Worker Mobility and Domestic Production Networks

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Abstract

We show that domestic production networks impact worker flows 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 firms move to a buyer or supplier of their original firm. This is a considerably larger share than would be implied by a random allocation of movers to firms. We find sizable gains associated with this form of hiring: higher worker and coworker wages, lower job separation rates, and faster firm growth. Hiring workers from a supplier is followed by a rising share of purchases from that supplier. These findings indicate that human capital is transferable along the supply chain and that human capital accumulated while working at a firm is complementary with the intermediate products or services produced by that firm.

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1 Introduction

The trading of productive inputs–such as materials, capital goods, or services–between buyers and suppliers composes the fabric of an economy. Workers can also move from one firm to another, bringing with them a fundamental input of production: their human capital. The increasing availability of data on firm-to-firm transactions and of employer-employee matched data has enabled researchers to study in greater details economies' production networks and, separately, worker mobility across firms. However, the connection between the flows of traded goods (and services) and those of workers has been largely unexplored, arguably because of data limitations. In this paper we fill this gap by by combining employer-employee records with data on all firm-to-firm transactions in the Dominican Republic and we ask: how is worker mobility affected by the domestic production networks, and what are the roots and implications of such connection?

We document that workers have a strong tendency to move to buyers or suppliers of their employer when they change job. We find that this form of hiring is associated with increases in worker and coworker earnings, longer job match duration, and increases in firm growth. In addition, buyers tend to increase their purchases from suppliers after they hire workers from them. These findings imply that a firm's buyer and supplier network directly impacts its employees' outside options and future labor market outcomes. They also highlight that one of the advantages occurring to firms with more numerous buyers and suppliers is the possibility to access a larger pool of suitable talent. Finally, our study suggests that human capital is highly transferable along the supply-chain, and points towards complementarities between the human capital acquired working at a firm and the inputs produced by that firm.

Our analysis focuses on formal firms between 2012 and 2017 and contains information on 1.6 million workers per year, almost 40 percent of the labor force of the Dominican Republic. We track over 760,000 job-to-job changes in consecutive years.We find that over 19 percent of 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 various random allocation approaches, the share of workers moving to buyers or suppliers ranges only between 7 and 12 percent.

The patterns we document hold broadly across industries and municipalities, and irrespective of whether workers change their industry or municipality when changing jobs. They also hold regardless of the origin firm's size and are not driven by a few large highly-connected firms. Our findings are not driven by any observable assortative matching between firms. For instance, our results cannot by explained by workers moving to firms in nearby municipalities and firms being located near their buyers and suppliers. Nor are our results driven by workers of a certain industry being more likely to move to a specific downstream or upstream industry. Excluding workers moving within the same business group does not affect our findings. Workers also tend to move to buyers or suppliers following mass layoffs, suggesting that our findings are not purely driven by poaching. Our findings are similar when we replicate the analysis at the industry-level, with workers tending 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.

While moves to buyers and suppliers are common, we document important heterogeneity across workers and firms. Conditional on changing firm, workers in the top earnings quintile are three times more likely to move to buyers or suppliers than workers in the bottom earnings quintile. A longer tenure at the firm is also associated with a higher likelihood of moving to a buyer or supplier, conditional on leaving such a firm. Finally, we find that more productive firms are more likely to hire workers from their buyers and suppliers.

Employer-employee matches formed by workers who move to buyers and suppliers tend to be high-quality matches. The average length of worker-firm matches is 18 percent longer for workers who move to buyers or suppliers, relative to other workers who change firm. Also, earnings growth for job changers is roughly 2 percentage points higher the year after they move to a buyer or supplier (and this impact persists for, at least, four years). Specifically, consider two similar workers (e.g., same wage, age, and gender) working at the same firm, and moving in the same year to two different firms of the same size, in the same industry, and in the same municipality. We find that the worker who moves to a firm that was a buyer or supplier of the previous employer earns more (and stays longer in that firm) than the other. Also, given two similar workers who join the same firm at the same year, coming from two different firms operating in the same industry and location, the worker coming from the buyer or supplier earns more and it is likely to stay longer.

We then examine if these high quality matches lead to benefits for their employers as well. We document that a firm which hires from its buyers or suppliers experiences much faster increase in size (measured by sales, inputs, or number of suppliers/buyers) relative to a similar firm that hires the same number of workers (with the same pre-move earnings) from firms which are neither buyers nor suppliers. All in all, these results point to particularly large gains associated with workers moving to buyers or suppliers of their original firms, and that these gains are shared both by the workers and the firms.

What factors explain the frequency and the economic gains associated with these matches? The fact that moves to buyers and suppliers are more common for high-salary workers who remained longer at the firm suggests a potentially important role for human capital.

Employers are not the only ones benefiting from spillovers from new hires. We find that workers experience more rapid earnings growth when a new coworker is hired from a buyer or supplier than when a new coworker is hired from an unconnected firm. This evidence is suggestive of learning from coworkers, as described in Jarosch, Oberfield and Rossi-Hansberg (2019) who similarly find that workers experience larger earnings increases when they have higher earning coworkers. These spillovers to coworkers hold even after controlling for the earnings of the new hires, suggesting that this type of learning may be specific to buyer-supplier relationships. This positive impact on earnings persists even after the coworkers move to another firm, strengthening the case that this is due to learning as opposed to rent-sharing. These findings point to knowledge transfers as an important reason for which firms tend to hire from their buyers and suppliers.

Why would knowledge transfers from buyers and suppliers be particularly important? On the one hand, firms may be looking to acquire some missing know-how in order to in-source part of a production process that was previously outsourced. This may be important in environments with contracting frictions, which tend to be prevalent in emerging markets and developing economies (Startz, 2016; Boehm, 2018; Oberfield and Boehm, 2020). On the other hand, a firm may hire a worker from a buyer or a supplier because they may have specialized knowledge which is complementary with the inputs sourced from that supplier (or products sold to a buyer). That is, if a worker knows 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.

To disentangle these two stories, we study how the share of a firm's inputs from a given supplier changes between 2012 and 2017 if the firm hires workers from that supplier in the intervening years. Under the first explanation, the share of inputs purchased from a supplier should decrease as a buyer hires workers from it and production is in-sourced. Under the second explanation, the share of inputs purchased from a supplier should increase as new workers are hired, given their complementary skills. We find that firms are more likely to continue buying from the supplier and also to increase their spending share on that supplier. Hiring from suppliers does not therefore appear to be (mainly) motivated by the in-sourcing of tasks in the production process. Our evidence suggests instead that the complementary knowledge brought by workers increases the degree of supply-chain integration.

We consider alternative explanations for our findings, in particular the role of information frictions and referrals. Information frictions may lead firms to hire from their buyers or suppliers if managers have more information about these potential employees from having interacted with them in a work environment. This could increase the precision of the signal about worker types and lead to higher match quality. Given the large literature documenting the importance of referrals for alleviating information frictions in hiring processes (Topa, 2011; Brown, Setren and Topa, 2016; Burks, Cowgill, Hoffman and

Housman, 2015; Dustmann, Glitz, Schönberg and Brücker, 2016), lower information frictions between buyers and suppliers might facilitate better matching and explain some of our findings. Yet, information alone is unlikely to explain all the patterns in the data. The literature on referrals shows mixed evidence regarding whether referrals are more prevalent for high-wage (Glitz and Vejlin, 2019) or low-wage (Dustmann et al., 2016) workers, however we document that high earners are far more likely to move to buyers or suppliers than other workers. The results on co-workers learning are also more easily explainable by some knowledge being transferred thanks to the new hires. Furthermore, we find that the gains associated with this form of hiring are persistent (worker earnings) or increasing over time (firm growth), while the gains from the literature on referrals tend to be transitory (Dustmann et al., 2016). Finally, information frictions cannot explain our finding that workers disproportionately move to upstream or downstream industries even after dropping workers who move to immediate buyers or suppliers.

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).[1] 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 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, 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 don't 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

[1] 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 in the use of these clauses vary across countries. In the Dominican Republic, there is no provision that regulates the use of non-compete agreements.

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 (2018) infers the worker's 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, Hyatt, Kahn and McEntarfer, 2018): 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, Kuruscu, Tanaka and Wiczer, 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). Other papers have focused on specific dimensions of social networks such as the presence of ex-co-workers in a firm (Glitz, 2017) as well as family, neighbors, and acquaintances (Eliason, Hensvik, Kramarz and Skans, 2018). More recently, Caldwell and Harmon (2019) study how such networks determine workers' outside options and thus impact their bargaining power. Our paper contributes to this literature 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. Moreover, we document the importance of complementarities between the human capital acquired working at a firm and the input sourced by that firm. This finding is also connected to Beaumont, Hebert and Lyonnet (2019) who argue that firm human capital is a factor shaping firms' merger and acquisition decisions, while we find that it impacts firms' supply decisions.

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, the focus of our paper. Other papers use similar datasets but focus on different questions, including Demir, Fieler, Xu and Yang (2018), 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 2017. During the sample period, the country experienced a period of sustained economic development with an average real GDP growth of 5.3 percent per year, placing it among the fastest growing countries in Latin America. Inflation generally remained within the central bank's target, at 2.8 percent on average.

For the purpose of the analysis, we combine three different types of datasets: firm-level data, firm-to-firm transaction data, and employer-employee data. Our datasets are based on administrative records from the Directorate General of Internal Taxes, the Directorate General of Customs, and the Social Security Treasury.[2]

- Our first dataset contains annual firm-level information for the entire universe of "juridical persons" (i.e. legal entities) between 2012 and 2017. These are firms that registered at the Directorate General of Internal Taxes to obtain their tax identifier. We obtain annual data on revenue, expenditures, assets, and liabilities from tax forms IR1 and IR2, which are used to calculate the personal and corporate income tax owed, respectively. We aggregate monthly value-added within each year from tax form IT1, which is used to calculate value added taxes. From tax form IR3, which is used for tax withholding purposes, we obtain the payroll in each year. The main industry (ISIC 3) and the municipality where the firm is headquartered are also reported.[3]

- Our second dataset contains monthly information on firm-to-firm purchases and sales. This is obtained from tax form 606 (*Formato de Envío de Compras de Bienes y Servicios*) in which firms report their monthly purchases from domestic suppliers. In some cases, however, these suppliers are not juridical persons registered at the Directorate General of Internal Taxes, hence they are part of the informal sector. Yet, the transactions between firms of the formal sector with firms of the informal sector get recorded in the accounts of the former.[4] In the analysis, we restrict the sample to firms registered at the Directorate General of Internal Taxes—that is, firms of the formal sector—that made at least one transaction in a year, and we aggregate all monthly data to the annual level.

[2]The administrative records draw information from several tax forms, which need to be filled out by all 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.

[3]Form IR1 is the *Declaración Jurada de Impuestos sobre la Renta a las Personas Físicas*. Form IR2 is the *Declaración Jurada de Impuestos sobre la Renta a las Personas Jurídicas*. Form IT1 is the *Declaración Jurada de Impuesto a la Transferencia de Bienes y Servicios Industrializados*. Form IR3 is the *Declaraciýón pago de retenciones de asalariados*.

[4]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 purchase 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.

- Our third dataset contains detailed information on employees from the Social Security Treasury. Each month, employers have the obligation to report the wages of all employees to calculate social security contributions and withholding taxes. Employers need to include information about age, gender, and ethnicity of all employees. Employees are then classified in permanent or temporary workers, based on whether they have social security obligations. In our sample, we keep only firms that have at least one permanent employee.

Table 1 provides a helicopter view of the datasets we use in the subsequent analysis. We observe, on average, 35,703 firms during 2012–2017, of which 79 percent were both suppliers and buyers, 3 percent were suppliers only (i.e., not buying domestic inputs), and 18 percent were buyers only (i.e., not selling output to other domestic firms). These firms employed more than 1.6 million workers, or 36 percent of the country's labor force. Almost 1.6 million transaction per year generated sales for over US$27.6 billion (2010 US dollars) during the sample period, corresponding to 40 percent of the country's GDP, with average sales of US$18,000. Between 2012 and 2017, the number of firms increased by 30.3 percent. However, the shares of suppliers and buyers in the total number of firms remained broadly constant. Over the same period, the workforce rose by 21 percent.

Figure 1 plot the geographical distribution of firms and workers in 2017. 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.

As shown in Appendix A1, the production network in the Dominican Republic is concentrated along several dimensions. First, it is characterized by the presence of a few large well connected firms and many other small firms with few connections. To put things in perspective, the average firm in 2017 has marginally more buyers than suppliers (57 against 48), and the distribution of buyers per supplier is considerably more dispersed than the distribution of suppliers per buyer. Both distributions, however, are heavily right-skewed, indicating a large concentration of connections in a few firms. For instance, while the median supplier has 9 buyers, the supplier at the 99th percentile of the distribution has 769 buyers. Similarly, the median buyer has 30 suppliers, and the buyer at the 99th percentile of the distribution has 311 suppliers.

Another way to look at this is to compute the degree of assortativity between buyers and suppliers. A supplier that has many buyers is in general connected with buyers that

Table 1: Dataset Overview

a. *Firms*

Year	Firms	Share of buyers and suppliers	Share of buyers only	Share of suppliers only
2017	39,161	0.79	0.18	0.03
Average 2012–2017	35,703	0.79	0.18	0.03

b. *Workers*

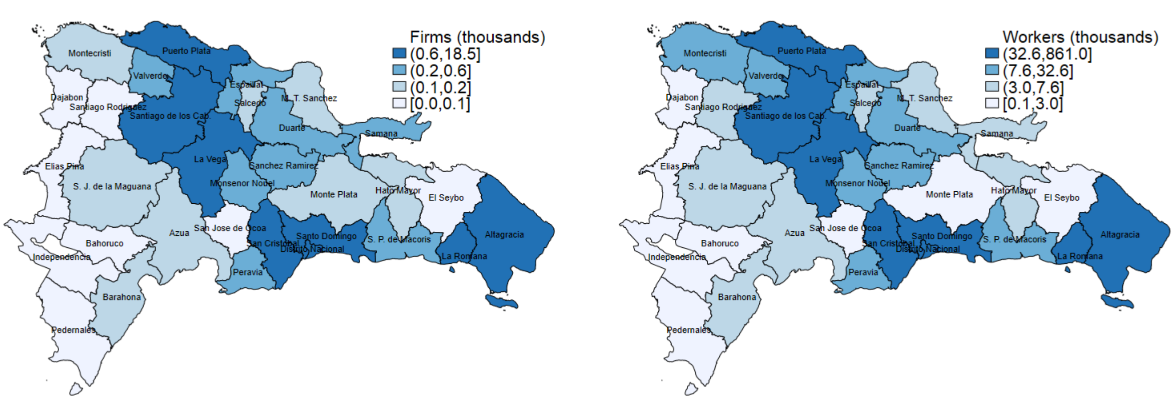
Year	Workers	Share of labor force	Share of permanent workers	Share of temporary workers
2017	1,804,299	0.37	0.62	0.38
Average 2012–2017	1,638,263	0.36	0.61	0.39

c. *Sales*

Year	Sales	Transactions	Sales as share of GDP	Sales per transaction
2017	28,596	1,841,948	0.36	0.016
Average 2012–2017	27,646	1,577,809	0.40	0.018

Notes: Sales are reported in millions of 2010 US dollars.

Figure 1: Distribution of Firms and Workers by Province in 2017



(a) Firms

(b) Workers

are buying only from a few suppliers, indicating a dependence of small buyers on large suppliers. Similarly, when firms have many suppliers, these suppliers sell to only a few buyers, pointing a dependence of small suppliers on large buyers.

Second, data on firms' sales also suggest a large degree of concentration. By 2017, sales reached US$28.6 billion, but one fourth of the firms in the sample sold less than US$10,000 and the top one percent of the firms sold at least US$11.9 million. The firms that have relatively more suppliers and buyers are also the ones selling the most, yet the number of buyers is not relevant for most firms' turnovers, suggesting that there exist few important buyers.

Third, a very large portion of firms has only a few workers and a small number of firms employ a lot of workers. For example, while the average firm in 2017 had 46 employees, 3.8 percent of the firms had one permanent employee, compared with one tenth of 1 percent of the firms with over 2,800 workers. Matching firm-level data with employer-employee data reveals that firms employing many workers are also the ones with many connections in the production network. We therefore check that the patterns documented in the paper are not driven only by these very large and heavily connected firms. Moreover, suppliers that employ more workers tend to sell to buyers that, on average, have a smaller workforce; and the same is true for buyers. These facts point to a dependence of small suppliers on large buyers, and a dependence of small buyers on large suppliers.

Importantly, many of these features are akin to the ones documented for other advanced economies, such as Belgium (Bernard et al., 2019b) and Japan (Bernard et al., 2019a), and emerging markets, like Costa Rica (Alfaro-Urena, Fuentes, Manelici and Vásquez, 2018).[5]

Movers About 10 percent of workers in our database report income from multiple firms in a given year. To track workers mobility across firms, we assign each employee to the employer that paid her the highest wage within a year, though we confirm that our findings hold under alternative assignments. We then classify the worker as a mover if the highest paying employer in a year is different than in the previous year. In any given year, 15 percent of workers drops out of the sample in the following year. This could be because of retirements or unemployment, however it could also occur if a worker moves to an informal firm, given our employer-employee database only covers formal firms.[6]

We observe 766,264 worker moves (between formal firms) between 2012 and 2017. Movers are younger, earn less, and are more likely to be male than non-movers. Specif-

[5] See Annex A1 for more details about similar patterns in these countries.

[6] Therefore, this paper documents the importance of domestic production networks in shaping worker mobility within the formal sector. Workers may also drop out of the sample if they retire or become unemployed.

ically, the mean age for a mover is 31, versus 36 for non-movers. The annual average (median) salary for an employee that is about to change job is about 64 percent (63 percent) higher than the salary of an employee that is staying in the same firm; and this holds even if we condition on the worker's age.[7] Female employees, who account for 36 percent of the observations in our data, have an 87 percent probability of being in the same firm during the following year, against 83 percent for male employees.

3 Workers Mobility Between Buyers and Suppliers

In this section we rely on the previously described datasets to document the importance of the domestic production network in shaping the movements of workers across firms. To do so, we compare the share of workers who move to buyers or suppliers of their original firm with the counterfactual share that we would expect to observe if worker flows were unrelated to the production network.

3.1 Data vs. Random Allocation

Out of the 766,294 workers who moved between firms during 2012–2017, 19.1 percent got hired by firms that were a buyer and/or supplier of their previous employer during the previous year.[8] This is despite the average firm only having a total of 90 buyers and suppliers, out of over 35,703 firms (see Appendix A1). As a point of comparison, 36 percent of workers move to a firm within the same (roughly) 2-digit industry.[9]

To what extent can this high share of moves to buyers and suppliers reflect random matching? To answer this, we construct the share of moves to buyers and suppliers under a random allocation of workers to firms following two approaches (Glitz and Vejlin, 2019; Hellerstein and Neumark, 2008; Carrington and Troske, 1997). In the first approach, we assign all workers who changed job to a random firm in the Dominican Republic. We then measure the share of randomly allocated workers that end up in a buyer or supplier of their previous employer and compare it to the share observed in the data. Randomly assigning workers to any firm in the Dominican Republic, however, ignores that not every worker will be able to work in every industry or move to any location. We therefore also randomly assign each worker to a firm which has the same characteristics as the firm

[7] For instance, a 35 years old worker who is about to move earns, on average, 27 percent less than one of the same age who is staying at the same firm.

[8] Also, 23 percent got hired by firms that were a buyer and/or supplier in either the previous or current year.

[9] There are 42 industries in our classification. The low share of movers who stay within the same industry 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 (2018) for Austrian 2-digit industries.

the worker actually moved to, such as industry, municipality, and size. In our second approach, we first define a firm having a 'job opening' if it hires a worker from another firm. Firms can have multiple job openings under this definition. We then randomly assign all moving workers to job openings.[10] In order to get a closer approximation to a worker's potential labor market, we consider random assignments of workers to job openings which were filled by workers with similar observed characteristics, including age, gender, and previous salary.

With sufficient conditioning variables, every worker would end up randomly assigned to the firm they actually moved to. To avoid this mechanical overfitting, we set a minimum group size for the random allocations of 50 job openings. The total sample size therefore shrinks as conditioning variables are added (our results are not sensitive to this choice).

We repeat the randomization procedure 100 times and measure the average share of workers who are allocated to a buyer or supplier of their previous employer. We construct standard errors for these shares based on the simulation draws. As these are negligibly small (e.g. in the order of 0.03 percentage points), we do not report them. (We also compute standard errors with an alternative bootstrapping procedure. Before each of the 100 iterations, we construct a synthetic sample of movers which are randomly selected–with replacement and keeping sample size constant–from the original sample. We then randomly allocate movers across job openings within this bootstrapped sample. Bootstrapped standard errors for the share of workers that randomly move to a buyer of suppliers are tiny, less than of 0.05 percentage points, and thus left unreported). To quantify the difference between the random allocation and data shares of workers who move to buyers or suppliers, we also report the odds ratio between them. This is the ratio of the odds that a worker moves to a buyer or supplier in the data (probability of moving to a buyer or supplier divided by the probability of not moving to a buyer or supplier) divided by the odds that a worker moves to a buyer or supplier under the random allocation.

We present our results in Table 2. The second row shows that randomly allocating workers to firms implies that 1.9 percent of them move to a buyer or supplier. This share increases to 4.3 percent if we randomly allocate workers to firms in the same industry and municipality as the one they moved to, and increases to 8.9 percent if we additionally condition on the firm size category. This last conditioning variable plays an important role because large firms both tend to hire more and also tend to have many buyers and suppliers. In all cases, the odds ratio is well above one, and is 2.4 in our most conservative scenario.

[10]Our definition of 'job openings' is restricted to new hires who were working in another firm in the previous year; job-to-job transitions. We get very similar results if we define the number of job openings at a firm as being the total number of new hires in a given year.

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

	Unconditional	Conditioning on:			
		Industry and municipality	Industry, municipality, firm size	Industry, municipality, age, gender	Industry, municipality, age, gender, salary
	(1)	(2)	(3)	(4)	(5)
Data	19.1	19.1	19.1	19.1	19.1
Random allocation across firms	1.9	4.3	8.9		
Odds ratio	12.1	5.3	2.4		
Random allocation across job openings	7.1	11.5	12.0	11.8	12.4
Odds ratio	3.1	1.8	1.8	1.8	1.7

Notes: The “Data” row reports the share of workers in the data who move to a buyer or supplier (as a share of workers who change firm). The “Random allocation across firms” row reports the share we obtain if moving workers are randomly assigned to firms. The “Random allocation across job openings” row reports the share we obtain if moving workers are randomly assigned to job openings. We define a firm as having a job opening if it hires a worker from another firm. For each approach to random allocation, we calculate the odds ratio as the ratio of the odds that a worker moves to a buyer or supplier in the data divided by the odds that a worker moves to a buyer or supplier under the random allocation. Column (1) reports the unconditional results; column (2) conditions on industry and municipality, so that workers are randomly assigned to firms in the same industry and municipality as the firm they actually moved to; column (3) also conditions on the firm size; in columns (4), we randomly assign each worker to a job opening in a firm which is in the same industry and municipality as the one the worker moved to, and which was filled by a worker of the same gender and age category; column (5) also conditions on the initial salary quintile. 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.

The fourth row of Table 2 shows that randomly allocating workers to job openings implies that 7.1 percent move to a buyer or supplier. This is much higher than in the random allocation to firms counterfactual, given that it captures the tendency of large firms to hire more and have more buyers and suppliers. This share is equal to 11.5 percent if we randomly allocate workers to job openings in the same industry and municipality as the one they moved to, and increases to 12.0 percent if we additionally condition on the firm size category. A benefit of the random allocation to job openings approach is that it allows us to control for worker characteristics. In the fifth column of Table 2 we show that if we condition on the age and gender of the worker as well as the industry and municipality of the firm, the share of workers who would randomly move to a buyer or supplier is 11.8 percent.[11] Finally, in the sixth column we also condition on the initial salary quintile of the workers, and find that the share of movers to buyers or suppliers increases to 12.4 percent, which is still well below the 19 percent we observe in the data. Even in this last case, the odds ratio is 1.7 and remains significantly greater than 1.

The main conceptual difference between the random allocation to firms and job openings approaches is that the latter fixes the set of vacancies and the characteristics of the worker that will eventually fill them. The former however does not restrict the set of potential employers to firms that actually hired someone. The job openings approach is likely to overstate the share of workers who move to buyers/suppliers under random matching. This is because there are many job openings in the Dominican Republic that likely went unfilled. Given our findings, these seem more likely to be job openings at firms that were not buyers or suppliers of many other firms. Moreover, given the benefits coming from hiring along the production network documented in this paper, it is reasonable to think that vacancies are sometimes opened with the purpose of hiring such a worker, and would not have been opened to hire someone else. On the other hand, the random allocation to firms approach likely understates the share of workers who move to buyers or suppliers under random matching, given there is no weighting by the existence of vacancies which are more likely for larger firms with many buyer and supplier linkages. However, both sets of statistics point towards the fact that the share of workers who move to buyers or suppliers of their previous employer is considerably larger than what would one would observe with random matching. In the remainder of this section we always use our most conservative approach, randomly allocating workers to job openings conditional on industry, municipality, age, gender, and salary quintile.

While our random allocation approach conditions on firm characteristics such as industry, geography, and size, a remaining concern is that assortative matching of pairs of firms on other characteristics could both explain worker movements and buyer/supplier

[11]Age categories are defined as below 25 years old, between 26 and 35, and 36 and above. This partitioning divides the movers into three groups of similar size.

linkages. In Appendix A2 we therefore implement a regression specification at the firm-pair level in which we estimate whether firms which have a supply-chain connection in period $t-1$ are more likely to see workers move between them in period t. This specification allows us to control flexibly for firm-pair characteristics, such as municipality-pairs and firms' size decile-pairs. These results show that firms with supply chain connections are indeed more likely to see workers move between them than otherwise unconnected firms, confirming the results from our random allocation approach.

We also explore whether there is geographic or industry heterogeneity in the share of workers moving to buyers or suppliers. Panel A in Table A13 reports this share separately by industry (that the worker is leaving), along with the random allocation share. For most industries, the share of movers is between 16 and 27 percent, though there are some outliers such as Education (6 percent) or Finance and Insurance (29 percent). In all cases, the share observed in the data is significantly larger than the random allocation share reported in column (2). In Panel B of Table A13 we examine whether there are different patterns for workers who remain in the same industry and municipality, and those who change industry and municipality. We find that similar shares of workers move to buyers or suppliers if they are changing both industry and municipality (18.3 percent) or staying in the same industry and municipality (22.9 percent). Again, the shares observed in the data are significantly higher than the random allocation shares.

3.2 Worker Heterogeneity

While we do not find large differences in worker mobility patterns based on geography or industry, in this subsection we explore which worker characteristics are important in explaining the tendency of workers to move to buyers or suppliers. In particular, we find a striking relationship between a worker's initial salary and the likelihood that they move up or down the supply chain.[12]

We group workers by salary quintile in the year before the move. We report in Table 3 the share of workers in each quintile who move to a buyer or supplier, as well as the random allocation share. We find that the importance of the production network in explaining worker mobility is much more important for workers at the top of the salary distribution than workers at the bottom. Table 3 shows that the share of workers moving to a buyer or supplier is 32.8 percent for workers in the highest salary quintile, almost three times larger than the share for workers in the bottom quintile. This is partly explained by the fact that higher salary workers tend to be in larger firms with more buyers and suppliers, as can be seen by the fact that the random allocation share also increases

[12] While young workers are more likely to change firm than older workers, we do not find that they are relatively more likely to move to buyers or suppliers.

from 7.9 percent in the bottom quintile to 19.1 percent in the top quintile. However, both the difference between the data share and the random allocation share and the odds-ratio are highest for workers in the top salary quintile, suggesting that worker salary is an inherently important characteristic for understanding these patterns of worker mobility.

Table 3: Worker Flows by Salary Quintile

	Salary Quintiles				
	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
Data	11.8	14.8	19.7	27.5	32.8
Random allocation	7.9	8.8	11.5	17.3	19.1
Odds-ratio	1.6	1.8	1.9	1.8	2.1
Number of movers	133,698	184,311	154,619	101,969	80,334

Notes: The probability of a worker moving to a connected firm 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 equivalent in terms of previous industry, municipality, gender, age group, and wage 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 also reports the odds ratios between the two probabilities. We first construct salary quintiles pooling all workers, not just movers. Total worker earnings in the year are used to construct the salary quintiles (the sum across all firms for which they reported positive earnings).

These findings provide some preliminary evidence that the role of the domestic production network in shaping worker flows across firms is related to human capital. An important aspect of worker human capital is on-the-job experience. We can construct a measure of job-specific human capital accumulation by measuring a worker's tenure at the firm. Unfortunately, our six-year panel limits our ability to detect very long matches between employers and employees. To maximize the cross-sectional variation in worker tenure, we focus on workers who changed firm between 2016 and 2017. In order to flexibly control for worker and firm characteristics when examining the role of tenure, we estimate the following equation:

$$TF_{d;o;2016} = {}_{d} + {}_{o} + tenure_{o;w;2016} + X_{d;o;2016} + X_{w;2016} + {}_{w;d;o} \quad (1)$$

where an observation is a worker w who moves to destination firm d from origin firm o. $TF_{d;o;2016}$ is a dummy for whether firm d was a buyer or supplier of o in 2016, and $tenure_{o;w;2016}$ is the observed duration of the match between the worker w and origin firm o, which can be up to five years. $X_{d;o;2016}$ is a set of firm-pair controls, while $X_{w;2016}$ is a set of worker controls.[13]

[13] We group firms in size deciles based on the revenue distribution and the permanent workforce distribution, and we include fixed effects for each pair of deciles. We also include dummy variables for each pair

Table 4: Worker Flows to Buyers/Suppliers and Job Tenure

	(1)	(2)	(3)
Tenure	0.029***	0.017***	0.005***
	(0.004)	(0.004)	(0.001)
Worker controls		X	X
Origin firm FE			X
Destination firm FE			X
Firm pair controls			X
Observations	147,241	147,238	117,307
R^2	0.011	0.037	0.535

Notes: One observation is a worker changing employer between 2016 and 2017. The dependent variable is a dummy equal to one if the mover move to a buyer or supplier of the previous employer. "Tenure" is the number of years for which we observe the mover working for the 2016 employer before moving. Worker level controls include age, gender, and salary quintile in the year before the move. Firm pair controls include fixed effects for each pair of firms' size deciles, each pair of firms' municipalities, each pair of firms' industries, and a dummy variable for whether the two firms have a business group relationship. Standard errors are clustered at the municipality level. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

The results in Table 4 show that workers with a longer tenure at a firm are more likely to move to a buyer and supplier, conditional on moving. The results are robust to the inclusion of worker controls (column 2), such as the initial salary. We find somewhat smaller, though still significant, estimates when we control for origination and destination firm FEs, and for firm-pair controls (column 3). One more year of tenure at a firm increase the probability of moving to a buyer or supplier by 3 percentage points (0.5) excluding (including) controls, approximately 15 percent (2.5 percent) of the baseline probability. This suggest that accumulated firm-specific human capital may be important above and beyond general worker skills and ability. We will return to this interpretation in Section 5 when we explore different explanations for our findings.

3.3 Firm Heterogeneity

What types of firms are more likely to be hiring from buyers and suppliers? We first explore whether firms self-select into different types of hiring, before exploring the importance of firm size.

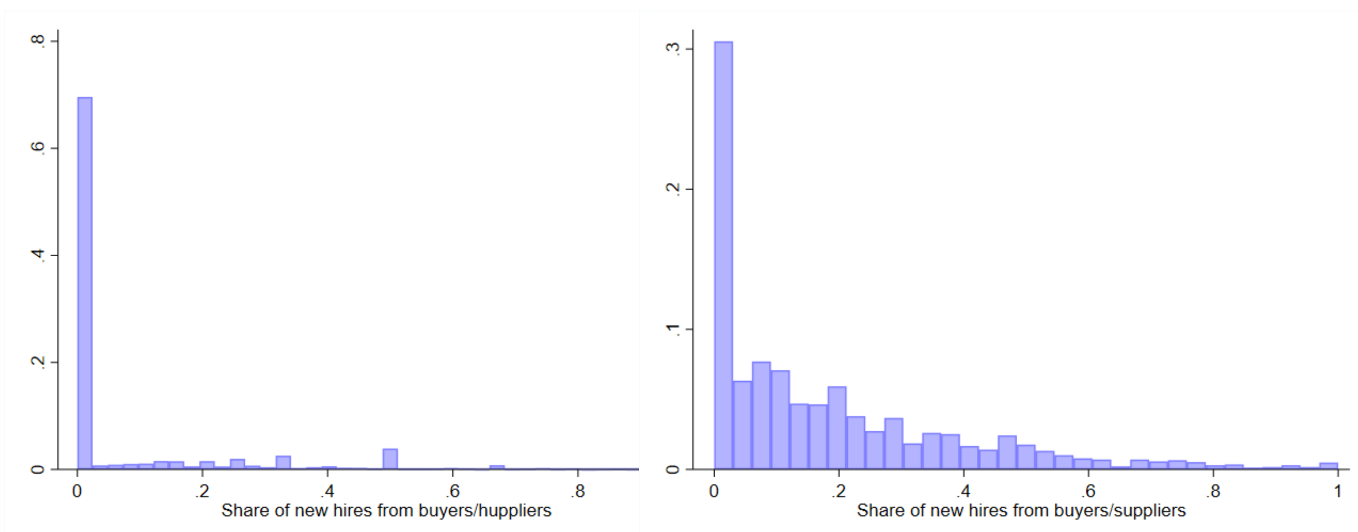
Hiring Patterns An important question is whether firms segment themselves into hiring only from buyers or suppliers compared to also hiring from other firms. Figure 2 plots

of municipalities (to control for the distance between firms), for each pair of industries, and for whether the two firms are part of the same business group. The worker controls include salary, age, and gender.

the distribution of the firm-level shares of new hires coming from buyers or suppliers, with subfigure (a) plotting the shares conditional on the firm hiring at least one worker (from any firm). 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. For larger firms with at least 10 hires, subfigure (b) shows that only 30 percent of firms do not hire from buyers or suppliers at all, while 52 percent of firms hire between 10 percent and 90 percent of workers from buyers or suppliers. It is clear that many firms tend to simultaneously hire both from their buyers and suppliers, and also from other firms. We also examine whether hiring from buyers and suppliers is a persistent habit at the firm-level. We estimate the serial correlation of the share of new hires coming from buyers or suppliers to be 0.24. While there is some persistence, it is relatively low.

Figure 2: Share of New Hires from Buyers and/or Suppliers

(a) 1 Hire (b) 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. The left subfigure (a) includes all firms that hire a worker from another firm, while the right subfigure (b) only includes firms that hire at least 10 workers from other firms.

Firm Size Our first exercise is construct the share of workers moving to buyers or suppliers excluding workers who move to or from 'large' firms, which we define as firms with more than 500 workers. These excluded firms are slightly more than one percent of the total number of firms in our database, but account for 40 percent of worker moves. The results are shown in the first column of Table 5. We find a slightly lower share of workers moving to buyers or suppliers when excluding large firms, 14.4 percent relative to our baseline of 19.1 percent. While the share of workers is slightly smaller than in our baseline, the gap relative to the random allocation is much larger. The random allocation share is much smaller when we exclude large firms, 3.8 percent as opposed to 12.4 percent with the full sample. This lower random allocation share reflects the fact that large firms both hire a lot of workers and have a lot more buyers and suppliers than small firms. Our findings are therefore even more striking when excluding these large firms.

In the remaining columns of Table 5 we do a similar exercise, grouping movers according to the size of their initial employer (measured by the number of permanent employees). The share of workers moving to a buyer or supplier is monotonically increasing in the quintiles of firm size, doubling from 10 to 20 percent when moving from the first to the fifth quintile. As the random allocation share also increases with firm size, the odds ratio declines however. Our findings show that, while workers leaving large firms are much more likely to be hired by buyers or suppliers, the difference relative to random matching is much more important for smaller firms.

Table 5: Worker Flows by Firm Size

	Less than 500 workers	Firm Size Quintiles				
		1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
Data	14.4	8.4	10.6	13.2	14.0	20.4
Random allocation	3.7	1.5	1.8	2.8	3.5	13.2
Odds-ratio	4.4	5.8	6.3	5.3	4.4	1.7
Number of movers	217,606	509	3,090	6,389	25,691	575,392

Notes: The probability of a worker moving to a connected firm 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 equivalent' in terms of previous industry, municipality, gender, age group, and wage 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 overfitting we drop workers that are in groups, defined by their covariates, which count less than 50 workers (results are similar if we do not).

3.4 Other Factors

In this subsection we explore some of the factors which could explain our findings. We start by examining whether workers remain disproportionately likely to move to buyers or suppliers when they get let go following a mass layoff. We then explore whether business group affiliations can explain our findings, before examining the role of social networks through ex-coworkers.

Mass Layoffs Our results so far do not condition on why workers are leaving their initial employer. We focus on employer-to-employer moves, which is consistent with workers being 'poached' by other firms. However, because our time-frame is annual, it is possible that some workers were let go by their original employer, briefly entering unemployment before being rehired by a buyer or supplier. Our findings may have different implications if they only reflect voluntary separations due to suppliers endogenously poaching high match-quality workers, as opposed to hiring out of unemployment following a termination by the initial employer. Because terminations may be due in part to poor individual worker performance, it is important to consider cases of exogenous job destruction. We therefore ask to what extent is this form of hiring still relevant when workers are let go involuntarily due to a firm-level shock?

To answer this question we follow the literature on unemployment scarring, which often focuses 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 re-examine the likelihood of workers being hired by a buyer or supplier of their original firm, but restricting the sample to workers that leave either (a) a firm experiencing a large layoff, defined as a drop in the number of employees of at least 25 workers *and* 30 percent of the original workforce, but that does *not* disappear from our data, or (b) a firm ceasing its activity, that we define as a firm dropping from our employer-employee data.[14]

The results for large layoffs are shown in column (2) of Table 6. The share of workers hired by buyers and suppliers is very similar to the share we see for all movers. 20.3 percent as opposed to 19.5 percent. The random allocation share is also somewhat lower, at 9.7 percent as opposed to 11.8 percent. If we focus on cases of firm closure in column (3), we find even higher data share, with 42.8 percent of workers moving to a buyer or supplier, though the random allocation share is also considerably higher at 27.5 percent. Overall, these findings suggest that hiring by buying and suppliers is not only related to the poaching high-quality workers, but is also relevant in cases of worker termination for exogenous reasons. These findings are particularly noteworthy given that the closure of a firm is likely to be a negative shock to its buyers and suppliers, making them less likely to hire at all.

Business Groups The existing literature has documented that internal labor markets of firms and business groups operate differently (Cestone et al., 2019), and that workers tend to move within a business group following a shock to one of the group's firms (Huneeus et

[14]Regarding the first criterion, most of the literature on mass layoffs considers a firm that contracts by 30% or more as experiencing a mass layoff (Flaaen, Shapiro and Sorkin, 2019). Regarding the second criterion, as we track only firms that have at least one permanent employee, firms dropping from the dataset may not necessarily imply business closures. In fact, a firm can in principle operate with temporary workers only. Also, if a firm changes its tax identifier, we would be categorizing it as a new firm.

Table 6: Factors Explaining Workers Moving to Buyers or Suppliers

	All movers	Large layoffs	Cease to have permanent employees	No moves withing business groups	Excluding former coworkers
	(1)	(2)	(3)	(4)	(5)
Data	19.5	20.3	42.8	17.4	13.1
Random allocation	11.8	9.7	27.5	11.1	7.2
Odds ratio	1.8	2.1	1.6	1.6	1.8
Number of movers	654,931	69,999	16,177	622,321	48,324

Notes: The probability of a worker moving to a connected firm 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 equivalent' in terms of previous industry, municipality, gender, age group, and wage 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); because of this adjustment the sample size declines as the number of controls increases. 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. "Large layoffs" are events in which workers leave a firms that lose at least 25 workers and 30 percent of the original workforce (but that remain in the data). "No moves withing business groups" exclude any worker who move between two firms such that either (a) one firm is among the top 10 shareholders of the other or (b) the two firms have one of their top 10 shareholders in common, or both. "Excluding former coworkers" corresponds to a selection of workers that moved between 2016 and 2017, excluding those that moved to a company that employs or employed previous coworkers.

al., 2018). Since firms of the same business group might also have vertical supply linkages, common ownership could potentially explain our results. We therefore use data on the shareholders of firms, and define two firms as having a 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. Using this definition, we find that 4.6 percent of workers who move go between two firms which have a business group relationship. In column (4) of Table 6 we exclude all these workers and re-estimate the data and random allocation share of workers who move to buyers or suppliers. We find similar numbers to our baseline, with 17.4 percent of movers in the data and 11.1 percent in the random allocation going to buyers or suppliers.

3.5 Input-Output Matrix and Worker Flows

Up until now we have focused on mobility patterns at the worker-level. We conclude this section by examining *industry-level* worker mobility patterns relative to the industry-level input-output connections. Given all pairs of industries n and m (with $m \neq n$), we consider the following linear relationship:

$$ShLeavers_{n \to m;t} = {}_{m} + {}_{n} + {}_{t} + ShTrade_{n;m;t} + {}_{n;m;t} \tag{2}$$

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. We compute the dependent variable in two different ways: either considering all workers or excluding the workers that move to a firm that was a buyer or supplier of their employer in the previous year.

Table 7: Trade and Worker Flows between Industry Pairs

	All workers		Excluding moves to direct buyers/suppliers	
	(1)	(2)	(3)	(4)
Share of sales	0.060**		0.026**	
	(0.028)		(0.013)	
Share of purchases		0.064**		0.043*
		(0.031)		(0.023)
Observations	5,117	4,768	5,117	4,768
R^2	0.707	0.690	0.740	0.725

Note: one observation is defined by a pair of industries and a year. The dependent variable is the share of all the working leaving an industry that move to the other. 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). Industries and year 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.

We present our results in Table 7. As shown in columns (1) and (2), we find a positive and significant correlation between inter-industry worker flows and trade. This correlation is still present, yet significantly weaker, if we exclude workers that move to a direct buyer or supplier of the previous employer. Specifically, the coefficient in column (3) is less than half of the one in column (1), while the one in column (4) is 15 percent smaller than the one in column (2).[15]

These results are important for two reasons. First, the correlation between worker flows and inter-industry trade is much weaker if we exclude those workers that move to direct buyers/suppliers. This reveals that the phenomenon we study in this paper shapes

[15]Since the mean and standard deviation of the alternative dependent variables are very similar, the regression coefficients are directly comparable.

the allocation of workers across industries. That is, the share of workers that moves from one industry to another is larger (or smaller) because of the tendency to move along the supply chain. Second, even excluding moves to direct buyers and suppliers, we still see that worker flows and the trade are correlated, indicating that workers tend to move more across vertically-connected industries. This is consistent with human capital being not only transferable along a specific supply chain; it is also transferable, though to a lesser extent, to firms that operate in upstream and downstream sectors.[16]

4 Worker-Firm Match Quality

In this section, we compare whether matches formed by workers moving upstream or downstream are different than other matches in terms of duration, worker and coworker earnings, and firm productivity growth. Our findings overwhelmingly point towards large economic gains associated with hiring from buyers and suppliers, benefiting both workers and firms.

4.1 Match Duration

We first examine whether workers hired by buyers or suppliers of their previous firm have lower separation rates and longer match duration. Due to the short sample (i.e., 2012–2017), we focus on workers changing firms at the beginning of the sample period (i.e., between 2012 and 2013) and observe for how long they remain at that firm they moved to, with the maximum being five. We find that, on average, worker-firm matches last 2.8 years if the hiring firm was a buyer or a supplier of the previous employer. This is about five months longer than the case in which the hiring firm did not have supply-chain relationship with the previous employer. The probability that a worker who moved between 2012 and 2013 still being at the same firm by 2017 is 29 percent for moves along the supply-chain, and only 21 percent for other moves.

To test whether this gap can be explained by differences in observable characteristics of workers and firms, we estimate the following worker-firm level regression:

$$D_{w;o;d} = \quad_{d} + \quad_{o} + \quad TF_{o;d;2012} + \quad X_{o;d} + \quad X_{w} + \quad_{w;d;o} \tag{3}$$

where w is a worker who was employed by firm o in 2012 and firm d in 2013. $D_{w;o;d}$ is either the duration of the match with firm d in years, or a dummy for whether the worker

[16]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. For instance, see section 4 or Equation 9.

is still employed by d in 2017. $TF_{o;d;2012}$ is a dummy variable indicating whether firm o was a buyer or supplier of firm d in 2012. We also include destination and origin firm fixed effects $_d$ and $_o$, a set of worker level controls (including age, gender, and earnings quintile in 2012), and a set of firm-pair controls. [17]

Table 8 reports the results of the estimation. Column (1), which does not include any controls, shows that a worker moving to a buyer or supplier remains at the firm for an average of 0.31 years (4 months) longer than a worker who does not move along the supply chain. Controlling for worker characteristics in Column (2) reduces this difference to 3 months. In column (3) we additionally control for origin and destination firm fixed effects as well as firm-pair controls. This specification therefore allows for match duration to vary across origin and destination firms, only exploiting variation in job duration rates coming from workers who leave the same firm with some moving to buyers or suppliers, and workers moving to the same firm with some coming from buyer and suppliers. Even in this specification, we find that match duration is still a month longer for workers who move to buyers or suppliers. In columns (4) to (6) of Table 8 we replace the dependent variable with a dummy for whether worker w is still employed at firm d in 2017. With no controls, we find that a worker is 8 percent more likely to remain at the firm if they moved to a buyer or supplier, with this probability decreasing to 2 percent when we include the full set of controls.

Table 8: Match Duration

	Duration in years			Same firm in 2017		
	(1)	(2)	(3)	(4)	(5)	(6)
Supplier/buyer	0.306***	0.246***	0.092***	0.078***	0.064***	0.018***
	(0.018)	(0.017)	(0.011)	(0.005)	(0.005)	(0.005)
Worker controls		X	X		X	X
Origin and destination firm FEs			X			X
Firm pair controls			X			X
Observations	134,413	134,408	104,975	134,413	134,408	104,975
R^2	0.006	0.029	0.342	0.006	0.025	0.311

Notes: The sample consists of workers that changed firm in 2013. The dependent variable in columns (1) to (3) is the duration in years of the match, and in columns (4) to (6) it is a dummy variable indicating whether in 2017 the employee still works for the firm that hired her in 2013. "Trade flow" is a dummy taking value one if the hiring and origin firm traded with each other in 2012. Worker level controls include age, gender, and wage in 2012. Firm pair controls include fixed effects for each pair of firms' size deciles, each pair of firms' municipalities, each pair of firms' industries, and a dummy variable for whether the two firms have a business group relationship. Standard errors are clustered at the municipality level. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

[17] The firm-pair controls include fixed effects for each pair of firms' size deciles, each pair of firms' municipalities, each pair of firms' industries, and a dummy variable for whether the two firms have a business group relationship.

4.2 Worker Earnings

Earnings of Movers We next examine whether workers hired by buyers and suppliers receive higher earnings after the move than workers who move to other firms. On average, earnings growth for movers to buyers/suppliers is 7.2 percent, while it is 8.6 percent for movers to other firms. However, as shown in section 3, workers who move to buyers/suppliers tend to have higher earnings than other movers, and low-salary workers tend to have much faster earnings growth than high-salary workers. We therefore explore this more systematically by estimating the following equation:

$$wage_{w;d;o;t+k} = {}_{d;k} + {}_{o;k} + {}_{k} wage_{w;d;o;t-1} + {}_{k} SB_{d;o;t-1} + {}_{k} X_{d;o;t-1} + {}_{k} X_{w;t-1} + {}_{w;d;o;t;k} \quad (4)$$

We restrict the sample to workers w who moved from origin firm o to destination firm d between $t-1$ and t. $wage_{w;d;o;t}$ denotes worker w's total earnings (in logs) in year t.[18] $SB_{d;o;t-1}$ indicates whether o was a supplier or buyer of d in year $t-1$. The firm-pair and worker controls $X_{d;o;t-1}$ and $X_{w;t-1}$ are the same as in equation (3). k ranges from 0 to 4 and determines the time horizon over which we evaluate the increase in worker earnings relative to $t-1$

Table 9 reports our results for worker earnings one year after the move (columns [1] to [3]) and four years after the move (columns [4] to [6]). Columns (1) only controls for lagged worker earnings and year fixed effects. We find that workers who move to buyers and suppliers have 17.6 percent higher earnings after one year relative to other movers, and still have 13.6 percent higher earnings after four years. Controlling for additional worker characteristics such as age and gender do not change this much, as shown in columns (2) and (5). However, these results may be confounded by the fact that higher-paying firms may be precisely those that hire from their buyers and suppliers. In columns (3) and (6) we therefore report our results with both origin and destination firm fixed effects, as well as additional firm-pair controls. We can therefore think of these estimates as capturing the earnings differential between two workers who move to the same firm, one from a buyer/supplier and the other from another firm. We still find that workers moving from buyers or suppliers have 2.2 percent higher earnings after one year, and 1.6 percent higher earnings after four years.

Figure 3 plots our estimates of this earning differential from the year of the move to four years after the move, using our full set of controls. We see that movers from buyers and suppliers experience particularly high earnings growth in the first year of the move (relative to other movers). Three quarters of this difference disappears a year after the move, though the remaining quarter persists up to at least four years. The higher ini-

[18] We use the total earnings in a year from all employers.

tial earnings gap is consistent with *uncertainty* about these workers' match quality being lower when hired, as described in Dustmann et al. (2016). Lower uncertainty enables workers to bargain for initially higher earnings, while other new hires earn less initially but experience faster earnings growth after the move as uncertainty about match quality gets resolved. However, the persistence of the earnings difference beyond four years suggests that this is unlikely to be solely a matter of uncertainty about match quality, but rather that workers hired from buyers and suppliers do have higher average match quality than other new hires.

Table 9: Worker Earnings Growth

	Earnings in $t+1$			Earnings in $t+4$		
	(1)	(2)	(3)	(4)	(5)	(6)
Earnings in t 1	0.385***	0.351***	0.273***	0.362***	0.339***	0.269***
	(0.017)	(0.035)	(0.025)	(0.021)	(0.019)	(0.006)
Supplier/buyer in t 1	0.170***	0.150***	0.023***	0.127***	0.106***	0.015**
	(0.015)	(0.013)	(0.007)	(0.021)	(0.019)	(0.006)
Worker controls		X	X		X	X
Origin and destination firm FEs			X			X
Firm pair controls			X			X
Observations	507,140	507,140	507,140	80,683	80,683	80,683
R^2	0.221	0.264	0.452	0.187	0.243	0.449

Notes: The dependent variable is ln(worker earnings) in $t+1$ or $t+4$. "Supplier/Buyer" is a dummy taking value one if the hiring firm was a buyer or supplier of the origin firm in the year before a worker move. Worker level controls include age, gender, and ln(earnings) in the year before the move. Firm pair controls include fixed effects for each pair of firms' size deciles, each pair of firms' municipalities, each pair of firms' industries, and a dummy variable for whether the two firms have a business group relationship. Standard errors are clustered at the municipality level. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

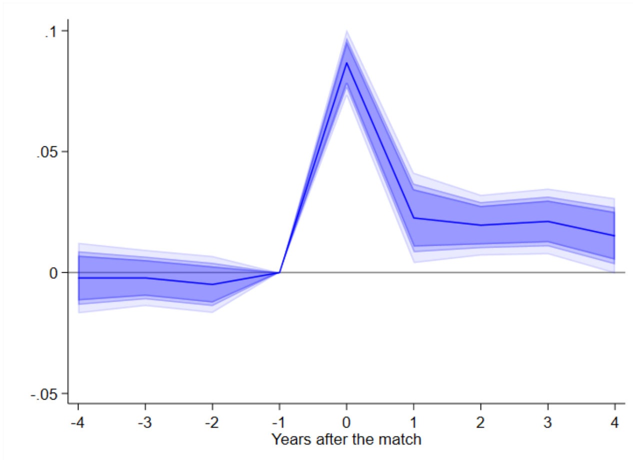
507,140 507,140 507,140 80,683 80,683 80,683

Earnings of Coworkers Jarosch et al. (2019) provide evidence that people working in teams learn from each other (in particular, workers learn from their high-wage coworkers) and that a competitive labor market would price this coworker learning, resulting in higher wages. Given our previous results, an important question is whether coworkers also benefit more when the firm hires new workers from buyers or suppliers. We explore this by examining if the earnings of a new employee's coworkers increase more if the new employee was hired from a buyer or supplier as opposed to another unconnected firm. We estimate the following specification:

$$wage_{w;i;t+k} = \quad + \quad wage_{w;t} + \quad H_{i;t} + \quad HSB_{i;t} + \quad X_{w;t} + \quad X_{i;t} \quad {}_{w;t} \tag{5}$$

where $wage_{w;i;t+k}$ is the log of the earnings of worker w in firm i at time $t+k$, with 1

Figure 3: Worker Earnings After Being Hired from a Buyer/Supplier



Notes: The line denotes the point estimate of the increase in wages between T and $T + k$ relative to T 1 for workers that moved to a buyer or supplier of their previous employers in T 1. The shaded area denotes the 90 percent confidence interval computed with standard errors clustered at the municipality level.

k 3. $H_{i;t}$ is a dummy variable that takes value one if firm i hired a worker in period t, and $HSB_{i;t}$ is a dummy variable that takes value one if firm i hired a worker from any of its buyers or suppliers in period t. We also control for the interaction of industry and year fixed effects, worker characteristics ($X_{w;t}$) such as gender and age deciles, and firm characteristics ($X_{i;t}$) such as employment growth and average wages.

The coefficients of interest are , which denotes the earnings increase when the hire is not from a buyer or supplier, and , which captures the additional earnings increase when the new hire is from a buyer or supplier. The sample is restricted to relatively small firms (with at most 100 workers following Jarosch et al. (2019)) to ensure that coworkers are actually working in teams and may plausibly learn from each other.

Table 10 presents our baseline results. These control for worker characteristics but not firm characteristics. Column (1) shows that earnings growth for employees of firms that hired new workers is 2.7 percent higher than the earnings of employees at firms that did not hire new employees. When the new hire is from a buyer or a supplier, the earnings increase is as large as 8.3 percent, or 5.6 percent more compared to firms that hired from outside the production network. This earnings differential between coworkers of new hires from buyers and suppliers and coworkers of new hires from other firms persists over the following two years and gets larger as time goes by, as shown in columns (2) and (3), likely reflecting the time needed for coworkers to learn and improve their performance. Specifically, coworkers earnings are 6 percent higher two years after the hiring and 7.7 percent higher three years after it. While these magnitudes are large, this is roughly half the size of the earnings growth for movers that we estimated in columns (2) and (5) from Table 9.[19]

Table 10: Hiring and Coworker Learning

	Earnings (All coworkers)			Earnings (Coworkers who moved)		
	1 year	2 years	3 years	1 year	2 years	3 years
	(1)	(2)	(3)	(4)	(5)	(6)
Earnings (year of new hire)	0.657***	0.582***	0.527***	0.478***	0.390***	0.357***
	(0.016)	(0.019)	(0.020)	(0.019)	(0.021)	(0.021)
New hire	0.037***	0.063***	0.052***	-0.043***	-0.036***	-0.043***
	(0.003)	(0.004)	(0.005)	(0.009)	(0.010)	(0.009)
New hire from buyer or supplier	0.048***	0.059***	0.063***	0.072***	0.082***	0.090***
	(0.005)	(0.008)	(0.013)	(0.007)	(0.011)	(0.016)
Observations	1,353,978	875,532	522,874	229,960	262,466	201,284
R^2	0.457	0.367	0.319	0.260	0.173	0.154

Notes: The dependent variable is the log of worker's wage in period $t+h$. "New hire" is a dummy variable that takes value one when the firm of the worker hires somebody; "new hire from buyer or supplier" is a dummy variable that takes value one when the firm of the worker hires somebody from any of its buyers or suppliers. In columns (4) to (6), the sample is restricted to workers who left their firm between year t (when new workers were hired) and year $t+k$. All specifications include a dummy variable for gender, age deciles, and industry-year fixed effects. Standard errors are clustered at the municipality level. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Our results are robust to a number of additional controls. Table A14 reports our results when we control for various firm characteristics, including employment growth between period t and $t+k$, and the average wage of coworkers (excluding new hires). Given that Jarosch et al. (2019) find that learning is particularly strong from high-wage coworkers, a confounding factor could be the fact that workers hired from buyers or suppliers have higher salaries than other new hires. However we show in columns (4) to (6) of Table A14 that our results remain after controlling for the average wage of new hires. Finally, in unreported results we also find that replacing the log of earnings with the growth rate of earnings as the dependent variable does not affect our findings.

Another concern is that our findings do not reflect learning from coworkers, but rather rent-sharing between workers and firms following a positive firm-level shock (Guiso, Pistaferri and Schivardi, 2005). This is particularly relevant as hiring along the production network is associated with sizeable productivity gains (subsection 4.4). This should not be relevant (or, be less relevant) for workers who later leave the firm however (job switchers). In columns (4) to (6) we therefore restrict our sample to job switchers, who were in firm i

[19]Note that the appropriate comparison is the specification without origin and destination firm fixed effects, as we can't control for these in our coworker regressions.

when new workers were hired in period t, but left the firm by period $t+k$. For this sample of workers we find that earnings tend to *decrease* if they switch following new hires by their firm, but *increase* if their firm hired new workers from buyers or suppliers. These results show that the benefits are incurred by the workers and are valued outside the firm, suggesting that they are due to learning from new hires rather than simply rent-sharing.

4.3 Hiring of buyers and suppliers and probability of moving

Moving to buyers and suppliers lead to substantial benefits for workers, and in fact workers tend to move to such firms more than other similar ones. These statements are all conditional on workers leaving their current employer. Are also workers more likely to leave their current job and find another when the possibility of moving to buyers and suppliers is higher?

To investigate the impact of hiring from buyers and suppliers on the probability of moving we calculate, for each employer, the average growth of the workforce of their buyers and suppliers (we take the average of buyers and suppliers separately and the average between the two) between year T and $T+1$ (buyers and suppliers are identified at year T). We then focus on permanent workers in our data in year T and $T+1$ and regress a dummy indicating whether the employer at time T is different than the one in year $T+1$ on the growth of buyers and suppliers. We therefore estimate the linear equation:

$$moving_{w;t+1} = \quad growthBuyerSupplier_{w;t;t+1} + \quad X_{w;t} + \quad {}_{w;t} \tag{6}$$

where the set of controls include ... . Results are presented in Table X. There is no statistically significant correlation between suppliers and buyers growth and probability of a worker changing firm. This may appear as a contradiction with early results. However, positive shocks of buyers and suppliers are correlated with positive shock of a worker's own employer. We therefore augment the specification by adding controls for the current employer's growth. The coefficient of buyers and suppliers growth become positive.

These results are consistent with hiring from buyers and suppliers improving workers' outside options. Workers are not more likely to move in general when such outside option improve as also their firm do better at the same time and workers are likely to benefit from positive shocks to their employers (Guiso et al., 2005). (In fact, in unreported results we also find that a worker wage increase when their firms' buyers and suppliers growth. Other unreported results confirm that, conditional on moving, workers are, unsurprisingly, more likely to move to buyers or suppliers than other firms if buyers and suppliers' workforce is growing.)

4.4 Firm Growth

[This section is still Work In Progress]

The previous subsection documented that workers experience wage increases when they are hired by a buyer or supplier, or when a new coworker is hired from a buyer or supplier. In this subsection we examine whether there are comparable gains for firms that hire a larger share of their workforce from buyers or suppliers. To do this we estimate the following firm-level regression:

$$y_{i;t+k} = \;_k y_{i;t} + \;_k H_{i;t} + \;_k HSB_{i;t} + \;_k X_{i;t \;\; 1} + \;_{i;t;k} \tag{7}$$

where $y_{i;t+k}$ is firm i's log sales in year $t+k$, with $k = 1; :::; 4$; $H_{i;t}$ is the total number of firm i's new hires between year $t \;\; 1$ and t, normalized by firm i's employment in year $t \;\; 1$; $HSB_{i;t}$ is the number of firm i's new hires from buyers or suppliers between year $t \;\; 1$ and t, also normalized by firm i's employment in year $t \;\; 1$.[20] We include industry, municipality, and year fixed effects and we also control for contemporaneous and lagged firm productivity, for the average wage of new hires, and for a set of other firm-level controls ($X_{i;t \;\; 1}$): sales, employment, and average wage (in logs). We don't include firm fixed effects as this may lead to a substantial bias given the relatively short panel (Nickell, 1981). We restrict the sample to firms that hired at least one worker from another firm between year $t \;\; 1$ and t.

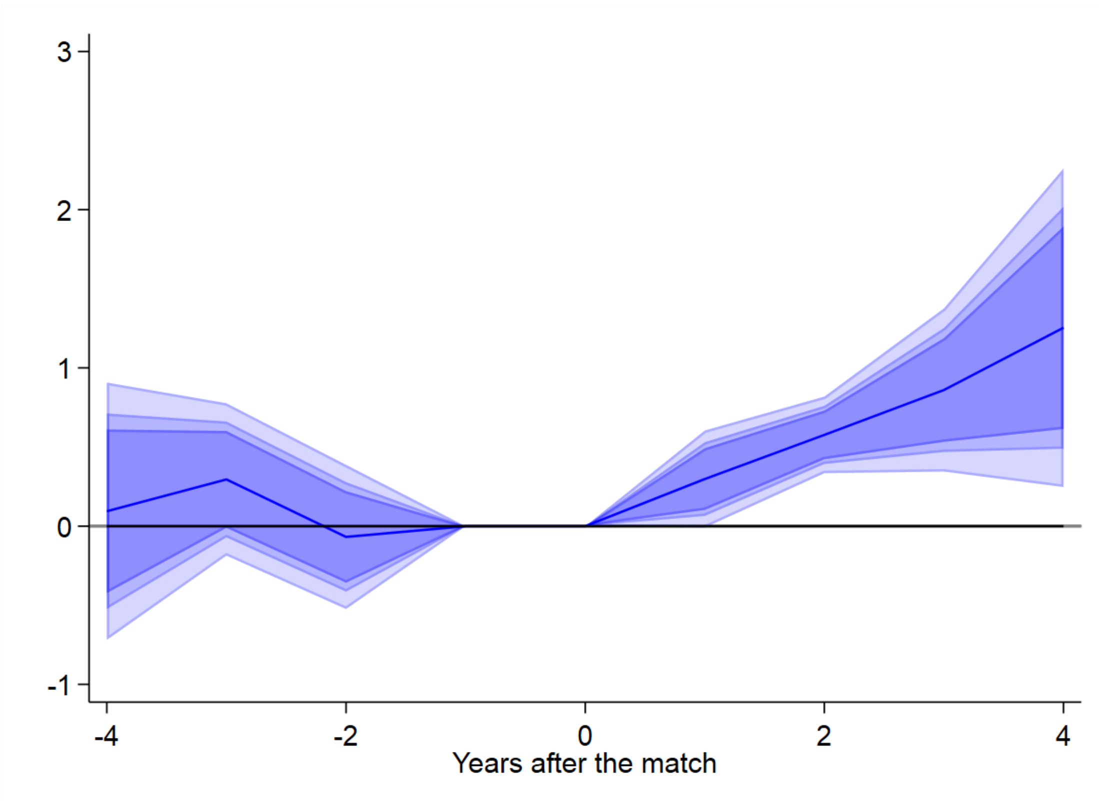
autoreffig:sales shows the estimates of the parameters $\;_k$, together with confidence intervals. The results show that firms that hire more workers from their buyers and suppliers experience a significant increase in size, which becomes larger over time. The magnitudes we estimate are sizeable. Similar results are found focusing on inputs or number of buyers/suppliers.

5 Possible Explanations

The propensity of workers to move to buyers and suppliers of their original firm, and the associated earnings and productivity increases which follow are robust features of the data we analyze. While social networks and referrals likely play some role in explaining these findings, we contend that hiring from buyers and suppliers may be a method to acquire human capital that is particularly valuable to the firm, and that there may be

[20] For instance, if a firm with 100 workers in year $t \;\; 1$ hires 10 workers, five of which from buyers and suppliers, then $H_{i;t \;\; 1} = 0{:}1$ and $HSB_{i;t \;\; 1} = 0{:}05$. Both variables are winsorized at the top 1 percent, while firm productivity is winsorized at the bottom and top 0.5 percent (the distributions of these variables are plotted in **??**). For our baseline results we weight observations by firm employment, though we report similar unweighted regression results in **??**.

Figure 4: Sales after hiring from buyers or suppliers



Notes: The line denotes the point estimate of a regression of log sales on the number of workers hired from a buyer or a supplier, normalized by the size of the previous year workforce. The full set of controls and fixed effects are used. The shaded areas denote the 90, 95, and 99 percent confidence intervals computed with standard errors clustered at the municipality level.

complementarities between this human capital and the inputs purchased from suppliers. In this section we document some additional facts supportive of this hypothesis.

5.1 Information Frictions or Human Capital?

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. This could be because managers are more easily able to acquire information about these potential employees, reducing the noisiness of the signal about worker types. It could also be because workers are more easily able to get referrals if they form social networks with workers in the buyers or suppliers of their current employer. Such 'buyer/supplier' labor markets having lower information frictions could also explain the longer job duration and higher wage premium earned by workers hired through this market (Dustmann et al., 2016). Given the large literature documenting the importance of referrals for alleviating information frictions in hiring processes (Brown et al., 2016; Burks et al., 2015; Dustmann et al., 2016; Glitz, 2017), it seems likely that such frictions explain in part why workers tend to get hired by buyers and suppliers.

Nonetheless, we document several data patterns which are difficult to explain with information frictions and social networks alone. For instance, if hiring through buyers and suppliers only reduces the *uncertainty* about the match quality of workers, we should expect the earnings increase of workers to be temporary (Dustmann et al., 2016). However, we find instead in subsection 3.2 that a sizeable share of the earnings premium associated with moving to buyers or suppliers is persistent over time, suggesting that workers hired from buyers and suppliers also have higher *expected* match quality. Similarly, in subsection 4.4 we document large firm productivity gains which are not only persistent but peak a few years after the hiring.

Two other patterns point towards an important role for knowledge spillovers rather than simple social connections. Firstly, we document in subsection 4.4 that the productivity gains associated with hiring from buyers and suppliers are stronger the more productive are the previous employers. This suggests that there are particularly strong productivity spillovers from hiring from buyers and suppliers, even relative to other high-productivity firms. Secondly, in subsection 3.2 we find that coworkers of new hires from buyers and suppliers also experience substantial earnings growth, even conditional on the earnings of the new workers. While this is consistent with workers bringing with them supply-chain specific human capital which spills over to coworkers, it is more difficult to rationalize as purely being driven by social networks reducing information frictions.

Finally, in subsection 3.5 we document that workers tend to move along more vertically-connected industries even when they do not move to a direct buyer or supplier of their previous employer. These moves are less likely to be due to social networks given that the previous and current employers are not directly linked. The next sub-section presents additional evidence that worker human capital may be supply-chain specific, and that there may be complementarities between hiring a worker from a firm and purchasing inputs from that firm.

5.2 Complementarities Between Inputs and Human Capital

A reason for hiring a worker from a supplier could be to acquire useful know-how in order to insource a larger share of the task that was previously outsourced. If this was an important factor, we might expect sales and purchase shares between firms to decline after workers move between them. On the other hand, workers hired from buyers/suppliers may bring supply-chain-specific human capital with them, which is complementary with the inputs purchased from the supplier. This would imply that sales/purchase shares would be expected to increase after workers move between buyers and suppliers. We explore this by estimating the following equation:

$$TF_{s\,!\,b;2017} = {}_{s} + {}_{b} + WF_{s\,!\,b;(2012to2017)} + X_{s;b} + {}_{s;b} \tag{8}$$

where an observation is a pair of firms where firm s was a supplier of firm b in 2012. The dependent variable $TF_{s\,!\,b;2017}$ is, alternatively, i) a dummy variable equal to one if b is still a buyer of s in 2017, ii) the growth of the share of purchases made by firm b from s between 2012 and 2017, or iii) the growth of the share of sales of firm s that is purchased by b between 2012 and 2017.[21] $WF_{s\,!\,b;(2012to2017)}$ is a dummy variable equal to one if we observe any worker moving from the supplier to the buyer between 2012 and 2017. ${}_{s}$ and ${}_{b}$ are firm fixed effects and $X_{i;j}$ is a set of firm-pair controls.[22] These controls aim to capture firm-specific heterogeneity (e.g., differential growth in sales or workforce over time), assortative matching between different types of firms, and the initial importance of each firm as a buyer/supplier for the other. We only include firms that are not not part of the same business group and such that the two firms still have buyers, suppliers, and permanent employees in 2017.

We present our results in Table 11. Column (1) shows that firms which hired from their supplier between 2012 and 2017 had a 2.7 percentage point higher probability of

[21] Growth rates are calculated as the change in the share divided by the average share, following Davis, Haltiwanger and Schuh (1996). This therefore varies between -2 and 2 and can accommodate zeroes. Results are similar if we use the difference in levels between the share of purchases/sales made in 2017 relative to 2012.

[22] As in the rest of the paper, these include the cross-product of dummy variables for each firm's location, industry, and decile of size, the ln(sales) value between the firms in 2012, the share of b's 2012 purchases made from firm s, and the share of s's 2012 sales sold to firm b.

still buying from that supplier in 2017. This is about 5 percent of the average probability that b was still a buyer of s in 2017 (46 percent). Column (2) shows that the share of b's purchases from s also increases by 12 percent if b hires from s, which is roughly a tenth of the standard deviation of the growth rate of purchase shares. This last result is not driven by extensive margin adjustments to buyer/supplier linkages. In column (3) we restrict the sample to firm-pairs where b purchased from s in both 2012 and 2017, and find that the share of purchases from the supplier increases also if workers were hired from supplier s. To summarize, buyers are more likely to continue purchasing from those suppliers from which they hire workers and, if they do, they purchase a larger share of their inputs from them. Similar results hold if we examine the share of supplier's sales going towards the buyer. While we focused so far on buyers purchasing from suppliers and workers moving from suppliers to buyers, we also find the same pattern in the reverse direction. Suppliers are more likely to continue selling to buyers in 2017, and also sell a larger share of their output to buyers, if they hired workers from the buyer between 2012 and 2017. These results are shown in section A3, where we also present further robustness checks for our findings in Table 11.

Table 11: Buyer/Supplier Linkages in 2017 and Worker Movements 2012 to 2017

	Any trade	Share of purchase		Share of sales	
	(1)	(2)	(3)	(4)	(5)
Worker flow	0.027***	0.123***	0.111***	0.134***	0.112***
	(0.003)	(0.014)	(0.014)	(0.014)	(0.0151)
Purchases > 0 in 2017			X		X
Observations	976,727	976,727	458,165	976,727	458,165
R^2	0.344	0.265	0.389	0.246	0.376

Notes: The sample consists of firm pairs that traded in 2012. Firm b was the buyer and firm s was the supplier in 2012. The dependent variable in columns (1) is a dummy variable for whether firm b makes any purchase from firm s in 2017, in columns (2) and (3) it is the difference growth of the share of purchase made by firm b from firm s between 2012 and 2017, and in columns (4) and (5) it is the growth of the share of sales of firm s that is purchased by b between 2012 and 2017. "Worker flow" is a dummy taking value one if any worker moves from the supplier to the buyer between 2012 and 2017. All regression include buyer fixed effects and supplier fixed effects; and firm-pair controls, which are the cross-product of dummy variables for each firm's location, industry, and decile of size, the amount of trade in 2012, the share of b's 2012 purchase from firm s, and the share of s's 2012 sales sold to firm b. Firm pairs are excluded if in any year the two firms had any business relationship defined as either of the firm being among the top 10 shareholders of the other, or having any of the top 10 shareholders in common. Standard errors are clustered at the municipality level. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Our results suggest that, by and large, the main reason for hiring a worker from a connected firm is not to insource tasks that the buyer was previously outsourcing to a supplier. Rather, the increase in purchases and sales between firms following worker moves is consistent with the hypothesis that there are complementarities in human capital along the firms' production network. That is, the knowledge accumulated by workers about how to produce a good may also be useful knowledge for firms that purchase that good as an intermediate input. However, an alternative possibility is that purchase shares between buyers and suppliers increase over time because of the social ties between the two firms. For example, managers may be more favorable towards buying more from a supplier if they have workers in their firm who can vouch for the reliability of the supplier. While we cannot test for this directly, in light of our previous results on firm productivity improvements in subsection 4.4, we evaluate whether firm productivity tends to improve more when workers are hired from buyers and suppliers *and* the purchases/sales share between the two firms increases. We detail our empirical specification and report results in section A3. We find that buyers that both hire from suppliers *and* increase their spending share on inputs from those suppliers also experience larger productivity gains. This provides more suggestive evidence that human capital complementarities, as opposed to social networks, may be explaining the data patterns we document.

6 Conclusion

In this paper we use a unique dataset on the universe of permanent formal employer-employee relationships in the Dominican Republic, together with data on firm-to-firm transaction to document a novel fact: workers tend to disproportionately move to the buyer or the supplier of their previous employer when they change jobs. This result is robust to restricting the sample to workers that move within the same industry and/or the same municipality. It is common in large as well as smaller firms, in all industries, and it also present for workers leaving firms that experienced large layoffs.

We find that being hired from a firm that has a trade relationship with the previous employer is associated with lower separation rates and higher wage growth. Hiring workers from trading partners is also important for firms, as it is associated with higher productivity growth. We interpret these results as evidence of a relatively higher match quality compared to matches that take place between unconnected firms.

Firms and workers appear to learn relatively more when hiring from connected firms, suggesting a crucial role for knowledge transfers. Specifically, we find that the probability of moving to connected firms is larger for higher wage workers. Also, firms' productivity increases more when they hire workers from buyers or suppliers. Finally, hiring from buyers and suppliers is also associated with faster wage growth for the new coworkers.

Finally, connected firms tend to strengthen their commercial relationship when a supplier's employee is hired by the buyer. This provides evidence against the hypothesis that hiring from a connected firm is mainly a way to insource certain tasks. This finding, instead, suggests that the complementarity between human capital and inputs along the production networks plays a role in explaining the large knowledge transfers we observe.

References

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

Alfaro-Urena, Alonso, Isabela Manelici, and José P Vásquez, "The Effects of Joining Multinational Supply Chains: New Evidence from Firm-to-Firm Linkages," 2019. Available at SSRN 3376129.

—, —, and Jose P Vasquez, "The Effects of Multinationals on Workers: Evidence from Costa Rica," 2019. Working Paper, Department of Economics, UC Berkeley.

—, Mariany Fuentes Fuentes, Isabela Manelici, and José P Vásquez, "Costa Rican Production Network: Stylized Facts," 2018. Documento de Investigación N. 002.

Autor, David H, David Dorn, Gordon H Hanson, and Jae Song, "Trade adjustment: Worker-level evidence," *The Quarterly Journal of Economics*, 2014, *129* (4), 1799–1860.

Beaumont, Paul, Camille Hebert, and Victor Lyonnet, "Build or buy? Human capital and corporate diversification," *Fisher College of Business Working Paper*, 2019, (2019-03), 018.

Becker, Gary S, "Investment in human capital: A theoretical analysis," *Journal of political economy*, 1962, *70* (5, Part 2), 9–49.

Bernard, Andrew B, Andreas Moxnes, and Yukiko U Saito, "Production Networks, Geography, and Firm Performance," *Journal of Political Economy*, 2019, *127* (2), 639–688.

—, Emmanuel Dhyne, Glenn Magerman, Kalina Manova, and Andreas Moxnes, "The Origins of Firm Heterogeneity: A Production Network Approach," 2019. National Bureau of Economic Research Working Paper No. 25441.

Bjelland, Melissa, Bruce Fallick, John Haltiwanger, and Erika McEntarfer, "Employer-to-Employer Flows in the United States: Estimates Using Linked Employer-Employee Data," *Journal of Business and Economic Statistics*, 2011, *29* (4), 493–505.

Boehm, Johannes, "The impact of Contract Enforcement Costs on Value Chains and Aggregate Productivity," 2018. Sciences Po Economics Discussion Paper 12.

Brown, Meta, Elizabeth Setren, and Giorgio Topa, "Do Informal Referrals Lead to Better Matches? Evidence from a Firm's Employee Referral System," *Journal of Labor Economics*, 2016, *34*, 161–209.

Burks, Steven V., Bo Cowgill, Mitchell Hoffman, and Michael Housman, "The Value of Hiring through Employee Referrals," *Quarterly Journal of Economics*, 2015, *130* (2), 805–839.

Caldwell, Sydnee and Nikolaj Harmon, "Outside options, bargaining, and wages: Evidence from coworker networks," *Unpublished manuscript, Univ. Copenhagen*, 2019.

Carrington, William J. and Kenneth R. Troske, “On Measuring Segregation in Samples with Small Units,” *Journal of Business Economic Statistics*, 1997, *15*, 402–409.

Cestone, Gacinta, Chiara Fumagalli, Francis Kramarz, and Giovanni Pica, “Insurance Between Firms: the Role of Internal Labor Markets,” 2019. BAFFI CAREFIN Centre Research Paper 2014-162.

Davis, Steven J and Till M Von Wachter, “Recessions and the Cost of Job Loss,” 2011. National Bureau of Economic Research No. 17638.

_ , John Haltiwanger, and Scott Schuh, “Small Business and Job Creation: Dissecting the Myth and Reassessing the Facts,” *Small Business Economics*, 1996, *8* (4), 297–315.

Demir, Banu, Ana Cecılia Fieler, Daniel Yi Xu, and Kelly Kaili Yang, “O-Ring Production Networks,” Technical Report 2018. Unpublished manuscript.

Dix-Carneiro, Rafael, “Trade liberalization and labor market dynamics,” *Econometrica*, 2014, *82* (3), 825–885.

Dustmann, Christian, Albrecht Glitz, Uta Schönberg, and Herbert Brücker, “Referral-Based Job Search Networks,” *Review of Economic Studies*, 2016, *83*, 514–546.

Eliason, Marcus, Lena Hensvik, Francis Kramarz, and Oskar Nordstrom Skans, “The Causal Impact of Social Connections on Firms’ Outcomes,” 2018. Centre for Economic Policy Research, Discussion Paper No. DP12135.

Fajgelbaum, Pablo D, “Labour market frictions, firm growth, and international trade,” *The Review of Economic Studies*, 2020, *87* (3), 1213–1260.

Farhi, Emmanuel and David Rezza Baqaee, “Supply and Demand in Disaggregated Keynesian Economies with an Application to the Covid-19 Crisis,” 2020.

Flaaen, Aaron, Matthew Shapiro, and Isaac Sorkin, “Reconsidering the Consequences of Worker Displacements: Firm versus Worker Perspective,” *American Economic Journal: Macroeconomics*, 2019, *11* (2), 193–227.

Gathmann, Christina and Uta Schönberg, “How general is human capital? A task-based approach,” *Journal of Labor Economics*, 2010, *28* (1), 1–49.

Gibbons, Robert and Lawrence F Katz, “Layoffs and Lemons,” *Journal of Labor Economics*, 1991, *9* (4), 351–380.

_ and Michael Waldman, “Task-specific human capital,” *American Economic Review*, 2004, *94* (2), 203–207.

Giupponi, Giulia and Camille Landais, "Subsidizing labor hoarding in recessions: The employment & welfare effects of Short Time Work," 2020.

Glitz, Albrecht, "Coworker Networks in the Labor Market," *Journal of Labor Economics*, 2017, *44*, 218–230.

— and Rune Vejlin, "Learning Through Coworker Referrals," 2019. IZA Discussion Paper No. 12270.

Guiso, Luigi, Luigi Pistaferri, and Fabiano Schivardi, "Insurance within the firm," *Journal of Political Economy*, 2005, *113* (5), 1054–1087.

Guvenen, Fatih, Burhan Kuruscu, Satoshi Tanaka, and David Wiczer, "Multidimensional skill mismatch," *American Economic Journal: Macroeconomics*, 2020, *12* (1), 210–44.

Haltiwanger, John C, Henry R Hyatt, Lisa B Kahn, and Erika McEntarfer, "Cyclical job ladders by firm size and firm wage," *American Economic Journal: Macroeconomics*, 2018, *10* (2), 52–85.

Hellerstein, Judith and David Neumark, "Workplace Segregation in the United States: Race, Ethnicity, and Skill," *Review of Economics and Statistics*, 2008, *90*, 459–477.

Huneeus, Cristobal, Federico Huneeus, Borja Larrain, Mauricio Larrain, and Mounu Prem, "The Internal Labor Markets of Business Groups," 2018. Unpublished manuscript.

Huneeus, Federico, "Production Network Dynamics and the Propagation of Shocks," 2018. Unpublished manuscript.

— , Kory Kroft, Kevin Lim, and David J Price, "Earnings Inequality in Production Networks," 2020. Unpublished manuscript.

Jarosch, Gregor, Ezra Oberfield, and Esteban Rossi-Hansberg, "Learning from Coworkers," 2019. National Bureau of Economic Research Working Paper No. 25418.

Krueger, B. Alan and Orley Ashenfelter, "Theory and Evidence on Employer Collusion in the Franchise Sector," 2018. National Bureau of Economic Research Working Paper No. 24831.

Lazear, Edward P, "Firm-specific human capital: A skill-weights approach," *Journal of political economy*, 2009, *117* (5), 914–940.

Lim, Kevin, "Endogenous Production Networks and the Business Cycle," 2018. Unpublished manuscript.

Lise, Jeremy and Fabien Postel-Vinay, "Multidimensional skills, sorting, and human capital accumulation," *American Economic Review*, 2020, *110* (8), 2328–76.

Marx, Matt, "The Firm Strikes Back: Non-Compete Agreements and the Mobility of Technical Professionals," *American Sociological Review*, 2011, *76* (5), 695–712.

Moscarini, Giuseppe and Fabien Postel-Vinay, "The relative power of employment-to-employment reallocation and unemployment exits in predicting wage growth," *American Economic Review*, 2017, *107* (5), 364–68.

Nickell, Stephen, "Biases in dynamic models with fixed effects," *Econometrica: Journal of the econometric society*, 1981, pp. 1417–1426.

Nimczik, Jan Sebastian, "Job Mobility Networks and Endogenous Labor Markets," 2018. Unpublished manuscript.

Oberfield, Ezra and Johannes Boehm, "Misallocation in the Market for Inputs: Enforcement and the Organization of Production," *Quarterly Journal of Economics*, 2020, *135* (4), 2007–20058.

OECD, "The Future of Work," 2019, *OECD Employment Outlook 2019.*

Sorkin, Isaac, "Ranking Firms Using Revealed Preference," *Quarterly Journal of Economics*, 2018, *133* (3), 1331–1393.

Startz, Meredith, "The Value of Face-to-Face: Search and Contracting Problems in Nigerian Trade," 2016. Available at SSRN 3096685.

Tintelnot, Felix, Ayumu Ken Kikkawa, Magne Mogstad, and Emmanuel Dhyne, "Trade and domestic production networks," 2018. National Bureau of Economic Research Working Paper No. 25120.

Topa, Giorgio, "Chapter 22 - Labor Markets and Referrals," in Jess Benhabib, Alberto Bisin, and Matthew O. Jackson, eds., *Jess Benhabib, Alberto Bisin, and Matthew O. Jackson, eds.*, Vol. 1 of *Handbook of Social Economics*, North-Holland, 2011, pp. 1193 – 1221.

Traiberman, Sharon, "Occupations and import competition: Evidence from Denmark," *American Economic Review*, 2019, *109* (12), 4260–4301.

A1 A Description of the Domestic Production Network

In this appendix we present key stylized facts about the domestic production network in the Dominican Republic. We start with an overview of the supplier-buyer connections, then we look at the employer-employee linkages, and finally we relate the stylized facts to data on firms' turnover. Some of the stylized facts presented in the following subsections have already been documented by Alfaro-Urena et al. (2018) for Costa Rica, Bernard et al. (2019a) for Japan, and Bernard et al. (2019b) for Belgium, suggesting that both in advanced economies and emerging markets many features of the domestic production network are alike.

A1.1 Suppliers and Buyers

We first look at the network of suppliers and buyers. Table A1 shows the number of buyers for each supplier, and the number of suppliers for each buyer, as well as some moments of their distributions. In 2017, the last year of the sample, the average supplier sold to 57 buyers, with a standard deviation of 364 buyers. On the other hand, the average buyer bought from 48 suppliers with a standard deviation of 68. This suggests that the average firm has more buyers than suppliers and that the distribution of buyers per supplier is considerably more dispersed than the distribution of suppliers per buyer. Both distributions, however, present a marked skewness to the right, pointing to a large concentration of connections in a few firms. The median supplier had 9 buyers, and the supplier at the 99th percentile of the distribution had 769 buyers (about 22 times more buyers than the median supplier); the median buyer had 30 suppliers and the buyer at the 99th percentile of the distribution had 311 suppliers (more than 10 times the number of suppliers for the median buyer). In other words, there are a few firms that are very well connected to the rest of the network. In fact, about one fourth of the suppliers in the sample have only 3 buyers and one fourth of the buyers have only 14 suppliers. Comparing data since 2012, it is evident that the concentration of connections in a few firms increased over time. This is especially marked for the one percent of the suppliers to the right of the distribution, that saw an increase of about 15 percent in the number of buyers in 5 years.

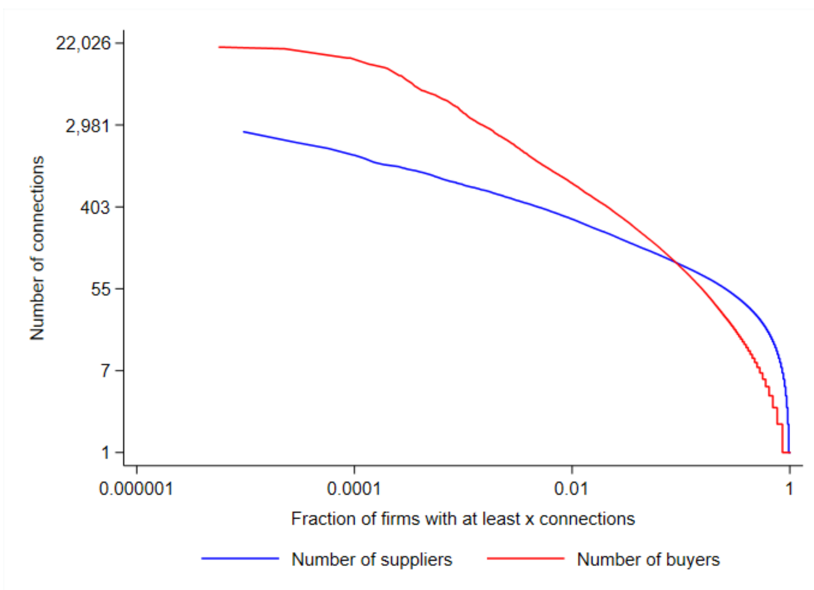
To visualize these facts, in Figure A1 we focus on 2017 and plot the inverse of the cumulative distribution function of the firms with a given number of connections. This confirms that both suppliers and buyers firms are connected with only a few counterparts, while a small number of firms are very well connected in the production network. For example, only 1 percent of the firms has more than 300 connections and only one hundredth of 1 percent have more than 1,100 connections.[23]

[23]The parameters estimated for the Pareto distributions of per-firm suppliers and per-firm customers are

Table A1: Number of Buyers per Supplier and Suppliers per Buyer by Year (Units)

Year	Mean	St. Dev.	10th	25th	50th	75th	90th	99th
a. *Number of buyers per supplier*								
2012	52	291	1	3	9	30	92	667
2013	53	312	1	3	8	28	91	687
2014	54	330	1	3	8	28	92	723
2015	55	345	1	3	8	28	94	750
2016	53	343	1	3	8	27	90	698
2017	57	364	1	3	9	28	94	769
b. *Number of suppliers per buyer*								
2012	44	63	5	12	27	53	93	296
2013	44	63	5	12	27	53	94	293
2014	45	64	5	12	28	56	98	302
2015	46	65	5	13	29	57	100	302
2016	44	64	5	12	27	54	96	293
2017	48	68	6	14	30	59	105	311

Figure A1: Number of Firms and Number of Connections, 2017



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

-0.30 and -0.43, respectively. These estimates are more negative for Costa Rica in Alfaro-Urena et al. (2018), We now take a look at the degree of assortativity between buyers and suppliers. That is, in the case of suppliers, we count the number of buyers for each supplier and we relate it to the average number of suppliers of those buyers. If there is positive assortativity, a supplier that is connected with a large number of buyers is connected with buyers that are in turn connected with a large number of suppliers. Figure A2 depicts a negative degree of assortativity. Hence, a supplier that has many buyers is in general connected with buyers that are buying only from a few suppliers, indicating a dependence of small buyers on large suppliers. The coef cient estimate from a linear regression suggests that an increase of 10 percent in the supplier's number of buyers is associated with a 1.4 reduction in the average number of suppliers. [24]

Figure A2: Buyers per Supplier and Average Number of Suppliers for Those Buyers, 2017

Notes: A third degree polynomial regression of the log of the number of suppliers for each buyer on the log of the average number of buyers for those suppliers is used to generate the gure. The shaded areas denote the 95 percent con dence intervals.

In Figure A3 we plot the degree of assortativity for buyers. That is, the number of suppliers for each buyer against the average number of buyers of those suppliers. The relationship for buyers is also negative, with a coef cient estimate from a linear regression suggesting that an increase of 10 percent in the buyer's number of suppliers is associated with a 2.6 percent reduction in the average number of buyers. We conclude that when

-0.58 for buyers and -0.73 for suppliers; and for Japan in Bernard et al. (2019a), -1.50 for buyers and -1.32 for suppliers.

[24] This estimate is in line with the one of other studies. Bernard et al. (2019a) report a negative correlation of -0.2 for Japan, and Alfaro-Urena et al. (2018) provide an estimate of -0.18 for Costa Rica.

firms have many suppliers, these suppliers sell to only a few buyers, pointing a dependence of small suppliers on large buyers. Moreover, the curve appears concave, with a flatter phase for small number suppliers, indicating that such dependence is particularly marked.

Figure A3: Suppliers per Buyer and Average Number of Buyers for Those Suppliers, 2017

Notes: A third degree polynomial regression of the log of the number of suppliers for each buyer on the log of the average number of buyers for those suppliers is used to generate the figure. The shaded areas denote the 95 percent confidence intervals.

Lastly, we look at the cross-sector heterogeneity. Table A2 shows that, in 2017, the average number of buyers per supplier was the highest in the "finance and insurance" industry, followed by "wholesale and retail" and "manufacturing". The least concentrated industries were "health", "education", and "construction". All sectors, however, are heavily right skewed. The industries with most buyers per supplier are, again, "finance and insurance", followed by "manufacturing" and "hotels and restaurants". The least concentrated industries are "education" and "real estate, renting, and business activities". While suppliers are also concentrated in a few firms, the right skew of the distribution is not as marked as in the case of the buyers. [25]

[25] The fact that the distribution of buyers per seller is more dispersed than that of suppliers per buyer is also highlighted by Bernard et al. (2019b) for Belgium and Alfaro-Urena et al. (2018) for Costa Rica.

Table A2: Number of Buyers per Supplier and Suppliers per Buyer, 2017
(Units)

Sector	Mean	St. Dev.	10th	25th	50th	75th	90th	99th
a. Number of Buyers per Supplier by Sector								
Agriculture, hunting, and forestry	22	53	1	2	5	17	53	242
Construction	16	62	1	2	4	11	27	230
Education	13	35	1	2	4	11	28	164
Finance and insurance	519	1513	1	3	16	200	1274	7625
Health	12	32	1	3	6	11	22	121
Hotels and restaurants	79	205	1	4	14	57	192	1081
Manufacturing	71	241	1	4	14	47	150	943
Other	22	181	1	3	7	17	38	176
Real estate, renting, and business activities	23	158	1	1	3	8	23	395
Transport, storage, and communications	50	478	1	3	8	23	61	651
Wholesale and retail trade	84	477	1	4	14	49	152	1063
b. Number of Suppliers per Buyer by Sector								
Agriculture, hunting, and forestry	45	53	4	12	28	61	104	281
Construction	51	56	6	16	35	67	114	277
Education	30	34	4	9	20	39.5	69	166
Finance and insurance	202	319	6	18	85	273	519	1439
Health	45	54	5	12	27.5	56	105	249
Hotels and restaurants	62	84	8	17	35	69	140	444
Manufacturing	67	98	7	17	37	77	147	519
Other	39	44	5	11	26	50	86	203
Real estate, renting, and business activities	31	39	3	8	19	38	69	194
Transport, storage, and communications	44	58	5	13	29	56	96	266
Wholesale and retail trade	49	63	7	15	33	62	105	277

A1.2 Workers

We now turn to the employer-employee linkages. Table A3 shows that since 2012 the number of workers per rm uctuated between 45 and 50, with an average standard deviation of 268 workers. In 2017, the average rm had 46 workers—of which 28 with permanent contracts and 18 with temporary contracts—with a standard deviation of 313 workers, pointing to a large dispersion. In 2017, the median rm had only 11 workers and one fourth of the rms in the sample had a maximum of 5 workers. Most of the workers were concentrated in the rms at the top one percent of the distribution, which had a minimum of 608 employees.

Table A3: Number of Workers per Firm
(Units)

Year	Mean	St. Dev.	10th	25th	50th	75th	90th	99th
2012	50	282	3	6	12	31	81	659
2013	46	258	2	5	11	29	74	624
2014	45	257	2	5	11	28	74	590
2015	45	250	2	5	11	28	74	582
2016	45	250	2	5	11	27	75	590
2017	46	313	2	5	11	27	74	608

Figure A4 plots the inverse of the cumulative distribution function of the number of workers in 2017. It con rms that a very large portion of rms have only a few workers and that only a few rms employ a lot of workers. For example, 3.8 percent of the rms in the sample had one single employee, compared with one tenth of 1 percent of the rms with over 2,800 workers.[26]

In Figure A5, we look at the relationship between number of connections and number of workers in 2017. Both in the case of suppliers and in the case of buyers, there appears to be positive relationship, suggesting that rms with a larger number of connections are also the ones employing a larger number of people. The coef cient estimates of linear regressions indicate that an increase of 10 percent in the number of connections is associated with a 4.1 percent increase in the number of buyers and with a 7.8 percent increase in the number of suppliers. Both relationship are convex, with a steeper phase of the polynomial for larger values of number of connections. This is especially true for the number of suppliers, which means that any additional connection is associated with a larger increase in the number of workers employed by these suppliers if the initial number of connections is already large.

We now compute the degree of assortativity between the number of workers of the

[26] These numbers are similar for suppliers and buyers.

Figure A4: Number of Firms and Number of Workers, 2017

Notes: The figure shows the inverse of the cumulative distribution functions of the number of workers per firm.

Figure A5: Number of Connections and Number of Workers, 2017

Notes: A third degree polynomial regression of the log of firm workers on the log of the number of connections is used to generate the figure. The shaded areas denote the 95 percent confidence intervals.

suppliers and the average number of workers of the buyers for those suppliers. Figure

A6 points to a mildly negative relationship. This means that suppliers that employ more workers tend to sell to buyers that, on average, have a smaller workforce. A linear regression suggests that a 10 percent increase in the workforce of the suppliers is associated with a 1.1 percent decline in the average number of workers of the buyers of those suppliers.

Figure A6: Number of Workers of Suppliers and Average Number of Workers of Buyers for Those Suppliers, 2017

Source: Source: Authors' calculations.
Notes: A third degree polynomial regression of the log of the number of workers of suppliers on the log of the average number of workers of the buyers for those suppliers is used to generate the gure. The shaded areas denote the 95 percent con dence intervals.

The evidence for buyers con rms the previous stylized fact. Figure A7 also displays a negative relationship, suggesting that buyers with a small workforce tend to buy from suppliers that employ many workers. The opposite is also true, buyers with a large workforce buy from suppliers employ only a few people. The coef cient estimate of a linear regression suggests that a 10 percent increase in the workforce of the buyers is associated with a 1.6 percent decline in the average number of workers of the suppliers for those buyers. Overall, these gures point to a dependence of small suppliers from large buyers, and a dependence of small buyers from large suppliers.

Finally, we look at the heterogeneity in the number of workers across sectors. Table A4 shows the distribution of workers across rms per sector in 2017. The sectors that employ most workers, on average, are " nance and insurance" with 658 workers and manufactur-

Figure A7: Number of Workers of Buyers and Average Number of Workers of Suppliers for Those Buyers, 2017

Source: Source: Authors' calculations.
Notes: A third degree polynomial regression of the log of the number of workers of buyers on the log of the average number of workers of the suppliers for those buyers is used to generate the gure. The shaded areas denote the 95 percent con dence intervals.

ing with 110 workers; while "real estate, renting, and business activities" and "education" employ the least, 19 and 31 workers respectively. Some sectors, however, are more concentrated than others. As an example, the rm at the top one percent of the distribution of the "manufacturing" sector employs 1,946 workers, or 17.7 times the amount of workers employed by the average rm in the sector. Using the same metric, the least concentrated sector appears to be "education", where the rms in the top one percent of the distribution employ 6.6 times the the amount of workers employed by the average rm, respectively.

A1.3 Sales

We nally look at rms' sales. Table A5 shows that since 2012 domestic sales increased by 7.6 percent reaching US$28.6 billion in 2017. However, as new rms entered the market, the average turnover fell by 16 percent to US$0.9 million, and its standard deviation declined by 38 percent to US$14.7 million. Despite lower sales dispersion, most of the rms in the sample registered relatively low sales. For instance, in 2017, one fourth of

Table A4: Number of Workers per Firm by Sector, 2017
(Units)

Sector	Mean	St. Dev.	10th	25th	50th	75th	90th	99th
Agriculture, hunting, and forestry	71	160	3	6	17	64	177	766
Construction	32	113	2	5	11	26	67	333
Education	31	41	4	9	18	36	71	206
Finance and insurance	658	1597	4	12	72	394	2154	7782
Health	53	125	3	5	12	39	135	590
Hotels and restaurants	79	293	4	8	17	38	108	1170
Manufacturing	110	571	3	7	18	57	193	1946
Other	31	101	2	4	9	23	60	421
Real estate, renting, and business activities	19	58	2	4	7	16	36	215
Transport, storage, and communications	48	176	3	6	14	35	86	716
Wholesale and retail trade	32	333	2	4	9	22	54	298

the rms in the sample sold less than US$0.01 million. The top one percent of the rms in the sample, on the other hand, sold at least US$11.9 million. The sales values for the different percentiles suggest that the turnover for the top one percent of the rms in the sample remained broadly unchanged, while the decline took place for other rms.

Table A5: Sales by Year
(Millions of 2010 US dollars)

Year	Total	Mean	St. Dev.	10th	25th	50th	75th	90th	99th
2012	26,581	1.065	23.758	0.002	0.011	0.058	0.253	0.957	11.943
2013	26,685	0.982	21.923	0.002	0.010	0.052	0.225	0.877	11.234
2014	28,392	0.982	20.433	0.002	0.010	0.051	0.225	0.880	11.551
2015	27,438	0.910	15.570	0.002	0.011	0.053	0.236	0.934	11.907
2016	28,185	0.898	13.832	0.002	0.011	0.055	0.244	0.934	11.838
2017	28,597	0.887	14.674	0.002	0.011	0.054	0.237	0.908	11.887

In Figure A8, we explore if the rms with the largest sales are also the ones with the largest number of connections, either suppliers or buyers. We nd indeed a positive correlation, as in Bernard et al. (2019a) and Alfaro-Urena et al. (2018). The estimates from a linear regression suggest that an increase of 10 percent in the number of suppliers (buyers) is associated with an 8.8 (14.2) percent increase in sales. [27] Interestingly, the gure shows that the slope of the curves becomes steeper for larger numbers of connections, indicating disproportionally higher sales for those rms with a lot of connections.

[27] These estimates are also in line with the evidence for Costa Rica. Alfaro-Urena et al. (2018) nd that an increase of 10 percent in the number of suppliers (buyers) is associated with an 8.9 (12) percent increase in

Figure A8: Sales and Number of Connections, 2017

Notes: A third degree polynomial regression of the log of firm sales on the log of the number of connections is used to generate the figure. The shaded areas denote the 95 percent confidence intervals.

Similarly, we look at whether the firms with the largest sales sell to more municipalities than the ones with smaller sales. Figure A9 displays a positive relationship, indicating that the geographical presence matters for the turnover. A linear regression suggests that a 10 percent increase in the number of municipalities served by the suppliers is associated with a 14.0 percent rise in sales; and that a 1 percent increase in the number of municipalities from which firms buy their inputs is associated with 21.9 percent rise in sales.

But does a firm have a higher turnover because it sells to many buyers or because it sells more to each buyer? To answer this question, Figure A10 plots the predicted value of the 10th, 50th, and 90th percentile suppliers' sales in 2017 as a function of the number of buyers to which they sell. As the three curves are broadly parallel for most values of the number of buyers, we conclude that in general the number of buyers is not relevant for the turnover of the firm, consistent with Bernard et al. (2019b) for Belgium and Alfaro-Urena et al. (2018) for Costa Rica. However, differently from other studies, there are marked nonlinearities such that firms with a very large number of buyers tend to have similar sales, indicating that for those firms the number of buyers is a relevant factor in determining sales.

We now look at sales heterogeneity across sectors. As shown in Table Table A6, sales

sales.

Figure A9: Sales and Number of Municipalities, 2017

Notes: A third degree polynomial regression of the log of sales on the log of the number of municipalities where suppliers sell and buyers buy is used to generate the gure. The shaded areas denote the 95 percent con dence intervals.

are largely concentrated in two sectors, “manufacturing” and “wholesale and retail trade”. In 2017, these two sectors accounted for 70.7 percent of domestic sales. Since 2012, the sectoral shares remained broadly stable, with the largest changes being an increase of 3 percentage points in “wholesale and retail trade” more than offset by a decline in the share of “manufacturing”.

Table A7 shows the distribution of sales across rms by sector in 2017. The sector recording the largest sales by rm is “ nance and insurance”, with an average by rm of US$8.2 million. This is much larger than in any other sector. Speci cally, this is 2.7 times larger than the sales for the average rm in the “manufacturing” sector (the sector with the second largest average sales by rm) and about 8 times larger than the sales for the “agriculture, hunting, and forestry” sector (the sector with the third largest average sales by rm). Across almost all sectors, sales are concentrated in a very few rms. Firms in the top one percent of the “ nance and insurance” sector, for example, registered sales for US$132 million, which is about 17 times the sales for the average rms.

Table A8 shows the distribution of transactions between suppliers and buyers across sectors in 2017. It is immediately clear that there is a large asymmetry in the distribution of the transaction value for all sectors, with the average transaction value much larger than the median transaction value. [28] For example, the largest average transaction took

[28] This nding is consistent with the evidence of Bernard et al. (2019b) and Alfaro-Urena et al. (2018) for

Table A6: Share of Sales per Sector by Year
(Percent)

Sector	2012	2013	2014	2015	2016	2017	Total
Agriculture, hunting, and forestry	2.2	2.5	2.4	2.6	2.7	2.7	2.5
Construction	3.5	3.3	3.1	3.9	4.2	4.1	3.7
Education	0.0	0.0	0.0	0.1	0.1	0.1	0.1
Finance and insurance	3.4	3.3	3.2	3.6	3.7	3.8	3.5
Health	0.5	0.7	0.9	1.3	1.4	1.3	1.1
Hotels and restaurants	1.1	1.0	1.2	1.3	1.3	1.3	1.2
Manufacturing	40.8	39.7	38.3	36.7	33.3	34.5	37.0
Other	8.0	7.8	7.4	7.9	8.1	7.9	7.9
Real estate, renting, and business activities	1.3	1.3	1.4	1.4	1.5	1.5	1.4
Transport, storage, and communications	7.5	7.8	7.5	8.4	8.4	8.0	8.0
Wholesale and retail trade	31.7	32.5	34.6	32.9	35.3	34.8	33.7

Table A7: Sales by Sector, 2017
(Millions of 2010 US dollars)

Sector	Total	Mean	St. Dev.	10th	25th	50th	75th	90th	99th
Agriculture, hunting, and forestry	763	1.054	3.727	0.005	0.022	0.112	0.580	2.283	18.236
Construction	1,171	0.460	1.543	0.004	0.019	0.078	0.301	0.946	7.593
Education	18	0.034	0.098	0.000	0.001	0.004	0.020	0.068	0.579
Finance and insurance	1,079	8.236	28.416	0.003	0.017	0.197	1.803	16.153	132.589
Health	383	0.396	1.315	0.002	0.008	0.054	0.274	0.931	4.546
Hotels and restaurants	384	0.299	1.668	0.001	0.003	0.018	0.091	0.466	4.509
Manufacturing	9,861	3.036	41.506	0.003	0.018	0.091	0.475	2.258	41.595
Other	2,258	0.351	1.954	0.002	0.011	0.045	0.168	0.547	5.398
Real estate, renting, and business activities	437	0.322	1.809	0.003	0.010	0.037	0.122	0.443	5.675
Transport, storage, and communications	2,299	1.029	11.324	0.004	0.021	0.096	0.376	1.198	12.463
Wholesale and retail trade	9,944	0.778	8.295	0.002	0.009	0.051	0.230	0.872	10.669

Notes: Values in US dollars are de ated with the US producer price index.

Figure A10: Percentiles of Sales and Number of Buyers, 2017

Notes: Third degree polynomial quantile regressions of the log of sales on the log of the number of connections are used to generate the gure. Regressions are run for the 10th, 50th, and 90th percentiles. The shaded areas denote the 95 percent con dence intervals.

place in the “agriculture, hunting, and forestry” sector, amounting to US$49,000; and the smallest average transaction was recorded in the “hotels and restaurants sector”, for US$4,000. Median transactions, however, are much smaller than the average ones, at US$17,000 and US$200 in the “agriculture, hunting, and forestry” sector and in the “hotels and restaurants” sector, respectively.

Belgium and Costa Rica, respectively.

Table A8: Firm-to-Firm Transaction Value by Sector, 2017
(Millions of 2010 US dollars)

Sector	Mean	St. Dev.	10th	25th	50th	75th	90th	99th
Agriculture, hunting, and forestry	0.049	0.341	0.000	0.000	0.002	0.011	0.055	0.952
Construction	0.029	0.291	0.000	0.000	0.001	0.006	0.028	0.485
Education	0.003	0.012	0.000	0.000	0.001	0.002	0.005	0.026
Finance and insurance	0.016	0.156	0.000	0.001	0.002	0.007	0.021	0.224
Health	0.032	0.195	0.000	0.000	0.001	0.008	0.045	0.609
Hotels and restaurants	0.004	0.129	0.000	0.000	0.000	0.000	0.002	0.043
Manufacturing	0.043	1.481	0.000	0.000	0.001	0.006	0.026	0.439
Other	0.016	0.204	0.000	0.000	0.001	0.004	0.017	0.221
Real estate, renting, and business activities	0.014	0.146	0.000	0.000	0.000	0.002	0.014	0.217
Transport, storage, and communications	0.021	0.511	0.000	0.000	0.001	0.004	0.013	0.229
Wholesale and retail trade	0.009	0.284	0.000	0.000	0.001	0.002	0.008	0.108

Notes: Values in US dollars are de ated with the US producer price index.

A2 Assortative Matching Between Firms

In this appendix we ensure that our findings in Section 3, based on a random allocation approach, are not explained by firm-pair characteristics correlated with both supply-chain linkages and worker flows. To do this, we estimate firm-pair level regressions controlling for a large set of firms' characteristics. Our specification is:

$$WF_{o\,!\,d;t} = \quad_{o} + \quad_{d} + \quad TF_{o;d;t\quad 1} + \quad X_{o;d;t} + \quad_{o;d;t} \tag{9}$$

where $WF_{o\,!\,d;t}$ is a dummy variable taking value one if any employee of firm d (destination) in year t, was working for firm o (origin) in period $t \quad 1$. $TF_{o;d;t\quad 1}$ is a dummy variable which takes value one if firm o was either a buyer or supplier of firm d in period $t \quad 1$. $X_{o;d;t}$ is a set of firm-pair characteristics. We also include firm fixed effects, $\quad_{o}$ and $\quad_{d}$, to control for observable and unobservable firm characteristics. We restrict the sample to firms o that had at least one worker leave between $t \quad 1$ and t, and firms d that hired at least one new worker between $t \quad 1$ and t.

The inclusion of firm-pair characteristics in the specification allows us to control for certain types of assortative matching between firms. For example, if large firms are more likely to trade with each other and their workers are more likely to move between them, this might cause a spurious correlation between trade and worker flows, which would not be captured by the firm fixed effects. Thus, we group firms in size deciles based on the revenue distribution and the permanent workforce distribution and we include fixed effects for each pair of deciles. We also include dummy variables for each pair of municipalities (to control for the distance between firms), for each pair of industries, and for whether or not the two firmsare part of the same business group.

The parameter describes the relationship between worker flows and domestic production linkages. To interpret the magnitude of the coefficient, we compute the odds-ratio of the probability of two firms being connected through a worker flow, calculated at the mean of the dependent variable:

$$OddsRatio = \frac{\overline{WF} + \quad}{1 \quad (\overline{WF} + \quad)} \quad \frac{1 \quad \overline{WF}}{\overline{WF}} \tag{10}$$

where $\overline{WF}$ is the sample average of the dependent variable.

Estimating equation (9) with all firm-pair combinations is computationally challenging. We therefore adopt a sub-sampling procedure. This consists of selecting a 0.5% random subset of all potential connections and estimate the parameter and the associated odds-ratio. We then repeat the procedure with 25 different sub-samples and report the mean value for the quantity of interest, together with the sample standard deviation. Regressions are weighted by the number of employees in firm o, as these are workers that can potentially leave the firm. To be consistent, we weight by the number of employees also when computing $\overline{WF}$ to obtain the odds-ratio.

We report the regression results in Table A9. Column (1) presents the estimates of equation (9) with only year fixed effects. In column (2), we include firm fixed effects, both for the origin firm and the destination firm. Column (3) presents the results of the full specification, which features firm-pair controls. The coefficient on trade flow is positive and statistically significant, confirming that workers disproportionately move between firms that trade with each other. The magnitude ranges between 0.9 and 1.7 percent, with an associated odds ratio between 5.6 and 9.2. In the specification with the most controls in column (3), the probability of two firms having a labor connection is 0.9 percentage points higher if they traded in the previous year, with an odds ratio of 5.6. This is a very large effect, as the unconditional (weighted) probability of two firms sharing a labor connection is about 0.2 percentage points. Importantly, the result of a positive association between trade flows and worker movements is robust to the inclusion of firm-pair controls, mitigating the concern that our findings are driven by assortative matching between firms.

In column (4), we additionally distinguish between upstream and downstream worker flows and we find that workers disproportionately move both upstream and downstream. Finally, in column (5) we exclude all firm pairs in which one of the firms (or both) is in the top 10 percent of the workforce distribution. The coefficient on trade flows is smaller and equal to 0.16 percentage points. However, given that the average (weighted) probability of observing worker flows between two firms in this sub-sample is much smaller, we obtain a much larger odds-ratio of about 300, suggesting that domestic production networks are relatively more important for movements of workers across small and medium firms.

Table A9: Worker Flows And Trading Firms

	(1)	(2)	(3)	(4)	(5)
Trade flow	0.016***	0.011***	0.009***		0.002***
	(0.006)	(0.003)	(0.003)		(0.001)
Upstream flow				0.010***	
				(0.004)	
Downstream flow				0.011***	
				(0.005)	
Year FE	X	X	X	X	X
Firm FE		X	X	X	X
Firm-pair controls			X	X	X
Excluding firms in top size decile					X
Weighted average of dep. variable	0.002	0.002	0.002	0.002	0.000
Odds ratio	9	7	5	6 (up) 6 (down)	323
Observations per subsample	15 million	15 million	15 million	15 million	11 million
Average adjusted R^2	0.003	0.055	0.071	0.072	0.007

Notes: The dependent variable is a dummy variable indicating whether at least one of the employees working at firm o in year $t \quad 1$ works at firm d in year t. "Trade flow" is a dummy taking value one if the hiring and origin firm traded with each other in $t \quad 1$. Worker level controls include age, gender, and wage in 2012. Firm pair controls include fixed effects for each pair of firms' size deciles, each pair of firms' municipalities, each pair of firms' industries, and a dummy variable for whether the two firms have a business group relationship. Point estimates are obtained by OLS on 25 randomly selected subsamples of 0.5 percent of firm pairs. Each observation is weighted by the number of employees of the origin firm. The average of the coefficients estimated across subsamples and the average of the dependent variable are reported. Odds ratios are computed as $\frac{\overline{WF}+}{1 \quad (\overline{WF}+ \quad)} \quad \frac{1 \quad \overline{WF}}{\overline{WF}}$ where $\overline{WF}$ is the sample average of the dependent variable. Standard errors are clustered at the municipality level. The standard deviation of the OLS coefficients are reported in parentheses. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

A3 Firm trade after worker movements: robustness and extensions

In this section we present several exercise which complement the findings of subsection 5.2.

We first test whether worker movements from a buyer to a supplier are also followed by an increase in trade between the two firms. We find that to be the case, as reported by Table A10. The magnitude is also fairly similar: the probability of observing trade between the firm pairs in 2017 is 2.9% higher if any of buyer's employees was hired from the supplier, thus very close to the 2.7% impact of observing a movement from the supplier to the buyer.

Table A10: Trade in 2017 and worker movements 2012 to 2017 (from buyer to supplier)

	Any trade	Share of purchase		Share of sales	
	(1)	(2)	(3)	(4)	(5)
Worker flow from buyer to supplier	0.029***	0.145***	0.120***	0.133***	0.121***
	(0.002)	(0.012)	(0.012)	(0.011)	(0.011)
Conditional on trading in 2012	X	X	X	X	X
Conditional on trading in 2017			X		X
Observations	976,727	976,727	458,165	976,727	458,165
R^2	0.344	0.265	0.389	0.246	0.376

Notes: The sample consists of firm pairs that traded in 2012. Firm b was the buyer and firm s was the supplier in 2012. The dependent variable in columns (1) is a dummy variable for whether firm b makes any purchase from firm s in 2017, in columns (2) and (3) it is the growth of the share of purchase made by firm b from firm s between 2012 and 2017, and in columns (4) and (5) it is growth of the the share of sales of firm s that is purchased by b between 2012 and 2017. "Worker flow" is a dummy taking value one if any worker moves from the buyer to the supplier between 2012 and 2017. All regression include buyer fixed effects and supplier fixed effects; and firm-pair controls, which are the cross-product of dummy variables for each firm's location, industry, and decile of size, the amount of trade in 2012 (in logs and levels), the share of b's 2012 purchase from firm s, and the share of s's 2012 sales sold to firm b. Firm pairs are excluded if in any year the two firms had any business relationship defined as either of the firm being among the top 10 shareholders of the other, or having any of the top 10 shareholders in common. Standard errors are clustered at the municipality level. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

We then investigate whether the impact of movements from suppliers to buyers is driven by the extensive margin only or whether the number of workers moving is also important. We therefore estimate the linear equation:

$$TF_{s \to b;2017} = {}_{s} + {}_{b} + HSNorm_{s \to b;(2012 to 2017)} + X_{s;b} + {}_{s;b} \tag{11}$$

where $HSNorm_{s \to b;(2012 to 2017)}$ is the number of workers moving from the supplier to the buyer, normalized by the workforce of the buyer in 2017. We include only firm pair such that $HSNorm_{s \to b;(2012 to 2017)} > 0$. Results, reported by Table A11 reveal that the more workers move from the supplier to the buyer, the more likely the two firms are to continue trading and to trade more. The first column reveals that if a buyer where to hire all its workers from the supplier, the probability of observing the two firms trading in 2017 would be 54 percentage points higher (the sample average is 68%).

Table A11: Trade in 2017 and worker movements 2012 to 2017 (intensive margin)

	Any trade	Share of purchase		Share of sales	
	(1)	(2)	(3)	(4)	(5)
Worker flow from supplier to buyer	0.541**	2.361***	2.641***	2.153***	2.292***
	(0.204)	(0.488)	(0.293)	(0.359)	(0.387)
Conditional on trading in 2012	X	X	X	X	X
Conditional on trading in 2017			X		X
Observations	16,076	16,076	10,859	16,076	10,859
R^2	0.512	0.414	0.482	0.418	0.486

Notes: The sample consists of firm pairs that traded in 2012 and such that we observe at least one worker moving from the supplier to the buyer between 2012 and 2017. Firm b was the buyer and firm s was the supplier in 2012. The dependent variable in columns (1) is a dummy variable for whether firm b makes any purchase from firm s in 2017, in columns (2) and (3) it is the growth of the share of purchase made by firm b from firm s between 2012 and 2017, and in columns (4) and (5) it is the growth of the share of sales of firm s that is purchased by b between 2012 and 2017. "Worker flow" the number of workers moving from the supplier to the buyer, normalized by 2017 workforce of the buyer. All regression include buyer fixed effects and supplier fixed effects; and firm-pair controls, which are the cross-product of dummy variables for each firm's location, industry, and decile of size, the amount of trade in 2012 (in logs and levels), the share of b's 2012 purchase from firm s, and the share of s's 2012 sales sold to firm b. Firm pairs are excluded if in any year the two firms had any business relationship defined as either of the firm being among the top 10 shareholders of the other, or having any of the top 10 shareholders in common. Standard errors are clustered at the municipality level. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

We perform some additional robustness exercise. We find that the results are similar if we focus on the difference between the share of purchase made by firm b from firm s in 2017 minus the same share in 2012 (or, the difference between the share of sales of firm s that is purchased by b in 2017 minus the same share in 2012): in fact firm pairs such that at least one worker move between the supplier to the buyer see an increase of 0.16 pp in the share of purchase made by the buyer between 2017 and 2012, which is about a tenth of the standard deviation of such a difference across pairs. We also find that the results hold if we condition on firms trading in both 2012 and 2013, so that we are sure to exclude one-time purchasers. These results are left unreported.

A4 Firm trade after worker movements: productivity impact

In subsection 5.2, we interpret the increase in the share of purchase as a sign of real complementarities. An alternative interpretation of those results is that a firm buys more from the previous employers of its workers simply because of the personal connection between these workers and their previous coworkers. In this appendix section we investigate whether the increases in purchase associated with hiring a worker form a supplier are also followed by economic gains for the buyer. In fact, such gains are to be expected if there are real complementarities between the human capital of a new hire and the products and serviced provided by her former employer.

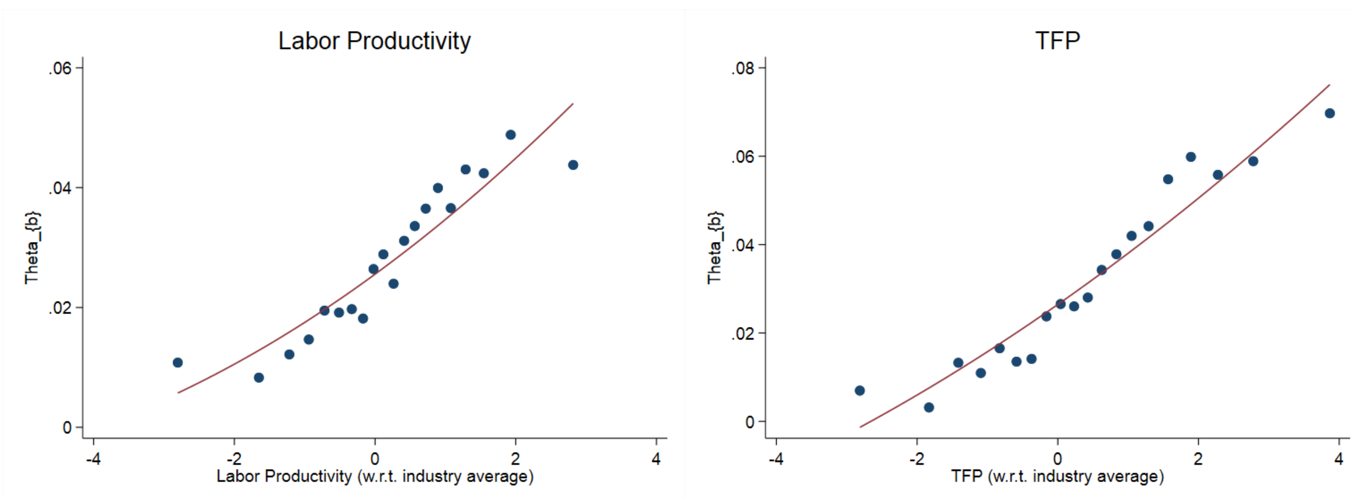
To do so, we focus on all the buyers b who hire at least some worker from their 2012 supplier and compute the increase of purchase made with these suppliers. This variable is defined as:

$$_b = \frac{\sum_s \quad Sh_{s \to b,(2012to2017)} \quad WF_{s \to b,(2012to2017)} \quad \mathbf{1}(\quad Sh_{b,s,(2012to2017)} > 0)}{NumEmployees_{b,2012}}$$

where, s is a firm that was a supplier of b in 2012, $\quad Sh_{s \to b,(2012to2017)} = 2 \frac{Sh_{s\to b,2012} \quad Sh_{s\to b,2017}}{Sh_{s\to b,2012} + Sh_{s\to b,2017}}$ is the growth between 2012 and 2017 of the share of purchase made by buyer b from supplier s, $WF_{s \to b,(2012to2017)}$ is a dummy variable equal to one if we observe any worker moving from the supplier to the buyer between 2012 and 2017, and $\mathbf{1}()$ is an indicator function. This quantity is normalized by the size of b's workforce in 2012.[29]

Firstly, we look at the unconditional correlation of $\quad_b$ with firm productivity in 2017; Figure A11 reveals a positive relationship.

Figure A11: Increase in purchase from Suppliers and Productivity



Notes: These figures plot the average share of the measure $\quad_b$ descibed in section A4 for each of the 20 quantiles of b's productivity in 2017. Productivity is measured as the log revenues over permanent employees (left panel) or as TFP (right panel), after controlling for industry fixed effects.

[29]The results of this section are robust to other modelling choices for $\quad_b$. In particular, results are similar if we include negative changes in the share of purchase made by firm b from suppliers it also hired from, so that $\quad_b = \frac{\sum_s \quad Sh_{s\to b,(2012to2017)} \quad WF_{s\to b,(2012to2017)}}{NumEmployees_{b,2012}}$.

We then estimate the following cross-sectional linear equation:

$$Prod_{b;2017} = \quad Prod_{b;2012} + \quad {}_{b} + \quad WFNorm_{\,!\,b;(2012to2017)} + X_b + \quad {}_{b} \tag{12}$$

where $Prod_{b;2017}$ is a productivity index, $WFNorm_{\,!\,b;(2012to2017)}$ is the number of 2012 suppliers from which firm b hired any worker, normalized by 2012 workforce. The set of controls X_b includes industry and location fixed effects, the log size of workforce in 2012 and the delta log workforce between 2017 and 2012, so to control for firm size and growth.

Table A12: Firm trade after worker movements: productivity impact

	Labor productivity in 2017		TFP in 2017	
	(1)	(2)	(3)	(4)
	0.212***	0.505**	3.077***	1.153***
	(0.054)	(0.222)	(0.601)	(0.136)
Number of suppliers firm hires from		0.0195		3.038***
		(0.253)		(0.223)
Productivity in 2012	0.707***	0.653***	0.898***	0.622***
	(0.026)	(0.028)	(0.011)	(0.045)
Firm controls		X		X
Observations	7,113	7,113	6,375	6,375
R^2	0.654	0.695	0.929	0.955

Notes: One observation is a firm which is active in both 2012 and 2017 and hired at least one worker from one of its suppliers in 2012. The dependent variable in columns (1) and (2) is the log of the ratio between sales and the number of permanent employees; the dependent variable in columns (3) and (4) is the total factor productivity. TFP regressions have less observations as a firm need to have positive values of all the inputs (VAT purchase, capital expenditure, temporary and permanent workers). The regressor is the increase in purchase made by the buyer from the supplier it hired some worker from, normalized by 2012 workforce. Its construction is described in section A4. Firm controls include fixed for firm location and industry, workforce size (as the log of number of permanent employees) in 2012 and the increase in workforce between 2012 and 2017. All regressions include year fixed effects. Standard errors are clustered at the municipality level. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Results are presented in Table A12. The coefficient is estimated to be positve: larger increases in trade with suppliers from which the firm also hired from are associated with a larger increases in productivity, with respect to 2012. The impact is sizeable: the interquartile range of the variable $_b$ is about 8 percentage points. This increase is associated with 4 percentage points in labor productivity and 9 percentage points higher TFP in 2017, conditional on productivity in 2012.

Thus, hiring from suppliers which have the potential to become even more important supplier is good for buyers' productivity. This confirms that the increase in trade between firms after a worker move from one firm to the other is likely to be driven by real complementarities associated with economic gains.

A5 Appendix Tables

Table A13: Share of Movers to Buyers or Suppliers by Industry and Municipality

	Data (1)	Random Allocation (2)	Odds Ratio (3)	Number of movers (4)
All Movers	19.5	11.8	1.8	654,931
Panel A: By Initial industry				
Agriculture	13	6	2.27	10,640
Construction	18	6	3.62	40,092
Education	7	3	2.18	3,013
Finance and Insurance	29	23	1.36	17,737
Health	16	10	1.60	6,383
Hotels & Hospitality	22	13	1.92	97,891
Manufacturing	17	14	1.30	128,166
Other	13	5	2.88	133,203
Real Estate	17	7	2.54	9,163
Transportation	18	11	1.86	58,416
Wholesale and Retail Trade	27	18	1.74	150,227
Panel B: Switching Industry and/or Municipality				
Switching industry	18.3	11.5	1.7	346,033
Same industry	21.5	12.9	1.9	256,804
Switching municipality	15.6	10.2	1.6	257,606
Same municipality	22.6	13.4	1.9	345,733
Switching industry and municipality	18.3	11.5	1.7	346,033
Same industry and municipality	22.9	13.8	1.9	159,362

Notes: 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 'job openings' 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 A14: Robustness: Hiring and Coworker Learning

	Earnings of coworkers			Earnings of new hires		
	1 year	2 years	3 years	1 year	2 years	3 years
	(1)	(2)	(3)	(4)	(5)	(6)
ln(earnings)	0.654***	0.580***	0.527***	0.630***	0.546***	0.496***
	(0.017)	(0.020)	(0.020)	(0.017)	(0.020)	(0.021)
New hire	0.030***	0.055***	0.045***			
	(0.004)	(0.004)	(0.004)			
New hire from buyer/supplier	0.042***	0.049***	0.053***	0.034***	0.043***	0.050***
	(0.005)	(0.008)	(0.014)	(0.003)	(0.007)	(0.013)
Employment growth	0.097***	0.069***	0.056***	0.107***	0.065***	0.053***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)
Average coworker ln(earnings)	0.009***	0.014***	0.015***	0.026***	0.033***	0.030***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)
Average new hire ln(earnings)				0.033***	0.035***	0.034***
				(0.001)	(0.001)	(0.001)
Observations	1,338,821	846,099	492,453	901,358	565,823	328,055
R^2	0.460	0.376	0.333	0.455	0.363	0.319

Notes: The dependent variable is the log of worker's wage in period $t + k$. "New hire" is a dummy variable that takes value one when the firm of the worker hires somebody; "new hire from buyer or supplier" is a dummy variable that takes value one when the firm of the worker hires somebody from any of its buyers or suppliers. All specifications include a dummy variable for gender, age deciles, and industry-year fixed effects. Employment growth is calculated between period t and $t + k$. Average coworker earnings are measured in year t and exclude new hires. Average new hire earnings are measured in period t. In columns (4) to (6) the variable New Hire is omitted because the specification is restricted to firms that have at least one hire in the year (otherwise average earnings of new hires would be missing). Standard errors are clustered at the municipality level. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.