# Worker Mobility and Domestic Production Networks

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## Abstract

We show that domestic production networks impact worker mobility between firms. Data on the universe of firm-to-firm transactions for the Dominican Republic, matched with employer-employee records, reveals that almost 20 percent of workers who change firm move to a buyer or supplier of their original employer. This share is considerably higher than predicted by other worker and firm characteristics. Using an event-study approach, we show that moving to a buyer or supplier results in a 9 p.p. decrease in separation rates and a persistent 7 p.p. increase in earnings relative to other movers. Two thirds of the earnings increase stems from moves to higher-wage firms. The remaining third is explained by a match-specific premium, which we argue is the result of a good human capital fit. We investigate what underpins this human capital fit and show that (i) skill-requirements are similar along the supply-chain, and (ii) supply linkages get stronger following a hire from a buyer or supplier. We show that the supply-chain fit of human capital has important aggregate consequences. Our findings likely have broader relevance, as workers in the United States also have a strong tendency to move between more vertically integrated industries.

# 1   Introduction

How workers and firms match has a large impact on worker outcomes – there are large differences in productivity and wages between firms and substantial costs of workers being in jobs that are not a good match for their skills.[1] Job changes can help workers find better matches—and allow high productivity firms to expand their workforce—but labor market frictions slow down and curb this process (Haltiwanger, Hyatt, Kahn and McEntarfer, 2018; Albagli, Canales, Syverson, Tapia and Wlasiuk, 2020). Yet, our understanding of how workers find employers which are good matches for them remains limited.

This paper presents new evidence that firm production networks are important for understanding worker mobility and labor market outcomes. Using matched administrative data from the Dominican Republic, we first show that moves along the supply-chain — i.e. to a buyer or a supplier of a worker's original employer — are very common and are an important way that workers transition to high-paying and high-labor productivity firms. We then use an event-study strategy to show that supply-chain moves are followed by large earnings gains relative to other movers, which partly reflects a good fit of human capital along the supply-chain. This form of hiring therefore has important consequences for worker earnings and aggregate productivity because it leads to better matches between workers and firms.

The new facts we document are from matched administrative datasets combining annual employer-employee records with firm-to-firm transactions for the universe of firms in the Dominican Republic. Our analysis focuses on formal firms between 2012 and 2019 and contains information on more than 1,220,000 workers per year. We track over 1,150,000 job changes over consecutive years. While the Dominican Republic is our empirical setting, we show that many characteristics of its domestic production network and labor market closely resemble those ones of other countries, including both advanced economies and other emerging markets. We also rely on industry-level data to argue that our findings could be relevant for the United States as well.

We find that 1 out of 5 workers who change firm move to either a buyer or supplier of their original employer. This is considerably more than would be implied by random matching of workers to firms, even conditional on worker and firm characteristics. Under our random allocation approach, the share of workers moving to buyers or suppliers

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[1]For instance, Lachowska, Mas and Woodbury (2020) find that most of the negative impact of a job displacement is due to the loss of employer-employee specific productivity component; Lise and Postel-Vinay (2020) study multidimensional human capital and find mismatch between job and skills is very severe for Cognitive skills—which are slow to acquire over time—but less severe for Manual or Interpersonal skills; Guvenen, Kuruscu, Tanaka and Wiczer (2020) document that skill mismatch depress current wage growth and also leaves a scarring effect reducing wages in the future. Traiberman (2019) finds that workers accumulate occupation-specific human capital and they are hurt when their occupations are displaced by import competition, as learning new skills requires time.

is only 11 percent. Workers move both downstream and upstream: 13 percent of job changers move to a buyer and 12 percent to a supplier of their current employers. The patterns we document are not driven by any observable assortative matching between firms, hold broadly across industries, municipalities, and firm size groups, and irrespective of whether workers move between industries or municipalities when changing jobs. For instance, we show that our results are not driven by explained by local labor markets overlapping with buyer-supplier networks.

Workers with higher human capital, as measured by earnings, educational attainment, and job tenure, are the most likely to move along the supply chain–conditional on moving. Moves along the supply chain tend to reallocate workers to higher-wage firms (up the firm wage ladder) and to higher-productivity firms (up the firm productivity ladder). Among workers in the middle quintile of earnings, the share moving to a firm with higher average wages is 69% for supply-chain movers and only 61% for other movers. Similarly, the share of workers moving to firms with higher labor productivity is higher for supply-chain movers. This follows from the fact that high-wage, high-productivity and high-growth firms hire a larger share workers from their buyers and suppliers.

To estimate the consequences of moves along the supply-chain, we adopt an event-study approach: we compare the earnings and separation rates of workers that move to buyers/suppliers of their previous employer with the ones other movers with similar pre-move characteristics. Other movers offer a relevant control group as they have similar pre-move trends, mitigating the concern that the observed gains reflect previously determined confounding factors. We find large and persistent gains for workers moving to buyers or suppliers. Controlling for worker characteristics, separation rates after four years are 9.3 percentage points lower for supply-chain movers, while earnings are 6.7 percent higher.

The gains of moves to buyers/suppliers could be explained by the fact that supply-chain moves are up the job ladder – i.e. towards firms that have lower separation rates and higher average wages – or also because of a higher match-specific component. To disentangle these two sources of gains, we re-estimate our specifications including origin firm $\times$year and destination firm $\times$year fixed effects, which control for any firm-specific (and time-varying) factors that can impact workers' wages. We find economically and statistically significant differences in separation rates and earnings for supply-chain movers, of 2.4 percentage points and 2.2 percent respectively. These gains result from better worker-firm matches created along the supply chains and do not attenuate over time.[2] Of the

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[2]We also show that augmenting our specification with a set of firm-pairs controls, such as the cross-product of industries and locations of the origin and destination firms, does not materially impact the results, mitigating the concern the supply-chain confounds other moves' characteristics, such as moves to more distance parts of the country.

6.7 percent earnings gap four years after a move, 4.5 percent (two thirds) is explained by the fact that supply-chain movers tend to move up the firm quality ladder to higher-wage firms and 2.2 percent (one third) is explained by a higher match-specific quality for supply-chain movers. We do a back-of-the envelope exercise to show that this supply-chain premium increases average worker earnings by 1.2 percent.

We show that our results are robust to a wide variety of checks. For example, we find that the earnings premium of supply-chain movers is present even for workers who remain at their destination firm, and so higher separation rates among non-supply-chain movers do not explain our findings. We also find that the importance of supply-chain specific human capital for post-move earnings is far more important for workers with higher pre-move earnings. Moves up the job ladder explain nearly all of the earnings gap for low-wage workers, while they explain only two thirds of the earnings gap for high-wage workers. Finally, we also find that new coworkers see more rapid earnings growth when their firm hires workers from a buyer or supplier, even conditional on total hiring and the average wage of new hires.

The higher quality of worker-firm matches along the supply-chain – especially for high earners – indicates that movers are benefiting from a supply-chain-specific dimension of their human capital, that is a component of human capital which is transferable across jobs at buyers and suppliers. Human capital transferability is often related to similarity of tasks to perform and required skills across jobs (Lazear, 2009; Gathmann and Schönberg, 2010). Thus, one explanation for our findings is that jobs at buyers and suppliers are more similar in terms of skills and task requirements. To shed light on this hypotheses we examine whether buyers and suppliers are assortatively matched by workers' tertiary education.[3] We find that buyers with a higher share of workers with a specific college degree (e.g., civil engineering or marketing) tend to have suppliers with a higher share of workers with the same college degree. This is evidence that jobs at buyers and suppliers tend to require more similar human capital. While our previous findings are robust to controling for workers' college educations, this evidence suggests that assortative matching on other unobservable aspects of human capital could contribute to the transferability of human capital along the supply-chain.

However, there are additional reasons for which workers' human capital would be a good fit along the supply chain. On the one hand, firms may be looking to acquire some missing know-how to in-source part of a production process that is currently outsourced. This may be important in environments with contracting frictions, which tend to be prevalent in emerging markets and developing economies (Startz, 2021; Boehm, 2018; Oberfield and Boehm, 2020). On the other hand, transfer of supply-chain specific human

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[3]Complementary, Demir, Fieler, Xu and Yang (2020) show that buyers and suppliers tend to assortatively match on average wages.

capital could lead to larger gains from firm-to-firm trade. Such supply-chain component of human capital could be directly related to the production process: that is, if workers know how to produce a product or a service, then they may know something valuable about how to use this input in the production of other goods. Or it could be embedded in their personal connections that help diminishing contractual frictions between the buyer and the supplier.

To disentangle these two stories, we examine how the firm-to-firm trade evolves when a worker moves between a buyer to a supplier (or viceversa). Using a difference-in-difference approach, we find that a buyer and a supplier are 6.3 percentage points more likely to continue trading, and trade 4.4 percentage points larger amounts if they do trade, when a worker move between one firm the the other. Our specifications control for buyer×year, supplier ×year and firm-pair fixed effects, in order to isolate changes in firm-pair gains from trade following the worker movement. The increase in trade happens regardless of whether the worker moves downstream or upstream. Hiring from buyers or suppliers does not therefore appear to be (mainly) motivated by the in-sourcing of tasks in the production process. Instead, the evidence points towards supply-chain specific human capital leading to increased gains from firm-to-firm trade following worker movements between buyers and suppliers. Highlighting the role of workers' human capital in shaping firm-to-firm connection is–to the best of our knowledge–an important novelty of this paper.

We consider alternative explanations for the observed gains from moving to buyers and suppliers that are not related to human capital transferability: smaller unemployment scarring, lower uncertainty, or differences in bargaining power. Job losses followed with long unemployment spells lead to depreciation of workers' human capital and decline in future earnings (Mincer and Ofek, 1982; Jarosch, 2021). As we rely on yearly data, the wage gains from moving to buyers/suppliers might be due to workers experiencing shorter unemployment spells and–thus smaller unemployment scarring–when moving to connected firms, perhaps because of lower search costs. However, we find similar wage gains on movers that earn more in the new job: as this set of workers is unlikely to have experienced significant scarring, shorter unemployment spells are not a major driving of our findings.

Hiring workers of buyers/suppliers is likely to be associated with lower uncertainty about the job applicant. Lower uncertainty may then be associated with higher wages as firms consider these new hires a more likely to be a good fit for the vacancies, akin to what documented in the referrals literature (Topa, 2011; Brown, Setren and Topa, 2016; Burks, Cowgill, Hoffman and Housman, 2015; Dustmann, Glitz, Schönberg and Brücker, 2016; Pallais and Sands, 2016; San, 2020). However, the literature studying coworker networks establishes that the gains stemming from lower uncertainty tend to dissipate over time

(Dustmann et al., 2016; Glitz and Vejlin, 2019), as employers learn about their employees and dismiss those that are less good fits. However, we find that the earnings gap between supply-chain movers and other movers do not seem to decline, at least for the first four years of the new job, even conditional on workers remaining at the destination firm. This indicates that this uncertainty channel has a more limited role in explaining our findings. Similarly, more information on the growth prospect of the hiring firms may allow new hires from buyers or suppliers to extract larger rents in the bargaining process. However, such gains are also likely to shrink as others workers of the firm also learn about its prospectus. The fact that we find persistent earnings gains is thus also evidence against differences in bargaining power due to better information at the time of hiring. Furthermore, we find that when a firm hires a worker from a buyer or supplier, the coworkers also experiences some earning gains. This points towards creation of surplus associated with these new hires more than their ability to extract larger rents than other movers.

To shed further light on the breadth of our findings, we replicate our analysis at the industry level. We find that workers tend to move across industries that are more vertically-integrated. This remains the case, though to a lesser extent, if we drop workers that move to a direct buyer or supplier. The industry level patterns are consistent with human capital being valuable, at least to a certain extent, to downstream and upstream firms even though these do not directly trade with the worker's current employer. We are also able to replicate this exercise to the United States, relying on publicly available data on Job-to-Job transaction and IO matrix. We document a similar tendency of movers to move more across industries that are more vertically-integrated. This points towards the findings of this paper having external validity beyond the empirical setting of the Dominican Republic.

**Policy Implications**    Our paper has meaningful implications for several policy-relevant debates, such as the use of non-compete covenants (NCCs) for workers and 'no poaching' agreements between employers (Krueger and Ashenfelter, 2018).[4] NCCs prevent an employee from competing with her employer in the future, for instance by establishing a competing business or working for a competing firm. While firms may attempt to enforce NCCs to prevent workers sharing valuable knowledge with their competitors, such clauses tend not to apply to workers who move to buyers or suppliers, another source of knowledge diffusion. However, there is little evidence about whether informal no poaching arrangements are common between employers in the same supply chain. On the one

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[4]These agreements are often criticized as they may result in career detours, effectively impeding a more efficient allocation of labor (Marx, 2011; OECD, 2019).The lawfulness and enforceability of these clauses vary across countries. In the Dominican Republic, there is no provision that regulates the use of non-compete agreements.

hand, employers may hope to avoid losing their best employees and may have enforcement mechanisms given the importance of these buyer-supplier relationships. On the other hand, we find that such worker moves are followed by strengthening supply chain relationships, suggesting these spillovers may benefit both sides and that punishment due to poaching may not be common.

We find that workers who leave their jobs during mass layoffs move to buyers or suppliers of their previous employers. This may be in part due to these mass layoffs being rare events which do not lead to complete supply-chain collapses. During a crisis that is large and heterogeneous across sectors, such as the COVID-19 pandemic, it is likely that large parts of a supply chain may be disrupted while demand and supply shocks propagate across the production networks (Farhi and Baqaee, 2020). Our findings suggest that such supply-chain crises may have particularly destructive effects on workers and allocative efficiency, given that worker moves along the supply-chain seem to be of particularly high match quality. This might provide more reason to implement policies such as short-time-work (STW) arrangements, which preserve the matches between workers and firms (Giupponi and Landais, 2020).

**Related Literature** Large parts of the economics literature define local labor markets based on industry and geographic units. However, these boundaries may often not be adequate to capture the set of firms over which workers search. For example, Bjelland, Fallick, Haltiwanger and McEntarfer (2011) show that in the U.S. 60 percent of job flows happen across broadly defined sectors. Nimczik (2020) infers the workers' endogenous labor market in Austria based on observed worker flows across firms, while Cestone, Fumagalli, Kramarz and Pica (2019) and Huneeus, Huneeus, Larrain, Larrain and Prem (2018) document the prevalence of worker moves across firms in the same business groups. Sorkin (2018) uses worker movements between firms to infer employees' preferences over jobs. Our main contribution to this literature is documenting that firm production networks are an important dimension of workers' labor markets.

Our paper relates to the literature documenting the importance of job-to-job transitions for wage growth and reallocation of labor across the economy (Moscarini and Postel-Vinay, 2017; Haltiwanger et al., 2018; Albagli et al., 2020): in fact, we highlight the special role played by job-to-job transitions over the supply chain. Recent papers have also documented a large cost for the mismatch between workers skills and the job they occupy (Guvenen et al., 2020; Lise and Postel-Vinay, 2020). We contribute to this topic by suggesting that production networks may be an important factor mitigating such mismatch.

An extensive literature documents the importance of referrals for job-finding and the quality of worker-job matches (Dustmann et al., 2016; Burks et al., 2015; Brown et al.,

2016; Pallais and Sands, 2016). Other papers focus on specific dimensions of social networks such as the presence of ex-coworkers in a firm (Glitz, 2017; Caldwell and Harmon, 2019) as well as family, neighbors, and acquaintances (Eliason, Hensvik, Kramarz and Skans, 2018). Our paper contributes by showing that not only are worker networks important, but so are firm networks.

Our paper is also related to the literature on the importance of domestic production networks for firm performance (Bernard, Dhyne, Magerman, Manova and Moxnes, 2019b; Bernard, Moxnes and Saito, 2019a; Alfaro-Urena, Manelici and Vásquez, 2019a) and shock propagation (Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi, 2012; Tintelnot, Kikkawa, Mogstad and Dhyne, 2018; Lim, 2018; Huneeus, 2018; Farhi and Baqaee, 2020). We contribute by documenting the interaction between production networks and worker mobility, and its impact on labor market outcomes.

We also contribute to the literature studying how general or specific (and how transferable) human capital is (Becker, 1962; Gibbons and Waldman, 2004; Lazear, 2009; Gathmann and Schönberg, 2010). In particular, we study how human capital is transferred along the production network and our results suggests it has a supply chain component.

Our work follows several empirical studies at the intersection of international trade and labor economics. While this literature is mostly concerned with the impact of international trade on the labor markets (Autor, Dorn, Hanson and Song, 2014; Dix-Carneiro, 2014; Traiberman, 2019) or the impact of labor market frictions on export decisions (Fajgelbaum, 2020), we study trade and worker flows across firms within a country.

Finally, our paper is among the first to combine data on the firm production network with employer-employee information. Most closely related, Huneeus, Kroft, Lim and Price (2020) combine employer-employee data with firm-to-firm transaction data to study the impact of heterogeneity in buyer-seller linkages on earnings inequality. However, they do not look at the relationship between production networks and worker flows, which is the focus of our paper. Other papers use similar datasets but focus on different questions, including Demir et al. (2020), who provide evidence of assortative matching in terms of product quality and worker skills along production networks, and Alfaro-Urena, Manelici and Vasquez (2019b), who assess the impact of multinational firms on workers in Costa Rica.

The rest of the paper is structured as follows. Section 2 describes the data and the empirical setting. Section 3 documents that firms hire disproportionately from their buyers and suppliers. Section 4 presents evidence about the large economic gains associated with this type of hiring practice. Section 5 lays out possible explanations for our findings and presents supportive evidence. Section 6 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 percent 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 percent on average. For the purpose of the analysis, we combine four datasets that draw on administrative records from the Directorate General of Internal Taxes; the Directorate General of Customs; the Social Security Treasury; and the Ministry of the Economy, Planning, and Development.[5]

- The first dataset contains firm-level information for the entire universe of firms that file for the income tax at the Directorate General of Internal Taxes.[6] 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 firms' capital. The main industry (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.[7] This allows us to identify all the domestic buyers and suppliers of each firm. Purchases by formal firms from informal suppliers (not registered at the Directorate General of Internal Taxes) get recorded in the accounts of the former.[8] In the analysis, we restrict the sample to formal sector firms that make at least one transaction per year.

- The third dataset contains detailed information on employees from the Social Security Treasury. Each month all employers have the obligation to report payments

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[5]The administrative records come from several tax forms which need to be filled out by all economically active entities. Of these, 92 percent submit the tax forms electronically, allowing for a wide 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.

[6]The information comes from 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*).

[7]The information comes from tax form 606 (*Formato de Envío de Compras de Bienes y Servicios*).

[8]The typical example is a firm of the formal sector buying from another firm that is not registered at the Directorate General of Internal Taxes. In this case, 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.

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 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 corresponds to the average of the three months multiplied by 12. Employees are classified in 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. For all employees, we also observe their age, gender, and ethnicity.

- The fourth dataset includes information on tertiary education 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.

Table 1 provides a helicopter view of the datasets we use in the subsequent analysis. We observe over 44 thousand firms per year. The median firm in the sample employs 7 workers and has an annual turnover of almost 30 thousand USD, which grew at a rate of 8.9 percent per year. In the average year, these firms employ more than 1.2 million workers, which represent 26.1 percent of the country's labor force. The wage of the median worker is 260 USD and it grew at an average annual rate of 5.6 percent over the period covered by the sample. The firm-to-firm level dataset includes almost 2.5 million transaction per year, of which 25.9 percent take place between firms of the same industry. We find that the median firm, on average, had 8 buyers and 28 suppliers.

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 | 260 | 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 averages over 2012–2019.

Figure 1 plots the geographical distribution of the average number of firms and workers over the national territory. Unsurprisingly, most of the firms and workers are headquartered in the provinces surrounding the capital Santo Domingo (Distrito Nacional, Santo Domingo, and San Cristobal), 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 majority of the rest of the firms and workers are based in the areas connecting these three poles.

**Measuring Worker Mobility**   We define a 'mover' as any worker whose highest-paying employer in year $t$ is different from the highest-paying employer in year $t-1$.[9] We observe 1,152,279 worker moves between 2012 and 2019 implying that on average 13 percent of workers change employer from one year to the next. Movers tend to be younger, earn less, and more likely to be males 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 benefit of this definition is that it limits the duration of potential unemployment spells between jobs to at most 10 months. This is useful as we do not have information on the reason for which workers stop working at a firm and unemployment spells can affect the interpretation of our results. Under this definition, we observe 272,935 moves between 2012 and 2019.[10]

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

[10]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 job once a year for two consecutive years is dropped, as well as any worker moving at the end of our sample.

Figure 1: Geographical Distribution of Firms and Workers



(a) Firms                        (b) Workers
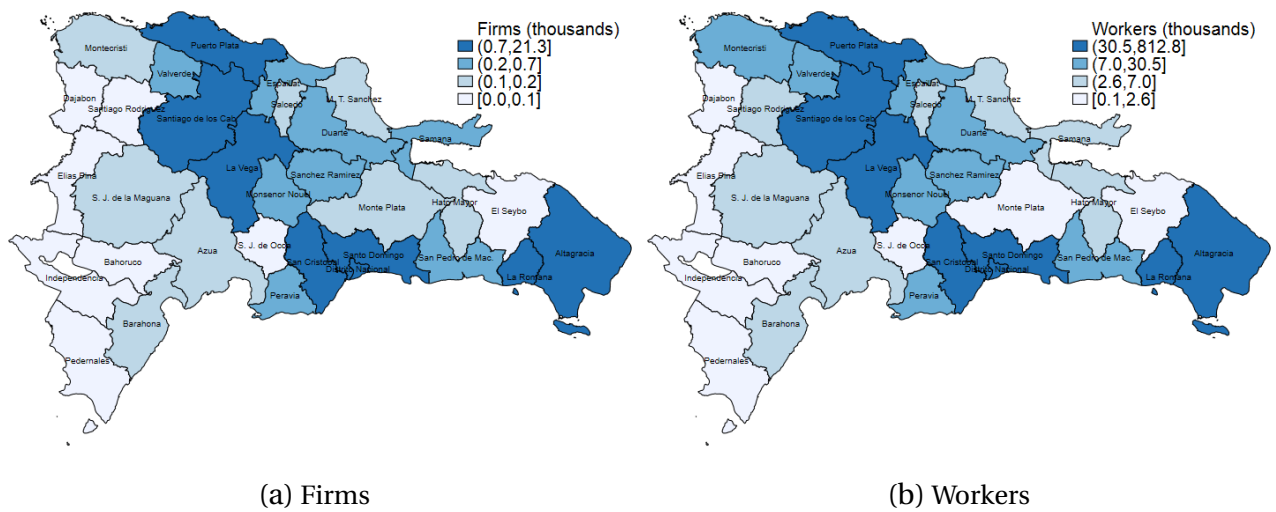
Notes: The figure displays the average number of firms and workers during 2012–2019.

# 3    Workers Mobility Between Buyers and Suppliers

In this section we document the key stylized fact in this paper—a large share of job chang-ers in the Dominican Republic move to buyers or suppliers of their previous employer. Also, we show that workers tend to move to upstream or downstream industries even in the U.S., which suggests that our results likely hold in other countries. Finally, we show that moves up along the supply-chain tend to be up the firm wage and labor productivity ladder, and firms hiring from buyers/suppliers have higher productivity growth.

## 3.1    Data vs. Random Assignment to Job Openings

Out of the 1,152,279 workers who moved between firms during 2012–2019, 18 percent were hired by a buyer and/or supplier of their employer in the previous year. These are strikingly large proportions, given that the median firm only has only 8 buyers and 28 suppliers. For comparison, 43 percent of workers move to a firm within the same 2-digit industry.[11]

We show this finding visually in two network graphs in Figure 2. 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 random firms and for each of these we draw one of their buyers or suppliers. There are two takeaways. Firstly, there are a lot more worker movements between buyers and suppliers than be-tween random firms. Secondly, firms tend to be larger in the sample of buyers and sup-pliers than in the random sample. It follows that part of the difference in the panels below could be that buyers and suppliers are larger and tend to hire more workers from other firms. More generally, factors other than the supply-chain could help explain why almost one fifth of workers tend to move between buyers and suppliers: e.g. supply-chains tend to be co-located and workers tend to search for jobs locally.

To measure how much these factors matter in explaining workers' tendency to move along the supply chain, we construct the share of moves to buyers and suppliers under a counterfactual random allocation of workers to firms which could plausibly form part of their labor market (Glitz and Vejlin, 2019; Hellerstein and Neumark, 2008; Carrington and Troske, 1997). We first define a firm 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 moves to buyers or suppliers under this counterfactual allocation.[12] In

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[11]There are 42 industries in our classification. This is similar to the 40 percent found in Bjelland et al. (2011) for U.S. NAICS super-sectors, and the 25 percent found by Nimczik (2020) for Austrian 2-digit indus-tries.

[12]Our definition of job openings is restricted to new hires who were working in another firm in the previ-ous year (i.e., job-to-job transitions). We get very similar results if we define the number of job openings at

Figure 2: Worker Flows Between Firms

(a) Random Firms                          (b) Trading Firms
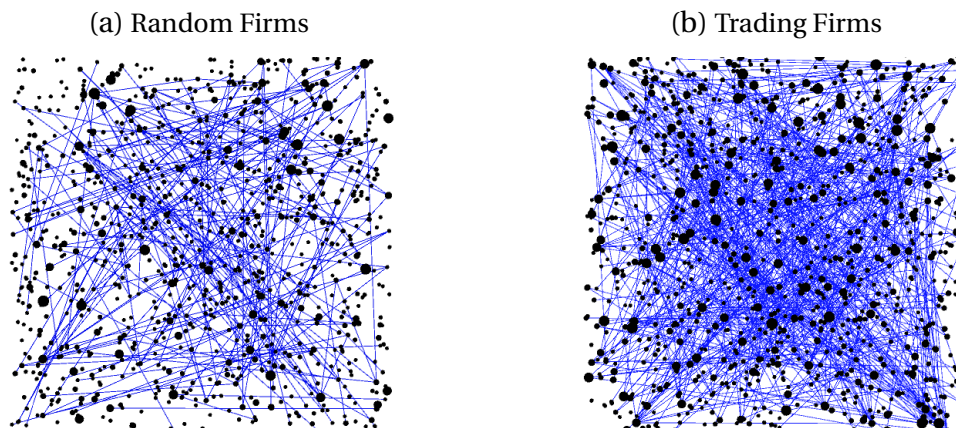


Notes: The nodes denote firms, with their size proportional to the number of employees. Blue edges denote there is at least one worker moving between the two firms. Panels (a) uses a sample of 1,000 randomly selected firms in 2019. Panels (b) uses a sample of firm pairs in 2019 that traded in 2018 and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

order to make sure the random assignment captures each mover's potential labor market, we restrict the set of job openings to which a worker can be assigned to those that were filled by workers with similar characteristics. In particular, we only assign workers to job openings filled by workers in the same age decile, same pre-move earnings quintile, of the same gender, moving to the same destination industry, and to the same destination municipality.

We repeat the randomization procedure 100 times and report the average share of workers who are allocated to a buyer or supplier of their previous employer as well as the corresponding odds ratios in Table 2.[13] To avoid mechanical overfitting of our algorithm, we restrict the set of movers to those with a potential labor market of at least 50 job openings. The total sample size therefore shrinks as conditioning variables are added.[14] In the first column we show that under random assignment (within age-earnings-industry-municipality groups) we would only expect 11 percent of workers moving to buyers or suppliers, compared to the 19 percent we observe in the data. The corresponding odds ratio is 1.8. The second column reports the same numbers only including within-year

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a firm as being the total number of new hires in a given year.

[13]We also construct standard errors for these shares in two different ways. First, we compute the standard deviation of the shares based on the simulation draws. Second, we adopt a bootstrapping procedure where–at each iteration–we build a synthetic subsample drawn from the original sample of movers and then randomize synthetic movers across job openings. Standard errors are negligibly small using either procedure (usually between one and two magnitude smaller than the mean shares). We thus do not report them.

[14]With a sufficiently large number of conditioning variables, every worker would be assigned to the firm they actually moved to. We therefore set a minimum size for each group and ensure that the results are not sensitive to alternative lower bounds.

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

|  | All Movers | Within-Year Movers | Buyers Only | Suppliers Only | Top 5 Buyer or Supplier |
|---|---|---|---|---|---|
|  | (1) | (2) | (3) | (4) | (5) |
| Data | 19 | 29 | 13 | 12 | 8 |
| Random allocation | 11 | 14 | 7 | 7 | 3 |
|  |  |  |  |  |  |
| Odds ratio | 1.8 | 2.6 | 1.9 | 1.8 | 2.8 |
| Number of movers | 1,019,242 | 202,522 | 1,019,242 | 1,019,242 | 1,019,242 |

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 first column includes all movers while the second column only includes within-year movers. The third to fifth columns include all movers but measure the share of movers to buyers only, suppliers only, and the firms top 5 buyers or suppliers respectively.

movers. We find that the gap is even larger: 29 percent in the data and 14 percent under random assignment. The third and fourth columns show that the there is little difference in the share of workers moving to buyers vs. suppliers. Finally, in the fifth column we report the share of workers moving to one of their top 5 buyers or suppliers. We find that this share is 8 percent in the data but the share under random assignment is only 3 percent, with the odds ratio of 2.8. This finding shows that worker movements are not only affected by the existence of a supply-chain connection, but also by how strong are the ties with buyers and suppliers.

We show in Table A1 that our findings are not driven by a number of other factors. For instance, the tendency of workers to move along the supply chain survives after conditioning on firm size category, workers' tertiary degree, and excluding workers moving across firms that have some common ownership.[15] In Table A2, we also show that the tendency to move to buyers and suppliers is present in all industries. It is present for workers changing or staying in the same industry/municipality. The share of supply-chain movers is somewhat higher in the two most economically relevant provinces (Districto National and Santo Domingo), than in the rest of the country, but in both cases the share is higher than under random assignment.

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[15]Cestone et al. (2019) and Huneeus et al. (2018) show that common business ownership is also important for understanding worker mobility. We define two firms as being in the same business group relationship 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.

**Regression approach à la Kramarz and Thesmar (2013)**   We further test whether supply chain linkages explain worker movements beyond other observable factors via a regression approach. Specifically, we follow the literature exploring the relationship between social networks and labor market outcomes and corporate governance, which estimates the impact of connection between a worker and a potential employer on the probability of hiring (Kramarz and Thesmar, 2013; Kramarz and Skans, 2014; San, 2020).

The framework is based on a linear model for the probability that a mover $w$, which works for firm $o(w)$ in year $t-1$, moves to the hiring firm $e$ in year $t$:

$$P_{e,w,t} = \phi(e,t,X_w,X_{o(w)}) + \beta \cdot SB_{e,o(w),t-1} + u_{d,w,t} \tag{1}$$

The probability $P_{d,w,t}$ is a function of the dummy variable $SB_{e,o(w),t-1}$, which takes value one if firm $e$ is a buyer and/or supplier of $o$ during year $t$, plus a set of controls $\phi(e,t,X_w,X_{o(w)})$. This model is extremely flexible in controlling for assortative matching on observable worker (and origin firm) characteristics, as the function $\phi$ is allowed to be different for each employer and year. That is, each single firm may have a tendency to hire workers of certain characteristics (e.g., working in a certain industry and in a certain location) and such tendency may change over time. The model also assumes that $u_{d,w,t}$ is uncorrelated with the dummy variable $SB$ conditional on $\phi(e,t,X_w,X_{o(w)})$ (and thus assortative matching on unobservable characteristics is assumed away).

We estimate Equation 1 following the estimation procedure proposed by Kramarz and Thesmar (2013).[16] Our findings confirm and strengthen the main finding that workers tend to move to buyers and suppliers. The coefficient $\beta$, which captures the impact of supply chain linkages on the probability of being hired by buyers or suppliers is positive and statistically different from zero using the same controls as in the random allocation procedure. Thus, it does not appear that our main results are driven by the choice of focusing on the random allocation algorithm.

**Industry Results and External Validity**   Our novel datasets allow us to study mobility patterns at the worker-firm level. Availability of matched firm-to-firm trade and employer-employee data for research is still scarce however, limiting our ability to verify the external validity of our findings. To verify the broader representativeness of these patterns, we examine how industry-level worker mobility patterns correlate with industry-level input-

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[16]Under the assumption that the characteristics $X_w$, $X_{o(w)}$ have all discrete values, we can define a 'class' $c$ as the set of movers which share all the same characteristics (except for $SB$). Thus, the linear probability model can be re-written as: $P_{e,w,t} = \phi(e,t,c(w)) + \beta \cdot SB_{e,o(w),t-1} + u_{d,w,t}$, where $\phi(e,t,c(o))$ 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 1 is unfeasible. However, Kramarz and Thesmar (2013) show that the parameter of interest $\beta$ can be estimated in a computationally convenient way.

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:

$$ShLeavers_{n \to m,t} = \phi_m + \phi_n + \gamma \cdot ShTrade_{n,m,t} + \eta_{n,m,t} \qquad (2)$$

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 purchase made from industry $m$.

For the Dominican Republic, we aggregate our worker and firm-level data to the 2-digit industry level. We compute the dependent variable in two different ways: including and excluding the workers that move to a firm that was a buyer or supplier of their employer in the previous year. For the United States, we use (1 digit) industry-level Job-to-Job flows provided by US Census Bureau and 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.

Table 3: Trade and Worker Flows between Industry Pairs

| | Dominican Republic | | | | USA | |
|---|---|---|---|---|---|---|
| | All Workers | | Excluding Moves to Buyers/Suppliers | | All Workers | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Share of Sales | 0.166** | | 0.092* | | 0.121** | |
| | (0.064) | | (0.048) | | (0.051) | |
| Share of Purchases | | 0.292*** | | 0.215*** | | 0.213* |
| | | (0.067) | | (0.061) | | (0.099) |
| Observations | 1,806 | 1,806 | 1,806 | 1,806 | 182 | 182 |
| $R^2$ | 0.626 | 0.642 | 0.637 | 0.649 | 0.542 | 0.553 |

Notes: one observation is defined by a pair of (2 digit for DR, 1 digit for US) industries and a year. The dependent variable is the share of all the working leaving an industry that move to the other. For DR: This dependent variable is calculated counting ether all movers (columns 1 and 2) or excluding workers that move to a firm that was a direct buyer or supplier of the previous employer (columns 3 and 4). 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 purchase made by one industry from the other (columns 2 and 4). For the US the variables are calculated from Job-to-Job flows provided by US Census and based on LEHD (available here: https://lehd.ces.census.gov/data/) and from IO matrix from BEA (available here: https://www.bea.gov/industry/input-output-accounts-data). Industries fixed effects are included. Standard errors are double-clustered at the two industries level. We exclude industries with few movers, that is in the bottom 10% in terms of number of leavers that go to a different industry, or in the bottom 10% in terms of sales/purchases. Standard errors are clustered at the municipality level. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Table 3 shows our results for 2014.[17] As shown in columns (1) and (2), we find a posi-

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[17]Our results similar if we average or pool across different years. The U.S. data is available up to 2015.

tive and significant correlation between inter-industry worker flows and trade. This correlation is still present, albeit weaker, if we exclude workers that move to a buyer or supplier of the previous employer. Specifically, the coefficient in column (1) is almost 50% larger than the one in column (3), while the coefficient in column (4) is just above half of the one in column (2). Even excluding moves to buyers and suppliers, we still find that worker flows and the trade are correlated, indicating that workers tend to move more across vertically-connected industries more generally. [18]

Importantly, we find similar industry-level results in Table 3 for the Dominican Republic and the U.S.; workers disproportionately tend to move between upstream and downstream industries. While we cannot directly test whether supply-chain moves are common in other countries, these results suggest that our findings for the Dominican Republic likely have broader external validity.

## 3.2   Heterogeneity

What factors affect workers' likelihood to move to buyers or suppliers? In this subsection we investigate heterogeneity across worker and firm characteristics.

**Worker Heterogeneity**   In Figure 3 we document heterogeneity along two dimensions capturing different aspects of a worker's human capital: pre-move earnings and tenure at a worker's previous employer.[19] In both panels we report the share of supply-chain movers in the data, random assignment, and the odds ratio. The left panel of Figure 3 shows that the share of supply-chain movers is increasing in worker earnings, from 11 percent in the bottom earnings quintile to 27 percent in the top earnings quintile. However, this is in part due to the fact that high-wage workers tend to work for large firms with large buyers and suppliers, as captured by the fact that the share of supply-chain movers under random assignment also increases in worker earnings. Overall, the odds ratio is not mononotically increasing in worker earnings across the whole distribution, though it is at its highest for workers in the top earnings quintile, and even higher for workers in the top 5 percent and top 1 percent of the earnings distribution. The right panel of Figure 3 strikingly shows that the share of supply-chain movers and the the odds-ratio are increasing in a worker's tenure at the origin firm. This finding suggests that the accumulation of supply-chain-relevant human capital or knowledge may be an important may be relevant for understanding our findings. We return to this interpretation in Section 5.

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[18]We specify "to a lesser extent" as 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.

[19]in order to be able to accurately measure tenure we restrict attention to movers between 2018 and 2019. We can therefore identify a worker's tenure at the origin firm for up to 7 years.

To further explore the importance of human capital in explaining the high share of supply-chain moves, we also report heterogeneity by level of education in Panel Table A2. 24 percent of movers with a college degree move to buyers or suppliers, compared to 18 percent of movers without a college degree and the odds ratio is also higher (1.8 vs. 1.6). While our education data is limited, these findings provide additional evidence that human capital is a potential driver of our findings.

Figure 3: Heterogeneity

(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.

In Table A2 we also present heterogeneity by gender, age, and ethnicity. Supply-chain moves are similarly common for men and woman and for white and non-white workers. We do not see a clear relationship with age.

**Involuntary vs. Voluntary**   Our results so far do not differentiate between workers who leave their initial employer voluntarily and those who are let go. To understand the mechanisms underpinning these moves, it is useful to know whether our findings are driven by workers being poached by buyers or suppliers or if they are hired out of unemployment. We therefore consider two different subsets of workers where we can better differentiate between voluntary and involuntary layoffs.

Our alternative 'within-year' mover definition captures movers with shorter potential unemployment spells between jobs, and hence is more likely to reflect voluntary moves. We showed in Table 2 that the share of supply-chain movers is considerably higher for 'within-year' movers compared to all movers; 29 vs. 19 percent in the data and an odds

ratio of 2.6 vs. 1.8. This is suggestive evidence that supply-chain moves are if anything even more common among voluntary job transitions.

We isolate involuntary layoffs following the literature focusing on mass layoffs to isolate job separations due to firm-level shocks (Gibbons and Katz, 1991; Davis and Von Wachter, 2011; Flaaen, Shapiro and Sorkin, 2019). We define a mass layoff as a situation where a firm's employment falls by at least 30 percent and at least 25 workers. Our sample includes 2,535 instances of mass layoffs (74,703 workers) 2012 and 2019. 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 next year. The share workers being hired by a buyer or supplier following a mass layoff is very similar to the share we see for all movers: 18 percent as opposed to 19 percent. The random allocation share is also somewhat lower, at 9 percent as opposed to 12 percent.

Overall, these findings suggest that supply-chain moves are common for both voluntary and involuntary worker transitions, though they are particularly frequent for voluntary transitions. This suggests a potentially important role for on-the-job search in explaining our findings.

## 3.3    Climbing Up the Supply-Chain Ladder

Job-to-job transitions contribute to allocate workers to firms that pay higher wages and have higher productivity (Haltiwanger et al., 2018). To the extent that there are benefits to firms hiring from their buyers or suppliers we should also expect a strong firm wage ladder among supply-chain hires. This is because high-wage firms are more likely to successfully poach by offering higher wages. Conversely, moves along the supply-chain may allow workers to move to firms in which they expect to earn a higher wage. We explore this by documenting the job ladder dimension of supply-chain moves in this sub-section.

The left panel of Figure 4 plots the share of movers who go to a higher wage firm (i.e. up the firm wage ladder) by pre-move earnings quintile, separately for supply-chain movers and other movers. Regardless of the workers' initial earnings, supply-chain moves are more likely to be up the firm wage ladder. This difference is substantial, averaging just under 10 percentage points.

Similarly, the right panel of Figure 4 shows that supply-chain movers are also more likely to move to firms with higher labor productivity, thus improving the allocation of workers across the economy (Albagli et al., 2020).

Conversely, we can measure the firm wage and labor productivity ladder from the firm-side. The left and right panels of Figure 5 show binned scatter plots of the share of workers hired from buyers or suppliers against average wages and labor productivity

Figure 4: Share of Workers Hired from Buyers and Suppliers vs. Productivity and Wages

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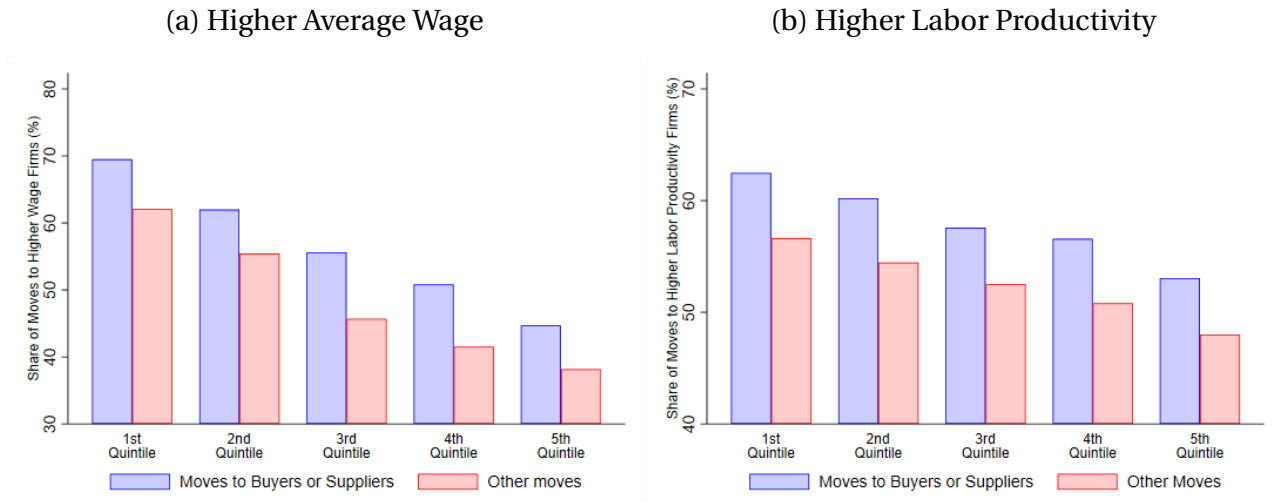


Notes: These figures plot the share of workers who move to higher-wage (left) or higher-labor productivity (right) firms, separately for movers to buyers or suppliers and other movers.

respectively (controlling for industry fixed effects).[20] It is very clear in both cases that high wage and high labor productivity firms disproportionately hire from buyers or suppliers, with the share increasing more than four-fold between the top and bottom decile of wages and labor productivity.[21]

Finally, we show in Figure 6 that firm growth is associated with a higher share of hires from buyers or suppliers. The left panel shows a binned scatter plot of growth in firm sales from 2012 to 2019 against the share of hires from buyers or suppliers, controlling both initial firm sales, the total number of hires over this period, the average earnings of new hires, and total employment in a firm's buyers or suppliers. The figure clearly shows that growing firms hire a larger share of workers from their buyers or suppliers, even conditional on total hiring. Similarly, the right panel of Figure 6 shows that this is also true for firm productivity growth.[22] These findings suggest that there may be rents from hiring from a firm's buyer or suppliers.

Overall, these findings suggest that moves to buyers/suppliers may imply important gains for workers. We explore the sources of these gains more extensively using an event-study approach around worker moves in the next section.

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[20]The patterns are also robust to controlling for movers characteristics or firms' total number of buyers or suppliers.

[21]We show in Figure A2 that firms do not segment themselves into hiring only from buyers or suppliers compared to also hiring from other firms. 69 percent of firms do not hire any workers from buyers or suppliers, while 6 percent of firms hire only from buyers and suppliers. This leaves 25 percent of firms who hire both from buyers or suppliers and from other firms.
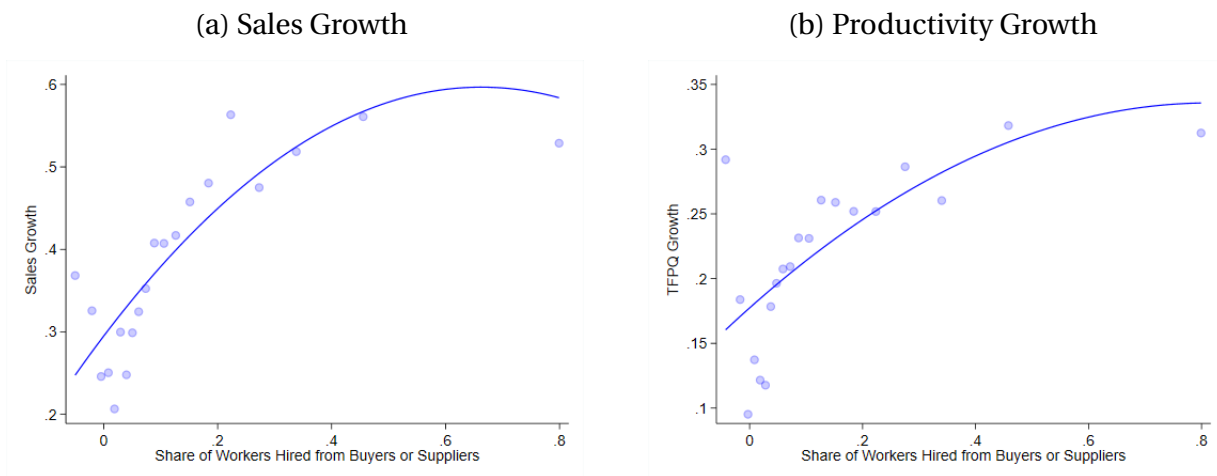
[22]Productivity is measured as firm sales raised to the $\frac{\sigma}{\sigma-1}$ setting $\sigma = 4$, divided by a Cobb-Douglas aggregate of intermediates, capital and labor costs.

**Figure 5**: Share of Workers Hired from Buyers and Suppliers vs. Productivity and Wages

(a) Average Wage

(b) Labor Productivity
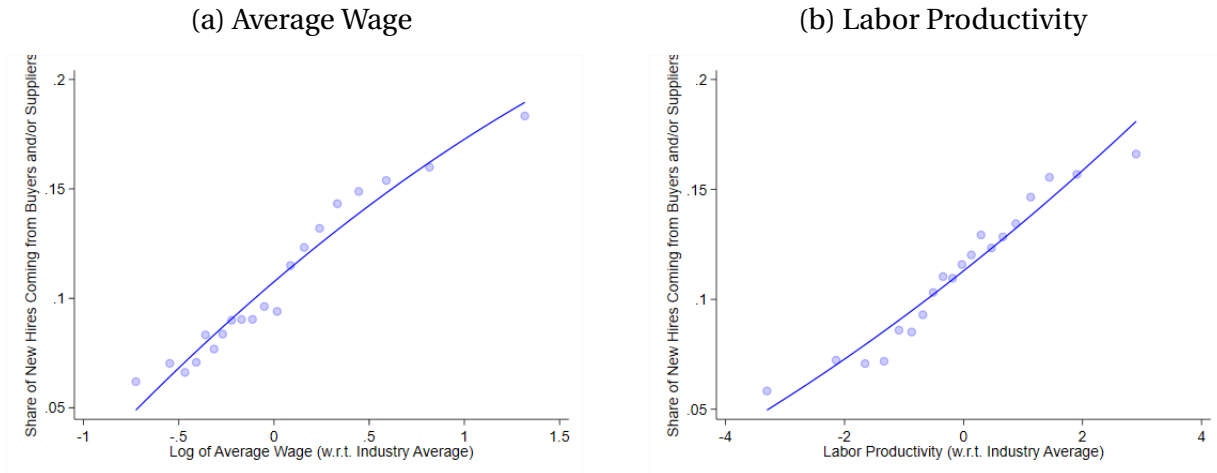


Notes: These figures plot the average share of new hires coming from buyers and/or a suppliers for each of the 20 quantiles of productivity (revenues per permanent worker) or average log wages of permanent workers. Both variables are first demeaned at the industry level and then averaged at the firm level, in order to capture cross-sectional variation.

**Figure 6**: Firm Growth vs. Share of Workers Hired from Buyers and Suppliers

(a) Sales Growth

(b) Productivity Growth



Notes: These figures show binned scatter plots of firm sales and productivity growth from 2012 to 2019 against the share of workers hired from buyers and suppliers over the same period. Controls include initial firm sales (productivity), the log-total number of new workers hired, the average earnings of new hires, and total employment in the firm's buyers and suppliers. Productivity is measured as firm sales raised to the $\frac{\sigma}{\sigma-1}$ setting $\sigma = 4$, divided by a Cobb-Douglas aggregate of intermediates, capital and labor costs.

# 4 Worker-Firm Match Quality

In Section 3, we showed that a large share of job changers move to buyers or suppliers of their previous firm. We also provided evidence that these worker-firm matches are up the firm wage ladder and associated with rents for firms, consistent with higher match quality. In a competitive labor market, higher match quality should also be reflected in worker earnings. We investigate this by estimating separation rates and earnings dynamics for workers moving to buyers and suppliers compared to workers moving to other firms. We differentiate between the role of sorting into different firm types ('moving up the job ladder') and of higher match quality at a given destination firm. Finally, we test for the presence of spillovers to the earnings of other workers within the firm.

Our goal is to understand the dynamics of separation rates and earnings following moves between firms. Because we only have annual data, we cannot rule out completely that a worker who changes firm from one year to the next was unemployed or out of the labor force in the intervening period. To mitigate this concern, we use the more conservative definition of job-to-job movers in this section, focusing on workers who change firm within the same year.[23] This restriction limits the length of a potential unemployment spell, though it does not allow for leeway in cases where workers move job-to-job from one year to the next.

## 4.1 Separation Rates

We first examine whether workers hired by buyers or suppliers of their previous firm have lower separation rates than workers who move outside the supply-chain. Figure 7 plots the share of movers in year $t$ who separated from their destination firm up to 6 years after the move. As the horizon gets farther, the number of years over which we can observe a move shrinks; for example, for the 5-year horizon we can only include workers who moved in 2013 or 2014. The figure shows that separation rates are lower for workers who move to buyers or suppliers of their previous employer at all horizons. This difference is 9.2 percentage points, averaging across horizons.

However, as described in Section 3, workers who move to buyers or suppliers are measurably different to other movers—they have higher pre-move earnings and they tend to move to larger and higher-wage firms. These differences in worker characteristics could contribute to differences in separation rates, and would bias our estimates of how much higher match quality is along the supply-chain. We control for observable measures of

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[23]As described in Section 3, we identify workers that changed job in year $t$ as those employees whose primary employer changed from year $t-1$ to $t+1$, and that they received earnings from both firms in year $t$.[24]

Figure 7: Separation Rates—Raw Data



Notes: This figure shows the share of movers in year $t$ who have separated from the destination firm by year t+$k$. Separation rates are reported for both for workers who move to a buyer or supplier, and for workers who move to firms outside the supply chain. Given the definition of within-year job to job movers, separation rates are zero by construction for $k$=1 and are therefore not shown. Separation rates are calculated for each horizon and move year, and then averaged across move years. The set of move years available depends on the horizon considered, e.g. only workers who move in 2013 or 2014 are included when calculating 5-year separation rates.

sorting in the following regression:

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

where $i$ is a worker who moves from origin firm $o$ to destination firm $d$ in year $t$. $S_{i,o,d,t+k}$ is a dummy variable which equals one if the worker separated from the destination firm by year $t + k$ and zero otherwise.[25] $SB_{o,d,t-1}$ 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. $X_{i,t-1}$ are a set of worker-level controls which include log(earnings) in the year before the move, age deciles, and gender. To account for the fact that supply-chain movers may sort into firms with lower separation rates, we also control for destination firm fixed effects. Because future separation rates may also depend on the characteristics of the origin firm, we include origin firm fixed effects too. Finally, we include a set of origin-destination firm controls to allow for separation rates depending on the joint characteristics of the origin and destination firm. We include fixed effects for the interaction of origin and destina-

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[25]We do not differentiate between separations where the worker moves to another formal firm in our employer-employee database or where the worker drops out of the formal sector altogether.

tion firm size quintiles, municipalities and industries, and whether the two firms have common ownership. We double cluster our standard errors at the origin and destination firm-level.

We run the regression in Equation 3 for horizons $k = 2, \ldots, 6$ and report the results in Table 4.[26] The top panel shows the results controlling for year fixed effects and worker characteristics such as pre-move earnings, but without either firm or firm-pair controls. We find that separation rates are on average 8.5 percentage points lower for workers who move to buyers or suppliers, confirming that the selection of workers on income contributes moderately to the 9.2 percentage point difference in the raw data. This difference could be in part explained by workers who move to buyers/suppliers sorting into firms with more stable positions. The bottom panel of Table 4 includes both firm fixed effects and firm-pair controls, and confirms that movers to buyers or suppliers are nonrandomly sort into firms with lower separation rates. Average separation rates are only 2.6 percentage points lower once we control for origin and destination firm fixed effects, though this difference is both economically and statistically significant at all horizons.

To summarize, out of a 9.2 difference in separation rates in the raw data, 0.7 is explained by worker characteristics alone, 5.9 is explained by workers sorting into firms with lower separation rates, and 2.6 reflects a higher match-specific quality for movers who stay within the supply-chain.

## 4.2   Worker Earnings

We next examine whether workers hired by buyers or suppliers have different earnings dynamics than other movers. We first plot the raw data in Figure 8. Panel (a) plots median earnings for a balanced panel of workers who moved in 2015 and for whom we measured earnings in every year from 2012 to 2019. We normalize earnings in 2014 to one for both workers who move to buyers or suppliers and for other workers. It is clear that following a move, an earnings gap opens up between the two types of movers, which persists even four years after the move.[27] This earnings gap is present despite the fact that workers who move to buyers or suppliers tend to have higher earnings before the move 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 entirety of the pre-move earnings distribution.

---

[26]Recall that our definition of movers conditions on the primary employer of the worker being the destination firm in period $t + 1$, and so separation rates by construction are zero for $k = 1$.

[27]We note that both types of movers see a particularly rapid rise in earnings during the move year. This could partly reflect that we measure earnings in the move year as the maximum of earnings from the origin and destination firm.

Table 4: Separation Rates - With Controls

|  | Worker Controls | | | | |
| Horizon | 2 | 3 | 4 | 5 | 6 |
| --- | --- | --- | --- | --- | --- |
| Buyer or Supplier | -0.075*** | -0.096*** | -0.093*** | -0.087*** | -0.076*** |
|  | (0.007) | (0.010) | (0.010) | (0.011) | (0.011) |
|  |  |  |  |  |  |
| Observations | 214,721 | 161,770 | 111,452 | 69,324 | 32,595 |
| $R^2$ | 0.012 | 0.017 | 0.020 | 0.021 | 0.019 |
|  | Worker and Firm Controls | | | | |
| Horizon | 2 | 3 | 4 | 5 | 6 |
| Buyer or Supplier | -0.021*** | -0.024*** | -0.024*** | -0.027*** | -0.036*** |
|  | (0.005) | (0.006) | (0.006) | (0.008) | (0.011) |
|  |  |  |  |  |  |
| Observations | 167,055 | 125,036 | 84,935 | 52,134 | 23,998 |
| $R^2$ | 0.357 | 0.381 | 0.393 | 0.402 | 0.413 |

Notes: This table shows the results from the worker-level regression in Equation 3. 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.

Figure 8: Earnings Dynamics of Movers—Raw Data

(a) Median Earnings

(b) Earnings Growth
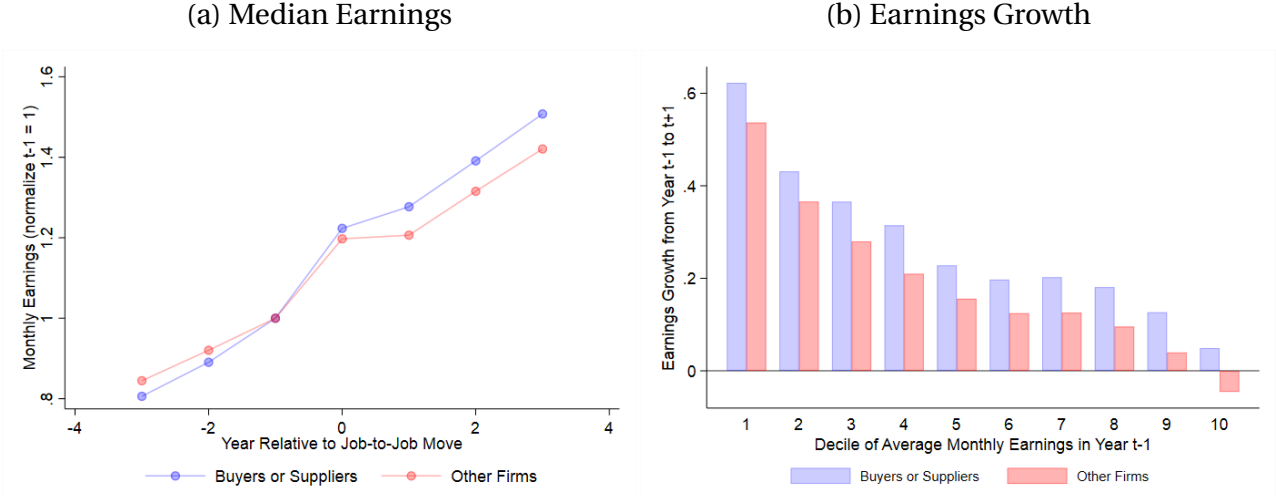


Notes: Panel (a) in this figure shows the median earnings of workers who moved job-to-job within a year for three years before and three after the move year. We keep a balanced panel of workers who had positive earnings in all 7 years (restricting the years in which workers moved to 2015 and 2016), and 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 of the supply chain. The sample includes 49,940 workers in total, 13,393 of which moved to buyers or suppliers. Panel (b) shows average earnings growth (winsorized at the top and bottom 1%) for within-year job-to-job movers between the pre-move and post-move year, by earnings decile in the pre-move year. The sample includes 273,003 workers, 65,773 of which moved to buyers or suppliers.

As with separation rates, non-random sorting of workers to high-wage firms could play an important role in explaining these patterns, and would bias estimates of a supply-chain-specific earnings premium. We control for observable measures of sorting in the following earnings regression which is analogous to Equation 3:

$$E_{i,o,d,t+k} = \alpha^k + \delta^k X_{i,t-1} + \beta^k SB_{o,d,t-1} + \phi^k_{o,t} + \phi^k_{d,t} + \gamma^k X_{o,d} + \eta_{i,d,o,t,k} \qquad (4)$$

where $i$ is a worker who moves from origin firm $o$ to destination firm $d$ in year $t$. The only difference relative to Equation 3 is that the dependent variable $E_{i,o,d,t+k}$ is the log of average monthly earnings.[28] We run this regression at horizons $k = -3, \ldots, 4$ in order to test for differential pre-trends for workers who moved to buyers or suppliers. Differential pre-move earnings dynamics would be concerning as it would suggest that workers who move outside of the supply-chain are not a valid control group for workers who move along the supply-chain. As before, we double cluster our standard errors at the origin and destination firm-level.

The left panel of Figure 9 plots the earnings dynamics around the move year of supply-chain movers relative to other movers, controlling only for worker characteristics (pre-move earnings, age, and gender). Movers to buyers or suppliers are on similar earnings

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[28]Recall that earnings are defined in our data as average monthly earnings for the months in which the worker was employed.
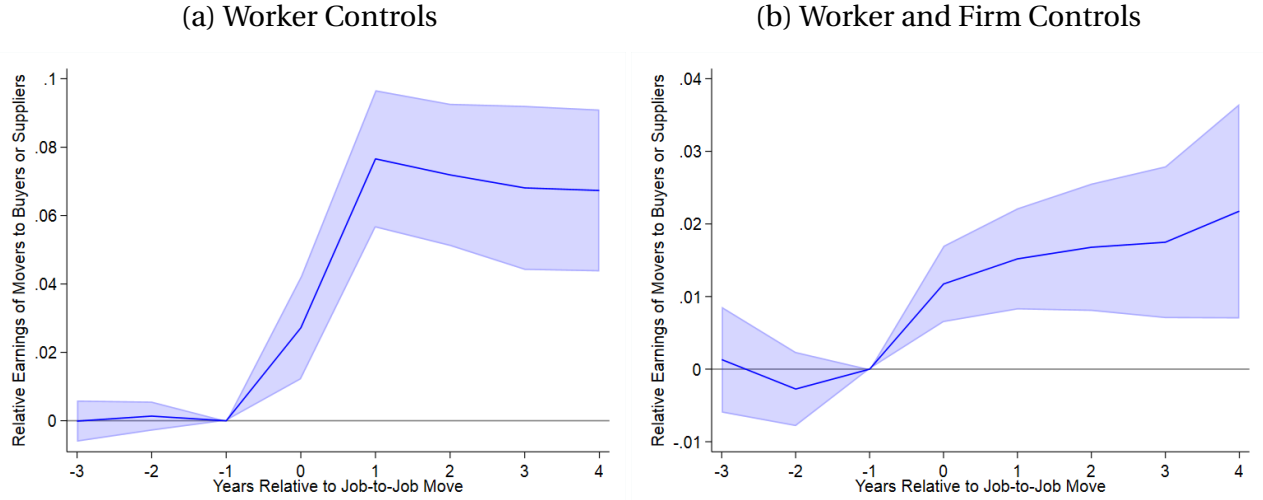
trends before the move, but a large earnings gap opens from after the move. Supply-chain movers have 7.7 percent higher earnings the year after the move than non-supply-chain movers, gradually declining to 6.7 percent four years after the move. This large earnings gap could be due to a) supply-chain movers sorting into higher-wage firms, or b) a supply-chain-specific earnings premium. We explore the role of sorting to high-quality firms in the right panel of Figure 9, which controls for firm fixed effects and firm-pair controls. These estimates can be thought of as capturing the earnings differential between two workers with similar pre-move earnings who move to the same firm, one from a buyer or a supplier and the other from outside the supply-chain. 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 percent, increasing to 2.2 percent by the fourth year after the move.[29] Of the 6.7 percent earnings gap four years after a move, 4.5 percent (two thirds) is explained by the fact that supply-chain movers tend to move up the firm quality ladder to higher-wage firms and 2.2 percent (one third) is explained by a higher match-specific quality for supply-chain movers.

The interpretation of our estimated coefficients as the causal impact of moving along the supply-chain is contingent on assuming that, conditional on observables, non-supply-chain movers form a credible control group for supply-chain movers. A threat to identification is a shock which increases a worker's future earnings potential while simultaneously making the worker more likely to move to a buyer or supplier in period $t$. To the extent that such shocks were realized in the years before the move, they would also affect earnings dynamics from $-3 \leq k \leq -2$. We are therefore reassured by the lack of pre-trend in earnings before the move. However, we acknowledge that a shock in year $t$ which increases a worker's future earnings potential while simultaneously making the worker more likely to move to a buyer or supplier in period $t$, remains a threat to identification.

It is important to examine whether the earnings premium we estimate is driven by workers who stay in their destination firm or by a left tail of poorly matched workers who quickly leave the firm they move to. This is particularly relevant given the higher separation rates we showed in Sub-Section 4.1, and it is informative for distinguishing between potential explanations for our finding. For example, lower uncertainty about match quality for workers within vs. outside the supply-chain would imply a shrinking earnings premium for workers who remain at the destination firm (as modeled in Dustmann et al. (2016) in the context of referrals). Figure 10 plots the coefficient on the supplier or buyer dummy from Equation 4, with the additional restriction of the sample to

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[29]We show in Appendix Figures A5 that the inclusion of firm-pair controls does not change the results relative to our specification with origin-year and firm-year fixed effects. This is reassuring as it suggests that other unobservable match-specific confounding factors are unlikely to affect our results.

Figure 9: Earnings Dynamics of Movers—With Controls

(a) Worker Controls

(b) Worker and Firm Controls



Notes: This figure plots the coefficient $\beta$ from Equation 4 for each horizon $k$, along with the 95% confidence interval. 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.

workers who 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 and without firm and firm-pair fixed effects. We do not see any tendency for the earnings gap to shrink over time. This is consistent with persistently higher match-quality for workers moving from along the supply-chain.

**Heterogeneity**    We found in Section 3 that high-salary workers are particularly likely to move to buyers or suppliers, conditional on moving. We therefore explore the extent to which the earnings premium associated with moving along the supply-chain varies with workers' pre-move earnings. We extend Equation 4 to allow for the earnings premium associated with moving to a buyer or supplier to depend on whether a mover's earnings is above or below the median earnings of movers in period $t-1$:

$$E_{i,o,d,t+k} = \delta^k X_{i,t-1} + \beta_l^k SB_{o,d,t-1} \cdot I(E_{i,t-1} < median) + \beta_h^k SB_{o,d,t-1} \cdot I(E_{i,t-1} \geq median)+$$
$$\phi_{o,t}^k + \phi_{d,t}^k + \gamma^k X_{o,d} + \eta_{i,d,o,t,k}$$
$$(5)$$

We report the coefficients $\beta_l^k$ and $\beta_h^k$ in Figure 11 along with 95% confidence intervals.[30] The top two sub-figures show the results controlling only for worker controls. We find that

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[30]We find qualitatively and quantitatively similar results when we run the regression in Equation 4 separately for workers with above and below median earnings.

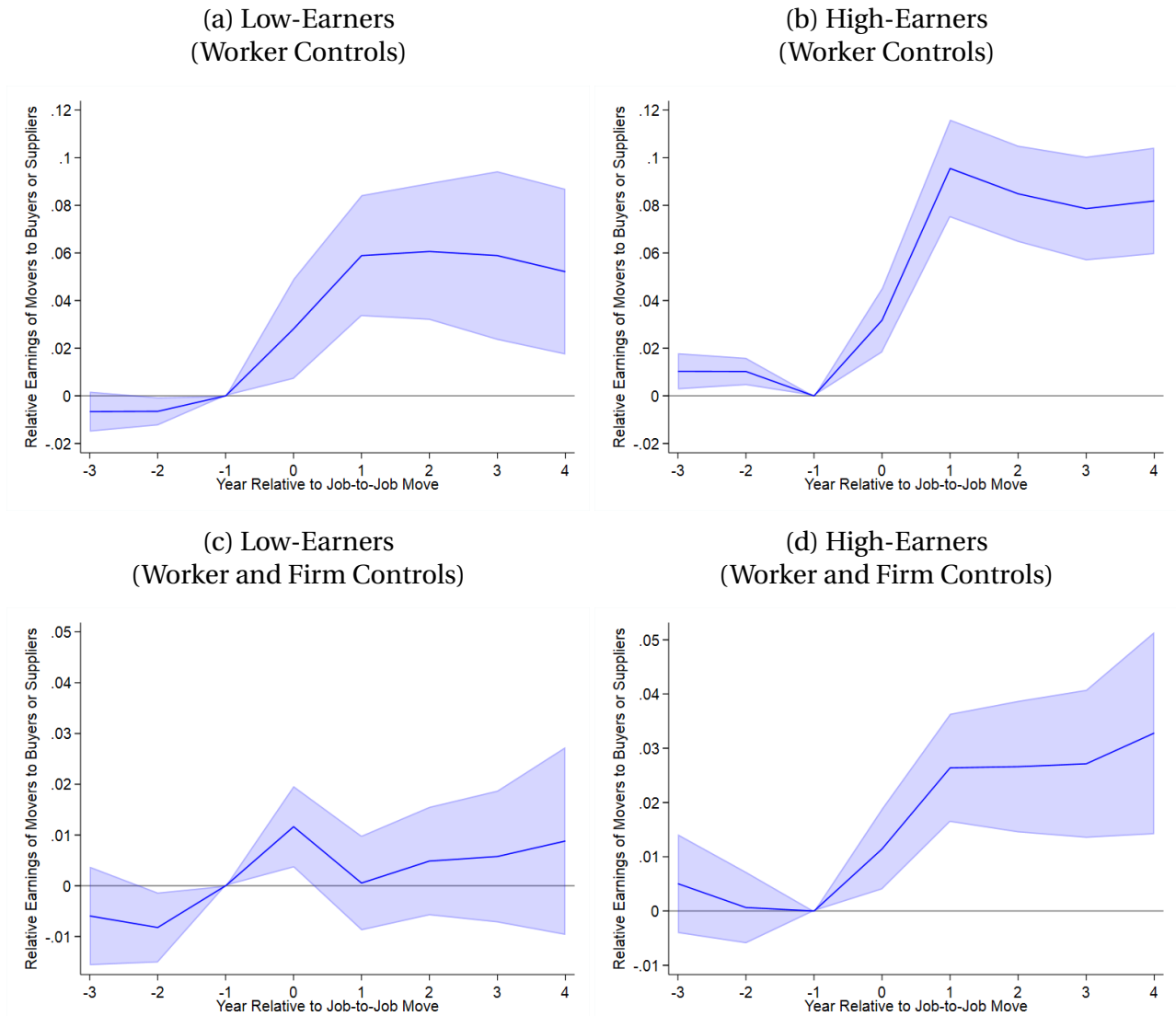### Figure 10: Earnings Dynamics of Movers Who Stay At Destination Firm
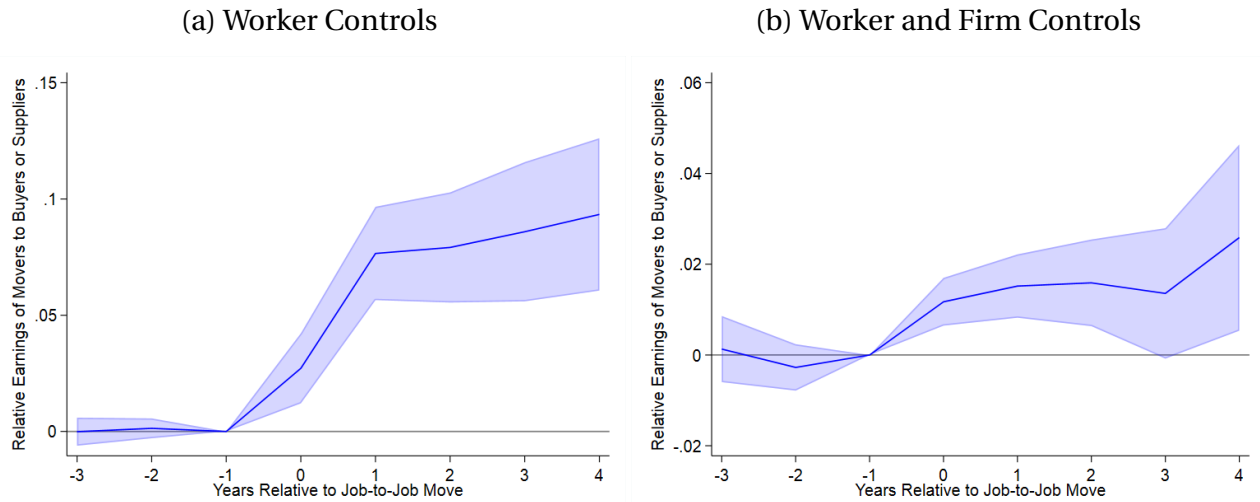
(a) Worker Controls                           (b) Worker and Firm Controls



Notes: This figure plots the coefficient $\beta$ from Equation 4 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.

for both low-earners and high-earners there is a substantial earnings premium following moves to buyers or suppliers, with no evidence of differential pre-trends. The earnings premium is statistically significant at 3.7 percent higher for high-earners one year after the move, though this gap shrinks to a statistically insignificant 2.9 percent four years after the move. As before, this earnings premium could be driven by sorting to high-quality firms or because of higher supply-chain specific match quality. The bottom two sub-figures show the results including firm fixed effects and firm-pair controls. We find a large earnings premium for high-salary workers of 2.6 percent one year after the move and 3.3 percent four years after the move, substantially higher than the 1.5 and 2.2 percent premiums we found for our full sample of workers. Indeed, the bottom left panel of Figure 11 shows a small and statistically insignificant earnings premium for low-earning 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 firm quality ladder to higher-wage firms with lower separation rates. However, only initially high-earning workers have higher match-specific returns to their human capital along the supply-chain.

In unreported heterogeneity exercises, we find that movers to buyers on average see a larger increase in earnings compared to movers to suppliers, though this is accounted for entirely by sorting on the firm margin - we do not see statistically significant dif-

## Figure 11: Earnings Dynamics of Movers By Pre-Move Earnings

(a) Low-Earners
(Worker Controls)

(b) High-Earners
(Worker Controls)



(c) Low-Earners
(Worker and Firm Controls)

(d) High-Earners
(Worker and Firm Controls)



Notes: This figure plots the coefficient $\beta_l$ (left panels) and $\beta_h$ (right panels) from Equation 5 for each horizon $k$, along with the 95% confidence intervals. The top panels 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.

ferences once we include firm fixed effects. In addition, we don't see 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 industry. This is consistent with supply-chains being particularly helpful in enabling workers to find good jobs in industries in which they are less familiar. Finally we find that the earnings premium is largest for workers who move to one of their firms' top buyers or suppliers. The magnitude of the supply-chain link therefore matters for the earnings premium, rather than the presence of a firm in the supply-chain alone.

**Back of the Envelope Calculation**   We do a simple back-of-the-envelope exercise to evaluate how important our findings are for average earnings. We find that 19 percent of movers go to buyers or suppliers, and we estimate a persistent match-specific premium of 2.2 percent over other movers. We consider an economy in which workers enter the labor force at age 20 and retire at age 65. On average, we find that 13 percent of workers change firm from one year to the next, 19 percent of which move to a buyer or supplier. In any given year, 2.5 percent of workers therefore move along the supply-chain. We assume that the probability of changing firm and of moving to a buyer or supplier are the same for all ages, as is the earnings premium from moving to a buyer or supplier. Moving to a buyer or supplier therefore implies a permanent increase in the level of worker earnings until retirement. We hold constant the wage of entrants to the labor force, which implies that the supply-chain premium increases average earnings by increasing the slope of workers' life-cycle earnings. Overall, we find that, absent this supply-chain premium, average earnings would be 1.2 percent lower. The supply-chain earnings premium is a quantitatively important in determining worker earnings.

## 4.3   Coworker Earnings

Jarosch, Oberfield and Rossi-Hansberg (2021) document that workers with high-wage coworkers see more rapid earnings growth, consistent with human capital spillovers between workers within the firm. It follows that workers could also learn from new hires, and in particular workers hired from buyers or suppliers if the latter have supply-chain specific human capital. 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:

$$E_{i,d,t+k} = \alpha + \rho \cdot E_{i,t} + \phi \cdot \bar{E}_{-i,t} + \delta H_{d,t} + \beta SB_{d,t} + \gamma X_{i,t} + \omega X_{d,t} + \varepsilon_{i,d,t,k} \qquad (6)$$

where $E_{i,d,t+k}$ is the log of 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.[31] We control for worker characteristics such as earnings in period $t$, as well as age deciles, and gender. Following **?**, we control for the average earnings of a worker's coworkers in period $t$. We control for 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, potentially translating into higher wage growth. All our specifications include industry×municipality× year fixed effects. We cluster standard errors at the firm-level.

The sample is restricted to workers $i$ who are at the same firm $d$ from $t - 1$ to $t + k$, and we restrict our sample to firms with at most 100 workers in all years. This latter restriction ensures that coworkers are working in small-enough teams that they may plausibly learn from new hires. We also consider a specification in which we restrict our sample to firms that hired in period $t$, and then condition on the log of average monthly earnings of new hires at the firm, given our previous evidence that supply-chain movers tend to be high-earners. Our estimates of spillovers to other workers are caveated by the fact that we cannot control for firm fixed effects, given that hiring varies only at the firm-level. To interpret our estimates causally requires that, conditional on hiring workers from another firm, workers at firms that hire from buyers or suppliers would be expected to have similar earnings growth to workers at firms that did not. Our controls for employment and sales growth at the firm-level alleviate concerns that firms hiring from buyers/suppliers were on different growth trajectories which might impact worker earnings.

Table 5 presents our results for horizons $k = 1, \ldots, 3$. The first three columns show our estimates from Equation 6. Similarly to **?** 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 which are hiring at least one worker from another firm in period $t$, and we additionally control for the average salary of new hires. This is an important control given that we have previously shown

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[31]Because we are no longer estimating the earnings dynamics of movers, we define a firm has having hired a worker from its buyers or suppliers if the worker's primary employer changed from one year to the next. This corresponds to our baseline year-to-year definition of job movers rather than the more conservative within-year mover definition we used when examining the earnings dynamics of movers.

evidence of selection of high-salary workers for movers 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. All in all, our analysis of coworker earnings is consistent with human capital spillovers from supply-chain hires.

Table 5: Hiring and Coworker Learning

| Horizon | Earnings (All firms) | | | Earnings (Firms with $\geq 1$ new hire) | | |
|---|---|---|---|---|---|---|
|  | 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 6 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.

# 5    Sources of Supply-Chain Human Capital

Moving to buyers/suppliers is an important way for workers to move to jobs that are a better fit for them. This section investigates the reasons for these gains from movements along the supply chains.

We first study three potential explanations for the larger match-specific productivity component which are based on the transferability of human capital along the supply chain. The first is about the similarity of skills required to work at buyers and suppliers of the current employer. The second presumes the need to insource tasks currently performed by other firms. And the third is about the impact of worker movements on gains from firm-to-firm trade. We describe these three hypotheses in detail and provide empir-

ical evidence in favor of the skills' similarity and for increase in gains from firm-to-firm trade. We find no evidence, instead, supporting the insourcing hypothesis.

We then consider alternative stories that could also lead to worker movements and wage premia along the supply chain even if employees of a firm were not inherently a better fit for their employers' buyers or suppliers–that is if our earnings regressions were not capturing match-specific productivity gains for moves along the supply chain but some other correlated factors. This could happen because of lower uncertainty on workers' quality, stronger bargaining power, or smaller unemployment scars. We discuss evidence against these alternative stories playing a major role in explaining the quality of match along the supply chain. We therefore infer that transferability of human capital along the supply chain is indeed the major factor in explaining the gains from moving to buyers/suppliers.

## 5.1 Assortative Matching

Working at different firms require a different combination of skills (Lazear, 2009; Gathmann and Schönberg, 2010). A possible reason for which the human capital of a firm's employees is useful to buyers or suppliers is that firms that trade together also tend to rely on a more similar combination of skills. To test this hypothesis, we examine if buyers and suppliers rely on workforce with more similar competencies and knowledge according to observable dimensions.

On the one hand, gains from trade between firms can partially stem from differences, rather than similarities, in knowledge and know-how. On the other hand, recent literature shows that manufacturers with more skilled workers mainly purchase their inputs from suppliers with a highly skilled workforce (Demir et al., 2020), and assortative matching in general is a common features of many social/economic networks. Similarity of workforce skills for firms trading with each other can be the result of different factors. For instance, resorts and tour operators in the tourism industry might specialize in serving tourists from a specific destination and thus employ workers with similar language skills. Also, supply chains might require similar technical knowledge to produce, maintain, and operate certain machines. Similarly, firms operating with each other in the real estate sector may request knowledge about construction from their employees.

While we do not directly observe the full spectrum of workers' skills, we have information on tertiary education. Since some technical knowledge is typically acquired through higher education, we rely on this information to test whether there is some assortative matching based on the type of tertiary education workers obtained. Specifically, we focus on engineers, as knowledge of engineering process is an essential input of many productions. An engineering degree reveals specific technical knowledge and there exist several
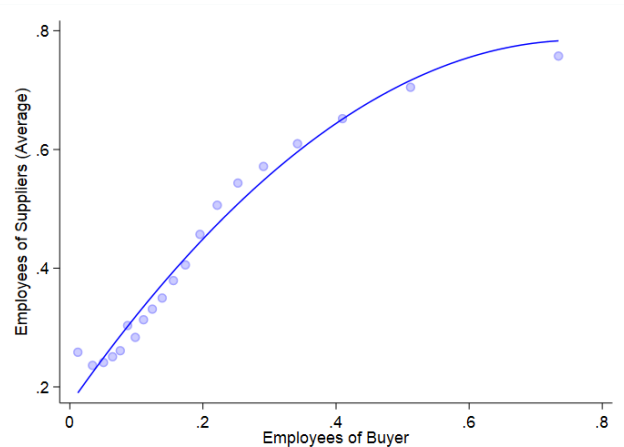
different sub-category of engineering, allowing for a detailed investigation of knowledge heterogeneity across firms.

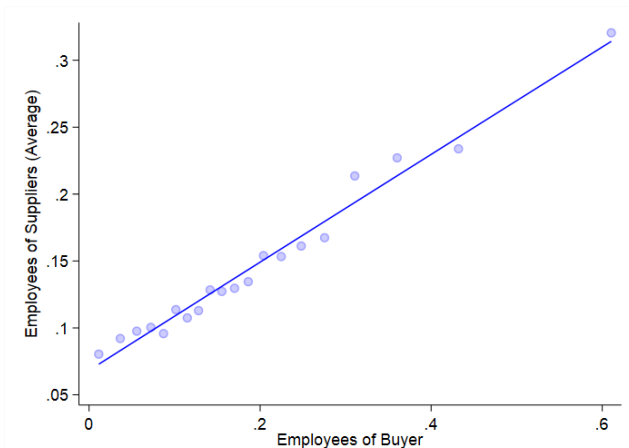Figure 12: Assortative Matching on Skill Use—Hiring of Engineers

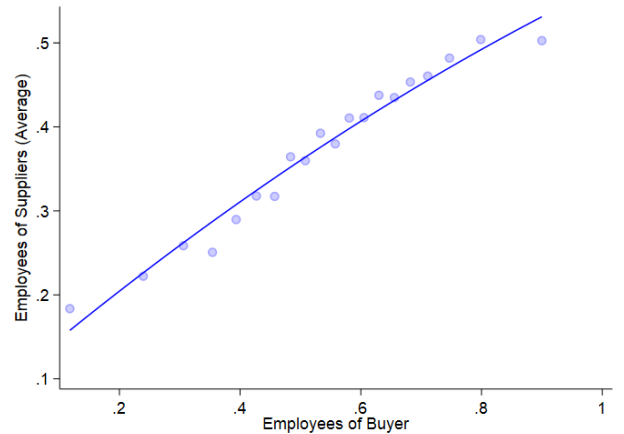(a) Share of Engineers to Employees with Tertiary Education
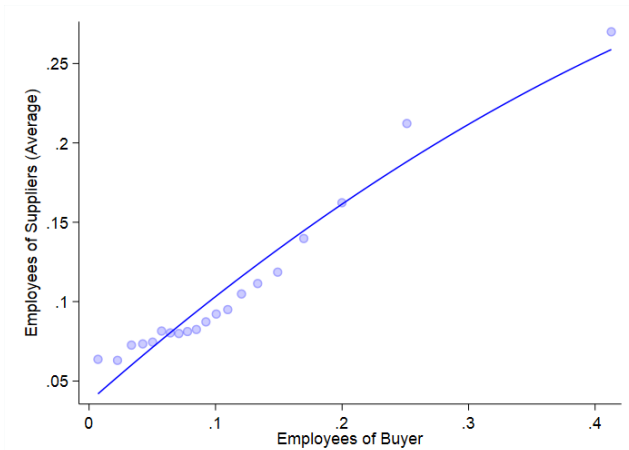
(b) Share of Civil Engineers to Total Engineers



(c) Share of Electric/Electronic Engineers to Total Engineers

(d) Share of Industrial Engineers to Total Engineers



For each firm with at least one employee with tertiary education in our data, we compute the share of employees with an engineering degree to the total number of employees with tertiary education.[32] Then, we compare a buyer's share of engineers with the average

[32]Our data covers degrees obtained 2007 to 2018, allowing us to observe education only of younger cohorts. However, as we compute the share of engineers over total graduates, both numerator and denominator are subject to the same selection.

across its suppliers and find a positive correlation: firms who hire more engineers purchase more from firms with more engineers, as illustrated by the upper left panel of Figure 12. Similarly, for different types of engineering degrees (i.e., civil, electric/electronic, industrial, and mechanical), we compute the share of engineers of each category to the total number of engineers employed by each firm (Figure 12). These shares capture more directly the extent to which some specific technical knowledge is present in the workforce. We find that firms that hire more engineers of a certain type buy more inputs from firms that also hire the same type of engineers. Results are robust to controlling for several firm-level characteristics—including the size of workforce, average wages, industry, and location—or focusing on one year of data only. We also perform the same analysis looking at workers that obtained business-related degrees (*"negotio"*), which represent 40% of graduates in our sample. As shown in Figure A3 and Figure A4 of the appendix, we find similar patterns.

Clearly, tertiary education is only one way through which human capital can be acquired, and most of heterogeneity in workers' skills and competences are unobserved.[33] Nonetheless, the presence of similarity along one observable dimension of human capital indicates that at least some specialized skills are important for both buyers and suppliers. These findings support assortative matching as an explanation of why human capital is transferable along the supply chain.

## 5.2 Gains from Firm-to-Firm Trade

Another reason for hiring a worker from a buyer or supplier could be to acquire useful know-how to insource some tasks that were previously outsourced. The gains from insourcing could be shared with the worker in terms of higher wages. If this meachanism is at play, then we should expect movements of workers across firms to be associated with lower gains from trade between the origin and destination firm (as some tasks have been insourced) and thus less trade.

At the same time, workers hired from buyers/suppliers may bring supply chain specific human capital with them which may, in turn, increase the gains from firm-to-firm trade. This could be because of complementary of the human capital with the inputs purchased from the supplier / sold to the buyer. That is, a worker's knowledge about how to produce a good or provide a service may also be useful knowledge for firms that purchase that good/service as an intermediate input; similarly knowledge about how to use or sell a product can be useful for a firm that produces it. Such complementarity can

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[33]In fact, in the appendix we report that including the type of degree among the conditioning variables of the random allocation exercise (section 3) explains a minor part of high education workers' tendency to move to buyers and suppliers (see Table A3).

arise because of the knowledge of the processes required to produce or sell a good or a service. Gains from firm-to-firm trade can also increase because of strengthened trust between buyer/supplier due to the personal connection between the new hires and their coworkers.

Insourcing and increase in gains from firm-to-firm trade have opposite implications for trade between the buyer and supplier when the worker move between the two firms. To test these predictions, we estimate the following equation:

$$y_{b,s,t} = \phi_{b,s} + \phi_{b,t} + \phi_{s,t} + \beta FirstWorkerFlow_{b,s,t} \tag{7}$$

where buyer $b$ and supplier $s$ are two firms that traded at the beginning of our sample (i.e., 2012) and $y_{b,s,t}$ is either a dummy for whether they trade in year $t$ or the log of the amount traded. The regressor of interest $FirstWorkerFlow_{b,s,t}$ is a dummy equal to one if we observe any worker flow between $b$ and $s$ up to year $t$. That is, let $T$ be the year such that we observe *for the first time* any worker moving between $b$ and $s$ (or viceversa): then $FirstWorkerFlow_{b,s,t} = 1$ if $T \leq t$. We add firm-pair ($\phi_{b,s}$), buyer-year ($\phi_{b,t}$), and supplier-year ($\phi_{s,t}$) fixed effects. The inclusion of firm-pair fixed effects allows us to focus on changes in trade over time as a function of the observed worker movements. We include only firms that are present in the employer-employee data for all years. The specification's ability to capture differences in trade after the first worker move between the firms hinges on observing such event. However, since workers tend to follow coworkers in their movements, when we observe a worker movement in first couple of years of the sample, this might indicate that worker flows were present also before the beginning of the sample. We therefore exclude from our baseline estimation all firm pairs such that we observe worker movements in 2015 or before (i.e. $T \leq 2015$).

We estimate Equation 7 by OLS.[34] The coefficient of interest is $\beta$, which captures the causal impact of worker flows on trade under the assumption that the timing of these workers' moves is uncorrelated with transitory shocks affecting firm-to-firm trade (Wooldridge, 2010): this assumption is weaker than in most empirical settings as the included fixed effects absorb all the potential confounding shocks at the buyer-year and supplier-year level, leaving only firm-pair time-varying shocks as residual threats to a causal interpretation of the results. We mitigate these threats by focusing only on firms that traded in the past, so that they "know" each other already, and by dropping firms that at any time are part of the same business group.

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[34]Recent econometric literature points out that the estimation of two-way fixed effect models as in Equation 7 can be biased, especially if the "treatment" effect is heterogeneous across time. We do not expect this to be the case in our setting. In fact, we re-estimate the model relying on an imputation estimator proposed by Borusyak, Jaravel and Spiess (2021) to overcome these limitations and find very similar results, see Table A5

Table 6: Firm trade and worker movements

| | Log Amount / Intensive Margin | | | | Any Trade / Extensive Margin | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| First Worker Move | 0.119*** | 0.044*** | 0.020*** | 0.045*** | 0.120*** | 0.063*** | 0.061*** | 0.060*** |
| | (0.012) | (0.010) | (0.008) | (0.010) | (0.006) | (0.003) | (0.002) | (0.003) |
| | | | | | | | | |
| Observations | 5,106,109 | 5,028,320 | 5,181,035 | 4,452,432 | 11,902,848 | 11,807,792 | 12,033,816 | 6,786,560 |
| $R^2$ | 0.822 | 0.854 | 0.857 | 0.858 | 0.645 | 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 amount of the trade between buyer $b$ and supplier $s$ (columns 1 - 4) or a dummy for whether we observe any amount traded (columns 5 - 8). We include firm-pair that traded in 2012, and 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6 reports the results with standard errors clustered at the firm-pair level. Buyers and suppliers trade more, both on the intensive (columns 1 to 4) and extensive margin (columns 5 to 8), following a worker movement between the two firms. The impact is sizeable: the amount traded (conditional on trade) increases by 4 to 12%. The probability of trade increases by 6 to 12 pp, which is 15 to 30% of the baseline probability. Comparing columns (1) and (5) with (2) and (6) reveals that the estimated increase in trade is larger when we do not control for buyer-year and supplier-year fixed effects. This is consistent with the fact that firms hiring from buyers/suppliers grow more, and thus trade more.

The rest of the table presents the estimate of the change in trade following a worker move comparing firms that share a buyer-supplier relationship to unconnected firms. Column (3) reveals that the estimated impact on the intensive margin is smaller when we do not exclude firm pairs for which we observe worker flows in the first couple of years in the sample. This result in line with the conjecture that we cannot cleanly pin down the timing of the first worker move for these firms (and thus there might be some measurement error in the regressor of interest). Columns (4) and (8) shows that results are robust to focusing on buyer-supplier pairs that traded both in 2012 and 2013, thus excluding one-off transactions.

To trace the timing of the increase in trade associated with the worker movements across firms, we consider a parsimonious "dynamic" event study specification:

$$y_{b,s,t} = \phi_{b,s} + \phi_t + \sum_{k=-K, k \neq 1}^{J} \beta_k \cdot WorkerFlow_{b,s,\tau=t-k} + \eta_{b,s,t} \qquad (8)$$

where $WorkerFlow_{b,s,\tau=t-k}$ is a dummy equal to one if we observe any worker flow

between $b$ and $s$ (or vice-versa) in year $\tau = t - k$. The $\beta_k$ coefficient captures the evolution of trade before and after a worker movement. As we include firm-pair fixed effects, it is not possible to estimate all the $\beta_k$, and thus the most common normalization $\beta_{k=-1} = 0$ is adopted. We set $J$ and $-K$ equal to 3 and -3, which corresponds to the longest period given the sample at our disposal. Figure 13 reports the estimates of $\beta_k$, together with 90, 95, and 99% confidence intervals, which show that the increase in purchases/sales happens at the same time of the worker movements between firms and appears to be persistent.[35]

Our results indicate that gains from firm-to-firm trade increase when a worker move between two firms who trade together, indicating this is a potential reason to hire such workers. Conversely, we find no evidence for the role of insourcing of tasks.

Figure 13: Worker Flows between Buyers and Suppliers and Trade



(a) Some Trade

(b) Log Sales
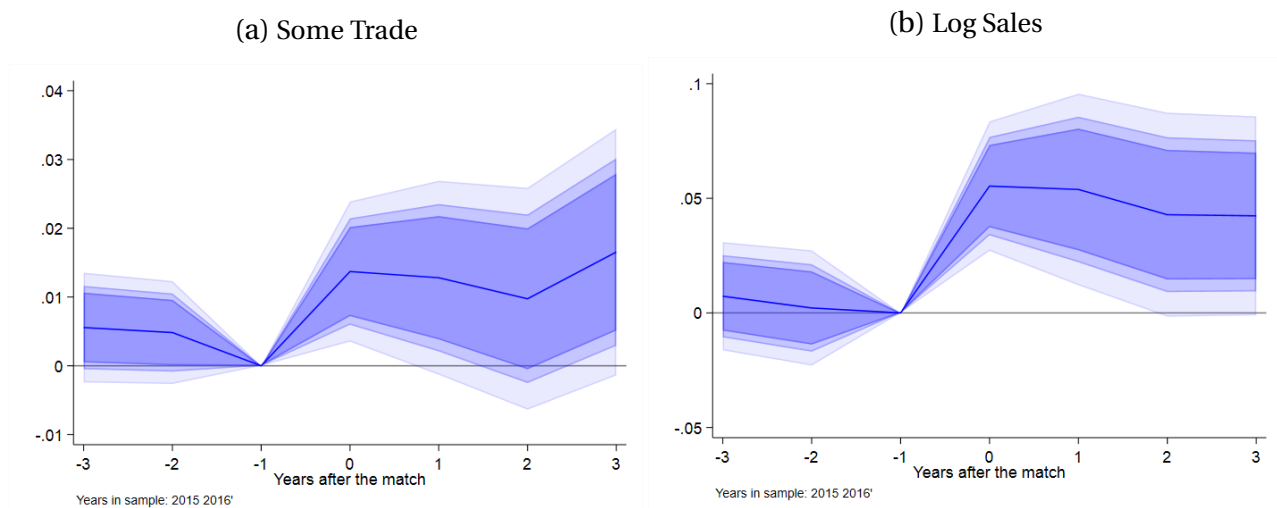
Notes: This figure plots the coefficients $\beta_k$ from a dynamic two-way (year and firm-pair) fixed effect regression of probability of trading (left panel) or log amount traded (right panel) on a set of dummies for whether a worker moved between the two firms in the year $t - k$ (see Equation 8). We normalize $\beta_k = 1$. The figure also reports the 90, 95, and 99% confidence intervals. Standard errors are twoway clustered at the buyer and supplier level.

## 5.3 Unemployment Scars, Uncertainty, Bargain

**Unemployment Scars** Job losses followed with long unemployment spells lead to depreciation of workers' human capital and decline in future earnings (Mincer and Ofek, 1982; Jarosch, 2021). An interpretation of our findings is that movements to buyers/suppliers

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[35]To estimate Equation 8, we include only observations such that we observe the firm pair for 3 years before and after the worker's move, limiting our sample to the period 2015–2016. In the appendix we show that results are broadly consistent if we use different specifications, for instance focusing only on the first observed worker movement.

are beneficial to workers because they shorten the period of unemployment after a job loss and avoid the consequent decline in human capital. That is, if workers who lose their job first look for a new employment at buyers/suppliers, then the one that are hired by these firms will have spent less time in unemployment with respect to other workers. (This alternative interpretation would change the economic mechanism behind our results but not their relevance for workers or productivity.) Unfortunately, a limitation of our data is that we do not observe the date of beginning or end of employment, nor we observe the reason of the dissolution of an employment-employee match.

While we cannot control directly for unemployment duration, we focus our analysis of earning dynamics (section 4) on within-year moves to limit the presence of very long unemployment spells. Moreover, some of our results are inconsistent with earnings gains being caused by job losses and lower time in unemployment for workers hired by buyers/suppliers. We replicate our earning results focusing on workers who experience an increase in wage rate with respect to the previous job. We find wage gains from moves along the supply chain also for job changes which do not appear to be associated with any "scarring". When we focus instead on workers with wage below median, we find that two new hires of the same firms receive the same wage regardless on whether they come from a buyer/supplier of the current employer. As low paying jobs also have also low job security (Jarosch, 2021), gains from avoiding or shortening post-displacement unemployment should be particularly important for low wage workers. Therefore, absence of gains for move along the supply chain for these workers is also evidence that job losses and unemployment spells are unlikely to be a main explanation of why we observe gains from movements along the supply chain.

**Uncertainty**   Information frictions may lead firms to hire from their buyers or suppliers even if these workers are not inherently better suited to fill a vacancy. Hiring from firms connected along the supply chain can in fact limit the uncertainty about the job applicants' qualities and the fit with the position. Managers can for example acquire information about employees of buyers/suppliers through direct collaboration, knowledge of the business/operation of their previous employers, or through referral network created through interactions between employees of buyers and suppliers.

A sizeable literature studies the role of uncertainty in worker-firm matches, in particular with respect to the role of referrals in hiring decisions (Brown et al., 2016; Burks et al., 2015; Dustmann et al., 2016; Glitz, 2017; Caldwell and Harmon, 2019). The idea is that hiring firms face lower information asymmetry about the job applicants and these, thanks to referral networks, not only are more likely to be hired, but also tend to bargain higher wages and experience lower separation rates. In addition, the wage premium of job applicants hired through referral networks fades away over time as the employer learns about

the fit with the workers hired (Dustmann et al., 2016). That is, the information rents are short-lived as poor matches are dissolved and workers' productivity gets reflected in their wages.

As shown in Section 4, we find instead persistent gains in wage and separation rates for workers moving along the supply chains. These gains are similar for workers who stay at the same firm for several years compared to all workers. Thus, we argue that hires along the supply chain are "better" matches and not just "safer" hires, and that lower uncertainty about the job applicants' fit is not a main factor explaining the gains associated with hiring along the supply chain. The finding that workers move more across more vertically integrated industries–even when they do not move do direct buyers/suppliers– also points towards transferibility of human capital downstream/upstream rather than gains from lower uncertainty on job applicants' fit.

**Bargaining**   A related story could be that employees of buyers and suppliers have better knowledge about the performance prospects of the potential employer and are then able to bargain for higher wages when they are hired by high-growth firms. While we are not aware of any paper formally modelling this mechanism, these gains should also fade away as worker staying at the firm acquire more similar information about its profitability. Thus, this story is also difficult to square with the persistence of wage gains.

Differences in bargain power and attitude are a primary driver of wage gaps as women can be reluctant to negotiate for higher pay (Biasi and Sarsons, 2022). We find that men and women similarly tend to move to buyers/suppliers and the wage gains from such moves are also statistically indistinguishable. This is evidence against bargaining power playing a role for the gains from moving along the supply chain. Furthermore, the finding that wages of coworkers also tend to raise when coworkers are hired from buyers/suppliers points towards larger surplus rather than larger share of surplus being appropriate from the new hires.

# 6   Conclusion

How workers match with firms is increasingly important for earnings and productivity. Nonetheless, our understanding about factors that determines workers' allocation across jobs is far from complete. Similarly, while the micro- and macro- importance of human capital is well recognized, knowledge about which elements determine the transferability of human capital across jobs is also incomplete.

In this paper, we open the black-box of matching models and show that workers are more likely to be hired from buyers and suppliers of their previous employers. We find

that this is a beneficial force for the economy as matches formed along the supply chain are of better quality, as measured by earnings and separation rates. We present evidence that the gains from movement along the supply chain stem from the transferability of human capital along the supply chain. This transferability appears to be due to similarity in skills required to work at buyers/suppliers and on the impact that human capital has on gains from firm-to-firm trade.

This paper is also the first to document that human capital and worker flows are a determinant of the gains from firm-to-firm trade and impact firms' supplying decisions.

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# A1   Appendix Tables

Table A1: Other Factors Affecting Share of Movers to Buyers or Suppliers

|  | Data | Random Allocation | Odds Ratio | Number of Movers |
|---|---|---|---|---|
|  | (1) | (2) | (3) | (4) |
| *Conditioning on:* | | | | |
| Origin industry and municipality | 19 | 11 | 1.8 | 1,019,242 |
| Firm Size Category | 20 | 13 | 1.6 | 875,028 |
| No Common Ownership | 17 | 11 | 1.6 | 971,804 |
| Tertiary Degree (Broad) | 26 | 17 | 1.7 | 37,078 |
| Tertiary Degree (Specific) | 26 | 18 | 1.7 | 20,821 |

Notes:

Table A2: Heterogeneity in Share of Supply-Chain Moves

| | Data | Random Allocation | Odds Ratio | Number of Movers |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A: By industry* | | | | |
| Agriculture | 13.0 | 6.3 | 2.2 | 10,499 |
| Construction | 18.2 | 5.9 | 3.6 | 39,319 |
| Education | 6.8 | 3.2 | 2.1 | 3,038 |
| Finance and Insurance | 28.7 | 23.1 | 1.3 | 17,747 |
| Health | 15.7 | 10.3 | 1.6 | 6,391 |
| Hotels & Hospitality | 21.9 | 12.9 | 1.9 | 96,844 |
| Manufacturing | 17.4 | 14.1 | 1.3 | 126,267 |
| Other | 12.8 | 4.9 | 2.9 | 131,000 |
| Real Estate | 16.8 | 7.3 | 2.6 | 9,153 |
| Transportation | 18.2 | 10.7 | 1.8 | 57,770 |
| Wholesale and Retail Trade | 27.1 | 17.7 | 1.7 | 148,056 |
| | | | | |
| *Panel B: By geography* | | | | |
| Excluding National District and Santo Domingo | 15.7 | 10.9 | 1.5 | 216,970 |
| Only National District and Santo Domingo | 21.6 | 12.6 | 1.9 | 429,114 |
| | | | | |
| *Panel B: Switchers vs. Stayers* | | | | |
| Switching Industry | 18.4 | 11.5 | 1.7 | 362,264 |
| Same Industry | 21.2 | 12.6 | 1.9 | 283,820 |
| Switching Municipality | 15.6 | 12.0 | 1.4 | 278,875 |
| Same Municipality | 22.7 | 12.0 | 2.1 | 367,209 |
| Switching Industry and Municipality | 14.0 | 11.3 | 1.3 | 176,935 |
| Same Industry and Municipality | 22.8 | 12.4 | 2.1 | 181,880 |
| | | | | |
| *Panel D: By gender* | | | | |
| Men | 20.3 | 12.6 | 1.8 | 463,853 |
| Women | 18.0 | 10.5 | 1.9 | 182,231 |
| | | | | |
| *Panel E: By age* | | | | |
| Younger than 25 | 18.2 | 12.8 | 1.5 | 178,184 |
| Older than 25 | 20.4 | 12.9 | 1.7 | 274,902 |
| Older than 35 | 19.9 | 10.0 | 2.2 | 192,998 |
| | | | | |
| *Panel F: By ethnicity* | | | | |
| White | 21.8 | 12.4 | 2.0 | 48,022 |
| Other | 19.5 | 12.0 | 1.8 | 576,697 |
| | | | | |
| *Panel G: By education level* | | | | |
| No Tertiary Education & Born after 1984 | 17.7 | 12.1 | 1.6 | 512,914 |
| Any Tertiary Degree & Born after 1984 | 23.8 | 15.4 | 1.7 | 38,666 |
| Any Tertiary Degree | 24.2 | 15.3 | 1.8 | 56,456 |

Notes: The probability of a worker moving to a buyer or supplier is calculated as the observed share of workers that move to a firm which was a buyer or a supplier of their previous employer. The probability of a worker randomly moving to a connected firm is estimated by randomly reshuffling movers across vacancies occupied by workers which are observationally similar in terms of previous industry, municipality, gender, age group, and salary quintile; we perform 100 simulations and report the average share of movers across simulations that are randomly allocated to a firm which traded with their previous employer. To avoid over-fitting we drop workers that are in groups, defined by their covariates, which count less than 50 workers (results are similar if we do not). The table reports the odds ratios between the two probabilities. A test for the equality of the two probabilities rejects the null that the two probabilities are statistically equivalent at the one percent significance level in all cases.

Table A3: Share of Movers to Buyers or Suppliers by Education

| | Data | Random Allocation | Odds Ratio | Number of Movers |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Conditioning on industry, municipality, gender, age group, and salary quintile* | | | | |
| No Tertiary Education and Born after 1984 | 17.7 | 12.1 | 1.6 | 512,914 |
| Any Tertiary Degree and Born after 1984 | 23.8 | 15.4 | 1.72 | 38,666 |
| Any Tertiary Degree | 24.2 | 15.3 | 1.77 | 56,456 |
| Any Tertiary Degree and area of study | 25.6 | 16.7 | 1.71 | 37,078 |
| Any Tertiary Degree and curricula | 26.1 | 17.5 | 1.66 | 20,821 |

Notes: The probability of a worker moving to a buyer or supplier is calculated as the observed share of workers that move to a firm which was a buyer or a supplier of their previous employer. The probability of a worker randomly moving to a connected firm is estimated by randomly reshuffling movers across vacancies occupied by workers which are observationally similar in terms of previous industry, municipality, gender, age group, and salary quintile; we perform 3 simulations and report the average share of movers across simulations that are randomly allocated to a firm which traded with their previous employer. To avoid over-fitting we drop workers that are in groups, defined by their covariates, which count less than 50 workers, thus increasing conditioning variables decrease sample size (results are similar if we do not). The table reports the odds ratios between the two probabilities. As we observe degrees obtained from 2007 on, we classify workers as having no tertiary education if they are born from 1985 on (so having at most 22 years in 2007) and are not in the tertiary education data. For workers with tertiary education we keep information only about the highest degree. Areas of study is a broader classification than curricula. For instance, business and engineering are areas of study, while marketing and civil engineering are curricula. There are 14 areas of study and 69 curricula, but after dropping small cells we have 8 areas and 20 curricula.

Table A4: Firm Trade and Worker Movements Upstream and Downstream

| | Log Amount or Intensive Margin | | | | Any Trade or Extensive Margin | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| First Move Downstream | 0.106*** | 0.029** | 0.013 | 0.028** | 0.114*** | 0.061*** | 0.055*** | 0.057*** |
| | (0.016) | (0.013) | (0.009) | (0.013) | (0.007) | (0.004) | (0.003) | (0.004) |
| First Move Upstream | 0.109*** | 0.049*** | 0.025*** | 0.053*** | 0.103*** | 0.054*** | 0.053*** | 0.053*** |
| | (0.013) | (0.011) | (0.008) | (0.012) | (0.006) | (0.003) | (0.002) | (0.003) |
| Observations | 5,106,109 | 5,028,320 | 5,181,035 | 4,452,432 | 11,902,848 | 11,807,792 | 12,033,816 | 6,786,560 |
| $R^2$ | 0.822 | 0.854 | 0.857 | 0.858 | 0.645 | 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 amount of the trade between buyer $b$ and supplier $s$ (columns 1 - 4) or a dummy for whether we observe any amount traded (columns 5 - 8). We include firm-pair that traded in 2012, and 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Firm trade and worker movements: Borusyak et al. (2021) estimator

| | Log Amount / Intensive Margin | | | | Any Trade / Extensive Margin | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| First Worker Move | 0.143*** | 0.059*** | 0.046*** | 0.054*** | 0.120*** | 0.062*** | 0.069*** | 0.060*** |
| | (0.009) | (0.009) | (0.007) | (0.009) | (0.002) | (0.002) | (0.002) | (0.002) |
| | | | | | | | | |
| Observations | 5,565,621 | 5,564,988 | 5,718,856 | 4,528,231 | 11,902,848 | 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 amount of the trade between buyer $b$ and supplier $s$ (columns 1 - 4) or a dummy for whether we observe any amount traded (columns 5 - 8). We include firm-pair that traded in 2012, and 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 et al. (2021) imputation estimator.

# A2  Appendix Figures

Figure A1: Trade and Worker Flows between firms

(a) Trade flows between random firms
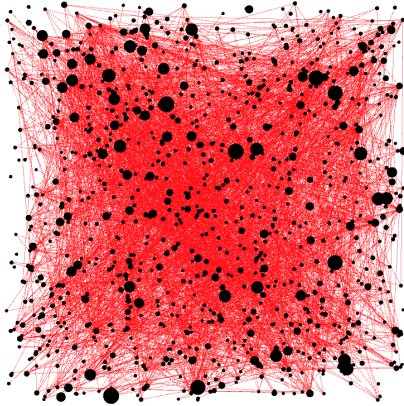
(b) Trade flows between trading firms
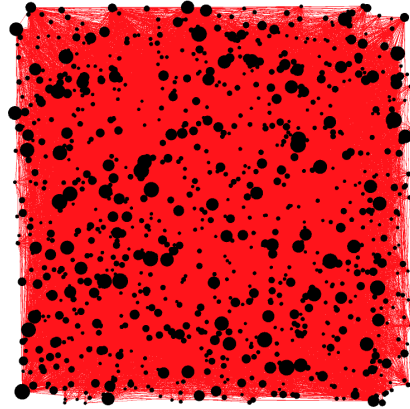
(c) Worker flows between random firms
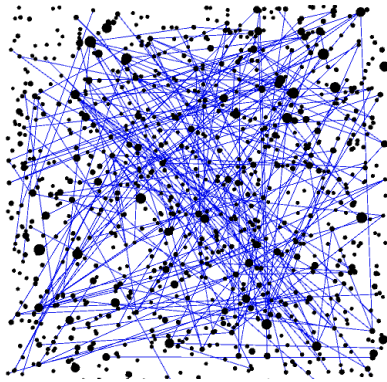
(d) Worker flows between trading firms
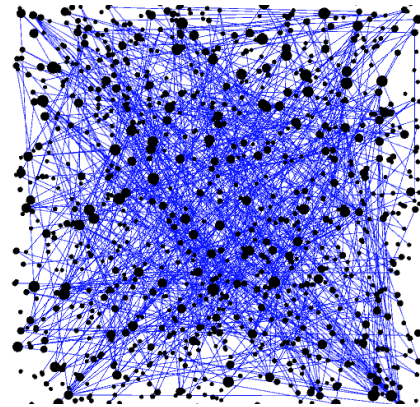


Notes: The nodes denote firms, with their size proportional to the number of employees. Red edges denote the firms that traded. Blue edges denote at least one worker moving between the two firms. Panels (a) and (c) use a sample of 1,000 randomly selected firms in 2019. Panels (b) and (d) use a sample 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.

## Figure A2: Share of New Hires from Buyers and/or Suppliers

(a) At Least One Hire                          (b) At Least 10 Hires
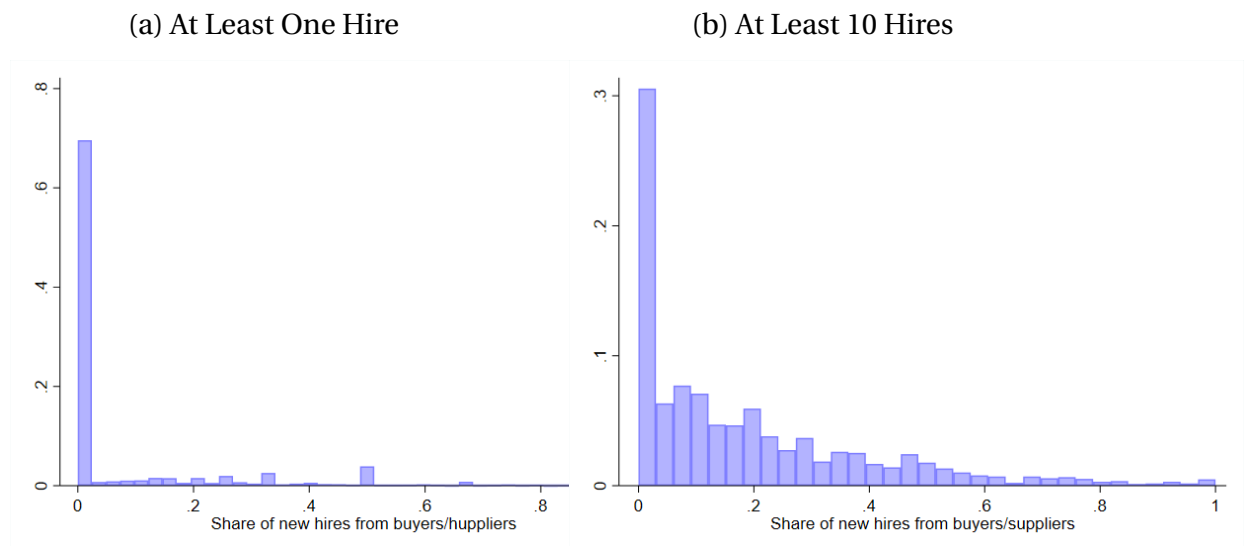


Notes: This figure plots the firm-level distribution of the share of new hires coming from buyers or suppliers. We look at movers between 2012 and 2013, though we find similar results for other year pairs. Panel (a) includes all firms that hire a worker from another firm, while panel (b) only includes firms that hire at least 10 workers from other firms.

Figure A3: Assortative Matching on Skill Use—Hiring of Engineers (with controls)

(a) Share of Engineers to Employees with Tertiary Education
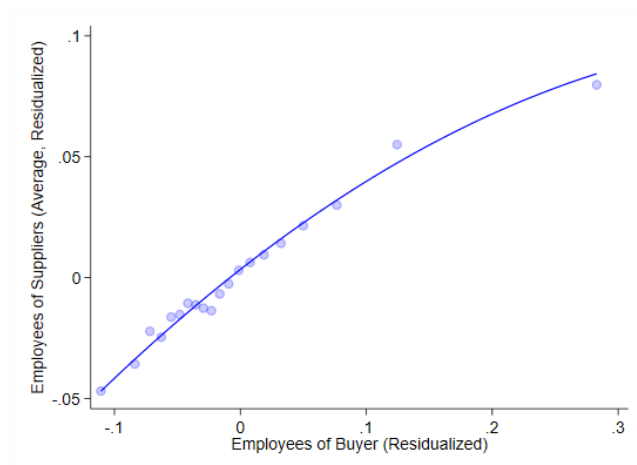
(b) Share of Civil Engineers to Total Engineers
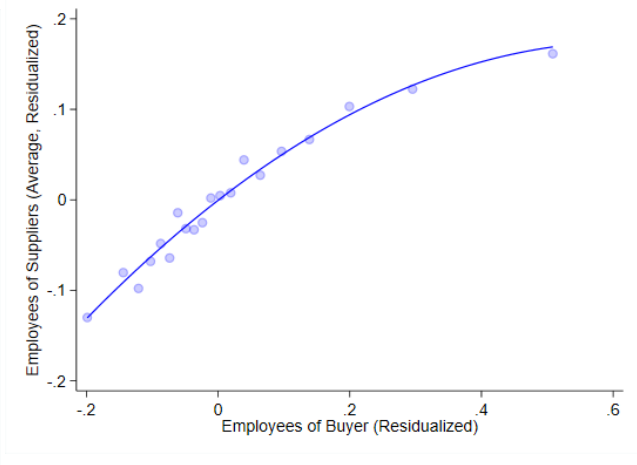


(c) Share of Electric/Electronic Engineers to Total Engineers
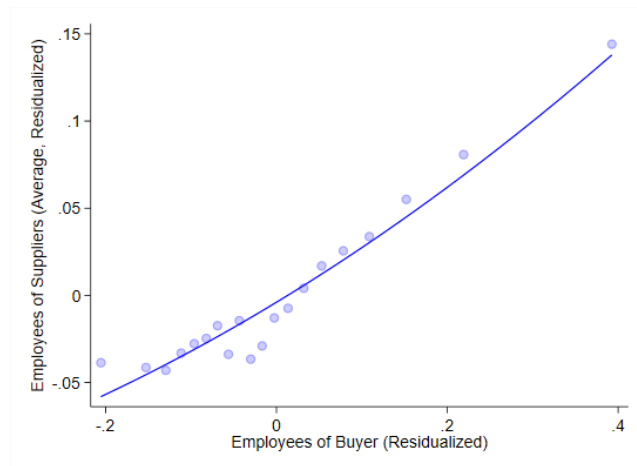
(d) Share of Industrial Engineers to Total Engineers
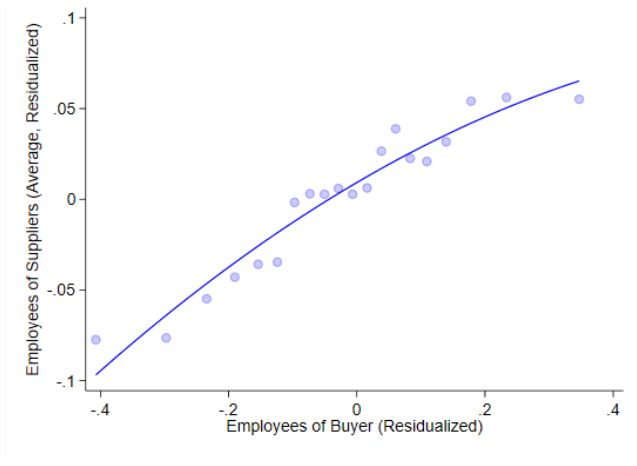


Notes: The figure replicates Figure 12 adding a set of firm-level controls: industry-year and municipality-year fixed effects, the (log) number of suppliers, the (log) number of employees, the (log) average number of suppliers' employees, the (log) average wage, the (log) average wage of suppliers' employees, the share of workers with tertiary education, suppliers' average share of workers with tertiary education.

## Figure A4: Assortative Matching on Skill Use—Hiring of Business Graduates
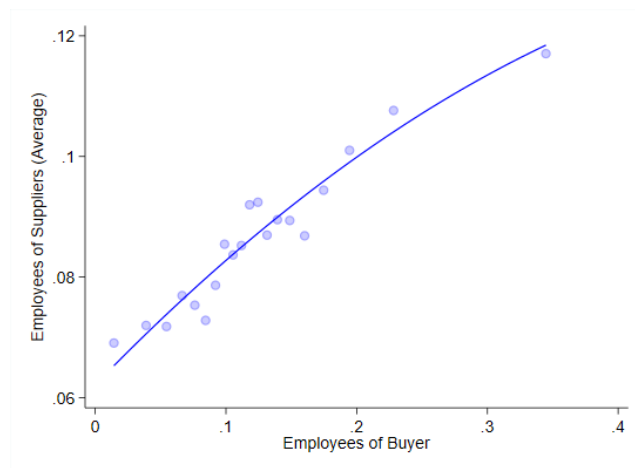
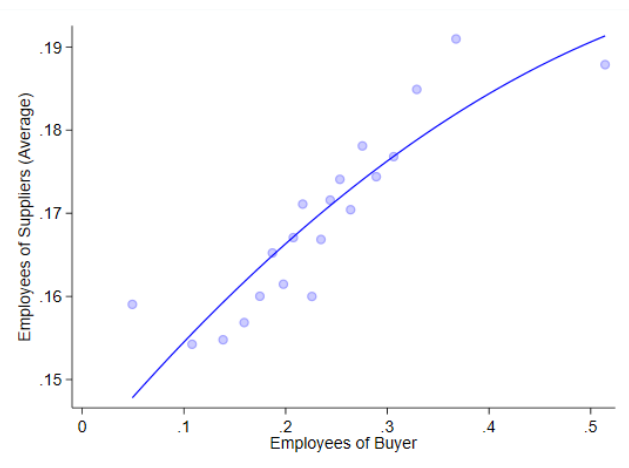(a) Share of Employees with Business-Related Degree
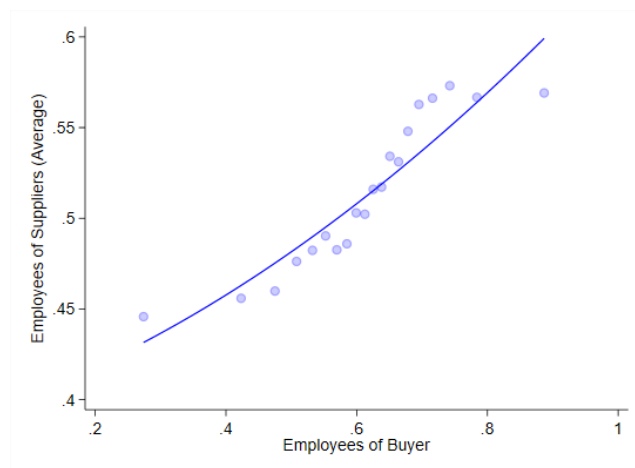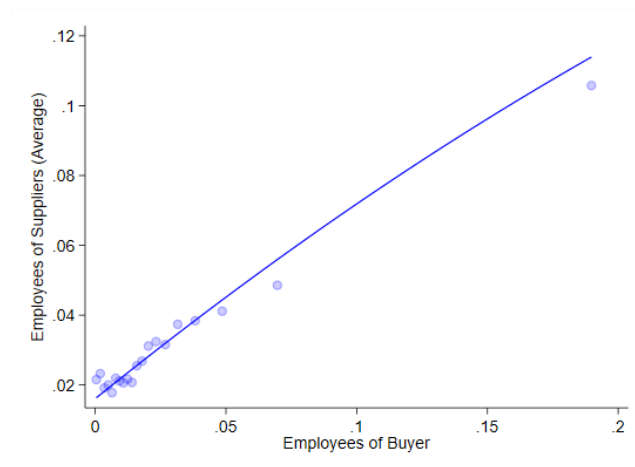
(b) Share of Employees with Accounting Degree
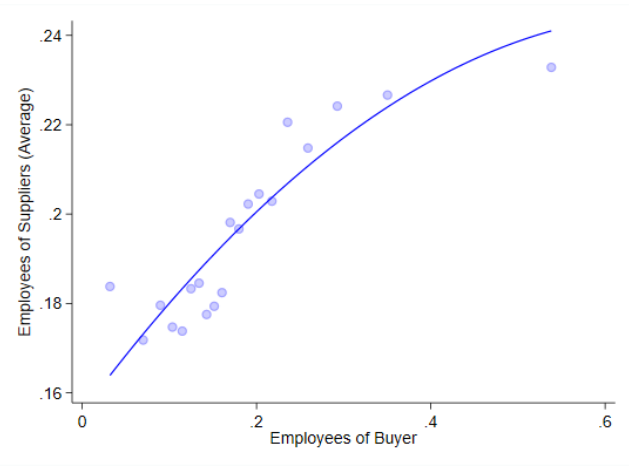
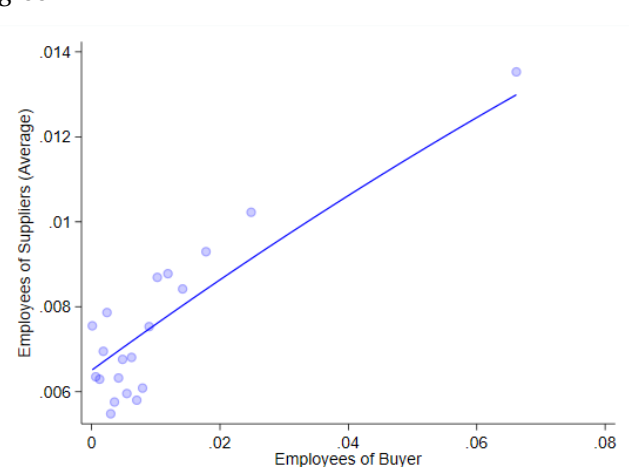(c) Share of Employees with Marketing Degree

(d) Share of Employees with Management Degree
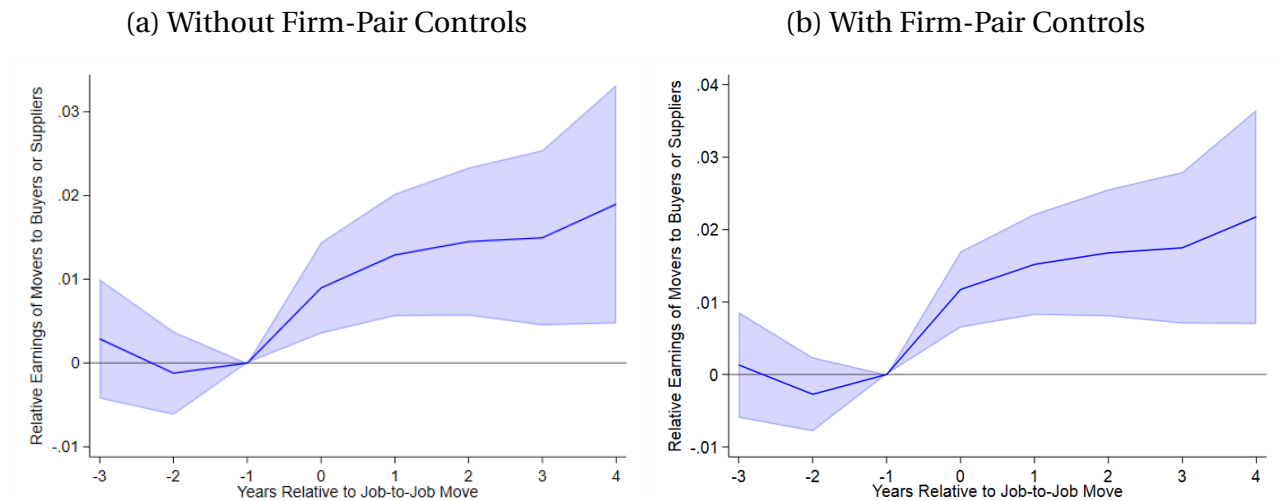
(e) Share of Employees with Tourism Degree

(f) Share of Employees with Economics/Finance Degree

Notes: All shares are in terms of employees with tertiary education.

**Figure A5:** 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 $\beta$ from Equation 4 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.