or buyers of their previous employer, and secondly document heterogeneity across worker and firm types.

3.1 Worker Mobility in Production Networks

Approximately one-fifth of the workers who changed firms between 2012–2019 were hired by a supplier or buyer of their previous employer. The two network graphs in Figure 1 visually illustrate this finding for a sub-sample of employers. In the left panel, we show the number of worker movements (blue edges) between 1,000 random firms (nodes, scaled by total firm employment). In the right panel, we draw 500 firms randomly, and for each of these, we draw one of their suppliers or buyers at random, thereby oversampling firms with supply linkages. There are two takeaways. First, there are a lot more worker movements between suppliers and buyers than between random firms. Second, firms tend to be larger in the sample of buyers and suppliers than in the random sample.

Given that suppliers and buyers typically account for fewer than 1/1000th of firms in the economy, it is striking that 18.4% of moves are to suppliers or buyers. For comparison, 43% of workers move to a firm within the same 2-digit industry, of which there are 42.[8] However, the panels below highlight one reason why this comparison is misguided. The

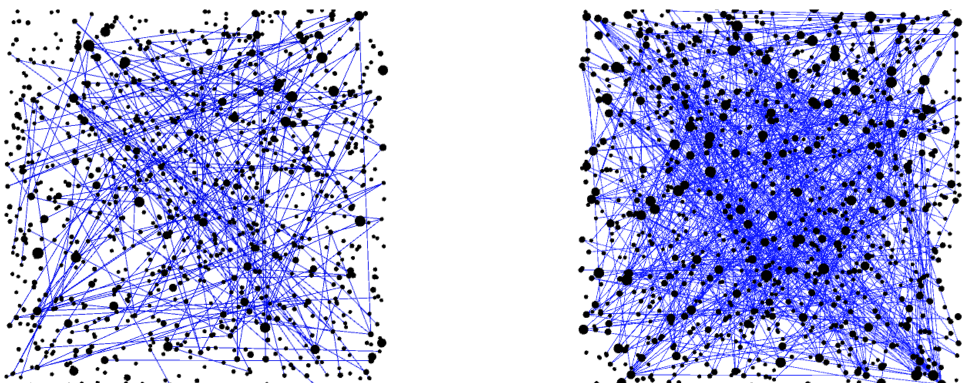
[7]Note that, under this alternative definition, a worker who leaves his employer in December and joins a new employer in January is not counted as a 'within-year' move. Also, a worker who changes jobs once a year for two consecutive years is dropped, as well as any worker moving at the end of our sample.

[8]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%).

typical supplier or buyer is larger than the typical firm in the economy, which implies that the share of *job openings* at suppliers and buyers is much higher than the share of *firms* they account for. Moreover, the correlation between production networks and worker flows could be due to other factors, such as an overlap between employees' labor markets and firms' product markets: e.g., supply chains tend to be co-located and workers tend to search for jobs locally.

Figure 1: Worker Flows Between Firms

(a) Random Firms (b) Trading Firms



Notes: The nodes denote firms, with their size proportional to the number of employees. Blue edges denote 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 A5 additionally shows the edges connecting buyers and suppliers.

To deal with this, we construct the share of moves to suppliers and buyers under a counterfactual random allocation of workers to firms that could plausibly form part of their labor market (Glitz and Vejlin, 2021; Bernard and Zi, 2022). We first define a firm as having a job opening for every worker it hires from another firm. We then randomly assign movers to job openings and measure the share of workers who move to suppliers or buyers under this counterfactual allocation. We repeat the randomization procedure 100 times and report the average share of workers who get allocated to a buyer or supplier of their previous employer as well as the corresponding odds ratios in Table 3 (bootstrapped standard errors are negligibly small and thus left unreported).[9]

By randomly allocating workers to job openings rather than firms, this approach captures the fact that larger firms have more suppliers and buyers and tend to hire more

[9]To avoid mechanical overfitting, we restrict the set of movers to those with a potential labor market of at least 50 job openings. In fact, with a sufficiently large number of conditioning variables, every worker would be assigned to the firm they actually moved to. For this reason, we set a minimum size for each group. The total sample size, therefore, shrinks as conditioning variables are added. Our results are not sensitive to alternative choices of the lower bound.

workers. Accordingly, column (1) of Table 3 shows that we would expect 6.7% of workers to move to suppliers or buyers if moving randomly to any job opening, compared to the 18.4% we observe in the data. The corresponding odds ratio is 3.2. Column (2) randomizes movers only to job openings filled by workers from the same origin municipality and industry. Thus, the random share encompasses 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. In columns (3) and (4) we 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. Doing so only slightly increases the random share to 11.4%, with the odds ratio remaining stable at around 1.8. Lastly, in column (5) we restrict movers to be randomly allocated to job openings filled by workers with the same university degree.[10] The sample size shrinks considerably because we only have information on university education for workers who graduated after 2007 (see Appendix A1). While both the random and data share of supply chain movers increase, the odds ratio declines only moderately to 1.7. This mitigates the concern that workers move to suppliers and buyers because they tend to have more similar occupations insofar as a university degree is a strong predictor of occupational choice.

Table 2: Share of Workers Who Move to Buyers or Suppliers vs. Random Allocation

Conditioning Factors	None	Industry & Municipality	+ Age & Gender	+ Earnings Quintile	+ College Degree
	(1)	(2)	(3)	(4)	(5)
Data	18.4	18.4	18.6	18.7	25.4
Random	6.7	10.9	11.1	11.4	16.9
Odds ratio	3.2	1.9	1.8	1.8	1.7
# movers	1,152,279	1,143,023	1,111,083	1,019,242	17,091

Notes: The table reports the share of movers who move to suppliers or buyers along with the random allocation share, the corresponding odds ratio, and the number of movers. The first column shows results where movers are randomly allocated to any job opening. Column (2) additionally restricts the random allocation to job openings filled by workers from the same origin municipality and industry. Column (3) additionally restricts the random allocation to job openings filled by workers in the same age quintile and of the same gender. Column (4) additionally restricts the random allocation to job openings filled by workers in the same pre-move earnings quintile. Column (5) additionally restricts the random allocation to job openings filled by workers with the same university degree.

We consider additional robustness checks shown in Appendix Table A8. In particular, we find similar results if we define groups of job openings based on the industry and loca-

[10]There are 66 such degrees, which include industrial engineering, civil engineering, medicine, pharmacy, marketing, economics and finance, and others.

tion of the *destination* employer. We also consider random allocations which preserve the destination firm's rank on the job ladder (as proxied by average wages or size) by including firm size groups or average firm wages deciles as conditioning factors in our random allocation procedure. The data share of supply chain movers remains far above the random share, with the odds ratio declining only slightly to 1.6 and 1.7 respectively. We also find similar results if we exclude firm-pairs that are under common ownership, given that workers tend to move within the same business group (Cestone, Fumagalli, Kramarz and Pica, 2019; Huneeus, Larrain, Larrain and Prem, 2021a). Lastly, we adopt the regression approach proposed by Kramarz and Thesmar (2013). This alternative approach allows us to control for detailed measures of assortative matching between workers and firms, as described in Appendix A5. We show that our results remain supportive of supplier-buyer connections having a sizeable role in explaining worker movements across firms.

Quantifying the importance of unobservable factors using future suppliers or buyers To evaluate the importance of *unobservable* factors that could drive both worker flows and trade between firms—e.g., similar occupational compositions between suppliers and buyers—we measure the data and random share of workers who move to *future* suppliers and buyers. If high mobility rates between suppliers and buyers are entirely explained by firm-pair characteristics other than the supply chain connection, then we would not expect to see any difference in the odds ratios for moves to current vs. future suppliers and buyers. We define a future supplier or buyer as a firm that is 1) operating in the year the worker moves, 2) not a supplier or buyer in the move year or any year prior, and 3) is a supplier or buyer at some point after the move year. We restrict our sample to movers in 2015 or 2016 to ensure that we have a long enough window on both sides of the move to accurately identify future suppliers or buyers. We report the results in column (2) of Table 3. We find that 4.2% of movers in the data move to a future supplier or buyer. The random share is 3%, implying an odds ratio of 1.4. This is significantly greater than one but also significantly smaller than the corresponding value for current suppliers and buyers of 1.8. Unmeasured factors, therefore, play some role in explaining worker mobility between suppliers and buyers, but a very large remaining share is specifically related to the current supply chain link.

The role of social networks and referrals A remaining possibility is that worker movements between firms are the instigating factor that leads both to the creation of supplier-buyer linkages and future mobility between firms through ex-coworker networks. We evaluate the importance of this channel by repeating our random allocation exercise for movers in 2018 after dropping workers who moved to a firm in which one of their ex-coworkers were employed.[11] We report results in column (3) of Table 3. The share of movers between suppliers and buyers is 17.5% and the random share is 11.5%, implying an odds ratio of 1.6. This indicates that the endogenous creation of supply chain links through worker movements can at most be a minor contributor to mobility between suppliers and buyers.

To further understand if job-finding in supply chains relies entirely on a worker having direct contact with suppliers or buyers, we repeat our random allocation approach for indirect suppliers and buyers, i.e., buyers of buyers or suppliers of suppliers. We measure the share of workers who move to one of the top 3 buyers of their firm's top 3 buyers, or top 3 suppliers of their firm's top 3 suppliers.[12] Column (4) of Table 3 shows that the share of movers is 1.2% in the data, and 0.9% in the random allocation, implying an odds ratio of 1.3. This is significantly greater than 1, suggesting that social connections are unlikely to be the only driver of mobility between suppliers and buyers.

A survey-based benchmark An alternative approach to compare the frequency of hiring within the supply chain to other hiring channels is to use a survey-based benchmark. We therefore included a question in the firm-level survey of the Central Bank of the Dominican Republic asking about hiring practices for skilled workers. This allowed us to ask firms directly how much they value production network experience in comparison to experience in a similar job position, experience in a competitor, academic studies, and receiving a referral. We provide more details about the survey in Appendix A1 and show the complete set of survey results in Table A2 and Table A1. Experience in a similar job position and academic studies were the two factors most commonly deemed "very important" or "the most important". Notably, over one-third of firms responded that experience in one of the company's buyers or suppliers is either "very important" or "the most important factor", with this share being very similar to the responses for both experience at a competitor and referrals. While based on a relatively small survey of firms, these results confirm our findings in the administrative data that experience along the supply chain is something that many firms take into account when hiring.

Mobility Across Industries and External Validity Is the tendency of workers to move along the supply chain a special feature of the Dominican Republic? While we do not have access to matched firm-to-firm trade and employer-employee data outside the Dominican Republic, we can examine how *industry*-level worker flows correlate with industry-

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

[12] We exclude any firm that also happens to be a direct supplier or buyer. We restrict our attention to the top 3 suppliers and buyers because the number of second-degree connections increases explosively.

Table 3: Random Allocation Approach: Robustness and Heterogeneity

	Baseline (All Movers)	Future Suppliers and Buyers	Excluding Ex-Coworkers	2nd degree connections	Within-Year Movers
	(1)	(2)	(3)	(4)	(5)
Data	18.7	4.2	17.5	1.2	30.5
RA	11.4	3.0	11.5	0.9	14.7
Odds ratio	1.8	1.4	1.6	1.3	2.6
# movers	1,019,242	229,473	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.

level input-output linkages both in the Dominican Republic and in the United States thanks to publicly available datasets. Such analysis is presented in section A6. We find that workers indeed tend to move more across more vertically integrated *industries* in both countries. The extent to which workers move upstream or downstream is quantitatively similar in the two countries, suggesting that our findings for the Dominican Republic have broader external validity.

3.2 Heterogeneity

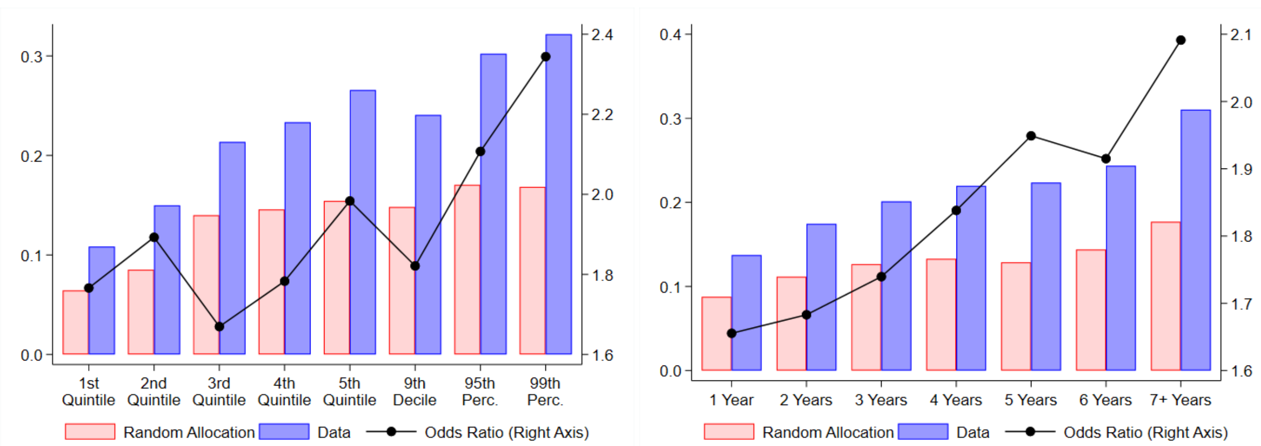
We explore heterogeneity in the tendency of workers to move between suppliers and buyers in Table A9. There is little difference in the share of workers moving from suppliers to buyers or from buyers to suppliers. We also explore the extent to which the strength of the production relationship between firms affects worker mobility. We find that workers are relatively more likely to move to one of their top 5 suppliers or buyers. This share is 8% in the data and the random share is 3%, implying an odds ratio of 2.8 which is considerably higher than the 1.8 we find for all suppliers and buyers.

The job search process may differ for workers who are currently employed and those that are unemployed. To check that our findings reflect on-the-job search by workers, we identify a set of moves that are more likely to be voluntary. We first restrict our attention to 'within-year' movers which by construction limits the potential duration of unemployment spells to 10 months. We additionally restrict the sample to movers whose average monthly earnings in the destination firm were higher than in the origin firm in the year of the move. Given that workers tend to suffer earnings declines following involuntary job losses, this sub-sample of movers should contain a relatively higher proportion of voluntary moves than the full sample. Column (5) of Table 3 shows that the share of supply chain movers is considerably higher for 'within-year' movers compared to all movers; 31% vs. 19% in the data and an odds ratio of 2.6 vs. 1.8.

The ways workers find jobs vary considerably with their skills and education (Lester, Rivers and Topa, 2021; Carrillo-Tudela, Kaas and Lochner, 2022). We therefore document heterogeneity along two dimensions of workers' human capital in Figure 2: pre-move earnings and tenure at the original employer. The share of supply chain movers increases from 10% to 27.5% between the bottom and top earnings quintile, with the corresponding odds ratios increasing from 1.8 to 2.1. Similarly, the share of supply chain movers increases from 15.1% for workers with tenure under 2 years to 29.2% for workers whose tenure is at least 6 years, with the corresponding odds ratios increasing from 1.7 to 2.0. Similarly, Table A9 reports that workers with tertiary degrees are relatively more likely to move to suppliers or buyers than workers without a college degree. Job-finding in the production network is therefore relatively more important for high-skilled workers.

Figure 2: Heterogeneity in the Share of Movers to Buyers and Suppliers

(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 assignment 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, attention is restricted to movers between 2018 and 2019 so that worker tenure at the origin firm can be identified for up to 7 years.

Lastly, we provide additional heterogeneity analysis in Appendix Table A9. The disproportionate likelihood of workers moving along the supply chain holds across all industries, for workers changing or staying in the same industry/municipality, for men and women, for white and non-white workers, and for different age groups.

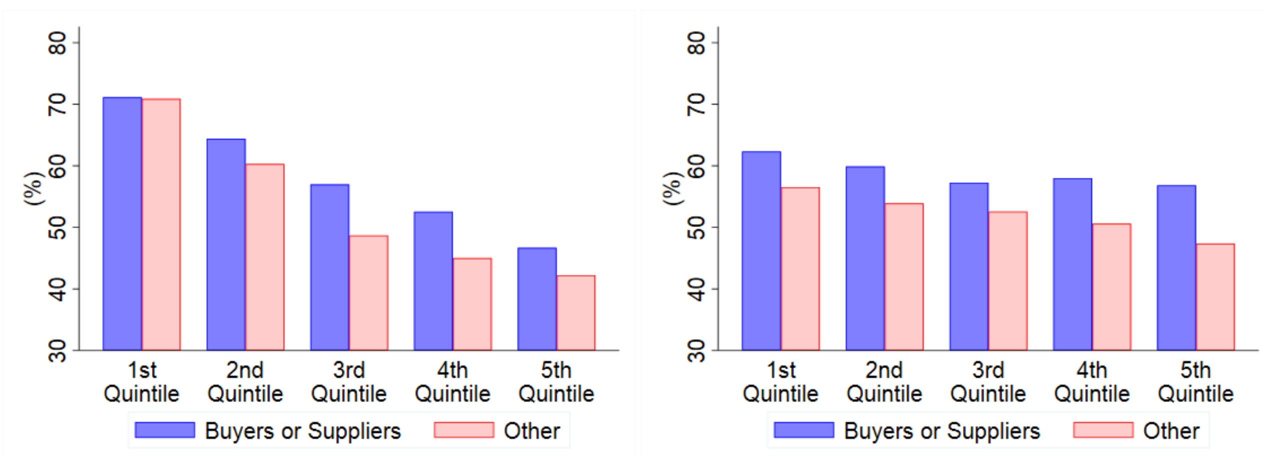
4 Climbing up the Supply Chain Ladder

Job-to-job transitions are hugely important because they enable workers to move to better firms (i.e. up the job ladder), as captured in a large class of labor search models (Burdett and Mortensen, 1998). These transitions up the job ladder play an important role both in determining workers' life-cycle earnings path, as well as in reallocating workers to high-wage firms. In this section, we ask whether the high likelihood of finding a job at a buyer or supplier affects workers' likelihood of moving up the job ladder.[13]

A simple way to examine this is to measure the share of workers who move to a destination firm with higher average wages or higher labor productivity than their origin firm. Conditioning on a worker's initial earnings quintile, the share of workers who move to higher-wage firms is 5 percentage points higher for supply chain movers than for other movers (see Figure 3).

Figure 3: Share of Workers Hired from Buyers and Suppliers vs. Wages and Productivity

(a) Higher Average Wage (b) Higher Labor Productivity

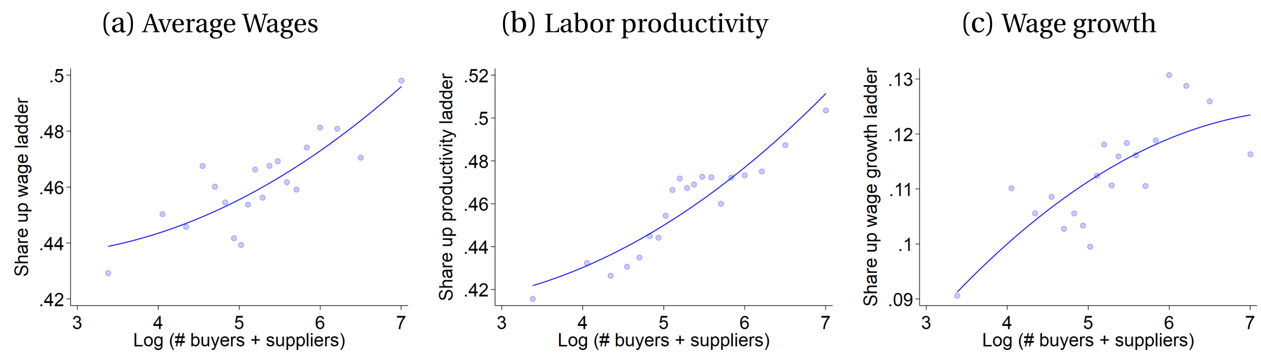


Notes: These figures plot the share of workers who move to higher-wage (left) or higher-labor productivity (right) firms, separately for movers to buyers or suppliers and other movers.

Moreover, Figure 4 shows that workers at firms with more suppliers and buyers, conditional on moving, are more likely to move to firms with higher wages, higher labor productivity, and experiencing higher wage growth. These results hold even when conditioning on worker and firm characteristics, such as the origin firm's average wages, size and productivity.

[13]Note that we showed in the previous section that workers are more likely to move along the supply chain irrespective of the firms' relative positions on the job ladder.

Figure 4: Moving Up Firm Ladder vs. Number of Buyers and Suppliers



Notes: The figure plots the share of job changers that move to a firm with a higher average wage (panel a) or higher labor productivity (revenues per permanent worker, demeaned at the industry level, panel b) or the average wage growth (delta log, panel c) for each of the 20 quantiles of the origin employer's number of buyers and suppliers. Controls include year, worker's gender, age decile, origin employer's log and employer's quintile of the number of employees, productivity, average wage, and sales. Wage growth results are qualitatively similar if we consider a longer horizon, such as wage growth over 5 or 7 years.

To provide a quantitative estimate of the importance of the supply chain for *net* reallocation along the firm wage ladder, we follow Haltiwanger et al. (2018). We define net job flows at firm i as $NJF_i = H_i - S_i$, where H_i are hires from other firms and S_i are separations to other firms between years $t-1$ and t. We then decompose net job flows into two terms: net job flows *along* the supply chain $(H_i^s - S_i^s)$ and net job flows *outside* the supply chain $(H_i^o - S_i^o)$:

$$NJF_i \equiv H_i - S_i = (H_i^s - S_i^s) + (H_i^o - S_i^o) \tag{1}$$

We aggregate these net job flow measures separately by firm group (high vs. low wage) and scale them by total employment within the group in period $t-1$ to construct the net job flow rate. Given that there were no major economic cycles between 2012 and 2019 in the Dominican Republic, we report the average across all years in Table 4. The first column shows that the net job flow rate is positive for high-wage firms but negative for low-wage firms, indicating a strong firm wage ladder. These patterns are qualitatively and quantitatively similar to the ones for the U.S. (Haltiwanger et al., 2018). The second and third columns decompose these overall patterns into the two components from Equation 1. Net supply chain job flows account for three-quarters of the net job flows of high-wage firms (we find very similar results when ranking firms by labor productivity rather than average wages.). Mobility along the supply chain is therefore an important source of net employment growth for high-wage firms. For low-wage firms, however, the negative net job flow rate is almost entirely accounted for by a negative net job flow rate from other firms. Net supply chain job flows therefore account for around a third of the gap in net job flow rates between high-wage and low-wage firms.

Table 4: Firm Wage Ladder

	Net Job Flows	Net Job Flows from Buyers/Suppliers	Net Job Flows from Other Firms
	(1)	(2)	(3)
High-Wage Firms	0.83	0.65	0.18
Low-Wage Firms	-1.25	-0.09	-1.17

Notes: The table reports the average net job flow rates from 2013 to 2019 by firm wage groups, as well as the terms from the decomposition shown in Equation 1, in percentage points. All variables are normalized by previous year group employment. High/low-wage firms are respectively defined as firms in the top and bottom quartiles of the distribution. We measure average wages from the employer-employee dataset.

4.1 Why are Supply Chain Moves up the Job Ladder?

Previous literature has documented that higher-productivity firms tend to have more suppliers and buyers (Bernard et al., 2022, e.g.). Given that high-productivity firms tend to also pay high wages, a possible explanation for the importance of supply chain moves for the firm wage ladder is that the share of high-wage firms among a typical worker's set of suppliers and buyers is higher than outside the production network. We find strong evidence for this in the left panel of Figure 5 (see further details in section A4). Firms in the top quintile of average wages represent approximately 50% of the suppliers and 40% of the buyers of the average worker. Conversely, firms in the bottom quintile of average wages represent less than 10% of buyers or suppliers for the average worker.[14] We find very similar results when ranking firms by labor productivity rather than average wages. It follows that, even if workers do not direct their search within the production network toward higher-paying firms, the typical job opportunity at a supplier or buyer is more likely to be at a higher-paying firm than the typical job opportunity outside the production network.

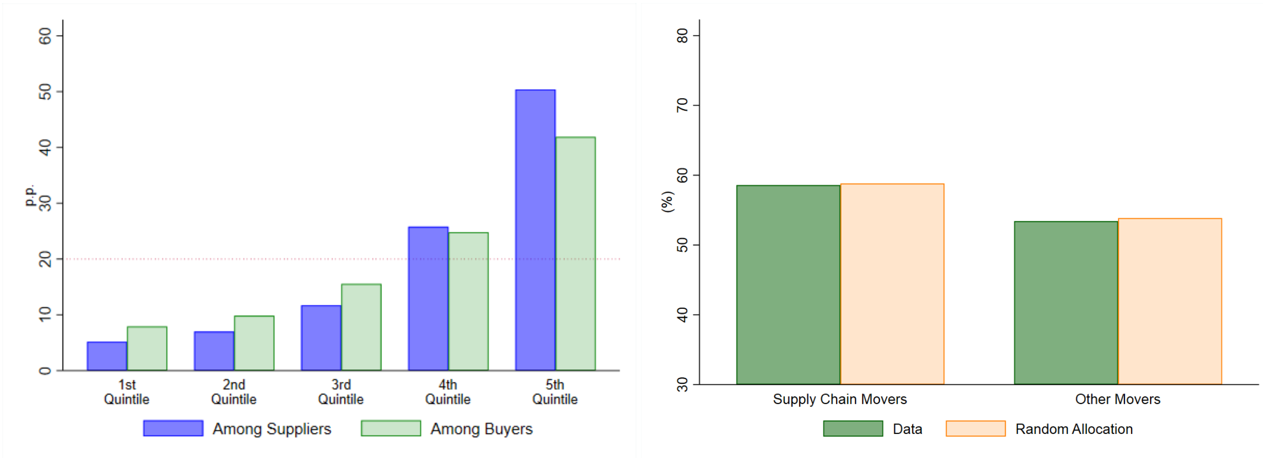
To what extent do these properties of production networks explain the tendency of supply chain movers to move up the job ladder? To answer this, the right panel of Figure 5 compares the share of supply chain movers who move up the job ladder in the data compared to our random allocation approach. We find that the probability of moving to

[14]An additional well-established property of production networks is negative degree assortativity—highly connected firms sell to more customers, but their average customer purchases from a relatively small number of suppliers (and similarly for highly-connected suppliers) (Bernard and Zi, 2022). Consistent with negative degree assortativity, Figure A7 shows that high-wage and high-productivity firms are relatively more over-represented among the suppliers and buyers of workers of low-productivity firms. However, these differences are quantitatively small.

Figure 5: Production Networks and the Firm Wage Ladder

(a) Wages Dist. for Suppliers and Buyers

(b) Share of Movers Up the Firm Wage Ladder



Notes: The left panel plots, for each quintile of the distribution of average wages paid, the share of firms among buyers and suppliers that belongs to that specific quintile. The shares are constructed at the worker level and the figure is built as follows. First, firms are divided into quintiles of wages. Second, for each firm, we compute the share of its buyers (or its suppliers) that belong to each of the five wage quintiles. Thus, for each firm, two sets (one for buyers and one for suppliers) of five shares are computed. Third, the shares are averaged across firms weighting by the number of employees of each firm. If the distributions of firms' average wages among buyers and suppliers were the same in the whole economy, the bars would all be at 20 pp (dotted horizontal line). The right panel shows the share of movers moving up the firm wage ladder, separately for supply chain movers and other movers, in both the data and random allocation (conditioning on industry, municipality, age, gender and pre-move earnings). The shares are first constructed within each earnings quintile, and then aggregate across quintiles using the same set of weights for supply chain movers and other movers.

a higher paying firm is the same in the data and the random allocation. The high propensity of supply chain moves to be up the job ladder, therefore, does not imply any form of directed search on behalf of workers. Rather, it follows from the inherent distribution of firm wages in production networks. This finding highlights an important distinction between production networks and social networks for job search. Job search in the production network has an inherently high likelihood of leading to matches with higher-wage firms, while this is not necessarily the case for job search in social networks such as friend groups. Workers at firms with more suppliers and buyers therefore have a larger set of high-wage firms in their labor market, which can thereby explain the findings in Figure 4.

5 Worker Mobility and Earnings Dynamics

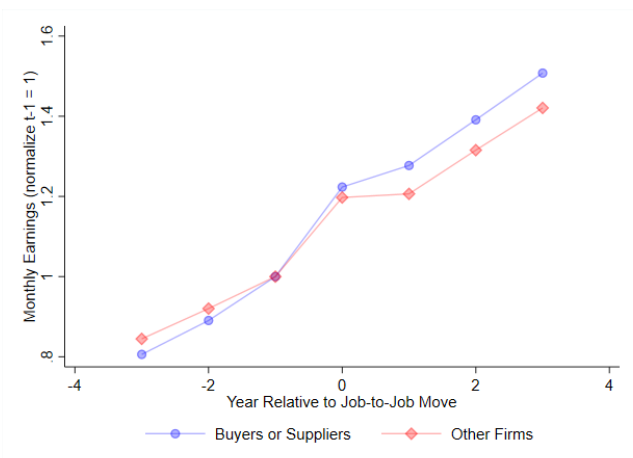
In this section, we use an event-study design to compare the changes in earnings of workers who move along the supply chain to those of other similar movers. In particular, we document that supply chain movers not only move to firms that pay higher wages, but also experience a larger increase in the match-specific component of earnings, which we label the "supply chain earnings premium".

5.1 Event-Study Specification

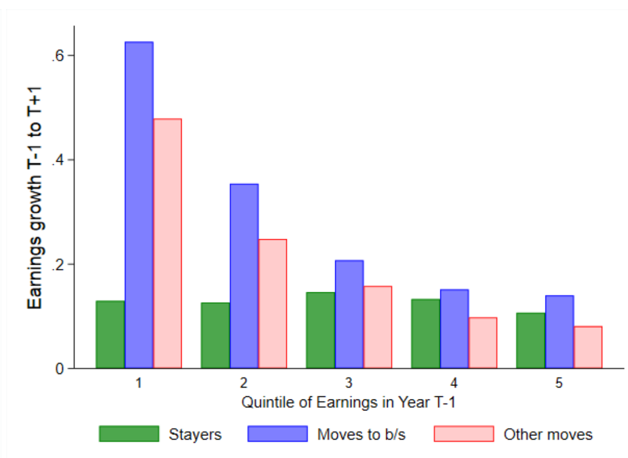
Figure 6 shows the earnings dynamics of movers to buyers or suppliers and to other firms. Panel (a) plots earnings for a balanced panel of workers who moved in 2015 and for whom we observe earnings every year from 2012 to 2019. We normalize earnings to one in 2014. Following a move, an earnings gap opens up between workers that move along the supply chain and those that move to unconnected firms, and the gap persists even four years after the move. This earnings gap is present despite the fact that workers who move to buyers or suppliers tend to have higher pre-move earnings (as documented in section 3) and therefore would be expected to have lower earnings growth. Panel (b) shows that there is indeed a decreasing relationship between earnings growth and pre-move earnings, but that earnings growth is higher for workers who move to buyers or suppliers across the entire earnings distribution.

Figure 6: Earnings Dynamics of Movers, Raw Data

(a) Earnings



(b) Earnings Growth



Notes: Panel (a) shows the median earnings of 'within-year' movers for three years before and three after the move year. We use a balanced panel of workers who had positive earnings in all 7 years (restricting the years in which workers moved to 2015 and 2016), and we normalize median earnings to 1 in the year before the move. We show separate earnings profiles for workers who move to a buyer or a supplier and for workers who move outside the supply chain. Panel (b) reports the median earnings growth (delta logs) between year $t-1$ and $t+1$ for within-year movers who go to a buyer or supplier of their previous employer, for within-year movers who go to other firms, and for workers who stay at the same firms; by earnings quintile in year $t-1$.

We estimate the differences between the earnings dynamics of movers to buyers or suppliers and to other firms, controlling for workers' and firms' characteristics with the following event-study specification:

$$E_{i,o,d,t+k} = \alpha^k + \delta^k X_{i,t-1} + \beta^k SB_{o,d,t-1} + \phi^k_{o,t} + \phi^k_{d,t} + \gamma^k X_{o,d} + \eta_{i,d,o,t,k} \tag{2}$$

where i is a worker who moves from origin firm o to destination firm d in year t; the dependent variable $E_{i,o,d,t+k}$ is the log of average monthly earnings paid by i's main employer in year $t+k$ (for the months in which the worker was employed); $SB_{o,d,t-1}$ 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 log(earnings) in the year before the move, age deciles, and gender; $X_{o,d}$ 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. We estimate the specification both including and excluding origin firm-year and destination firm-year fixed effects.

Since we are interested in the earnings dynamics following job-to-job transitions we focus on within-year movers (29% of which are to buyers or suppliers) to minimize the length of possible unemployment spells (see section 2). The sample includes workers that move in any year between 2012 and 2019. We run this regression for horizons $k = -3, \ldots, 4$ to test for differences in pre-trends and to measure the persistence of the earnings differential following a move. This allows us to check whether workers who move along the supply chain are differentially selected based on pre-move trends in (or shocks to) earnings. We double cluster our standard errors at the origin and destination firm level.[15]

The left panel of Figure 7 plots the earnings dynamics around the move year of supply chain movers relative to other movers, controlling for worker characteristics, but *excluding* firm fixed effects and firm-pair covariates (see Table A10 for the regression results). Earnings of movers to buyers and suppliers behave similarly to the ones of other movers up until the move, but a large earnings gap opens after the move. Our results show that supply chain movers have 7.7 percentage points (pp) higher earnings the year after the move than non-supply chain movers, gradually declining to 6.7 pp four years after the move. This large earnings gap can be due to a) supply chain movers sorting into higher-wage firms, and/or b) an earnings premium for workers moving within the supply chain.

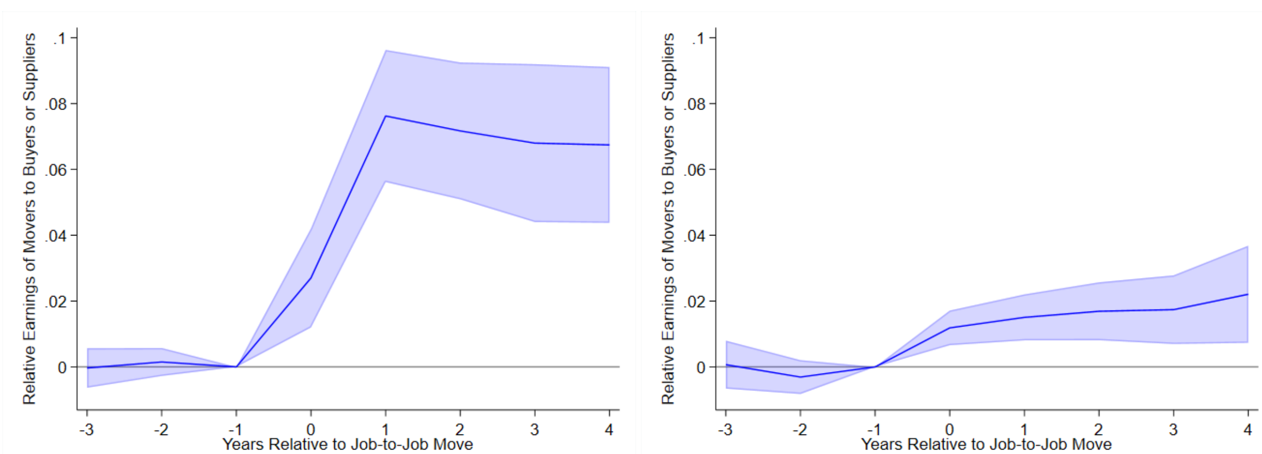
We control for differential sorting into high-wage firms in the right panel of Figure 7, which adds origin and destination firm-year fixed effects and firm-pair controls (we report the regression results in Table A11). The inclusion of destination-year and origin-

[15]This specification has the benefits of simplicity and flexibility regarding controls. It is also analogous to the local-projection approach to difference-in-differences of Dube, Girardi, Jorda and Taylor (2023). They show that this specification avoids the econometric problems with OLS estimation of two-way fixed effects which have been highlighted by recent literature (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021). An additional restriction in Dube et al. (2023) is to exclude from the control group workers who are treated in a period t > 0. While this reduces the sample size, we show in Figure A8 that the earnings premium is even larger if we impose this restriction.

year fixed effects ensures that the estimated coefficient on supply chain moves is neither driven by within-destination cross-time changes nor by within-origin cross-time changes, while controlling for worker characteristics and other firm-pair characteristics. This removes cross-time variation driven by worker sorting from and to specific origins and destinations, isolating changes in the match-specific component after the job change. The firm-year fixed effects also allow for the firm component of earnings to depend on whether a worker is joining a firm or leaving a 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)). As before, we do not see evidence of differential pre-trends, but we do estimate an earnings premium for supply chain movers one year after the move of 1.5 pp, increasing to 2.2 pp by the fourth year after the move. Of the 6.7 pp earnings gap four years after a move, 4.5 pp (two-thirds) is explained by the fact that supply chain movers tend to move up the firm ladder to higher-wage firms, and 2.2 pp (one-third) is explained by the improvement in the match-specific component of earnings. We label this latter component the supply chain earnings premium. In section 7 we discuss the causes of this novel fact.

Figure 7: Earnings Dynamics of Movers, With Controls

(a) Without Firm-Year Fixed Effects (b) With Firm-Year Fixed Effects



Notes: This figure plots the coefficient β from Equation 2 for each horizon k, along with the 95% confidence interval. Panel (a) includes year fixed effects and fixed effects for worker age deciles ($\leq$25, 26-35, etc..) 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. We also report the results in regression tables in Table A10 and Table A11.

Confounding factors and future suppliers and buyers Supply chains may be correlated with other confounding factors that make workers' labor markets and firms' output markets overlap. For instance, geographic and industry measures may not be disaggregated enough to accurately capture the relevant dimensions of workers' labor markets (Nimczik, 2020), especially given that we do not directly observe worker occupation. Reassuringly, the inclusion of firm-pair controls does not have a sizeable impact (Figure A9). The gains associated with moving along the supply chain are thus orthogonal to workers' movements across labor markets as defined by industry, location, or employer size. This suggests that other unobservable match-specific confounding factors are unlikely to affect our results.

Ex-coworker networks could also potentially explain the formation of firm-to-firm connections and job changes, as discussed in section 3. We evaluate their importance for the supply chain earnings premium by including an ex-coworker dummy in Equation 2 (panel (a) of Figure A10) and by restricting the sample to workers who move to firms in which they have no ex-coworkers (panel (b) of Figure A10). The supply chain premium remains almost identical despite these additional restrictions.

The baseline specification does not impose any restrictions on whether workers change firms again in $t \geq 2$. We therefore re-estimate the supply chain earnings premium for the sample of workers who stay at the destination firm after the move. Panel (a) of Figure 8 plots the coefficient on the supplier or buyer dummy from Equation 2, with the additional restriction that workers in the sample remain at their destination firm until horizon k (this restriction does not affect the estimates for $k \leq 1$). The earnings dynamics are very similar to those for our full sample of movers.

Lastly, to assess whether the presence of other unobservable connections between firms explains the supply chain earnings premium, we conduct a placebo test, analogous to that from section 3, where we compare the earnings dynamics of movers to current vs. future suppliers or buyers. We estimate the following equation:

$$E_{i,o,d,t+k} = \alpha^k + \delta^k X_{i,t-1} + \beta^k SB_{o,d,t-1} + \lambda^k FutureSB_{o,d,t-1} + \phi^k_{o,t} + \phi^k_{d,t} + \gamma^k X_{o,d} + \eta_{i,d,o,t,k} \quad (3)$$

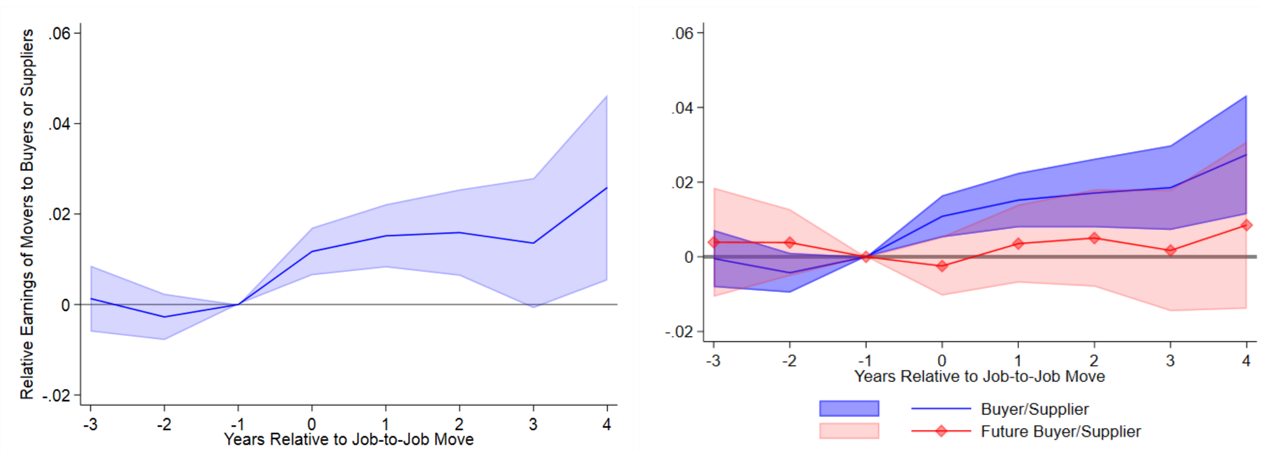
which is the same as Equation 2, except that it includes $FutureSB_{o,d,t-1}$, which is a dummy variable equal to 1 if firms d and o start trading for the first time in some year $t > 0$.

Figure 8 Panel (b) shows the earnings dynamics before and after the job changes for the two groups of movers, relative to the control group, including the full set of fixed effects.[16] Neither set of movers have differential pre-trends in earnings. Workers moving to current buyers and suppliers experience a large increase in earnings with respect to

[16]We exclude from the sample workers moving between firms that started trading in the same year as the job change, as we do not know whether the firms started trading before or after the worker move. The control group therefore includes firm pairs that never traded and firms that traded in the past but not t-1.

Figure 8: Robustness of Earnings Dynamics (with Firm-Year Fixed Effects)

(a) Stayers at Destination Firm (b) Future Suppliers or Buyers



Notes: Panel (a) plots the coefficient β from Equation 2 for each horizon k, along with the 95% confidence interval, where for k≥2 we condition on workers not separating from the destination firm. Panel (b) plots the coefficients β^k (blue) and λ^k (red) from estimating Equation 3 for each horizon k, along with the 95% confidence interval. Both panels include year fixed effects, fixed effects for worker age deciles (≤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.

the control group, while workers moving to future buyers and suppliers do not. We show additional robustness to dropping firm pairs that only traded for one year to compare across more stable supply linkages (Figure A6). These findings confirm that supply chain connections have a direct role in explaining the earnings premium and mitigate concerns about unobservable confounders.

Match Duration While we have focused on earnings so far in this section, excessively high turnover can be detrimental to workers and firms. In Appendix A8, we investigate whether worker-firm matches formed along the supply chain last longer than other matches. We find that separation rates are 7.4 pp lower for workers who move to buyers or suppliers during the first year compared to those moving to other firms, with the gap shrinking to 3.2 pp in the sixth year (controlling for pre-move characteristics). The lower separation rates for moves along the supply chain lead to four and a half months of longer observed match duration. This difference is in part explained by workers who move to buyers or suppliers being hired by firms with more stable positions. However, even when we control for origin and destination firm fixed effects, we estimate that matches formed along the supply chain last two months longer than other matches. There is therefore an equivalent supply chain match duration premium alongside the earnings premium.

Implications for Average Worker Earnings Based on the estimated persistent supply chain premium of 2.2 pp, we do a simple back-of-the-envelope exercise to evaluate how important supply chain job transitions could be for average earnings in an illustrative economy. We consider workers entering the labor force at age 20 and retiring at age 65. On average, we find that 13% of workers change firms from one year to the next, 19% of which move to a buyer or supplier. In any given year, 2.5% of workers therefore move along the supply chain. We assume that the probability of changing firms and of moving to a buyer or supplier is the same for all ages, as is the earnings premium from moving to a buyer or supplier. Thus, moving to a buyer or supplier implies a permanent increase in the level of worker earnings until retirement. We hold constant the wage of entrants to the labor force, which means that the supply chain premium increases average earnings by increasing the slope of workers' life-cycle earnings. Consistent with the data, we set baseline real wage growth to 2.8% per year. Overall, we find that, absent this supply chain premium, the average level of earnings in any given year would be 1.4% lower. We conclude that the supply chain earnings premium has a sizeable impact on average worker earnings.

5.2 Robustness and Heterogeneity

Panel Regressions with Worker Fixed Effects and the AKM Decomposition Equation 2 is our baseline specification as it directly compares earnings of movers to buyers and suppliers relative to other movers while controlling for a large set of factors that could affect post-move wage growth, including pre-move earnings. However, to test whether our results are sensitive to the choice of empirical specification, we also consider an alternative approach to estimating earnings dynamics around worker moves. We estimate the commonly used two-way fixed-effects regression (Abowd et al., 1999), augmented to include an indicator for moves within the supply chain. This allows for an additional buyer-supplier earnings premium beyond the usual firm premium. We also include controls for earnings quintile in the origin firm for movers; see A7 for implementation details. The earnings premium from moving along the supply chain estimated with this alternative model is qualitatively and quantitatively similar to the one obtained by estimating Equation 2.

Heterogeneity We documented in section 3 that high-salary movers are particularly likely to move to buyers and suppliers. We now explore the extent to which the earnings premium associated with moving along the supply chain varies with workers' pre-move earnings. We modify Equation 2 by interacting SB with a dummy variable for whether a mover's earnings are above or below the median earnings of movers in period $t-1$.

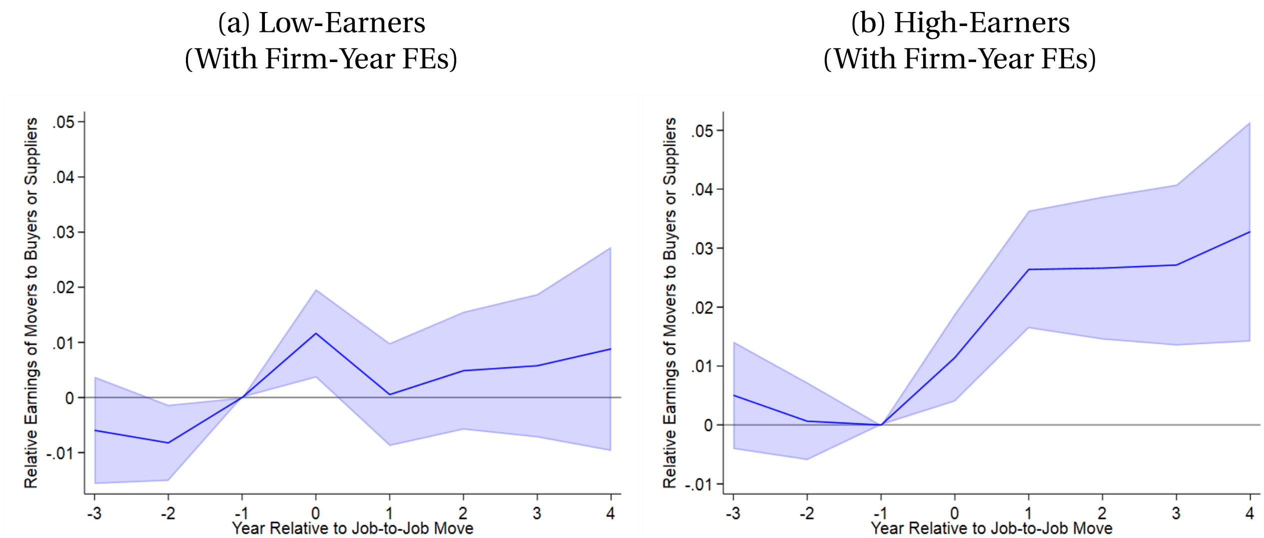
We present the results in Figure 9, which include firm fixed effects and firm-pair controls. We find a large earnings premium for high-salary workers of 2.6 pp one year after the move and 3.3 pp four years after the move, substantially higher than the 1.5 pp and 2.2 pp premiums for the full sample of workers. Indeed, the bottom left panel shows a small and statistically insignificant earnings premium for low-wage workers who move along the supply chain. This stark difference suggests that low-wage and high-wage workers may benefit from the supply chain labor market for different reasons. Both sets of workers benefit by moving up the ladder to higher-wage firms (see section 4). However, low-wage workers only initially earn a premium, even conditioning on origin and destination firm characteristics. These results are not driven by a correlation between the firm-specific skill premium and the tendency to hire on the supply chain, as we find quantitatively similar results when we run the regression in Equation 2 separately for workers with above and below median earnings.

We perform additional exercises, reported in Appendix Table A12, to investigate the heterogeneity of the supply chain earnings premium along several dimensions. We find evidence that the premium is larger for workers with longer tenure at their origin firm. We do not find significant differences in the supply chain earnings premium for young vs. old workers or men vs. women. We do find slightly larger earnings gains for workers who change industries. This is reassuring as it indicates that our results are not driven by supply chain movers remaining in the same narrowly defined industry while other movers move between narrow industries (within the 2-digit industries we observe).

6 Worker Mobility and Firm Outcomes

While we previously focused on worker outcomes, in this section we document new facts about changes in *firm*-level outcomes around worker moves, specifically firm-to-firm trade and coworker earnings. While firms' purchase and supply decisions are usually considered independent from hiring decisions, trade between a buyer and a supplier may change when workers move between the two firms for different reasons. On the one hand, worker moves between a supplier and a buyer may diminish firm-to-firm trade if the movers possess knowledge that allows the hiring firm to insource some previously outsourced tasks, or if the firm that loses the workers retaliates by severing the relationship. On the other hand, worker moves may lead to an increase in firm-to-firm trade if they help build trust between the firms, or if workers possess knowledge that complements the use of relationship-specific inputs in production. What happens to the earnings of incumbent workers of the hiring firms is also ambiguous: supply chain hiring may depress coworkers' earnings, for instance, if it reduces overtime or bonuses for in-

Figure 9: Earnings Dynamics of Movers By Pre-Move Earnings



Notes: This figure plots the coefficients from the earnings heterogeneity regression described in sub-section 5.2 for each horizon k, along with the 95% confidence intervals. The panels include year fixed effects and fixed effects for worker age deciles ($\leq$25, 26-35, etc..) 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.

cumbent workers. It may have a positive impact instead if it is associated with knowledge spillovers.

6.1 Firm-to-Firm Trade

We examine the dynamics of sales between the buyer and supplier around a worker move using the following event-study specification:

$$y_{b,s,t} = \phi_{b,s} + \phi_{b,t} + \phi_{s,t} + \beta FirstWorkerFlow_{b,s,t} + \varepsilon_{b,s,t} \tag{4}$$

where buyer b and supplier s are two firms trading at the beginning of the sample, $y_{b,s,t}$ is either a dummy for trade in year t (i.e., extensive margin) or the log of the value of sales (i.e., intensive margin), and $FirstWorkerFlow_{b,s,t}$ is a dummy equal to one if we observe any worker moving between b and s up to year t.[17] We include firm-pair ($\phi_{b,s}$), buyer-year ($\phi_{b,t}$), and supplier-year ($\phi_{s,t}$) fixed effects. We therefore focus on changes in within firm-pair sales over time as a function of the observed worker movements. We include only firms present in the dataset for all years and drop firm pairs that are part of the same business group. Since workers tend to move to firms in which they have ex-coworkers, we exclude from our sample all firm pairs between which we observe worker movements

[17] That is, let T be the year such that we observe *for the first time* any worker moving between b and s (or vice versa): then $FirstWorkerFlow_{b,s,t} = 1$ if $T \leq t$.

in 2015 or earlier. The coefficient β thereby captures the changes in firm-to-firm trade around the first worker move we observe between a buyer and supplier.

Table 5: Firm trade and worker movements

	Log Value (Intensive Margin)			Any Trade (Extensive Margin)		
	(1)	(2)	(3)	(4)	(5)	(6)
First Worker Move	0.059***	0.046***	0.054***	0.062***	0.069***	0.060***
	(0.009)	(0.007)	(0.009)	(0.002)	(0.002)	(0.002)
Observations	5,564,988	5,718,856	4,528,231	11,902,466	12,126,312	6,876,654
Buyer-year FEs	✓	✓	✓	✓	✓	✓
Supplier-year FEs	✓	✓	✓	✓	✓	✓
Include pre-2016 moves		✓			✓	
Trade in 2013			✓			✓

Notes: The dependent variable is either the log value of trade between buyer b and supplier s (columns 1 - 3) or a dummy for whether we observe any trade (columns 4 - 6). We include firm-pairs that traded in 2012 such that both firms are in the employer-employee dataset. The table reports estimates from a panel regression including firm-pair and year fixed effects. The dependent variable is a dummy variable which is equal to one iff we observe at least one worker moving between the two firms in the same or any previous year. Firm-pair clustered standard errors are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Estimation is performed via Borusyak, Jaravel and Spiess (2022) imputation estimator.

Table 5 reports the results.[18] We find that, after a worker moves between a buyer and a supplier, the origin and the destination firms trade more, both on the intensive margin (columns (1) to (3)) and the extensive margin (columns (4) to (6)). The impact is sizeable: the value of firm-to-firm sales increases by over 5 percent. The probability of trade increases by 6 pp, which is around 15% of the baseline probability. The results in column (2) show that the estimated intensive margin increase is smaller when we include firm pairs for which we observe worker flows in the first couple of years in the sample. This is consistent with there having been previous worker movements between these firm pairs, leading to attenuation bias. Columns (3) and (6) show that results are robust to focusing on buyer-supplier pairs that traded in 2012 and 2013, thus excluding one-off transactions in the base year. These results hold both for worker movements from buyers to suppliers and suppliers to buyers (Table A13). They suggest that supply chain movers may be hired to enhance trust between the firms, or may possess knowledge which complements the use of relationship-specific inputs in production: if workers know how to produce a good or service, they also know how to best use it as an input (and vice versa).

[18]Recent econometric literature points out that the estimation of two-way fixed effect models can be biased, especially if the "treatment" effect is heterogeneous across time. We therefore estimate Equation 4 relying on an imputation estimator proposed by Borusyak et al. (2022) to overcome these limitations. Results are very similar if we rely on OLS.

6.2 Spillovers to Coworkers

Jarosch et al. (2021) document the presence of knowledge spillovers from high-earning coworkers in Germany, showing that workers with high-wage coworkers experience more rapid earnings growth. We ask whether there is any evidence of similar wage gains for the new coworkers of workers hired along the supply chain. We expand the specification from Jarosch et al. (2021) to examine whether hiring from buyers or suppliers is associated with earnings gains for the existing workforce:

$$E_{i,d,t+k} = \alpha + \rho \cdot E_{i,t} + \phi \cdot \bar{E}_{-i,t} + \delta H_{d,t} + \beta SB_{d,t} + \gamma X_{i,t} + \omega X_{d,t} + \varepsilon_{i,d,t,k} \tag{5}$$

where $E_{i,d,t+k}$ is the log average monthly earnings of worker i in firm d at time $t+k$, with $1 \leq k \leq 3$. $H_{d,t}$ is a dummy variable that takes value one if firm d hired a worker in period t, 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 in period t, and zero otherwise. We control for worker characteristics such as earnings in period t, as well as age deciles and gender. We also control for the average earnings of a worker's coworkers in period t, and firm characteristics ($X_{d,t}$) including employment and sales growth from $t-1$ to t to account for pre-trends in firm growth. We also control for firm employment in period t given that small firms tend to have higher growth rates andindustry$\times$municipality$\times$ 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 from $t-1$ to $t+k$, and we restrict our sample to firms with at most 100 workers in all years.[19]

Table 6 presents our results for horizons $k = 1, \ldots, 3$. The first three columns show our estimates from Equation 5. Similarly to Jarosch et al. (2021) we find that workers with higher-wage coworkers have higher future earnings growth, with the effect becoming larger over time. We find that hiring from another firm is associated with future earnings growth for the existing workforce, but more importantly we find that hiring from a buyer-supplier is associated with 0.2 percent higher earnings after 1 year and 1 percent higher earnings after 3 years. The increase over time is consistent with spillovers taking time to accrue into coworkers' salaries. Columns (4) to (6) restrict the sample to firms that are hiring at least one worker from another firm in period t, and additionally control for the average salary of new hires. This is an important control given that we have previously shown that high-wage workers are more likely to move along the supply chain. Indeed, we find that a higher average salary of new hires is associated with higher earnings for the existing workforce. However, including these controls does not change the estimated higher earnings associated with hiring a worker from a buyer or supplier.

[19]This latter restriction ensures that coworkers are working in small enough teams that they may plausi-

Table 6: Hiring and Earnings of Coworkers

	(All Firms)			(Firms with $\geq$ 1 New Hire)		
Horizon	1	2	3	1	2	3
New hire	0.007***	0.014***	0.019***			-
	(0.001)	(0.002)	(0.002)			
New hire from buyer or supplier	0.002**	0.006***	0.010***	0.002**	0.056***	0.011***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)
Average coworker earnings	0.029***	0.057***	0.079***	0.023***	0.048***	0.064***
	(0.001)	(0.002)	(0.003)	(0.002)	(0.004)	(0.006)
Average earnings of new hires				0.009***	0.012***	0.016***
				(0.002)	(0.003)	(0.004)
Observations	1,085,694	704,804	455,453	714,207	452,086	284,769
R^2	0.950	0.907	0.873	0.947	0.904	0.871

Notes: This table shows the results from the worker-level regression in Equation 5 for different horizons 1≤k≤3. All regressions include controls for worker's log(average monthly earnings) in year t, municipality x industry x year fixed effects, as well as three firm-level controls: log(employement) in year t, as well as employment and sales growth between t-1 and t. The sample only includes workers who stay at the same firm between years $t-1$ and $t+k$. Standard errors are clustered at the firm level.

7 Channels

Why are workers more likely to find jobs along the supply chain? Why are there large and persistent earnings gains associated with these moves? The evidence so far suggests various possible explanations. One explanation is that information frictions are much lower within supply chains because workers form relationships with their counterparts in suppliers and buyers, and are thus more likely to learn about vacancies and receive referrals. Another explanation is that a firm may intrinsically value the human capital of its suppliers' and buyers' employees, who might be much more familiar with the firm's inputs, products, or processes. Also, a firm may want to hire a worker from its buyers and suppliers to strengthen the supply chain relationships, as employing an ex-worker from these firms might build trust, mitigating contracting frictions and hold-up problems.

To shed light on which of these channels are at play, we included a question in the periodic survey of 200 firms undertaken by the Central Bank of the Dominican Republic (see section A2 for details). 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 experience dealing with the worker while working for the*

bly learn from new hires.

previous employer", (v) *"To create trust and improve the relationship with the buyer or supplier"* , and (vi) *"Other reasons"*.

Table 7: Survey Question and Answers

If you have hired any worker from a buyer or supplier in the last three years, what were the reasons for such hiring?			
(1) Answer	(2) N of responses	(3) Share of firms	(4) Share of firms (employment-weighted)
(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%

Respondents can pick multiple options. 136 firms responded to the survey. The third and fourth columns report the share of firms that pick any option among the firms that do NOT pick option (i). All firms that picked option (i) did not pick any other option, except one firm that also picked option (vi) (thus this respondent is not considered when calculating the shares).

Survey results are presented in Table 7. While these must be taken with caution given the small sample sizes, 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% 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 firms included other reasons as an answer, suggesting the options provided were fairly comprehensive.

Referrals and positive experiences with the worker can be grouped into information-based reasons for hiring— the hiring firm is likely to have better information about the worker's characteristics and hence match quality. Similarly, workers that are in touch with their counterparts at suppliers and buyers 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, both lower information frictions within supply chains and workers' supply chain-specific skills and knowledge are the key reasons why workers move along the supply chain, as documented in section 3.

In the rest of the section, we consider explanations for the supply chain earnings premium, building on the firm responses from the survey. We provide additional evidence which points to supply chain-specific human capital as the most likely explanation for the premium and discuss why other explanations are unlikely to play a major role. We conclude the section with an overview of a parsimonious model capturing the main channels through which supply chains impact workers' on-the-job search and earnings

- including both the firm wage ladder and the supply chain premium. The model qualitatively replicates many of the empirical findings and illustrates how an increase in the density of domestic supply chains can increase average worker earnings and aggregate labor productivity.

7.1 The Supply Chain Premium: Information vs. Human Capital

The survey results show that one of the main reasons firms hire workers from suppliers or buyers is that these workers possess specialized knowledge of inputs or outputs that are valuable to the hiring firm. This knowledge is presumably acquired through work related to the inputs or services sold between the firms, and therefore an obvious interpretation of the earnings premium is that this is a return on a supply chain component of workers' human capital. The finding that firm-to-firm trade increases following worker moves also suggests that these worker-firm matches generate a particularly large surplus precisely because they enhance the productive use of relationship-specific inputs, and hence the gains from trade. This explanation is also consistent with the facts that high-wage and high-tenure workers are more likely to move along the supply chain, that the supply chain earnings premium is entirely driven by high-wage workers, and that such premium is larger for workers with longer tenure at the origin firm. It is also consistent with the evidence of knowledge spillovers to new coworkers from hiring along the supply chain, documented in section 6.

The survey shows that the other main reason firms hire along the supply chain is that they have better information about the workers of their suppliers and buyers relative to other job applicants, either through referrals or direct experience. This is unsurprising as a firm's workers and managers may regularly deal with their counterparts at suppliers and buyers. This informational advantage may contribute to explaining the supply chain premium through several channels highlighted in the large literature on referrals. Dustmann et al. (2016) show empirically and theoretically that lower uncertainty about the firm-worker match quality at the time of hiring results in higher initial wages for workers hired through referrals. Hiring from within the supply chain may thereby allow firms to screen job applicants more effectively. Workers selected in this way would be a better match with the hiring firm and therefore receive higher wages.[20] Better information may also impact earnings through the wage bargaining process: workers hired from within the supply chain may also have better information about the firm, such as its expected

[20] Lester et al. (2021) show in a survey of U.S. workers that hires with a 'business referral' have higher wages. However, in contrast to other referrals, they also tend to have *higher* separation rates than other workers, as they tend to get rapidly poached by other firms. This highlights one notable difference between business referrals and supply chain hires, given that we document *lower* separation rates for the latter in section 5.

performance. This additional information may enable them to bargain more aggressively for a larger share of the match surplus.

To shed light on whether the supply chain earnings premium is mainly driven by the supply chain-specific component of human capital or by the more abundant information available to firms and workers, we test three implications of human capital that should not be present in the information-based explanation. First, standard models of hiring under uncertainty about match quality predict a declining earnings premium over time for workers who stay at the new employer, as low-productivity matches are dissolved and earnings gradually reflect the true match quality (Jovanovic, 1979; Dustmann et al., 2016). The human capital difference is instead more likely to be persistent. Second, if the earnings premium is explained by the information available to the firm (or worker) at the time of hiring, it should be independent of what happens to the supply chain relationship after the worker moves. Conversely, if supply chain movers earn more because of their knowledge of relationship-specific inputs, outputs, and processes, we would expect the premium to depend on the continuation of the supplier-buyer link. Similarly, human capital explanations for the supply chain premium may be less likely to generate an earnings premium following a mass layoff, relative to information-based explanations, because gains related to these supply chain linkages may be less valuable as the origin firms are experiencing major negative shocks.

Earnings dynamics of stayers A common feature of models of hiring under uncertainty about match quality is that the wage premium of referred job applicants is transitory (Dustmann et al., 2016). The reason is that employers learn about the quality of their workers over time. This results in dynamic selection of non-referred workers, who initially have lower wages, but who either leave the firm if they are poorly matched or see their wages converge to the wages of referred workers. Relatedly, if workers have additional information about the firm that allows them to bargain more aggressively during the hiring process, this information advantage should also shrink after the move.

A simple test to determine whether information-related mechanisms explain our results is therefore to re-estimate the supply chain earnings premium for the sample of workers who stay at the destination firm after the move. We previously showed in Figure 8 the coefficient on the supplier or buyer dummy from Equation 2, with the additional restriction that workers in the sample remain at their destination firm until horizon k (this restriction does not affect the estimates for $k \leq 1$). The earnings dynamics are strikingly similar to those for our full sample of movers, with no tendency for the earnings gap to shrink over time.

The persistence of the earnings gap for stayers indicates that uncertainty about the worker's qualities is unlikely to be the main explanation for the supply chain earnings premium. Of course, if wages are fixed over time or wage increases are homogeneous across workers within the same firm, then initial differences in salary could persist regardless of the workers' performance. Similarly, if firing costs are prohibitive, there may be no dynamic selection. However, rigidity in labor markets is unlikely to be particularly pronounced in the Dominican Republic. Firing workers is not particularly difficult by international standards: the Dominican Republic scores close to the median in strictness of worker dismissals and firing costs according to the OECD Employment Protection Law database and IMF Structural Reform database, respectively. Furthermore, only a fifth of earning growth of stayers is explained by firm fixed effects in a given year. This suggests that there is flexibility in wage adjustments within the typical Dominican firm.

Firm-to-firm trade and the supply chain earnings premium In section 6 we documented that trade between buyers and suppliers increases following a worker move between the two firms. This could follow from workers having valuable knowledge of relationship-specific inputs which complements the use or production of these inputs in the destination firm.[21] 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. The supply chain earnings premium could then be a return to the worker for this increase in the firm's surplus. This story implies that the earnings premium should be contingent on the continuation of the supplier-buyer relationship after the worker has moved. 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 supplier-buyer relationship after the worker has moved.

We therefore investigate the relationship between the earnings premium and the post-move dynamics of supplier-to-buyer sales. To do so, we estimate the following specification:

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

which modifies Equation 2 by interacting the $t-1$ supplier-buyer dummy variable, $SB_{o,d,t-1}$,

[21] The increase in trade could also be due to mitigation of hold-up problems thanks to the personal connections of the new hires with the origin firm. As long as one considers both technical knowledge and social capital to be forms of human capital, this is still consistent with the human capital of the movers leading to the strengthening of the supply chain relationship. However, improving supply chain relationships is not one of the main reasons firms hire along the supply chain according to the survey results, pointing to a lesser importance of social capital and personal connections in our setting.

with a dummy indicating whether the two firms also traded after the worker move, $SB_{o,d,t+1}$. Panel (a) of Figure 10 shows that the supply chain premium is present only when the buyer and supplier continue trading after the worker has moved, and that there is no premium when the supply chain link breaks after the move.

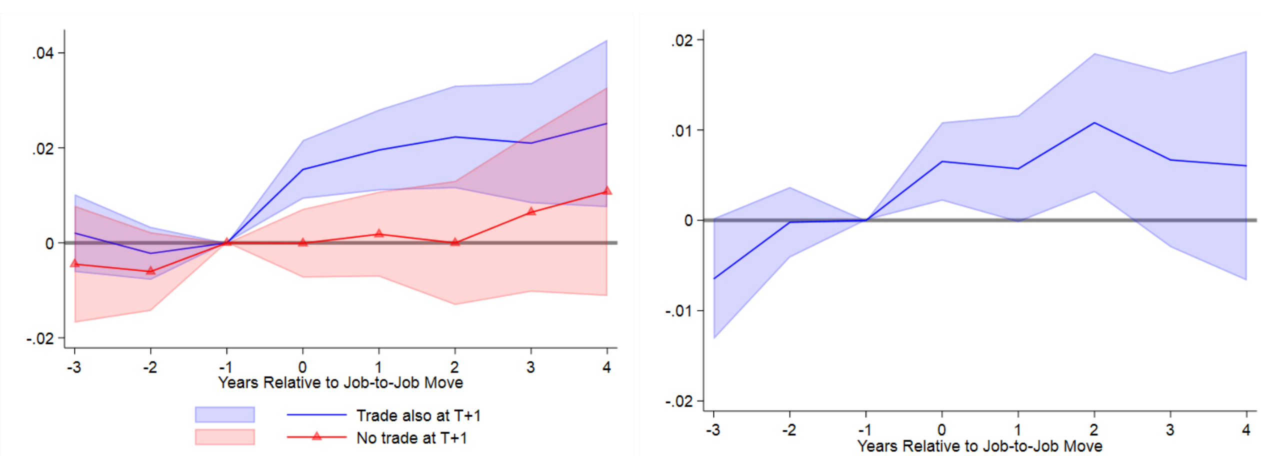
We also consider an alternative specification in which we restrict the sample to workers that move between buyers and suppliers only, $SB_{o,d,t-1} = 1$. We estimate:

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

where $TradeGrowth_{o,d,t+k}$ is the supplier to buyer sales growth between year $t-1$ (before the worker move) and year $t+k$.[22] Panel (b) of Figure 10 reports the β^k coefficients and the 95% confidence interval. The supply chain earnings premium is larger when supplier-to-buyer sales increase after the worker moves. The supply chain earnings premium and firm-to-firm trade thus appear to be closely interwoven. This evidence is more supportive of the supply chain-specific human capital explanation for the earnings premium than pure information-related explanations.

Figure 10: Earnings Dynamics of Movers–trade between firms before and after move

(a) Dummy for Trade in T+1 (b) Change in Trade Value



Notes: Panel (a) plots the coefficients β^k and ω^k from Equation 6 along with 95% confidence intervals. Panel (b) plots the coefficients β^k from Equation 7 along with 95% confidence intervals. The regressions include 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.

A potential concern with this interpretation is that supply chain relationships that break in T+1 or shrink after the move may have been less important linkages to start

[22]We compute growth rate as $growth(x) = 2 \cdot \frac{x_{t+k} - x_{t-1}}{x_{t+k} + x_{t-1}}$ to capture both the intensive and extensive margin of change in trade (Davis, Haltiwanger, Schuh et al., 1998).

with. We therefore perform two robustness checks. First, we define supply chain movers as workers who move across firms that trade both the year before the move and two years before, thus eliminating short-lived relationships and occasional trade. Second, we focus only on supply chain movers and we estimate a coefficient on a dummy equal to one if and only if the trade relationship continues during the year after the move, while controlling for the (log) of the amount of trade during the pre-move year. The results of these two exercises are presented in by Figure A11. They confirm that the supply chain premium is present only when the relationship is not severed after the worker move (first exercise) and that indeed there is a difference in post-move earnings between the two groups of supply chain movers even controlling for the amount of pre-move trade (second exercise).[23]

Mass Layoffs A significant literature focuses on mass layoffs to isolate job separations due to firm-level rather than worker-level shocks (Gibbons and Katz, 1991; Flaaen, Shapiro and Sorkin, 2019). Whether or not workers who leave their employers during a mass layoff earn a supply chain premium may provide additional evidence on the channels behind supply chain moves. Information-based channels could still potentially be relevant for these movers, to the extent that they can still obtain referrals. However, their supply chain-specific human capital is likely to be less valuable because the origin firm is experiencing a negative shock.

We define a mass layoff as a situation where a firm's employment falls by at least 30% and at least 25 workers. In contrast to the literature focusing on the long-run scarring effects of unemployment, we restrict our attention to workers let go during these mass layoff events who find another job by the following year. We first show that workers tend to find jobs on the supply chain even after mass layoffs. The share workers being hired by a buyer or supplier following a mass layoff is 18%, thus very similar to the share we see for all movers, against a random allocation counterfactual of 9% (see Table A8). We then re-estimate Equation 2 including only workers who move following a mass layoff. We find no evidence of a supply chain earnings premium for these movers (see Figure A12), although the estimates are quite noisy given the small sample size and must therefore be taken with caution. This set of results suggests that the production network is a job-finding network even for involuntary separations, and also that the supply chain earnings premium is more likely explained by human capital than information-based mechanisms.

[23]The estimates from these two exercises should be taken with caution, especially at longer horizons, because of the smaller sample sizes.

7.2 Alternative Explanations for the Earnings Premium

We now turn to some alternative explanations for the supply chain earnings premium which do not rely on either the presence of a supply chain-specific component of human capital or the information available to workers and firms.

Unemployment scarring Job losses followed by long unemployment spells lead to a depreciation of workers' human capital and declines in future earnings (Mincer and Ofek, 1982; Jarosch, 2021). Unfortunately, a limitation of our data is that we do not observe the exact date of the beginning or end of employment, nor do we observe the reason for the dissolution of an employer-employee match. A possible explanation of our findings is therefore that movements to buyers and suppliers are associated with shorter periods of unemployment after a job loss, thereby diminishing any decline in human capital during unemployment. That is, if workers who get laid off first look for a new job at buyers and suppliers, then the ones that are hired by these firms will have spent less time in unemployment than other workers.[24]

While we cannot control directly for unemployment duration, our baseline specification in section 5 focuses on within-year movers to limit the presence of long unemployment spells. While this set of movers is more likely to comprise voluntary job-to-job transitions than the full sample, we consider an even stricter restriction here which only includes within-year movers whose average earnings are higher in the destination firm than the origin firm in the year of the move.[25] We re-estimate our main specification with this sample of movers and show our results in Figure A13. The findings are very similar to our baseline, with an earnings premium of over 2 pp after 4 years for workers who move to buyers or suppliers, controlling for both worker and firm controls. Given that these moves are most likely to be job-to-job moves, these results strongly suggest that differences in unemployment spells or scarring between supply chain movers and other movers do not drive our findings.

In addition, in Figure 9 we showed that low-wage workers do not earn a premium once we condition on firm fixed effects. As low-paying jobs also tend to have low job security (Jarosch, 2021), gains from avoiding or shortening post-displacement unemployment should be particularly important for low-wage workers. This absence of gains for moves along the supply chain also suggests that job losses and unemployment spells are unlikely to be a main explanation for why we observe a premium from movements along the supply chain.

[24]This alternative interpretation would change the economic mechanism behind our result, though it would still have potentially important implications for worker welfare and productivity.

[25]We thereby drop any worker who experiences a nominal wage decline upon moving, both for supply chain movers and for other movers.

Moral hazard Another possible explanation for the earnings premium is that firms may be able to provide stronger incentives for workers hired along the supply chain to exert effort. For example, Heath (2018) documents that referrals are used to mitigate such moral hazard problems in the context of households in Bangladesh, because firms may be able to punish the referral provider. However, Heath (2018) finds that this mechanism is relevant only for low-wage workers, in particular when starting wages are close to a minimum or subsistence level. The reason is that, when the wage level of the shirking worker is low, the optimal contract (which rewards workers as a function of their ex-post output) may be unfeasible. The firm therefore exploits the connection between the new hire and referring worker and punishes both if the new hire shirks, thus mitigating the moral hazard problem. In contrast, we find that the earnings premium is only present for high-wage workers, for whom optimal contracts may be easier to design (e.g. through the use of bonuses). This somewhat dampens the concern that this type of moral hazard explains the earnings premium. However, this mechanism could still be relevant for high-wage workers who are concerned about reputational damage. For instance, new supply chain hires may still have friends and contacts in their previous firm who might learn about the worker's performance. This reputational channel is likely to be less important for indirect supply chain moves. However, we find an earnings premium even for moves to indirect suppliers and buyers, suggesting that this channel is less likely to play a major role.

In conclusion, there are many potential explanations for the supply chain earnings premium, including several information-related stories. However, the collection of results discussed in this section points towards the supply chain-specific component of human capital as the most likely explanation.

7.3 A Model of Job Search in Production Networks

In this paper, we present evidence that production networks are also job-finding networks; that supply chain movers tend to move to higher productivity and better-paying firms because of the structure of the production networks; and that human capital has a supply chain-specific component which results in a supply chain earnings premium for movers.

To formalize these channels, we propose a parsimonious model of on-the-job search (in the spirit of Postel-Vinay and Robin (2002) and Cahuc et al. (2006)) in production networks with two novel elements. First, workers are more likely to learn about job opportunities within their employer's supply chain, thus reducing search frictions similar to the role of social connections in Calvo-Armengol and Jackson (2004). Because high-wage and productivity firms have more buyers and suppliers (Bernard et al., 2022), job opportunities in the supply chain are more likely to be at better-paying firms. Second, workers are more likely to form more productive matches along the supply chain, consistent with the evidence of a supply chain earnings premium.

The model, presented in more detail in section A9, qualitatively replicates the main empirical patterns documented in the paper and provides a helpful lens through which to interpret these findings. It illustrates how an increase in the density of an economy's production networks (that is, an increase in the number of supply chain linkages, keeping fixed the number and the productivity of firms in the economy) can lead to an increase in average wages and aggregate labor productivity through worker mobility in production networks.[26] These benefits arise because supply chain hiring is more prevalent for high-wage and productivity firms. Thus, when the number of supply linkages increases, diminishing labor search frictions, more workers find jobs at high-wage than low-wage firms in equilibrium. Worker mobility along the supply chain also helps to create more productive employer-employee matches, further boosting wages.

These results highlight a new channel through which production networks and labor markets interconnect, and can help explain some important macroeconomic patterns. In recent decades supply chains have become much more globalized (Antras and Chor, 2021), which has coincided with a decline in labor market dynamism in the U.S. (Davis and Haltiwanger, 2014) and other advanced economies. The globalization of supply chains may have led to the breaking of many domestic supply chain linkages, to be replaced with foreign ones. Our findings suggest this process may have diminished workers' opportunities to climb the firm job ladder, contributing to the decline in labor market dynamism. Furthermore, contracting frictions, which are prevalent in emerging markets and developing economies, lead to sparser production networks (Oberfield and Boehm, 2020; Startz, 2021; Boehm, 2022). Our findings also suggest that this sparseness may contribute directly to the weakness of the job ladder relative to advanced economies (Donovan et al., 2023), suggesting that policies aimed at mitigating contracting frictions may, in turn, mitigate labor market frictions as well.

8 Conclusion

In this paper, we provide new insights into the job search and matching process by highlighting the essential role played by production networks. Using administrative records for the Dominican Republic, we document that workers disproportionately move to buy-

[26]We consider a counterfactual where the number of supply linkages increases proportionally for high and low-productivity firms, thus leaving the ratio between the number of connections of high versus low-productivity firms unaffected. This precludes extreme but unrealistic cases, such as networks where all firms are connected to all other firms.

ers or suppliers of their existing employer. These supply chain movers also tend to move to better-paying and more productive firms relative to workers moving to unconnected firms. We also document that these moves are associated with an increase in worker earnings which we label the supply chain earnings premium. Survey evidence 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. Additional evidence shows that this component of human capital is the most likely explanation of the supply chain earnings premium, while the structure of production networks can explain why supply chain movers disproportionately move to higher-wage firms.

Our 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 use of "no-poaching" clauses.

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Online Appendix

A1 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.

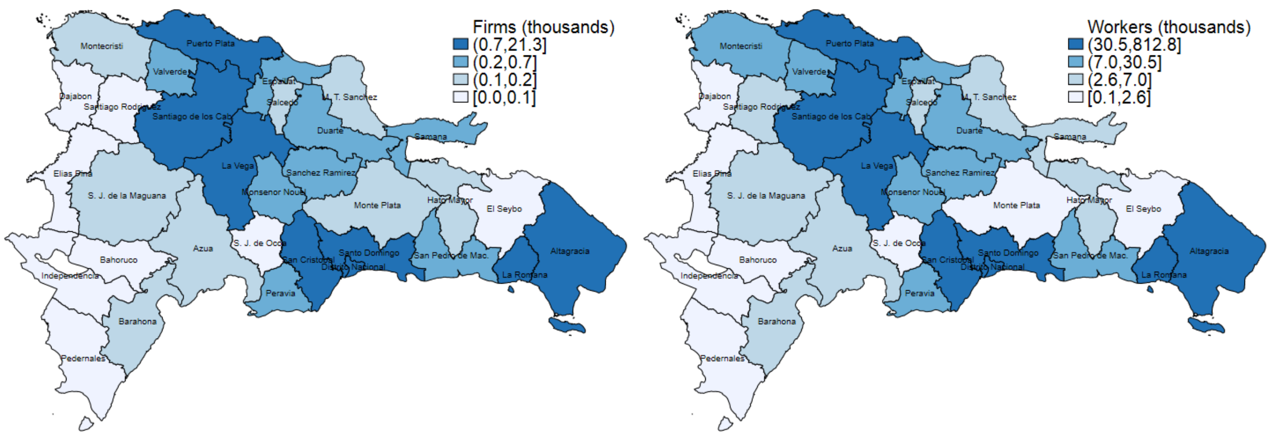
The firm-level information for the entire universe of firms that file income tax at the Directorate General of Internal Taxes is collected from the following records: form IR1 (*Declaración Jurada de Impuestos sobre la Renta a las Personas Físicas*), form IR2 (*Declaración Jurada de Impuestos sobre la 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.

Figure A1 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 most touristic provinces (Puerto Plata, La Romana, and Altagracia). The rest are primarily based in the areas connecting these three poles.

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 our 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.

Figure A1: Geographical Distribution of Firms and Workers



(a) Firms (b) Workers

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

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.

A2 Survey of the Central Bank of the Dominican Republic

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.[27] It is administered via face-to-face interviews, in which the interviewers collect information on the recent performance of the firm as 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 the survey wave of October-December, 2022. The first question asked "How important are the following factors when hiring skilled

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

workers?" Possible answers were: "(i) experience in the same or similar job position, (ii) experience in one of the company's competitors, (iii) experience in one of the company's buyers or suppliers, (iv) academic studies and the institution where the worker graduated, and (v) a referral from a personal connection or current employee of the company". Respondents could answer by selecting one of the following options: "not at all, one of many factors, one of the top three factors, the most important factor". The second question asked about the factors behind the decision to hire from buyers and suppliers. Specifically, the question was "if you have hired any workers from among one of your buyers or suppliers in the past three years, what were the reasons for these hires?". In this case, the possible answers were: "(i) had good experience interacting with the worker while they were at the previous firm, (ii) worker had specialized knowledge related to my inputs and/or products, (iii) to build trust or improve the relationship with the buyer or supplier, (iv) received a referral for the worker, (v) other reasons, (vi) I have not hired from my buyers or suppliers in the past three years."

The results from the first survey question are shown in Table A2 and Table A1. The full set of survey results is reported in Table A1. Table A2 reports the number of responses where each factor was categorized as either "very important" or "the most important", along with the share of firms reporting this, both unweighted and weighted by employment. The results from the second survey question are reported in Table 7, with the corresponding questions in Spanish reported in Table A3.

Table A1: Full Survey Results on Relevant Factors When Hiring

How important are these factors when hiring skilled workers?				
(1) Answer	(2) Not important	(3) Somewhat important	(4) Very important	(5) The most important factor
(i) experience in the same or similar job position	9	24	68	48
(ii) experience in one of the company's competitors	31	58	53	7
(iii) experience in one of the company's buyers or suppliers	48	47	43	9
(iv) academic studies and the institution where the worker graduated	22	40	69	18
(v) a referral from a personal connection or current employee of the company	39	45	50	11

Respondents can pick multiple options. 149 firms responded to the survey question.

A3 Informality

Our data covers only formal firms and workers that are formally employed with permanent contracts. We therefore miss information on informal employment and informal firms. More than 50% of the Dominican workforce work in informal firms according to the "Encuesta Nacional Continua de Fuerza de Trabajo". This is broadly in line with other

Table A2: Summarized Survey Results on Relevant Factors When Hiring

How important are these factors when hiring skilled workers? Response = very important or the most important factor.			
(1) Answer	(2) N of responses	(3) Share of firms	(4) Share of firms (employment-weighted)
(i) experience in the same or similar job position	116	78%	83%
(ii) experience in one of the company's competitors	60	40%	27%
(iii) experience in one of the company's buyers or suppliers	52	35%	30%
(iv) academic studies and the institution where the worker graduated	87	58%	75%
(v) a referral from a personal connection or current employee of the company	61	42%	31%

Respondents can pick multiple options. 149 firms responded to the survey question. The employment weights are obtained from firm responses in the survey.

Table A3: Survey Question and Answers

Si ha contratado alguń trabajador de sus empresas compradoras o proveedoras en los últimos tres años, ¿cuáles fueron los motivos de estas contrataciones?			
Answer	N of responses	Share of firms	Share of firms (employment-weighted)
(1) No ha contratado a nadie que trabajaba en empresas compradoras o proveedoras en los últimos tres años	98	.	.
(2) Teniá conocimientos especializados relacionados con los insumos y/o productos de la empresa	27	67%	62%
(3) Recibió referencias del trabajador	23	59%	35%
(4) Teniá buena experiencia interactuando con el trabajador mientras estaba en la empresa anterior	17	41%	28%
(5) Generar confianza o mejorar la relacioń con la empresa compradora o proveedora	8	20%	8%
(6) Otras razones	8	17%	22%

Respondents can pick multiple options. 136 firms responded to the survey. The third and fourth columns report the share of firms that picks any option among the firms that do NOT pick option (1). All firms that picked option (1) did not pick any other option, except one firm that picked also option (6) (thus this respondent is not considered when calculating the shares).

emerging markets and developing economies. In this appendix section, we discuss how the internal and external validity of our results may be impacted by the lack of coverage of the informal sector.

External Validity Informal firms are usually smaller, less productive, and exhibit lower growth rates than formal firms (La Porta and Shleifer, 2014) while informal workers receive lower wages and benefits. Small and less productive firms also have fewer buyers and suppliers (Bernard et al., 2022). We find that workers tend to move to buyers and/or suppliers in every industry, location, and firm size category. However, this tendency is stronger for workers with higher wages and hired from high-productivity firms. These facts provide some reassurance that the tendency to move within the supply chain is likely present also in the informal sector, but probably to a significantly smaller degree than in the formal one. The fact that the supply chain premium is entirely driven by high-wage formal workers suggests that the importance of supply chain-specific human capital is less likely to be important among informal workers. However, low-wage formal workers do have a high tendency to move up the firm wage ladder through supply chains. Based on this, we expect informal workers to still benefit from moving to better firms through buyer-supplier links.

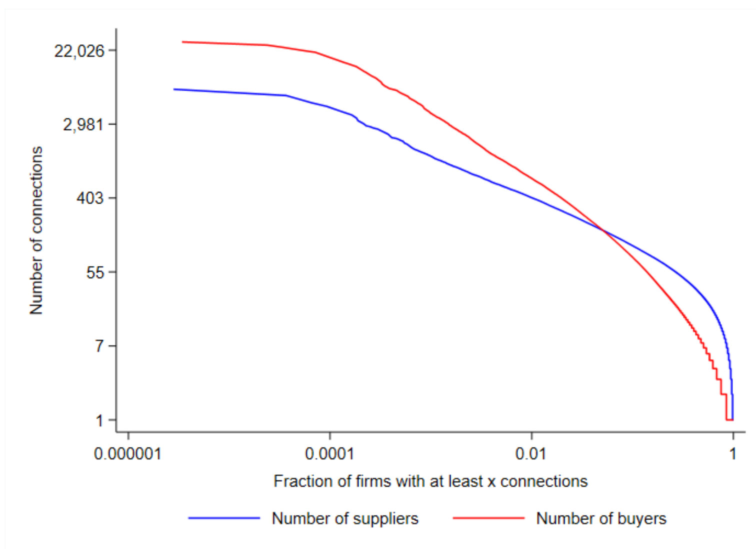
Internal Validity We also ask whether any of the empirical results may be biased because of the lack of information about the informal sector. Equation 2 compares workers moving to formal buyers or suppliers with workers moving to other formal firms. Our estimates are therefore entirely identified by comparing different types of formal-to-formal job transitions. Given that informal firms are less likely to be within the supply chain, and that movers to informal firms are likely to experience lower earnings growth, the supply chain earnings premium relative to *all* other movers should be even larger than the one we estimate.

In unreported exercises, we further check whether the rate at which workers drop out of the sample is different for working who previously moved to buyers or suppliers versus workers who previously moved to other firms. Dropping out of the sample could be due to moves to informality or outside the labor force altogether. We find that workers moving to buyers or suppliers are more likely to still be in the sample in the following year, although this difference is statistically insignificant once firms fixed effects are included. This indicates that a further benefit of moving within the supply chain is that workers are less likely to need to move to –potentially less appealing–jobs in the informal sector.

A4 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 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 A2. 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 percent 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 A2: Number of Firms and Number of Connections



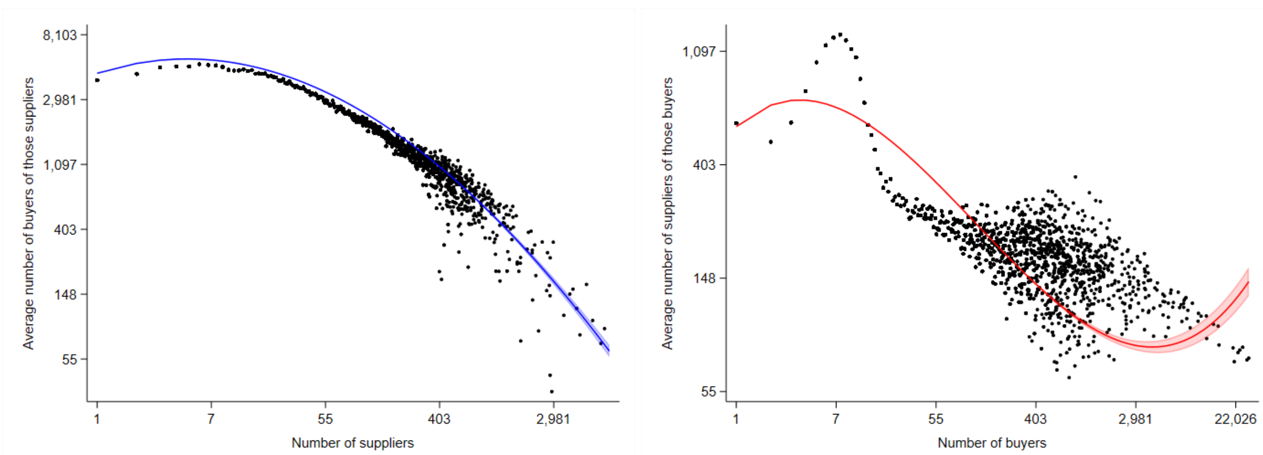
Notes: The figure shows the inverse of the cumulative distribution functions of the number of suppliers per buyer and of the number of buyers per supplier in 2019.

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 A3a 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 percent 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 A3b 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 percent in the buyer's number of suppliers is associated with a 0.7 percent 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 A3: Assortative Matching

(a) Suppliers per Buyer and Number of Buyers (b) Buyers per Supplier and Number of Suppliers



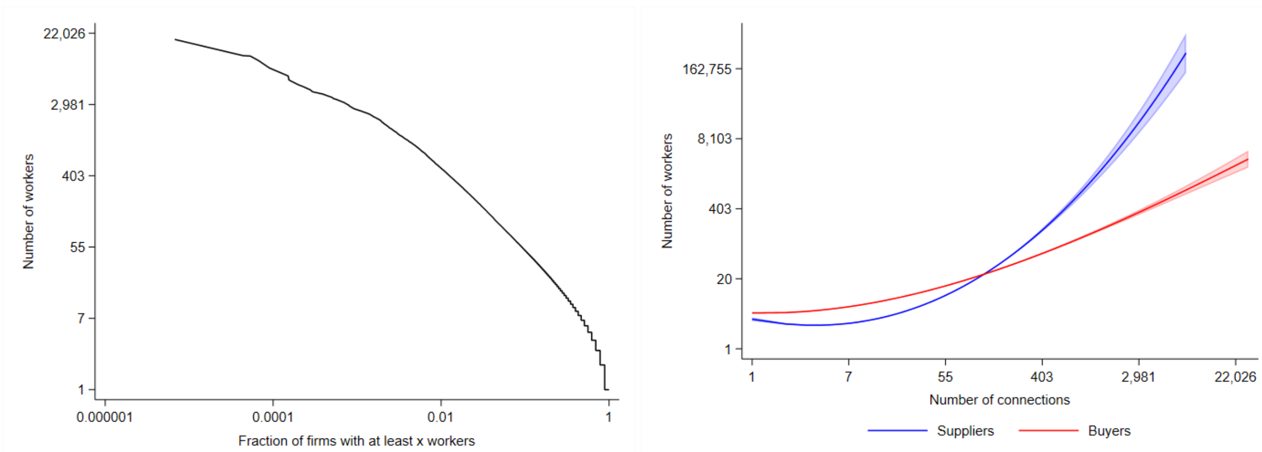
Notes: Panel (a) shows the predicted values of a third-degree polynomial regression of the log of the number of suppliers for each buyer on the log of the average number of buyers for those suppliers in 2019. Panel (b) shows the predicted values of a third-degree polynomial regression of the log of the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

We now turn to the distribution of workers in the production network. Figure A4a 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 percent of the firms had one single employee in 2019, compared with one percent with 470 employees and one hundredth of 1 percent with about 8,300 employees.

But do employees work in firms with more buyer and supplier linkages? In Figure A4b 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 percent in the number of connections is associated with a 4 percent increase in the number of employees at the firm for buyers and a 7 percent 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 A4: 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 percent confidence intervals.

A5 Regression approach à la Kramarz and Thesmar (2013)

We further test whether supply chain linkages explain worker movements using an alternative, regression-based approach. Specifically, 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.

The framework is based on a linear model for the probability that a mover i, who works for origin firm $o(i)$ in year $t-1$, moves to the destination firm d in year t:

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

The probability $P_{d,i,t}$ is a function of the dummy variable $SB_{d,o(i),t-1}$, which takes value one if firm d is a buyer and/or supplier of o during year t, plus a set of controls $\phi(d,t,X_i,X_{o(i)})$. This model is extremely flexible in controlling for assortative matching on observable worker (and origin firm) characteristics, as the function ϕ is allowed to be different for each employer and year. That is, every firm may have a tendency to hire workers of certain characteristics (e.g., working in a certain industry and in a certain location) and this tendency may change over time.

For characteristics X_i, $X_{o(i)}$ that all have discrete values, we can define a 'class' c as the set of movers that all share these same characteristics (except for SB). Thus, the linear probability model can be re-written as: $P_{d,i,t} = \phi(d,t,c(i)) + \beta \cdot SB_{d,o(i),t-1} + u_{d,i,t}$, where $\phi(d,t,c(i))$ is a set of employer $\times$ class $\times$ year fixed effects. Given that we observe more than 1,000,000 moves and that in each year we observe on average more than 16,000 hiring firms, direct estimation of Equation 8 would be very computationally challenging. However, Kramarz and Thesmar (2013) show that the parameter of interest β can be estimated in a computationally convenient way by collapsing groups of workers along the dimensions defined by the classes.

Table A4: 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.

We estimate Equation 8 following the estimation procedure proposed by Kramarz and

Thesmar (2013). We define a class as the combination of worker's origin industry, destination industry, earning quintile, gender, age category, decile of firm size and average wage (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. As reported in Table A4, we find the coefficient β to be positive and statistically different from zero. (We multiply coefficients and standard errors by 100 for ease of visualization.) That is, workers are more likely to move across firms that are connected by supply chain relationships, confirming the findings obtained using the random allocation approach, though the estimated odds ratios are larger than those in section 3. However, our preferred empirical method remains the random allocation approach because it does not impose the additive structure of Equation 8, which can be consequential when dealing with very small baseline probabilities.

A6 External Validity and Mobility Across Industries

The availability of matched firm-to-firm trade and employer-employee data for research is still scarce, limiting our ability to verify the external validity of our findings. However, we can examine how *industry*-level worker mobility patterns correlate with industry-level input-output connections both in the Dominican Republic and in the United States.

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

$$ShLeavers_{n \to m,t} = \phi_{m,t} + \phi_{n,t} + \gamma ShTrade_{n,m,t} + \eta_{n,m,t} \tag{9}$$

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 that are 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 use the available 1-digit industry-level data on job-to-job flows provided by the US Census Bureau which we merge with input-output tables from the Bureau of Economic Analysis. We standardize all the variables to have mean zero and variance one, so coefficients are comparable across samples.[28]

Table A5 shows the results. As expected, columns (1) and (2) show a positive and significant correlation between inter-industry worker flows and trade for the Dominican Republic. [29] Importantly, we find similar results for the U.S. Columns (3) and (4) show that workers tend to move disproportionately between upstream and downstream in-

[28]Our results are very similar without standardization.

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

dustries. While we cannot directly test whether supply chain moves are common in other countries, these results suggest that our findings for the Dominican Republic likely have broader external validity.

Table A5: Trade and Worker Flows between Industry Pairs

	Dominican Rep.		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: The dataset for the regressions in this table is at the industry-year level. For the Dominican Republic we use 2-digit industries, for the U.S. we use 1-digit industries. 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 that are sold to the other (columns 1 and 3) or the share of purchases made by one industry from the other (columns 2 and 4). For the US, we rely on the input-output matrix from Bureau of Economic Analysis (https://www.bea.gov/industry/input-output-accounts-data). The table focuses on years between 2012 and 2015 as US data are available up to 2015. All regressions include origin industry and destination industry-year fixed effects. Standard errors are double-clustered at the level of the two industries forming the pair. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

A7 Panel Regressions with Worker Fixed Effects and Connection with the AKM Decomposition

A cornerstone of the literature studying the determinants of worker earnings is the AKM decomposition introduced by Abowd et al. (1999):

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

where $E_{i,t}$ is log of earnings (or wage rate) of employee i of employer $d(i,t)$ at time t. α_i and $\phi_{d(i,t)}$ are employee and firm fixed effects. $X_{i,t}$ 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:

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

The goal when estimating this equation in the aforementioned literature is usually to assess the contribution of each element (in particular worker and firm fixed effects, and the correlation between the two) in explaining the dispersion of earnings across workers. Instead, we aim to re-examine the findings of section 5 through the lens of the AKM wage specification. For this specification, we also include "stayers" (workers who do not change employers for years $t-1$ to $t+1$), given that this helps identify the coefficients on $X_{i,t}$.[30]

Let $PostMove_{i,t}$ be a dummy variable equal to one if we observe worker i performing a job-to-job transition in year t or before, and zero otherwise. That is $PostMove_{i,t} = 0$ before the observed job-to-job move and for all the stayers. Let the 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 than c and the characteristics of the move to impact its value. In fact, Figure 6 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:

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

The parameter that we are interested in estimating, β, captures how the match-specific component of earnings differs for workers who move along the supply chain versus other workers, given the quintile of their initial earnings. It is essential to highlight that, while this specification is derived starting from the same earnings equation as AKM, we do *not* perform an AKM decomposition. We are interested in estimating the parameter β and not in estimating the worker and firm fixed effects which, in our setting, are only controls. Therefore, we circumvent the plethora of identification and estimation challenges faced by researchers interested in the consistent estimation of the distribution of α_i and $\phi_{d(i,t)}$ (Kline, Saggio and Sølvsten, 2020; Bonhomme, Holzheu, Lamadon, Manresa, Mogstad and Setzler, 2022).

We first estimate the more parsimonious equation:

[30] 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).

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

Equation 11 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 $\beta + \delta$. Because the firm fixed effects are excluded, the parameters β and δ captures changes in earnings due to both moves to different firms and to changes in match-specific fit.

OLS estimates of δ and β are reported in column (1) of Table A6. δ is positive, highlighting that job-to-job transitions are an important way that workers earn higher wages. The average gain is 6.7 percentage points. β is also positive and statistically significant, confirming that moves to buyers/suppliers lead to larger wage gains relative to moves to other firms.

To disentangle the change in earnings due to movements across different types of firms versus match-specific components, 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, although about half as large as in the specification without firm FEs: workers in general move to firms that both pay higher wages on average and that are also a better fit for them. β is also positive, indicating that moves to buyers/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, reported by column (3), are qualitatively and quantitatively similar.

These alternative estimates of the additional earnings premium from moving to buyers or suppliers are between 3.5 and 4.5 pp, falling to 0.8 pp in the most saturated specification including firm-year fixed effects. These estimates are smaller than the ones presented in section 5. One explanation is that job changes may be followed by larger earnings increases for workers starting from a lower base wage and that movers 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 full 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, reported in columns (4) to (6), show that when we control for heterogeneity in pre-move earnings, we find that the additional impact of moving to buyers/suppliers is 8.6 pp overall, which falls to 2.3 pp when we control for firm-year fixed effects. These estimates are close in magnitude to the estimates presented in section 5. In conclusion, the estimation results from Equation 10 are quantitatively and qualitatively similar to those from Equation 2 regarding the changes in earnings, and in particular of the match-specific component of earnings, following a worker move along the supply chain. The results of this section are reassuring as our main results are robust to the use of different empirical models.

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

	Earnings					
	(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.

A8 Match Duration Event Study

A poor fit between an employer and an employee can lead to the employee rapidly quitting or being let go. We investigate whether workers hired by buyers or suppliers of their previous firm have different separation rates than workers who move outside the supply-chain by estimating the following equation:

$$S_{i,o,d,t+k} = \alpha^k + \delta^k X_{i,t-1} + \beta^k SB_{o,d,t-1} + \phi^k_{o,t} + \phi^k_{d,t} + \gamma^k X_{o,d} + \eta_{i,d,o,t,k} \tag{12}$$

where i is a worker who moves from origin firm o to destination firm d in year t. The equation differs from Equation 2 only because the dependent variable $S_{i,o,d,t+k}$ is a dummy variable that equals one if and only if the worker separated (either by dropping from the employer-employee database or moving to another firm in our data) from the destination firm in year $t+k$, conditional on having been at the destination firm up to year $t+k-1$.

We estimate Equation 12 for horizons $k = 2, \ldots, 6$ and report the results in Table A7.[31] The top panel shows the results controlling for year fixed effects and worker characteristics, but without either firm or firm-pair controls. We find that separation rates are 7.4 percentage points 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 column (6), we substitute the dependent variable with the observed duration of the new match, expressed in number of years, for movers in 2013 (we can measure the duration of the post-move match up to six years for movers in 2013). We find that the lower separation rates for moves along the supply chain lead to a longer observed match duration of 0.383 years (4.5 months). This difference is in part explained by workers who move to buyers or suppliers sorting into firms with more stable positions. The bottom panel of Table A7 includes both firm fixed effects and firm-pair controls, and confirms that movers to buyers or suppliers non-randomly sort into firms with lower separation rates. Average separation rates are 2 percentage points lower, once we control for origin and destination firm fixed effects, during the first post-move year. The differences in separation rates are statistically indistinguishable from zero from the fourth year on (conditional on the match lasting at three/four/five years). This leads to observed match duration being 0.153 years longer. That workers who move along the supply chain experience lower separation rates–with or without controlling for firm fixed effects–is further evidence that they find better firms and that matches created along the supply chain are better than others.

A9 A Model of Job Search in Production Networks

In this paper we documented that (i) workers move disproportionately to firms within the supply chain, (ii) supply chain moves are disproportionately up the firm-wage and firm-productivity ladder, (iii) workers moving along the supply chain earn a persistent earnings premium over other new-hires of the same firm. We find that firms hire from within the supply chain both because they value these workers' human capital and because they have better information about them. The fact that more productive firms have more buyers and suppliers can fully explain why supply chain movers are more likely to move to more productive and higher-wage firms. Empirical evidence also points to human capital as being the main driver of the supply chain earnings premium.

To formalize the mechanisms underpinning these findings and study their implica-

[31] The separation rate in the year of the move is 0 by construction given our definition of within-year moves.

Table A7: 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 12. 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.

tions, we propose a simple model of on-the-job search in the spirit of Postel-Vinay and Robin (2002) and Cahuc et al. (2006), into which we embed search within and outside of the firm buyer-supplier network. Importantly, the model has three features that are based on the survey and other evidence presented in the paper: workers are more likely to learn about job opportunities within the supply chain (consistent with evidence that referrals are one reason to hire from suppliers or buyers), high-productivity firms are disproportionately represented in the supply chain (as documented in subsection 4.1 and also consistent with well-documented findings from the literature that high-productivity firms tend to have more buyers and suppliers (Bernard et al., 2022)), and workers are more likely to find good matches when moving along the supply chain (consistent with evidence on the supply chain-specific earnings premium). The first of these features captures the idea that production networks diffuse information about job opportunities. This is similar to the role social networks play in diffusing information about vacancies in Calvo-Armengol and Jackson (2004). The model also takes into account that production networks tend to have a higher share of high-productivity firms than in the economy overall.

These assumptions imply that workers are more likely to 'meet' a buyer/supplier than a firm outside the network, and these potential matches are more likely to be with high-productivity firms. However, these model features themselves would not necessarily predict that supply chain movers earn a premium over other new hires, conditional on moving to *the same employer*. The additional key assumption of the model is that workers are more likely to find good matches when 'meeting' a firm within the supply chain. This is consistent with the empirical evidence that there exists a supply chain-specific component of workers' human capital and that this is the most likely explanation for the supply chain earnings premium. We capture the presence of this supply chain knowledge in a reduced-form fashion by imposing that the probability of finding a good match in the supply chain is higher than outside the supply chain.

For clarity of exposition, we keep all elements of the model as simple as possible. The resulting closed-form solutions clearly illustrate how the spread of information about vacancies and higher match quality for supply chain movers can qualitatively explain the main empirical findings. The model also allows us how to explore how the size of the firm network and the extent to which it mitigates information frictions affect the allocation of workers across firm and job types. A downside of such simplicity is that this framework is not suited for quantitative exercises.

Model Description The model features a continuum of workers with mass normalized to 1 and a mass of firms M. Time is discrete, and both workers and firms live forever and do not discount the future. Firms can be low-productivity or high-productivity, with the share of high-productivity firms in the economy given by H. Firms produce output $y = a^Z x$ for each worker they are matched with, where x is worker-firm match quality, $Z \in \{L, H\}$ denotes firm productivity and $a^H > a^L$.

Each firm is exogenously connected to a mass of firms N which form its production network. The size of the network N^Z differs for high and low-productivity firms. If the size of the networks was uncorrelated with productivity ($N^H = N^L$), the share of high-productivity firms in every network would be H. However, consistent with the evidence discussed above, high-productivity firms have larger networks ($N^H > N^L$) and the share of high-productivity firms in the network is assumed to be higher than the overall share in the economy: $H^n > H > H^o$.[32]

Workers can be unemployed or employed. Employed worker matches get destroyed with exogenous probability δ. Unemployed workers get a flow value of unemployment b and employed workers get a fixed share β of the flow value of the match y. This simplification relative to the previous literature eliminates any impact of outside options on bargaining over the surplus, but does not affect the main mechanisms of interest in the model. Worker-firm match quality takes only two values $x \in \{x_1, x_2\}$. Match quality in low-productivity firms is always x_1.[33]

Workers costlessly search on and off the job. High-productivity firms do not hire from unemployment, and so unemployed workers receive offers from low-productivity firms each period with probability λ. We assume that the value of a vacancy to a firm is 0 and $b < a^L x_1$ so that unemployed workers accept any position they are offered.

Employed workers 'meet' firms every period with certain probabilities. With probability $P^{o,z} = pM(1 - N^Z)$, employed workers whose matches aren't exogenously destroyed meet a random firm outside the production network, where p is the likelihood of matching with any particular vacancy. With probability $P^{n,z} = \chi p M N^Z$ they meet a random firm within the production network. It then follows that $\frac{P^{n,z}}{P^{o,z}} = \chi \frac{N^z}{1 - N^z}$. The case where information about vacancies is the same inside and outside the supply chain is given by $\chi = 1$. In contrast, $\chi > 1$ corresponds to the situation where workers are more likely to learn about vacancies within the supply chain than outside it.

Conditional on meeting a high-productivity firm, a match quality x is drawn from $\{x_1, x_2\}$. The probability of drawing x_2 is γ_n within the network, and γ_o outside the net-

[32] Evidence of negative assortative matching on the number of buyers/suppliers (Bernard and Zi, 2022) suggests that the share of high-productivity firms in the network is higher for low-productivity firms ($H^{n,L} > H^{n,L}$). We indeed find that high-productivity firms are over-represented in production networks of low-productivity firms more than in production networks of high-productivity ones (see Figure A7), but the difference is small enough that we simply set $H^{n,L} = H^{n,H} = H^n$.

[33] While this assumption is mostly for simplicity, it also captures the idea that low-productivity firms provide low-skill jobs in which idiosyncratic skills and knowledge are not valuable. In this sense, it is consistent with the idea that worker-firm match quality is more important for high-productivity firms (Bagger and Lentz, 2019).

work. We assume $\gamma_n > \gamma_o$, which captures in a reduced form the idea that human capital is more transferable within the supply chain—workers who move within the network are more likely to get good productivity draws.

In contrast to Postel-Vinay and Robin (2002) and Cahuc et al. (2006), we assume perfect information about match quality when a worker and firm meet. This is because our preferred match quality explanation does not rely on imperfect information. Workers always move if they know they will receive a higher flow wage in their new job. In the case where workers' wages would be the same, we assume that non-wage motives to rank different firms come into play (Sorkin, 2018) and a tie-breaking rule whereby workers move with 50% probability. Workers at high-productivity firms with x_2 match quality don't search because they cannot get a better match.

We focus on the steady state of the model in which there is a constant share of workers in each state: unemployed (u), employed in L (l), H1 $(H$ and x_1, $s_{h1})$ or H2 $(H$ and x_2, $s_{h2})$. The model is straightforward to solve analytically, and we next turn to characterizing the features of the steady state. More detailed derivations are available upon request.

Matching the Empirical Findings We focus on three predictions of the model: (i) the share of movers within the production network, (ii) the share of movers moving up the firm productivity ladder within vs. outside the production network, (iii) the earnings premium for movers within vs. outside the production network.

The relative number of workers at low-productivity firms moving within vs. outside the network is given by the left-hand side of the following equation:

$$\chi \frac{1+H^n}{1+H^o} \frac{N^L}{1-N^L} > \frac{N^L}{1-N^L} \tag{13}$$

This is greater than the ratio if workers randomly met firms $\left(\frac{N^L}{1-N^L}\right)$ both because workers are more likely to meet firms in their network $\chi > 1$, and because they are more likely to get offers from high-productivity firms that they will accept $(H^n > H^o)$. We can obtain a similar expression for workers starting at high-productivity firms, with the ratio given by:

$$\chi \frac{H^n}{H^o} \frac{N^H}{1-N^H} \frac{1+\gamma^n}{1+\gamma^o} > \frac{N^H}{1-N^H} \tag{14}$$

The additional term $\frac{1+\gamma^n}{1+\gamma^o}$ captures the fact that workers moving within the network are more likely to have received a better match quality draw and therefore more likely to be willing to move.

Secondly, the share of workers moving from low to high-productivity firms within the network relative to outside the network is given by:

$$\frac{1+\frac{1}{H^o}}{1+\frac{1}{H^{n,}}} > 1 \tag{15}$$

which is greater than 1 because the share of high-productivity firms is larger within the network than outside: $H^n > H^o$.

Finally, the wage premium of workers who move between high-productivity firms within the network is larger for workers who move outside the network:

$$2\frac{x_2}{x_1}\frac{1}{1+\frac{1}{\gamma^n}} > 2\frac{x_2}{x_1}\frac{1}{1+\frac{1}{\gamma^o}} \tag{16}$$

The higher likelihood of getting x_2 draws implies that a larger share of movers are moving to a higher match, rather than staying in an x_1 match.

Implications for Aggregate Output The model allows us to study the impact of movements along the supply chain on the allocation of workers across firms. Aggregate output is given by $Y = l\alpha_L x_1 + s_h\alpha_H\left(\frac{s_{h1}}{s_h}x_1 + \frac{s_{h2}}{s_h}x_2\right)$ and is an increasing function of the share of workers in high-productivity firms (s_h) and the share of workers in high-matched firms ($\frac{s_{h2}}{s_h}$). Below we solve for these shares and show how they depend on the features of the production network. Firstly, the share of workers in high productivity firms is given by:

$$s_h = \frac{\lambda}{\delta+\lambda}\left(1-\frac{\delta}{pM\left[(1-N^L)H^o+\chi N^L H^n\right]+\delta}\right) \tag{17}$$

We highlight three properties of s_h.

1. $\frac{\partial s_h}{\partial \chi} > 0$: the diffusion of information about job opportunities to workers through the production network increases the equilibrium share of workers employed in high-productivity firms.

2. A transformation ζ which increases the probability of tentative matches outside the supply chain but decreases the probability of tentative matches in the supply chain by the same amount results in a fall in s_h. Information diffusion about vacancies is therefore particularly valuable along the supply chain because high-productivity firms are over-represented among buyers and suppliers.

3. $\frac{\partial s_h}{\partial N^L} > 0$ (for fixed H^o, H^n)[34]: denser production networks increase the share of workers in high-productivity firms.

[34]It should be noted that an increase in N^L is compatible with a constant H^o, H^n only if N^H also increases

Second, the share of workers in high-match quality jobs out of all workers at high-productivity firms is given by:

$$\frac{s_{h2}}{s_h} = 1 - \frac{\chi N^L H^n(1-\gamma_n) + (1-N^L)(1-\gamma_o)H^o}{(\chi N^H H^n \gamma_n + H^o(1-N^H)\gamma_o + \delta)\,(\chi N^L H^n + (1-N^L)H^o)} \tag{18}$$

We highlight three properties of $\frac{s_{h2}}{s_h}$.

1. $\frac{\partial \frac{s_{h2}}{s_h}}{\partial \chi} > 0$: the diffusion of information about vacancies in the production network increases the equilibrium share of workers employed in high-quality matches.

2. $\frac{\partial \frac{s_{h2}}{s_h}}{\partial \gamma_N} > 0$: the higher likelihood of high-quality draws in the production network increases the share of workers employed in high-quality matches.

3. $\frac{\partial \frac{s_{h2}}{s_h}}{\partial N^z} > 0$ (for fixed H^o, H^n)[35]: denser production networks lead to a higher share of workers being in high-quality matches.

The model provides a helpful lens through which to interpret our findings. It predicts that information diffusion and supply chain-specific human capital both increase the share of workers in high-productivity firms and increase average match quality in the economy. A novel insight that follows from this is that environments with denser firm networks may be characterized by higher wages and higher labor productivity. Consistent with this theoretical result, Figure 4 shows that job changers moving from employers with more numerous buyers and suppliers are more likely to move up the firm wage and productivity ladder, and experience higher wage growth (controlling for initial wage and other firm and worker characteristics). This is therefore a potentially important contributing factor to labor misallocation and the weakness of the job ladder in developing countries (Donovan et al., 2023), given that these countries tend to have severe contracting frictions and sparse domestic production networks (Boehm, 2022).

proportionally, and this is possible only as long as N^L N^H are "small enough", that is the production network is sparse. A limit case illustrates this point. If N^H is high enough that high-productivity firms are connected to all other firms, then the only way to make the production network denser is by increasing the number of connections of low productivity firms only. This would increase the share of low productivity firms in the production networks, thus decreasing H^n for a given H^o. However, since production networks, including in the Dominican Republic, are very sparse, it is reasonable to ignore such cases.

[35]Please, see previous footnote.

A10 Appendix Tables

Table A8: Robustness Exercises for 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 ($\leq$ 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.

Table A9: Heterogeneity in Share of Supply Chain Moves

	Data (1)	Random Allocation (2)	Odds Ratio (3)	Number of Movers (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 & 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 A10: Earnings Results, Main Specification without Firm-Year FEs

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 FEs	✓	✓	-	✓	✓	✓	✓	✓
Worker Controls	✓	✓	-	✓	✓	✓	✓	✓

Notes: This table plots the results from the regression in Equation 2 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 A11: Earnings Results, Main Specification with Firm-Year FEs

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 FEs	✓	✓	-	✓	✓	✓	✓	✓
Worker Controls	✓	✓	-	✓	✓	✓	✓	✓
Origin & Destination Firm FEs	✓	✓	-	✓	✓	✓	✓	✓
Firm-Pair Controls	✓	✓	-	✓	✓	✓	✓	✓

Notes: This table plots the results from the regression in Equation 2 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 A12: Heterogeneity in Earnings Event-Study Results, with Firm-Year FEs

	Tenure $\geq$ 4y	Age $<$ 30		Gender = Female		Industry Stayer	
	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	0
	(0.004)	(0.064)	(0.091)	(0.003)	(0.006)	(0)	(0)
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	.24	.51	.50	.32	.32	.44	.44

Notes: This table plots the results from the regression in Equation 2 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: Firm Trade and Worker Movements, Upstream and Downstream

	Log Value (Intensive Margin)			Any Trade (Extensive Margin)		
	(1)	(2)	(3)	(4)	(5)	(6)
First Move Downstream	0.029**	0.013	0.028**	0.061***	0.055***	0.057***
	(0.013)	(0.009)	(0.013)	(0.004)	(0.003)	(0.004)
First Move Upstream	0.049***	0.025***	0.053***	0.054***	0.053***	0.053***
	(0.011)	(0.008)	(0.012)	(0.003)	(0.002)	(0.003)
Observations	5,028,320	5,181,035	4,452,432	11,807,792	12,033,816	6,786,560
R^2	0.854	0.857	0.858	0.721	0.722	0.719
Buyer-year FEs	✓	✓	✓	✓	✓	✓
Supplier-year FEs	✓	✓	✓	✓	✓	✓
Include pre-2016 moves		✓			✓	
Trade in 2013			✓			✓

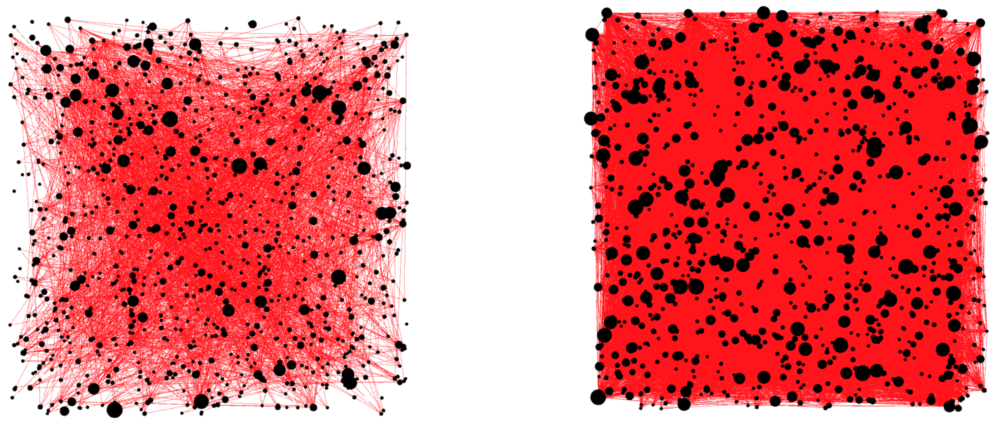
Notes: The dependent variable is either the log value of trade between buyer b and supplier s (columns 1 - 3) or a dummy for whether we observe any trade (columns 4 - 7). We include firm-pairs that traded in 2012 such that both firms are in the employer-employee dataset. The table reports estimates from a panel regression including firm-pair and year fixed effects. The dependent variable are two dummy variable which are equal to one iff we observe at least one worker moving upstream/downstream between the two firms in the same or any previous year. Firm-pair clustered standard errors are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A11 Appendix Figures

Figure A5: Trade Flows between firms

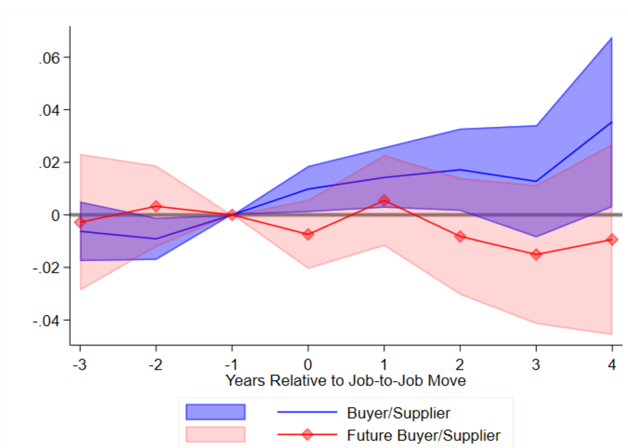
(a) Trade flows between random firms

(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).

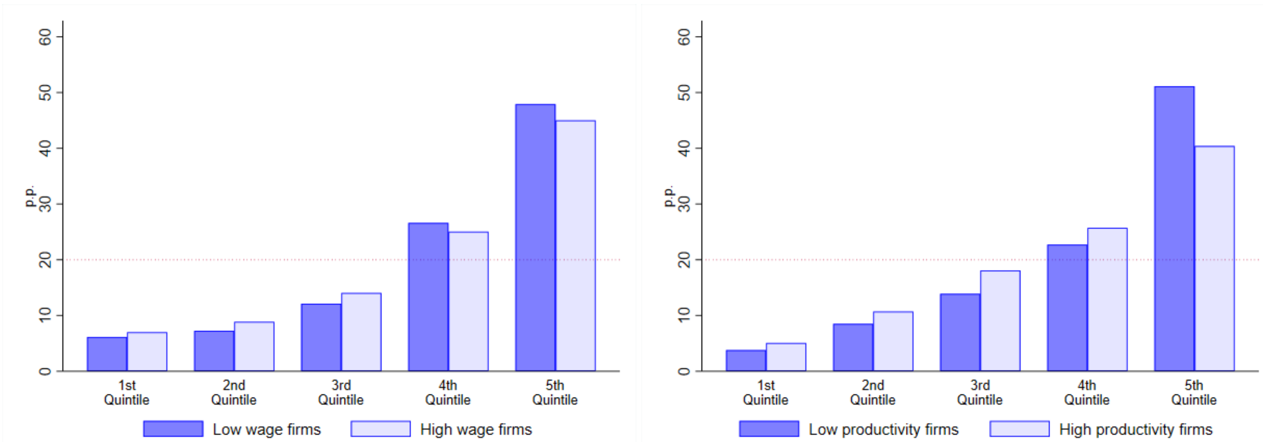
Figure A6: Earnings Dynamics of Movers–Moves to Current Buyers/Suppliers (blue) or Future Buyers/Suppliers (red). (Robustness)



Notes: This figure plots the coefficients β^k (blue) and λ^k (red) from estimating Equation 3 for each horizon k, along with the 95% confidence interval. These estimates differ from those reported by Figure 8 as the regressions here exclude workers that move across firms that (i) trade in 2012, or (ii) trade only once. The specification 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, 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.

Figure A7: Distribution of wages and labor productivity among buyers and suppliers (workers employed at high vs low productivity firms)

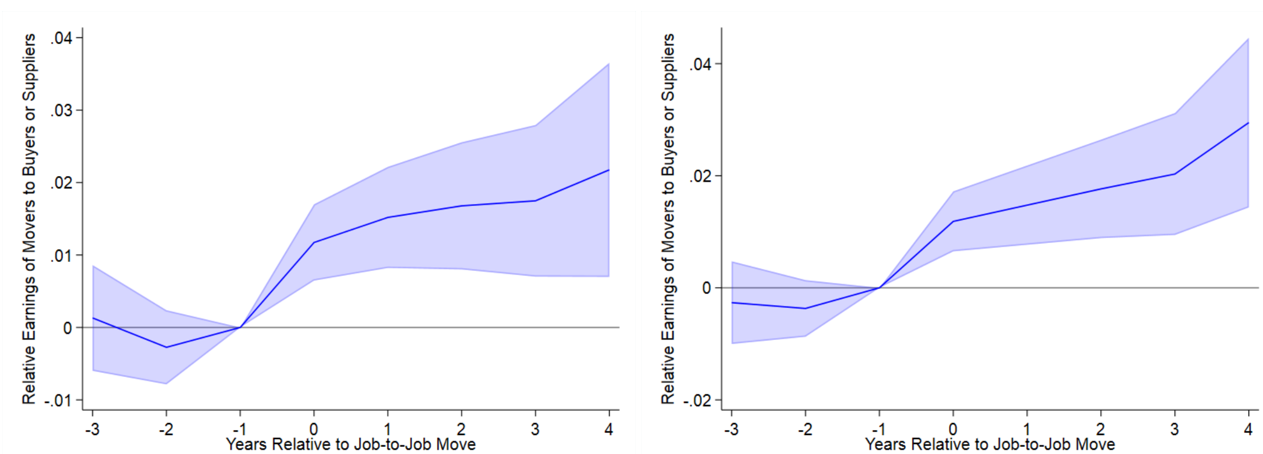
(a) By Quintile of Average Wage (b) By Quintile of Labor Productivity



Notes: This figure plots, for each quintile of the distribution of average wages (left panel) or labor productivity (right panel), the share of firms among buyers and suppliers that belong to that specific quintile. The shares are computed separately for workers that work at firms in the top vs bottom quintile of average wages (left panel) or labor productivity (right panel). The shares are computed at the worker level and the figure is built as follows. First, firms are divided into quintiles of wages or productivity. Second, for each firm, we compute the share of its buyers (or its suppliers) that belong to each of the five quintiles. Thus, for each firm, two sets (one for buyers and one for suppliers) of five shares are computed. Third, for each quintile we take the average across buyers and suppliers, so five shares for each firm are obtained. Fourth, the shares are aggregated across firms using a weighted average where the weights are given by the number of employees of each firm. In this way, the shares are computed from the point of view of workers. The aggregation is done separately for firms that belong to the bottom and top quintile of wage or productivity distribution, while other firms are ignored. If the distributions of firms' average wages or labor productivity among buyers and suppliers were the same in the whole economy, the bars would all be at 20 pp (dotted horizontal line).

Figure A8: Earnings Dynamics of Movers–Clean Controls Following Dube et al. (2023)

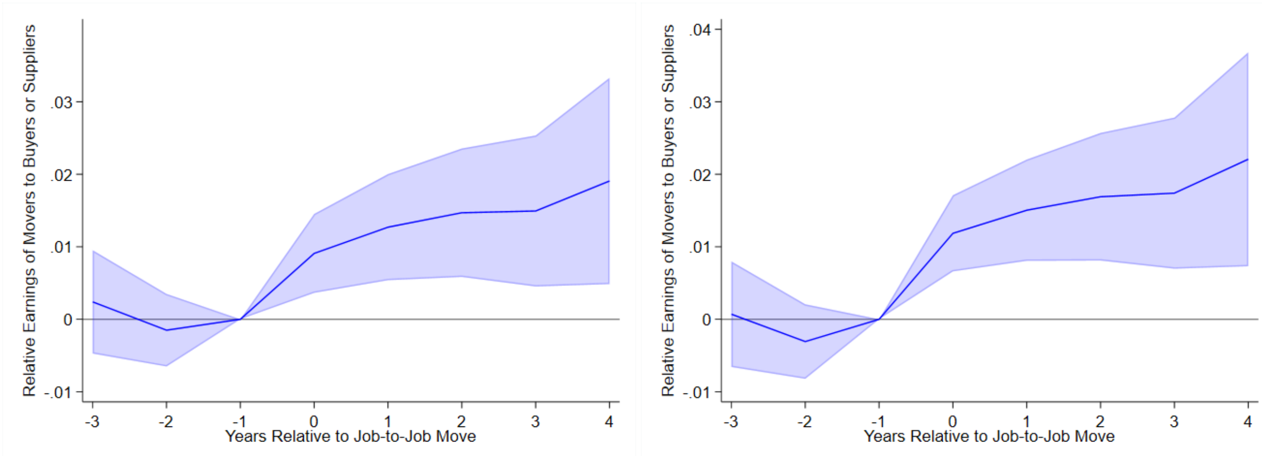
(a) Baseline (b) With Dube et al. (2023) Restrictions



Notes: The left figure plots the coefficient β from Equation 2 for each horizon k, 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.

Figure A9: Earnings Dynamics of Movers—With vs. Without Firm-Pair Controls

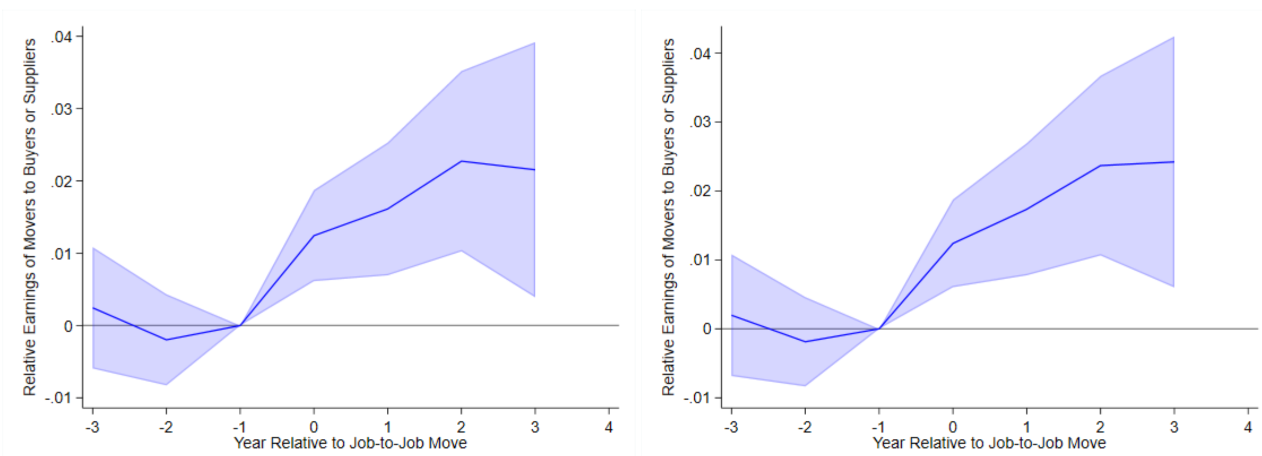
(a) Without Firm-Pair Controls (b) With Firm-Pair Controls



Notes: This figure plots the coefficient β from Equation 2 for each horizon k, 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.

Figure A10: Robustness to Ex-Coworker Networks

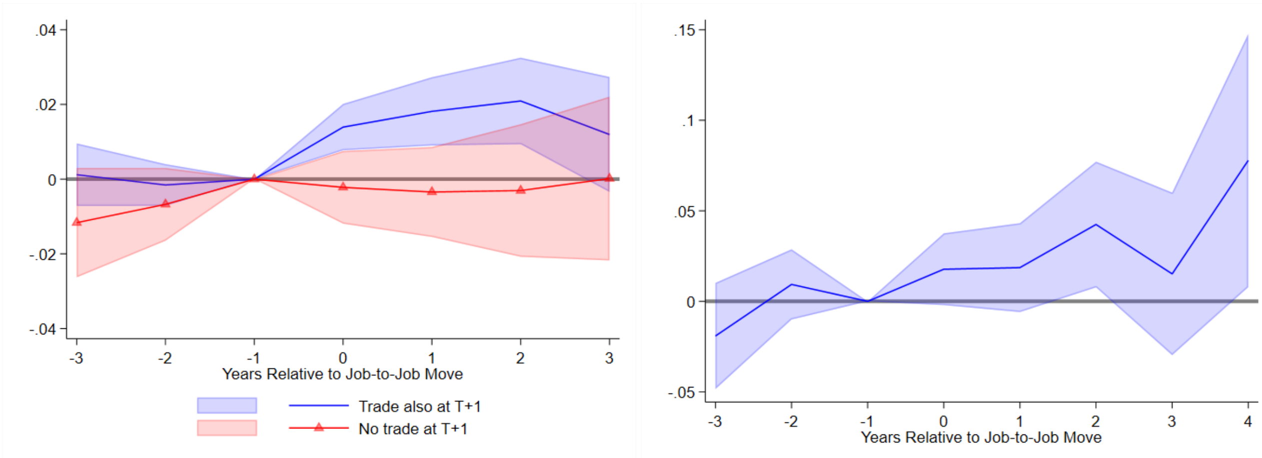
(a) Including Ex-Coworker Dummies (b) Dropping Moves to Ex-Coworkers



Notes: This figure plots the coefficient β from Equation 2 for each horizon k, 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.

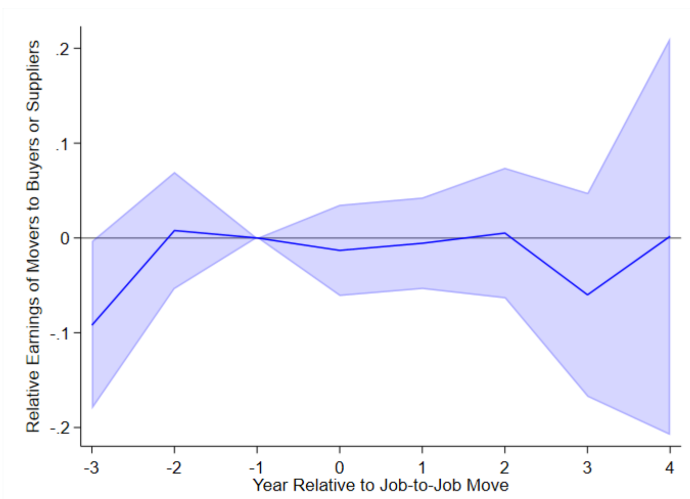
Figure A11: Earnings Dynamics of Movers—trade between firms (robustness)

(a) Two-year-in-a-row (b) Control for pre-move trade amoung



Notes: Panel (a) plots the coefficients β^k and ω^k from Equation 6 along with 95% confidence intervals. However, it differs from Figure 10 because two firms are labeled as suppliers or buyers if they trade both at $T-1$ and $T-2$. Panel (b) plots the coefficients β^k from Equation 7 along with 95% confidence intervals. However, it differs from Figure 10 because the variable $TradeGrowth_{o,d,t+k}$ is replaced with a dummy variable equal to one iff the origin and destination firm trade at $T+1$ and because the log amount of trade in year $T-1$ in added to the controls. The regressions include fixed effects for worker age deciles (≤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.

Figure A12: Supply Chain Earnings Premium for Mass Layoff Movers

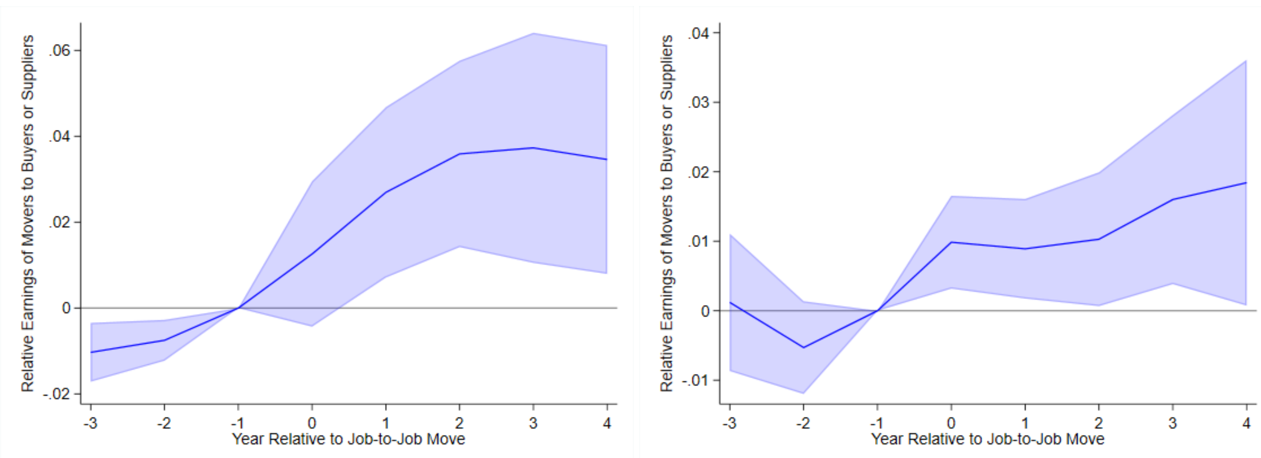


Notes: This figure plots the coefficients β^k from Equation 2, for each horizon k, together with 95% confidence intervals, estimated including mass layoff movers only. Workers are considered a mass layoff movers if they leave a firm which is decreasing permanent employment by at least 25 units and 30% 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 horizions (4 years). The regressions include year fixed effects and fixed effects for worker age deciles (≤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.

Figure A13: Earnings Dynamics of Movers with Earnings Increase in Year of the Move

(a) Without Firm-Year Fixed Effects

(b) With Firm-Year Fixed Effects



Notes: This figure plots the coefficient β from Equation 2 for each horizon k, along with the 95% confidence interval, where for k$\geq$2 we condition on workers not separating from the destination firm. The left panel includes year fixed effects and fixed effects for worker age deciles ($\leq$25, 26-35, etc..), gender and a dummy for whether the origin and destination firm have any common ownership. The right 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. The sample is restricted 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.