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Worker Mobility and Domestic Production Networks[*]

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Abstract

We show that domestic production networks shape worker flows between firms. Data on the universe of firm-to-firm transactions for the Dominican Republic, matched with employer-employee records, reveals that about 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 considerable gains associated with this form of hiring: higher worker wages, lower job separation rates, faster firm productivity growth, and faster coworker wage growth. Hiring workers from a supplier is followed by a rising share of purchases from that supplier. These findings indicate that human capital is easily transferable along the supply chain and that human capital accumulated while working at a firm is complementary with the intermediate products/services produced by that firm.

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1 Introduction

In this paper we show that production networks are important for understanding worker mobility across firms and the quality of matches between employers and employees. We document a strong tendency of workers who change jobs in the Dominican Republic to move to a buyer or supplier of their initial employer. This form of hiring is also associated with significant economic gains in terms of firm productivity growth, employee wage growth, and job match duration; both the employer and the new coworkers learn more from new hires when they previously worked at a buyer or a supplier; trading between two firms increases when a worker move from a supplier to a buyer.

These facts are novel, to the best of our knowledge. They are also important, we argue, because they fill an important gap in the economic literature and because they reveal some largely unknown features of human capital. In fact, a large literature has studied the process of job searching and the matching between workers and firms (Jovanovic, 1979; Pissarides, 1994); a different and more recent strand has focused on the features of domestic production networks and their impact on firm performance (Bernard et al., 2019a,b; Alfaro-Urena et al., 2019a). However, the interplay between the exchange of products (and services) between firms and worker movements has been mostly unexplored. We fill this gap by highlighting the importance of production networks in explaining worker movements and their labor market outcomes. Moreover, our findings highlight that human capital is highly transferable between buyers and suppliers, suggesting there exist a supply-chain specific component to it. They also reveal significant complementarities between the human capital acquired working at a firm and the input produced by that firm.

Combining employer-employee records with VAT data on all firm-to-firm transactions in the Dominican Republic, we find that almost 20 percent of workers who change firm move to either a buyer or supplier of their original employer.[1] This is considerably more than would be implied by random matching. Under a random assignment of movers to firms, the share of workers moving to buyers or suppliers is only 2 percent. We also consider a more conservative approach, assigning workers randomly to job openings which were filled by workers with the same observable characteristics. Under this random allocation procedure, which takes as given the set of job vacancies opened by firms and the characteristics of workers who fill them, the share of workers moving to buyers or suppliers would still be just a bit more than half of what we observe in the data (12 percent).

These patterns hold broadly across industries and municipalities, and irrespective of whether workers change their industry and municipality when switching jobs. They also

[1]The dataset covers the years 2012 to 2017, capturing over 1.6 million workers per year (36 percent of the labor force). During the sample period, we observe over 760,000 job changes.

hold regardless of the origin firm's size and are not driven by a few large highly-connected firms. Excluding workers moving between different firms of the same business group does not affect our conclusions. Even when workers experience mass layoffs, they tend to move to connected firms. We also show that our findings are not driven by assortative matching between firms. For instance, results do not depend on the fact that workers tend to move to firms in nearby municipalities while nearby firms are also more likely to trade with each other. Nor are the results driven by workers of a certain industry being more likely to move to a specific downstream or upstream industry. We finally show that workers are disproportionately more likely to move to their original firm's top buyer or supplier.

Hiring from buyers and suppliers is not only common, but also leads to high-quality matches and faster firm productivity growth. Separation rates for workers moving to a buyer/supplier are 2 to 3 percentage points lower than for workers moving to other firms. Earnings growth for job changers is also 7 percentage points higher when they move to a buyer or supplier. These differentials persist at least three to four years after the job change.[2] We also document that firm productivity growth is 2.8 percent higher following a successful hire from a buyer or supplier, relative to firms that hire from other firms. 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 high quality of these matches? We document that hiring from buyers and suppliers is much more common for high-salary workers, indicating that human capital of workers plays an important role: 32 percent of job changers in the top earning quintile move to a buyer/supplier, compared to only 12 percent of job changers in the bottom quintile. More specifically, the acquisition of knowledge possessed by the employers of buyers and suppliers may be a particularly important reason to hire these workers. Consistently with this hypothesis, we provide evidence of firms and coworkers learning from new hires coming from connected employers.

In fact, we find that firms experience more rapid productivity growth when they hire workers from high-productivity buyers and suppliers. The existing literature (Stoyanov and Zubanov, 2012; Serafinelli, 2019) finds evidence that worker transfers can be a source of knowledge spillovers between firms. These papers infer knowledge spillovers by showing that firms hiring workers from more productive firms experience more significant productivity growth. We complement their findings by showing that hiring from a high-productivity buyer or supplier leads to even more rapid productivity growth than hiring from an unconnected high-productivity firm. This indicates that knowledge of buyers'

[2]The short sample span does not allow us to estimate these effects at longer horizons.

and suppliers' employees is particularly valuable.

Employers are not the only one to learn from these new hires. We find that workers experience more rapid wage growth when a new coworker is hired from a buyer or supplier than when a new worker is hired from an unconnected firm. This provides suggestive evidence of learning from coworkers, as described in Jarosch et al. (2019) who similarly find that workers experience larger wage increases when they have higher earning coworkers. These findings point towards knowledge transfers as an important reason firms tend to hire from their buyers and suppliers.

So 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 particularly important in environments with important contracting frictions, which tend to be prevalent in emerging markets and developing economies (Startz, 2016; Boehm, 2018). On the other hand, a firm may want to hire a worker from a buyer or a supplier because she 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 she 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. In fact, under the first explanation, the share of inputs purchases from a supplier should decrease as a buyer hires workers from it and production is in-sourced. Under the second explanation, the supply linkages should be strengthened as new workers are hired, given their complementary skills. We find that firms are more likely to continue buying from a given supplier, and also to increase their spending share on that supplier, if workers have been moving from the supplier to the buyer. Therefore, hiring from suppliers does not appear to be (mainly) motivated by the in-sourcing of tasks/parts of the production processes. Our evidence suggests instead that the complementary knowledge brought by workers increases the degree of supply-chain integration.

The productivity gains associated with hiring from a firm's supplier are found to be larger when the share of inputs that is bought from that specific supplier is larger. This is additional evidence in favor of the importance of complementarities along the production networks: if such complementarities are present, then the related gains should be more sizeable when the complementary input is more important.

Finally, we consider alternative explanations for our findings, in particular the role of selection and information frictions. 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. Managers may simply be able to more easily acquire information about these potential employees, reducing the noisiness of the signal about worker types. 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, e.g.), we do not preclude that lower information frictions between buyers and suppliers might facilitate better matching and explain some of our findings. However, information alone is unlikely to explain all the patterns in the data. Information frictions cannot explain the fact that high-salary workers are particularly likely to move to buyers/suppliers, the evidence of knowledge spillovers we find, or the fact that purchase shares from a supplier when a firm hires workers from that supplier. Indeed, 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, and a pure selection mechanism wouldn't necessarily imply benefits to coworkers.

We furthermore directly test the importance of information frictions and referrals by examining the role of ex-coworkers (Glitz, 2017) in explaining which firms workers move to. Social networks are an important source of information on job availability, and coworkers are an important part of people's social networks. However, we find that after restricting our sample to workers who move to firms with no previous coworkers, we continue to find an important role for buyers and suppliers in explaining worker mobility. This therefore leaves a potentially important role for a complementarity between the human capital workers acquire at a firm and inputs sourced from that firm as an explanation for our findings.

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 at capturing the set of firms over which workers search. For example, Bjelland et al. (2011) show that in the U.S. 60 percent of job flows happen across NAICS supersectors. Nimczik (2018) infers the worker's endogenous labor market in Austria based on observed worker flows across firms, while Cestone et al. (2019) and Huneeus et al. (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' endogenous labor markets.

Our paper is also related to the literature on social networks and worker flows. 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 et al., 2018). Our paper contributes to this literature by showing that not only are worker networks important, but so are firm networks.

The findings on knowledge spillovers due to worker flows from high productivity firms are also in line with Stoyanov and Zubanov (2012) and Serafinelli (2019). Relatedly, Balsvik (2011) and Poole (2013) document the importance of knowledge flows from multinationals to domestic firms through worker moves. This paper contributes to this strand of literature by showing that these knowledge transfers from high productivity firms through worker mobility are particularly strong when workers move from buyers or suppliers.

Our paper is related to the literature on the importance of domestic production networks for firm performance (Bernard et al., 2019b,a; Alfaro-Urena et al., 2019a) and shock propagation (Acemoglu et al., 2012; Tintelnot et al., 2018; Lim, 2018; Huneeus, 2018). We contribute by documenting the interaction between production networks and worker mobility, and their impact on labor market outcomes.

Our results are also related to the literature on studying how general or specific (and how transferable) human capital is (Becker, 1962; Gibbons and Waldman, 2004; Lazear, 2009; Gathmann and Schönberg, 2010). We contribute to this literature by studying how human capital is transferred along the production network and our results suggests it has a sizeable supply chain specific component. Moreover, we document the importance of complementarities between the human capital acquired working at a firm and the input sourced by that firm.

Recent papers have documented a large cost for the mismatch between workers skills and the job they occupy (Guvenen et al., 2020; Lise and Postel-Vinay, 2020). We contribute to this topic by documenting that production networks are an important factor mitigating such mismatch.

Finally, our paper is among the first to combine data on the firm production network with employer-employee information. Most closely related, Huneeus et al. (2020) combine employer-employee data with VAT records 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 which use similar datasets but focus on different questions include Demir et al. (2018), who provide evidence of assortative matching in terms of products quality and worker skills along the production networks, and Alfaro-Urena et al. (2019b), who assess the impact of multinational firms on workers in Cost Rica.

The rest of the paper is structured as follows. Section 2 presents the data sources. Section 3 documents that firms hire disproportionately from their buyers and suppliers. Section 4 analyzes the quality of the employer-employee matches formed along the domestic production network. Section 5 presents the evidence on the importance of human capital and knowledge transfers to explain worker movements to buyers and suppliers. Section 6 proposes alternative explanations for our findings. Section 7 concludes.

2 Data

We combine three different types of datasets for our analysis: 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 of the Dominican Republic.[3]

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. We also aggregate monthly payroll within each year from tax form IR3, which is used for tax withholding purposes. The main industry (ISIC 3) and the municipality where the firm is headquartered are also reported.[4]

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.[5] 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.

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

[3]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.

[4]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.*

[5]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.

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.

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.

As discussed in Appendix A1, the production network in the Dominican Republic is characterized by the presence of a few large well connected firms and many other small firms with few connections.[6] To put things in perspective, the average firm in the sam-

[6]Some of these facts have been illustrated for some advanced economies—Bernard et al. (2019b) for Belgium and Bernard et al. (2019a) for Japan—and emerging markets—Alfaro-Urena et al. (2018) for Costa Rica. See appendix A1 for further details.

ple has marginally more buyers than suppliers (55 against 45), 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 that there are a few firms very well connected to the rest of the network. Another way to look at this is to count the connections of a firm's buyers and suppliers. 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. Similarly, when firms have many suppliers, these suppliers sell to only a few buyers, pointing a dependence of small suppliers on large buyers.

Firm size in terms of sales and number employees are also heavily skewed. Overlapping the production and the employer-employee networks 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.

2.1 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.[7]

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. Specifically, 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.[8] 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.

[7]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.

[8]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. These averages take into account any wage income received during the year, not just from the highest-paying employer.

3 Workers Move 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 mobility was unaffected by the production network. This counterfactual share is computed following two different methodologies, which reflect different assumptions.

3.1 Comparing Data to a Random Allocation of Movers to Firms

Out of the 766,294 workers who moved between firms over the sample period, 19.1 percent got hired by firms that were either a buyer or a supplier (or both) of their previous employer the year before the move, as reported in column (1) of Table 2. We refer to this as the probability that a worker moves to a connected firm conditional on the worker changing jobs, or $PC|L$. The share of movers to buyers and suppliers goes up to 23 percent if we include workers who moved to firms that traded with their previous employer in either the previous or the current year. As a point comparison, the share of workers that moved to a firm within the same industry is 35 percent, though the typical firm has an order of magnitude fewer buyers and suppliers than firms in the same industry.

To what extent can the high frequency of moves to buyers and suppliers reflect random matching? To answer this, we construct the share of workers who move to buyers or suppliers if they were randomly assigned to firms. Specifically, we first construct, for each firm, the share of other firms in the Dominican Republic that it trades with. Formally, we construct:

$$PTrade_i = \frac{TP_i}{(N-1)}$$

where TP_i is the number of trading partners of firm i (i.e., buyers and suppliers) in any given year, and N is the total number of firms that could potentially be trading partners of firm i. We include as potential partners only firms that are in the employer-employees data and, therefore, have at least one permanent employee.

The statistic $PTrade_i$, however, varies across firms as some firms have more buyers and/or suppliers than others. Thus, to compare $PC|L$ to $PTrade_i$, we need to aggregate the latter over firms. To calculate the probability that a mover randomly ends up working for a trading partner of their previous employer, we average the firm-level probability across the firms where the movers are working before the move. That is, we compute a weighted probability of trade connections, taking into account which firm each mover worked for. This is constructed as:

$$PTrade = \frac{1}{L}\sum_{w}\sum_{i} PTrade_i \cdot 1[w \in i] = \sum_{i}\frac{L_i}{L}\cdot PTrade_i = \sum_{i}\frac{L_i}{L}\cdot\frac{TP_i}{(N-1)} \quad (1)$$

where $1[w \in i]$ is a dummy variable equal to one if mover w is leaving firm i (i.e., w is employed in firm i in a year and is employed in another firm in the following year), L_i is the total number of workers leaving i in a year, and L is the total number of movers. This probability is 1.9 percent on average, as reported in column (2) of Table 2.[9] Therefore, a worker is about ten times more likely to move to a firm with a trading relationship with its current employer than to a random firm.

To quantify the differences between the probability of moving to a connected firm and the counterfactual probability of moving to a connected firm if workers were switching firms randomly, we compute the following statistic:

$$OddsRatio = \frac{PC|L}{(1-PC|L)}\cdot\frac{(1-PTrade)}{PTrade} \quad (2)$$

which is the ratio of the odds that a worker moves to a connected firm in data divided by the odds that a worker moves to a connected firm under the random allocation. Column (3) of Table 2 reports that for all movers the odds ratio is as large as 13. A test for the equivalence of the two probabilities safely rejects the null hypothesis of equality.[10]

3.2 Heterogeneity

We investigate how the importance of the domestic production networks in shaping worker mobility varies across different subsets of workers. First, we repeat the analysis focusing only on a subset of workers moving between two firms which operate in different industries and/or located in different municipalities. As expected, the results in Table 2 report larger odds ratios for workers that move across industries and/or municipalities. Yet, even for workers that remain within the same industry and municipality, the odds ratios remain sizable. For example, the odds ratio for workers changing industry is 11 while it is 8 for workers moving within the industry. The odds ratio almost doubles for workers changing municipality with respect to workers staying in firms within the same municipality. If workers change both industry and municipality the odds ratio reaches 28, while it is 4 for workers that move within industry and municipality. This is because the share of workers who move to a connected firm is lower among workers who change munici-

[9] The unweighted average of $PTrade_i$ across firms is 0.2 percent.

[10] The relevant z-statistic is computed as $z = (\hat{p} - p)/\sqrt{\frac{\hat{p}(1-\hat{p})}{N}}$, where $\hat{p}$ is the probability observed in the data and p is the counterfactual probability.

Table 2: Workers Flows and Domestic Production Network

	Probability of moving to connected firms (1)	Probability of randomly moving to connected firms (2)	Odds-ratio (3)	Number of movers (4)
All movers	19.1	1.9	13	766,294
Changing industry	17.7	1.9	11	496,620
Same industry	21.8	3.3	8	169,674
Changing municipality	15.3	1.5	12	356,096
Same municipality	22.5	4.4	6	410,198
Changing industry and municipality	17.7	0.8	28	196,620
Same industry and municipality	21.8	6.2	4	269,674
Within manufacturing sector	17.5	1.5	14	88,254
Excluding large firms	14.2	0.5	34	302,423
Large layoffs	20.1	0.7	38	19,323
Cease to have permanent employees	38.3	1.6	38	19,323
Excluding former coworkers	11.5	1.3	10	78,252

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 as in equation (1). 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. Industries are defined according to the most disaggregated definition available in the data. "Large firms" are those with 500 or more employees or more. "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). "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.

pality or industry, and firms are much more likely to trade with other firms in the same municipality or industry. Overall, these results confirm the importance of the production network in explaining worker flows.

We then focus on moves between firms operating in the manufacturing sector only, which is one of the largest in terms of number of workers and sales (see section A1 for details about the sector size). In this case, the odds-ratio is 14, which is similar to the one obtained when we consider all movers.

We then repeat the exercise excluding large companies, which we define as having 500 employees or more. The excluded firms are slightly more than 1 percent of the total, but account for about 40 percent of the movers. As shown in column (9), within this sub-sample only 0.5 percent of firms are connected, yet 14.2 percent of movers go to a connected firm. Thus, the odds-ratio is almost double than the one for all movers. That is, excluding the largest firms, which have more connections, makes our finding even more striking. In an additional exercise, we group movers according to the size of the previous employer (measured by the number of permanent employees). As shown in Table 3, the share of workers moving to a connected firm is monotonically increasing in the quintiles of firms' size, doubling from 10 to 20 percent when moving from the first to the fifth quintile. As the probability of two firms trading goes up by more than 20 times, the odds ratio declines. However, even for firms in the fifth quintile, the odds-ratio is as large as 10.

Table 3: Worker Flows by Firms' Size

	1^{st} quintile	2^{nd} quintile	3^{rd} quintile	4^{th} quintile	5^{th} quintile
Prob. of moving to connected firms	9.6	11.0	11.8	13.3	20.0
Prob. of randomly moving to conn. firms	0.1	0.1	0.1	0.2	2.3
Odds-ratio	193	154	118	79	10
p-value	0.000	0.000	0.000	0.000	0.000
Number of movers	4,499	11,472	19,543	54,579	676,197

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 as in equation (1). The table also reports the odds ratios between the two probabilities and the p-values for the test that probabilities are equal.

We now explore if our finding holds in a sample of workers that left their firms because of negative firm-level shocks rather than their own decision or their poor performance. This exercise is inspired by the literature on unemployment scarring, which focuses on mass layoffs to isolate firm-level shocks (Gibbons and Katz, 1991; Davis and Von Wachter, 2011). We therefore restrict the sample to workers that either leave (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.[11]

The results in Table 2 corroborate our main finding: 20.1 percent of the workers leaving a firm experiencing a large layoff end up in firms that were buyers or suppliers of their previous employee the year before the move. This probability goes up to 38.3 percent when we focus on workers leaving firms that layoff all their full-time workers. The probability that such events happen randomly are 0.5 percent and 0.7 percent, respectively, which is about a third than for the overall sample. As a result, the odds-ratio is 38 for both these groups of workers.

Previous literature has documented that internal labor markets operate differently (Cestone et al., 2019) and workers tend to move within a business group following a shock to one of the group's firms (Huneeus et al., 2018). Since firms of the same business group might trade with each other, common ownership could be an important confounding factor for our results. We then define two firms as having a "business group" relationship if either (a) one of the firm is one of the top 10 shareholders of the other or (b) they have

[11]The second criterion, however, may be subject to measurement error. 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.

in common at least one of the top 10 shareholders. Approximately 4.6 percent of workers moving between two firms have a "business group" relationship. When we exclude these workers, however, we find similar (unreported) results to the ones of the baseline.

3.3 An Alternative Random Allocation Approach

We consider an alternative approach of random assignment to test the robustness of our findings. Following Glitz (2017) and Glitz and Vejlin (2019), we define a firm has having a "job opening" if it hires a worker from another firm and we randomly assign workers to job openings. We ignore new hires that were not permanent employees of other firms in the previous year. Firms are allowed to have multiple job openings if they hire more than one worker. We then randomly reshuffle all workers who changed job across job openings, measure the share of randomly allocated workers that end up in a buyer or supplier of their previous employer, and finally compare it to the share observed in the data.

We reshuffle workers to firms conditional on some observed characteristics of workers and firms. Each worker is thus randomly allocated to a firm in the same industry and municipality as the firm she actually moved to. We similarly condition on observed characteristics of workers, and so a worker can only be randomly assigned to a job opening if they are of the same age, gender, or salary as the worker that actually filled that opening.[12]

We repeat the randomization procedure 100 times and estimate the counterfactual probability of randomly ending up in a connected firm as the average share of workers who are allocated to a firm that was trading with their previous employer. With sufficient conditioning variables, every worker would end up randomly assigned to the firm they actually moved to. To avoid this overfitting, we set a minimum group size for the random allocations of 50 (results are similar if we use a different minimum group size, such as 10). The sample size therefore shrinks as conditioning variables are added. We construct standard errors based on the simulation draws.

Table 4 reports the results. If we omit controls, we obtain an estimate of the random allocation of 7.1 percent. That is, if workers were randomly allocated across firms, 7.1 percent of them would end up in a firm that has a trade relationship with the previous employer. This probability reaches 11.8 percent when controls are included. Given that the observed probability is almost 20 percent, the random allocation index approach confirms our main result: workers are more likely to move along the domestic production network than to firms outside of the network. A test for the equality of the two probabilities confirms that they are statistically different from each other in all cases presented in

[12]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.

Table 4.

Table 4: Random Allocation across Job Vacancies

	Probability of moving to connected firms (1)	Probability of randomly moving to connected firms (2)	Odds-ratio (3)	Number of movers (4)
All movers (no controls)	19.1	7.1	3.1	766,294
All movers	19.5	11.8	1.8	654,931
Changing industry	18.3	11.5	1.7	346,033
Same industry	21.5	12.9	1.9	256,804
Changing municipality	15.6	10.2	1.6	257,606
Same municipality	22.6	13.4	1.9	345,733
Changing industry and municipality	18.3	11.5	1.7	346,033
Same industry and municipality	22.9	13.8	1.9	159,362
Within manufacturing sector	17.6	14.7	1.2	67,914
Excluding large firms	14.4	3.8	4.3	217,606
Large layoffs	20.3	9.7	2.4	69,999
Cease to have permanent employees	42.8	27.5	2.0	16,177

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. 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. Industries are defined according to the most disaggregated definition available in the data. "Large firms" are those with 500 or more employees or more. "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). "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.

The main conceptual difference between the random allocation to firms approach and the random allocation to job openings approach is that the latter fixes the set of vacancies and the characteristics of the worker that will eventually fill them. The former, instead, imposes only very mild restrictions on 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. In fact, in Section 4 and 5, we document several benefits associated with hiring workers from buyers or suppliers; it is thus reasonable to think that a firm may open a vacancy with the intent of poaching a specific worker from a connected firm, and that vacancy would not have been filled by another observationally similar worker. As we also show that workers benefit from moving to a buyer or supplier of their previous employer, it is possible that a worker may move to a specific industry because of the presence of a connected firm although she would not have applied to positions in that industry otherwise. Thus, the characteristics of workers and firms of who are matched may be endogenous to the trading linkages between firms. Furthermore, there are many job openings in the Dominican Republic that likely went unfilled. Given our findings, these were more likely to be job openings at firms that were not buyers or suppliers of many other firms.

On the other hand, the random allocation to firms approach likely understates the share of workers who move to buyers/suppliers under random matching, as there is no weighting by the existence of vacancies which are more likely for larger firms with many buyer/supplier linkages. This methodology also does not fully capture differences across industries and locations.

Given these considerations, the two methodologies provide an upper and a lower bound for the actual share of workers moving to connected firms that we would observe by chance if production networks were not affecting worker flows. 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 find with random matching.

The remainder of Table 4 confirm that our results hold for different subgroups of workers even under this more conservative random allocation procedure. Specifically, the impact of the trade network in shaping job changes is present within each group, for movers changing or staying in the same industry or location, excluding large firms, and focusing on firms experiencing large layoffs or ceasing to have permanent employees. The qualitative patterns are similar to the ones highlighted in Table 2 with the exception of workers changing industry and/or location. If anything, the odds-ratios are larger for the workers that stay in the same location or industry.

3.4 Robustness to Firm-Pair Level Regressions

We established that workers have a higher probability of moving to firms that are connected to each other in the production network and we showed that this holds across industries and municipalities. In this subsection we ensure that this finding is not explained by firm characteristics correlated with both trade and worker flows. To do this, we estimate a set of firm-pair level regressions controlling for a large set of firms' characteristics:

$$WF_{o \to d,t} = \phi_o + \phi_d + \beta \cdot TF_{o,d,t-1} + \gamma X_{o,d,t} + \eta_{o,d,t} \tag{3}$$

where $WF_{o \to d,t}$ is a dummy variable taking value one if any employee of firm o (origin) in year t was working for firm d (destination) in period $t-1$. $TF_{o,d,t-1}$ is a dummy variable which takes value one if firms o and d traded in period $t-1$, that is if o was a buyer or a supplier (or both) of firm d. $X_{o,d,t}$ is a vector of firm-pair characteristics that might explain both worker flows and trade patterns. We also include firm fixed effects, ϕ_o and ϕ_d, to control for observable and unobservable firm characteristics, such as the number of buyers or suppliers, average worker turnover, etc... We restrict the sample to firms o that had at least one worker leave between $t-1$ and t, and firms d that hired at least one new worker between $t-1$ and t.

The inclusion of firm-pair characteristics in the specification allows us to control for 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 firms have a business group relationship.

The parameter β 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:

$$OddsRatio = \frac{\overline{WF} + \beta}{1 - (\overline{WF} + \beta)} \cdot \frac{1 - \overline{WF}}{\overline{WF}} \tag{4}$$

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

Estimating equation (3) 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 β 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 5. Column (1) presents the estimates of equation (3) 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. According to the most saturated specification in column (3), the probability of two firms having a labor connection is 0.9 percentage point 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 distinguish between upstream (i.e., firm o buys from firm d) and downstream (i.e., firm o sells to firm d) 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 much more important for movements of workers across small and medium firms.

4 Quality of Firm-Worker Matches

Is the quality of the employer-employee matches—the surplus generated by the match—different for workers that get hired by buyers or suppliers compared to workers that move to other firms in the production network? We first look at the duration of the match. The idea is that a long-lasting employment is more likely to reflect a successful match while a short match may be due to a bad fit between the worker and the firm. Similarly, wages should convey some information about the match quality. They should, at least in part, reflect the marginal product of labor. We then shift the focus to the labor productivity of firms hiring workers from buyer and suppliers.

4.1 Match Duration

To investigate whether matches formed along production networks have different duration than others, we select 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. We do so because our sample is relatively short (2012–2017). Thus, the observed duration of matches formed between 2012 and 2013 is capped at 5. We find that, on average, matches last 2.8 years if the hiring firm was a buyer or a supplier of the previous employer. This is in contrast to a match duration of 2.4 years if the hiring firm did not have trade relationship with the previous employer. Thus, in the last year of our sample (2017), the probability of the worker still being at the same firm he moved to is 29 percent

Table 5: 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	✓	✓	✓	✓	✓
Firm FE		✓	✓	✓	✓
Firm-pair controls			✓	✓	✓
Excluding firms in top size decile					✓
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 $t-1$ 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 $t-1$. 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 $\frac{\overline{WF}+\beta}{1-(\overline{WF}+\beta)} \cdot \frac{1-\overline{WF}}{\overline{WF}}$ 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.

if he moved from a connected firm and only 21 percent if she came from an unconnected one.

To test whether this gap can be explained by differences in observable characteristics other than the hiring firm being a buyers or a supplier, we estimate the following specification:

$$D_{w,d,o} = \phi_d + \phi_o + \beta TF_{o,d,2012} + \gamma X_{o,d} + \delta X_w + \eta_{w,d,o} \tag{5}$$

where w is a worker who was employed by firm o (origin) in 2012 and firm d (destination) in 2013; $D_{w,o,d}$ is the duration of the match with firm d, measured, alternatively, as the number of years or with a dummy for whether the worker is still employed by d in 2017; and $TF_{o,d,2012}$ is a dummy variable indicating whether the two firms traded in 2012. We also include the previous and current employer fixed effects; a set of worker level controls, including age, gender, and earnings in 2012 (in levels, log, and a set of dummies for the relative quintile); and a set of detailed firm-pair controls, including 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.

Table 6 reports the results of the estimations. Columns (1) shows that the duration for a worker moving in 2013 between two firms that traded in 2012 is about 0.3 years longer than the one for a worker moving between two unconnected firms. In the richest specification of column (3)—which includes the full set of controls—the match duration is still 0.097 years (a month) longer for those that moved between connected firms.

The results are similar if we employ as a dependent variable a dummy indicating whether in 2017 the worker is still at the same firm she moved to in 2013. Column (4) shows the unconditional estimate, which suggests that a worker moving in 2013 between two firms that traded in 2012 is about 8 percent more likely to still be working in the new firm in 2017. The inclusion of employee controls reduces the probability to 6 percent, as shown in column (5). Column (6) indicates that, after including all controls, the probability of a moving worker to be at the same firm in 2017 is 2 percent higher if firms had a trading relationship.

We translate this longer duration for matches that happened among buyers and suppliers into attrition rates. To do it, for each year $t \geq 2013$, we compute the probability that a match lasts until year $t+1$, conditional on it lasting at least until year t. Formally, for duration $k = 1, .., 4$ and $t = 2012 + k$, we estimate the specification:

$$Pr(D_{w,d,o} > k | D_{w,d,o} \geq k) = \phi_{d,k} + \phi_{o,k} + \beta_k TF_{d,o,2012} + \gamma_k X_{d,o} + \delta_k X_w + \eta_{w,d,o} \tag{6}$$

where $D_{w,d,o}$ represents the observed duration (in years) of the match between worker w (who worked in firm o in 2012) and firm d, which she joined in 2013. Figure 1 plots the coefficient β_k for every duration k. The results confirm that matches between firms that

Table 6: Match Duration

	Duration in years			Same firm in 2017		
	(1)	(2)	(3)	(4)	(5)	(6)
Trade flow	0.310***	0.251***	0.097***	0.078***	0.065***	0.018***
	(0.017)	(0.017)	(0.010)	(0.005)	(0.005)	(0.005)
Worker controls		✓	✓		✓	✓
Origin firm FE			✓			✓
Destination firm FE			✓			✓
Firm pair controls			✓			✓
Observations	136,164	136,161	123,807	136,164	136,161	123,807
R^2	0.006	0.029	0.343	0.006	0.025	0.308

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.

had a buyer-supplier relationship tend to last longer, as they have about 2 to 3 percentage point lower probability to be dissolved in a given year, compared to matches between unconnected firms. We do not find a significant difference in the last year of our sample, but this is likely related to the shrinking sample size as the duration gets longer.

4.2 Wages

We now turn to wages. We compute the wage growth rate between the year before and the year after the worker's move and estimate the following equation:[13]

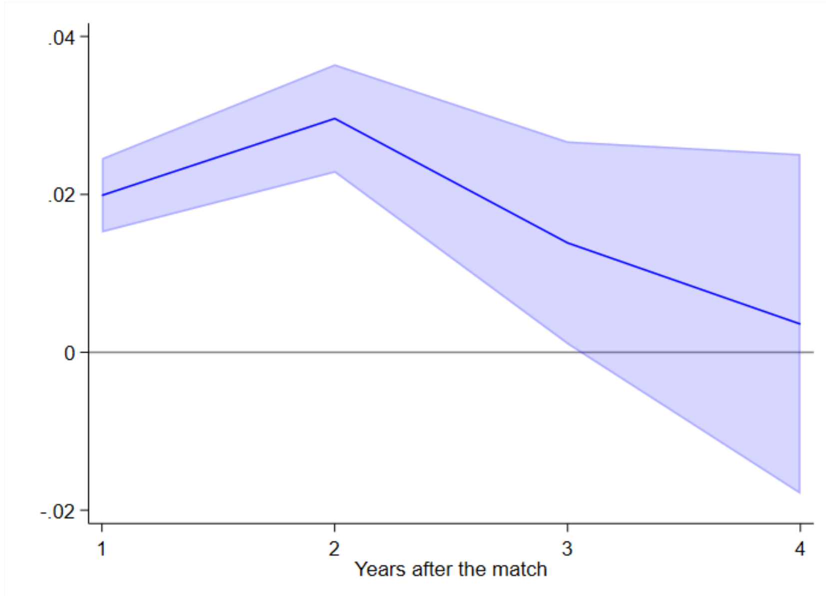
$$\Delta wage_{w,d,o,t} = \phi_d + \phi_o + \beta TF_{d,o,t-1} + \gamma X_{d,o,t-1} + \delta X_{w,t-1} + \eta_{w,d,o,t-1} \tag{7}$$

where $\Delta wage_{w,d,o,t}$ denotes the wage growth at time t for worker w, who was working in firm d in year t and in firm o in year $t-1$; and $TF_{d,o,t-1}$ indicates whether o was a buyer or a supplier of d in year $t-1$. The controls are the same as in equation (5), and we add the year fixed effects.

[13]We approximate the annual wage growth with log differences winsorized at top and bottom 1 percent. Results are robust to computing growth rates according to the formula of Davis et al. (1996), which is $wage = 2(wage_t - wage_{t-1})/(wage_t + wage_{t-1})$. To make the two time periods comparable we use the total wages in a year from all employers.

Figure 1: Probability of Staying at the same firm

(Percent)



Notes: The line denotes the point estimate of the probability that a match formed in year T between a worker and a firm that was a buyer or supplier of the worker's previous firm in $T-1$ lasts until year $T+k$, conditional on it lasting at least until year T. The shaded area denotes the 90 percent confidence interval computed with standard errors clustered at the municipality level.

Table 7 reports the results. Column (1) presents the unconditional estimate, which points to a negative correlation between the wage growth rate and the dummy for whether the worker was hired by a buyer or a supplier. However, when we include the worker-level controls, the correlation turns positive, as shown in column (2). In particular, the variable that changes the sign of the OLS coefficient is the quintile of the worker initial wage. In fact, workers with higher wages are more likely to move to buyers and suppliers but also tend to have lower relative wage growth when they change firm. Column (3) reports the results of the specification with all the control variables, which indicates that matches formed along the production network lead to an additional wage growth of approximately 7 percent.

To test whether the additional wage growth associated with moves among buyers and suppliers is persistent over time, we compute the total growth between the annual earnings in 2012 and the ones in each of the following years. For each $k = 1, ..5$, we estimate the following equation:

$$\Delta wage_{w,d,o,2012+k} = \phi_{d,k} + \phi_{o,k} + \beta_k TF_{d,o,2012} + \gamma_k X_{d,o,2012} + \delta_k X_{w,2012} + \eta_{w,d,o,k} \tag{8}$$

Table 7: Wage Growth

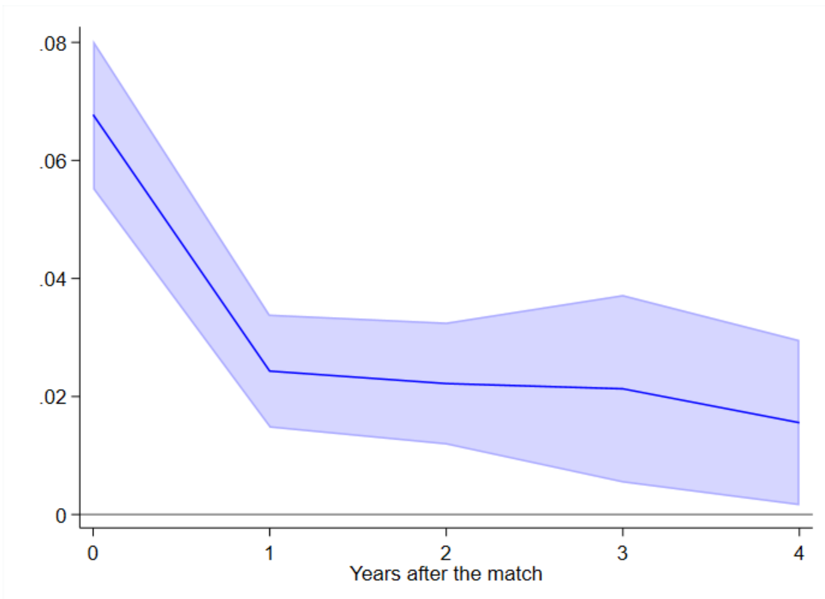
	(1)	(2)	(3)
Trade flow	-0.018**	0.196***	0.072***
	(0.007)	(0.009)	(0.005)
Year FE	✓	✓	✓
Worker controls		✓	✓
Origin firm FE			✓
Destination firm FE			✓
Firm pair controls			✓
Observations	766,257	766,253	747,519
R-squared	0.024	0.322	0.514

Notes: The dependent variable is the wage growth between the year before and the year after a worker move. "Trade flow" is a dummy taking value one if the hiring and origin firm traded with each other in the year before a worker move. Worker level controls include age, gender, and wage growth 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.

where β_k recovers the association between getting hired by a buyer or supplier and earning growth in any year between 2013 and 2017. The results in Figure 2 indicate that workers moving along the production network experience a more persistent wage growth. Specifically, about a third of the increase in earning growth persists for over 5 years.

Figure 2: Persistence of Wage Growth

(Percent)



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.

4.3 Productivity

Finally, we study whether firms that hire workers from buyers and suppliers have higher productivity and experience higher productivity growth. Specifically, we focus on labor productivity, measured as the the log of revenue per permanent employee. In fact, firms should be able to produce and sell more output per each worker if these workers are a better fit for their job and have higher human capital. We estimate the following specification:

$$prod_{d,t} = \phi_o + \beta TF_{d,o,t-1} + \gamma X_{d,o,t-1} + \delta X_{w,t-1} + \eta_{w,d,o,t-1} \quad (9)$$

where one observation is a worker w who changed firm between year t and $t-1$, $prod_{d,t}$

denotes the productivity of the destination firm d at time t, and $TF_{d,o,t-1}$ is the dummy indicating if firms d and o traded with each other in period $t-1$. The specification also includes the usual set of worker-level controls, $X_{w,t-1}$; fixed effects for the cross-product of location and industry of both firms, $X_{d,o,t-1}$; previous employer fixed effects, ϕ_o.[14] In this setting, each observation represents a worker who used to be employed by firm j in year $t-1$ and that moved to firm d in year t. However, since we do not observe the productivity of a worker or the surplus generated by a specific match, the dependent variable varies only at the firm-year level.

Table 8 presents the regression results. Column (1) reports the results of the unconditional specification, documenting that firms who hire along the production network tend to have higher labor productivity. Column (2) shows that given two workers with similar characteristics, leaving the same firm, the one who moves to a buyer or supplier of the previous employer ends up in a firm with higher productivity. The magnitude is sizeable as the coefficient is about 9 percent of the standard deviation of the productivity index.

One reason for which firms that hire from buyers and suppliers experience higher productivity is that these firms accumulate highly compatible human capital through these new hires. To shed light on this, we test whether these firms were just more productive before hiring from buyers or suppliers or if their productivity increase once they have hired along the production network. Therefore, we estimate the following equation:

$$\Delta prod_{d,t} = \phi_j + \rho \cdot prod_{d,t-1} + \beta TF_{d,o,t-1} + \gamma X_{d,o,t-1} + \delta X_{w,t-1} + \eta_{w,d,o} \tag{10}$$

where $\Delta prod_{d,t} = prod_{d,t} - prod_{d,t-1}$.

The results in columns (3) and (4) of Table 8 suggest that firms hiring from buyers and suppliers experience higher productivity growth after conditioning on the initial productivity level. The estimated coefficient is sizeable, representing (in the baseline specification of column 4) about 4.2 percent of one standard deviation of the productivity growth and almost 50 percent of its mean. To conclude, we investigate the persistence of such additional productivity growth by estimating, for $k = 0, .., 4$, the following equation:

$$\Delta prod_{d,t+k} = \phi_{o,k} + \rho_k \cdot prod_{d,t-1} + \beta_k TF_{d,o,t-1} + \gamma_k X_{d,o,t-1} + \delta_k X_{w,t-1} + \eta_{w,d,o,k} \tag{11}$$

[14]In a first stage, we purge the variation in labor productivity due to the use of other inputs or industry-specific factors by regressing the log of revenues per permanent worker on a set of other (log) inputs: intermediate inputs, capital (proxied by assets), number of temporary employees and industry fixed effects. We then use the residual from such a regression as a measure of labor productivity. A more structural approach would entail estimating total factor productivity. However, this would be problematic in our setting as we have a short panel, a noisy proxy for capital, and we do not observe prices for neither inputs nor output. The results of this section are robust to focusing on simple labor productivity, thus not controlling for other inputs.

Table 8: Firm Productivity

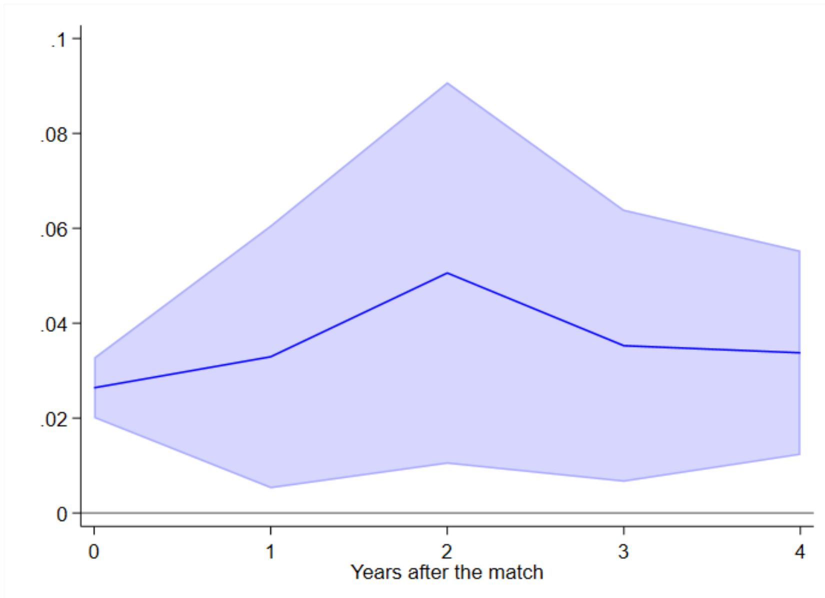
	Levels		Changes	
	(1)	(2)	(3)	(4)
Trade flow	0.286***	0.096***	0.106***	0.028***
	(0.021)	(0.010)	(0.022)	(0.006)
Lag of productivity			-0.219***	-0.250***
			(0.014)	(0.017)
Worker controls		✓		✓
Origin firm FE		✓		✓
Firm pair controls		✓		✓
Observations	704,813	695,354	630,300	620,755
R^2	0.024	0.348	0.238	0.375

Notes: The dependent variable in columns (1) and (2) is the productivity level (in logs) and the dependent variable in columns (3) and (4) is the change (delta logs) in productivity. "Trade flow" is a dummy taking value one if the hiring and origin firm traded with each other in the year before a worker move. Worker level controls include age, gender, and wage growth. 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. 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.

where $\Delta prod_{d,t+k} = prod_{d,t+k} - prod_{d,t-1}$. The estimates of β_k reported in Figure 3 indicate that the increase in productivity is persistent and statistically significant for about four years.

Figure 3: Persistence of Productivity Growth

(Percent)



Notes: The line denotes the point estimate of the increase in productivity from T to $T+K$ relative to $T-1$, for firms that hired workers from a buyer or a supplier in $T-1$. The shaded area denotes the 90 percent confidence interval computed with standard errors clustered at the municipality level.

We also consider some alternative specifications to investigate the relationship between hiring along the production networks and productivity. In particular, we reestimate (11) using productivity levels rather than productivity growth and we focus on firm-level, rather than worker-level, regressions. These specifications are presented in Section A2. The results confirm the findings of this section.

5 Human Capital and Knowledge Transfers

In this section we explore the role of human capital and knowledge transfers in explaining the tendency of workers to move to buyers and suppliers of their employers.

5.1 Flows of Higher Salary Workers

In this subsection, we explore if our main finding varies with wage. This exercise helps to shed light on the role of human capital, following a long-lasting literature that has relied on wages to proxy for human capital (Becker, 2009).

We group workers by quintile of the wage distribution of the year before the move. Then, we compute the probability of moving to a connected firm, to a random firm, and the odds ratio for all quintiles. As shown in panel a of Table 9, we find that the impact of the production network is more important for workers at the top of the wage distribution and less important for workers at the bottom. Specifically, the probability of a worker moving to a buyer or supplier of his current firm is 32 percent if the worker falls into the highest wage quintile; this is almost three times larger than the one for a worker in the first quintile. Comparatively, the probability that the same higher salary worker ends up in any firm of the production network is only 3.2 percent for the highest wage quintile and 1.6 percent for the lowest wage quintile. Thus, for workers in the highest wage quintile, the chances of moving to a connected firm are 14 times larger than the probability of moving to a random firm in the production network.

These differences are even starker when we focus on worker flows within the manufacturing sector. The results in panel b of Table 9 suggest that the probability of a working moving to a buyer or supplier is as high as 43 percent for workers in the top wage quintile, or five times higher than for workers in the bottom wage quintile. These figures compare to a counterfactual probability of randomly moving to a firm in the manufacturing sector of 2.9 percent for higher salary workers and 0.9 percent for lower salary workers. As a result, the odds ratios suggests that the chances of moving to a connected firm are 25 times larger for workers at the top of the wage distribution and are only 10 times larger for those at the bottom of the wage distribution. It is also interesting to notice that the number of movers is lower at higher quintiles, indicating high-paying jobs have lower turnover.

We conclude that hiring from buyers and suppliers is much more common for high-salary workers and that, more generally, both the share of workers moving to a connected firm and the odds-ratio increase in the wage quintiles. These findings provide suggestive evidence that the role of the domestic production network in shaping worker flows is related to human capital.

5.2 Spillovers from More Productive Firms

Intuitively, knowledge transfers could be particularly important for firm productivity when workers are hired from more productive firms. As argued by Stoyanov and Zubanov (2012), this could be because these workers bring with themselves some knowledge which

Table 9: Worker Flows by Wage

	Wage distribution				
	1^{st} quintile	2^{nd} quintile	3^{rd} quintile	4^{th} quintile	5^{th} quintile
a. *All moves*					
Prob. of moving to connected firms	11.6	14.6	19.4	26.8	31.8
Prob. of randomly moving to conn. firms	1.6	1.6	2.1	3.6	3.2
Odds-ratio	8	10	11	10	14
p-value	0.000	0.000	0.000	0.000	0.000
Number of movers	159,356	212,719	178,188	121,055	94,976
b. *Within manufacturing sector*					
Prob. of moving to connected firms	8.4	9.8	13.2	26.5	42.7
Prob. of randomly moving to conn. firms	0.9	1.0	1.2	2.4	2.9
Odds-ratio	10	11	13	14	25
p-value	0.000	0.000	0.000	0.000	0.000
Number of movers	18,246	24,294	19,918	12,917	12,879

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 as in equation (1). The table also reports the odds ratios between the two probabilities and the p-values for their equality test that probabilities are equal.

is present in the high productive firms and missing in the less productive ones. Following their approach, we calculate a "productivity gap" between the worker's previous and current employer. This gap is defined as the difference between the productivity of the previous employer minus the one of the current employer during the year before the worker's hiring if such difference is positive, and zero otherwise. Such gap is then a measure of how much one firm can learn from another firm.

To test whether hiring from a buyer or a supplier leads to larger increases in the hiring firm's productivity, we estimate the following specification:

$$\Delta prod_{d,t} = \phi_o + \rho prod_{d,t-1} + \beta TF_{d,o,t-1} + \tau gap_{d,o,t-1} + \psi TF_{d,o,t-1} \times gap_{d,o,t-1} + \gamma X_{d,o,t-1} + \delta X_{w,t-1} + \eta_{w,d,o,t} \quad (12)$$

where one observation is a worker w who changed firm between year t and $t-1$, $\Delta prod_{d,t}$ is the productivity growth of the destination firm d, $gap_{d,o,t-1}$ denotes the productivity gap between destination firm d and origin firm o at time $t-1$. The coefficient of interest is ψ, which reveals the marginal effect on productivity of hiring from connected firms when the productivity gap is large.

The results in column (1) of Table 10 confirm that firms' productivity increases when they hire workers from more productive firms. In line with the findings of Stoyanov and

Zubanov (2012), our results are suggestive of knowledge transfers. We also find that these knowledge transfers are larger when the previous employer was a buyer or supplier, as shown in column (2). The difference is sizeable: knowledge spillovers are about 40% larger when a worker is hired from a high-productivity firm that is also a buyer or a supplier. Finally, we test whether these knowledge spillovers are larger for workers that move within the same industry. We find support for this hypothesis, both within (column 8) and across (column 9) 3-digit industries.[15]

Table 10: Hiring and Firm productivity

	(1)	(2)	(3)	(4)
Trade flow	0.027***	0.009*	-0.016***	0.026***
	(0.006)	(0.005)	(0.005)	(0.007)
Productivity gap	0.097***	0.090***	0.130***	0.074***
	(0.024)	(0.025)	(0.049)	(0.016)
Productivity gap × trade flow		0.036***	0.047**	0.022***
		(0.006)	(0.019)	(0.007)
Sample	Full	Full	Within Industry	Change Industry
Observations	620,755	620,755	261,409	351,291
R^2	0.379	0.380	0.478	0.345

Notes: The dependent variable is the change in the log of labor productivity of the hiring firm after the hiring, computed as the residual of a regression of the log of revenues per permanent worker on industry fixed effects, log of firms' assets, the amount of firms' intermediate purchases, and the number of temporary workers. "Trade flow" is a dummy taking value one if the hiring and origin firm traded with each other in the previous year, and "productivity gap" is the difference between the productivity of the hiring firm and the origin one. All specifications include the lag of productivity, worker-level controls, fixed effects for the cross-product of location and industry of hiring and origin firms, previous employer fixed effects, industry fixed effects. Standard errors are clustered at the municipality level. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

5.3 Coworker Learning

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 benefit more when new em-

[15]We also find that these additional spillovers are significantly larger than zero 3 years after the move (unreported).

ployees are hired from buyers/suppliers than from unconnected firms. We explore this by examining if the wages of a new employee's coworkers increase more when the new employee was hired from a buyer/supplier than when the new employee was hired from an unconnected firm.

We estimate the following specification:

$$wage_{w,t+h} = \alpha + \beta wage_{w,t} + \delta D^{nh} + \lambda D^{nh*} + \gamma X_w + \epsilon_{w,t} \tag{13}$$

where $wage_{w,t+h}$ is the log of the wage of worker w at time $t+h$, with $1 \leq h \leq 3$ and $t = 2013$; D^{nh} is a dummy variable that takes value one when the firm employing worker w hires somebody in period t; and D^{nh*} is a dummy variable that takes value one when the firm employing worker w hires somebody from any of its buyers or suppliers in period t. The specification also features a vector of controls X_w, which includes gender and age deciles.

In this setting, the coefficients of interest are δ, which denotes the wage increase when the hire is from a firm outside of the domestic production network, and λ, which measures the wage increase from hiring from a buyer or supplier compared to hiring from a firm outside of the domestic production network. The sample is restricted to relatively small firms (i.e., with at most 100 workers) to ensure that coworkers are actually working in teams and can learn from each other.

Table 11 presents the baseline results. Column (1) shows that wage growth for employees of firms that hired new workers is 2.7 percent higher than the wages of employees at firms that did not hire new employees. When the new hire is from a buyer or a supplier, the wage increase is as large as 8.3 percent, or 5.6 percent more compared to firms that hired from outside the production network. This wage differential between coworkers of new hires from the domestic production network and coworkers of new hires outside the production network persists over the following two years and gets even larger, as shown in columns (2) and (3). Specifically, coworkers wages are 6 percent higher two years after the hiring and 7.7 percent higher three years after it.

When we focus exclusively on those coworkers that change firm during $1 \leq h \leq 3$, we still find that their wage is higher if their previous firm hired from a buyer or a supplier (unreported). By contrast, the salary of the coworkers falls if they moved and their previous firm hired from outside the production network.

Coworker learning might be stronger depending on whether the new hire is from a supplier or a buyer. We explore if this is the case by replacing D^{nh*} in equation (13) with two dummy variables: the first takes value one if the new hire is from a buyer and the second takes value one if the new hire is from a supplier. As shown in columns (4) to (6), we find that when the new employee comes from a supplier, coworkers experience a wage increase that is 5.4 higher than coworkers of new employees coming from outside of the production network. This compares to a wage increase that is only 2.8 percent higher when the new employee comes from a buyer. The difference, however, becomes smaller in the years after the hire, possibly indicating that the knowledge transfer from buyers is slower than from suppliers.

Table 11: Hiring and Coworker Learning

	Hiring from production network			Hiring from suppliers or buyers		
	1 year	2 years	3 years	1 year	2 years	3 years
	(1)	(2)	(3)	(4)	(5)	(6)
Ln wage	0.645***	0.583***	0.502***	0.644***	0.583***	0.502***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
New hire	0.028***	0.055***	0.047***	0.028***	0.056***	0.049***
	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)	(0.005)
New hire from buyer or supplier	0.057***	0.061***	0.079***			
	(0.005)	(0.006)	(0.007)			
New hire from buyer				0.028***	0.034***	0.055***
				(0.006)	(0.007)	(0.009)
New hire from supplier				0.054***	0.052***	0.055***
				(0.005)	(0.007)	(0.008)
Observations	1,378,117	892,476	533,509	1,378,117	892,476	533,509
R^2	0.429	0.353	0.276	0.429	0.353	0.277

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; and "new hire from buyer" and "new hire from supplier" are dummy variables that take value one when the firm of the worker hires somebody from its buyers or its suppliers, respectively. All specifications include a dummy variable for gender, age deciles, and a constant. Standard errors are clustered at the municipality level. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

These results are robust to several checks. Specifically, we find similar results when we include other controls, such as worker w's firm employment or employment growth, the average wage of worker w's coworkers in period t (excluding the new hires). The results are also broadly in line with the full sample of firms, though weaker with the full set of controls. Finally, replacing the log of wages with the growth rate of wages does not affect our findings.

6 Possible Explanations

Why is the human capital of buyers' and suppliers' employees particularly valuable for a firm? In this section we shed some light on this question by studying how the share of inputs purchased from a supplier changes after a worker is hired by a supplier, and by assessing the role played by information frictions.

6.1 Complementarities Between Inputs and Human Capital

Knowledge specialization is one of the very reasons of gains from trade between economic agents. A potential reason to hire an employee from a connected firm is to perform in-house a specific task that was outsourced to the trading partner. In fact, such a worker may bring the know-how necessary to accomplish this task, therefore decreasing the gains from trading with her previous employer. To test this hypothesis, we focus on all firm pairs which traded in 2012 and look at how movements of workers from suppliers to buyers impact their trading in 2017. We therefore estimate the model:

$$TF_{s\to b,2017} = \phi_s + \phi_b + \beta WF_{s\to b,(2012to2017)} + \gamma X_{s,b} + \eta_{s,b} \tag{14}$$

where the dependent variable is a measure of the amount that supplier s sells to buyer b in 2017, which is either a dummy variable equal to one if there is any purchase, or the difference between the share of purchase made by firm b from s in 2017 minus the same share in 2012, or difference between the share of sales of firm s that is purchased by b in 2017 minus the same share in 2012. $WF_{s\to b,(2012to2017)}$ is a dummy variable equal to one if we observe any worker moving from the supplier to the buyer between 2012 and 2017. ϕ_s and ϕ_b are firms fixed effects, $X_{i,j}$ is a set of firm-pair controls, including 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 made from firm s, and the share of s's 2012 sales sold to firm b. These controls aim to capture firm-specific heterogeneity (e.g. differential growth in sales or workforce over time), assortative matching between firms, and the importance of each firm as a trading partner for the other. We include only firm pairs that traded in 2012, that are not not part of the same business group, and such that the two firms still have buyers, suppliers, and permanent employees according to the 2017 data.

Results are presented in Table 12. Firms that hired from their supplier between 2012 and 2017 increase the probability of still trading with that supplier in 2017 by 3.6 percentage point (column 1). This is slightly less than a tenth of the average probability that the two firms are still trading (46 percent). The share of b's purchases from s also increases by 0.12 percentage points (column 2), which is about a tenth of a standard deviation of the change in shares between 2012 and 2017. Even when we restrict the sample to firm pairs that still trade in 2017 (column 3), the buyer's share of purchases from the supplier increases. That is, buyers are more likely to buy again from those suppliers from which they hire workers and, if they do, they purchase a larger share of their inputs. Similar results hold if we examine the share of supplier's sales going towards the buyer.[16]

Table 12: Trade in 2017 and worker movements 2012 to 2017

	Any trade	Share of purchase		Share of sales	
	(1)	(2)	(3)	(4)	(5)
Worker flow	0.036***	0.001***	0.002***	0.003***	0.001***
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
Conditional on trading in 2012	✓	✓	✓	✓	✓
Conditional on trading in 2017			✓		✓
Observations	1,101,114	1,038,014	475,555	1,101,114	475,555
R^2	0.369	0.391	0.375	0.507	0.414

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 between the share of purchase made by firm b from firm s in 2017 minus the same share in 2012, and in columns (4) and (5) it is the difference between the share of sales of firm s that is purchased by b in 2017 minus the same share in 2012. "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 (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. Standard errors are clustered at the municipality level. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

These results indicate that the main reason for hiring a worker from a connected firm is *not* to insource some of the tasks that the buyer was previously outsourcing to a supplier. Of course, this does not mean that there are no cases of firms poaching employees of their suppliers to move in-house part of the production processes. However, shaping the boundaries of the firm does not seem to be the main motivation beyond the patterns documented in this paper.

Conversely, the trade connection between firms becomes stronger after a worker transitions from one firm to the other. This points to larger gains from trade when human capital is transferred, perhaps because the firms' production and organization become more similar as they specialize in similar products or production processes. This evidence is consistent with the hypothesis that there exist complementarities in human capital along the firms' production network. That is, the knowledge accumulated by producing (or, the knowledge necessary to produce) a certain good or service is also useful

[16]The results are robust to considering several alternative specifications. For instance, they hold if we condition on firms trading in both 2012 and 2013, so that we are sure to exclude one-time purchasers. They are also robust to focusing on shorter time horizons, for instance considering all firm pairs that trade in a year T and then estimating the probability of trade in $T+2$ as a function of whether any worker moved from one to the other in $T+1$.

to understand how to use this input into the production of other goods. Thus, when a worker moves to a downstream firm, she knows how to use the input coming from her previous employer and the demand for such input increases, as we find in the data.

To provide further evidence of the presence of complementarities between the human capital of a worker and the input sourced by the previous employer of that worker, we examine whether the productivity gains of the firms hiring from their suppliers are larger when they hire from more important suppliers.[17] In fact, if such complementarities are one of the reasons behind the productivity gains from hiring along the production network, we expect these gains to be larger if the input that the firm buys from the previous employer of the new hire is an important input in its production. Therefore, for each time horizon $k = 0, 1, .., 4$ we estimate the following equation:

$$\Delta prod_{d,t+k} = \phi_{d,k} + \rho_k prod_{d,t-1} + \beta_k TF_{d\leftarrow o,t-1} + \psi_k TF_{d\leftarrow o,t-1} \times sh_{d\leftarrow o,t-1} + \gamma_k X_{d,o,t-1} + \delta_k X_{w,t-1} + \eta_{w,d,o,k} \quad (15)$$

where $TF_{d\leftarrow o,t-1}$ is a dummy variable equal to one if firm d is a buyer of firm o in year $t-1$ and $sh_{d\leftarrow o,t-1}$ is the share of d's purchases from o in all domestic purchases.

The coefficients ψ_k capture the impact of hiring a worker from a supplier that has a larger weight in d's purchases (measured before the new hiring) on productivity growth up to year $t+k$. In Figure 4 we plot the estimates of ψ_k, which reveal that the productivity gains of hiring from a supplier are larger when this supplier provides a larger share of the firm's inputs. For instance, the estimated initial impact of hiring a worker from a supplier in the top quartile in terms of the purchase share distribution (i.e., $\beta_0 + \psi_0 \cdot 6.7\%$) is about 3 times larger than one of hiring a worker from a supplier in the bottom quartile (i.e., $\beta_0 + \psi_0 \cdot 0.05\%$). This evidence is consistent with the presence of sizeable complementarities along the production networks.

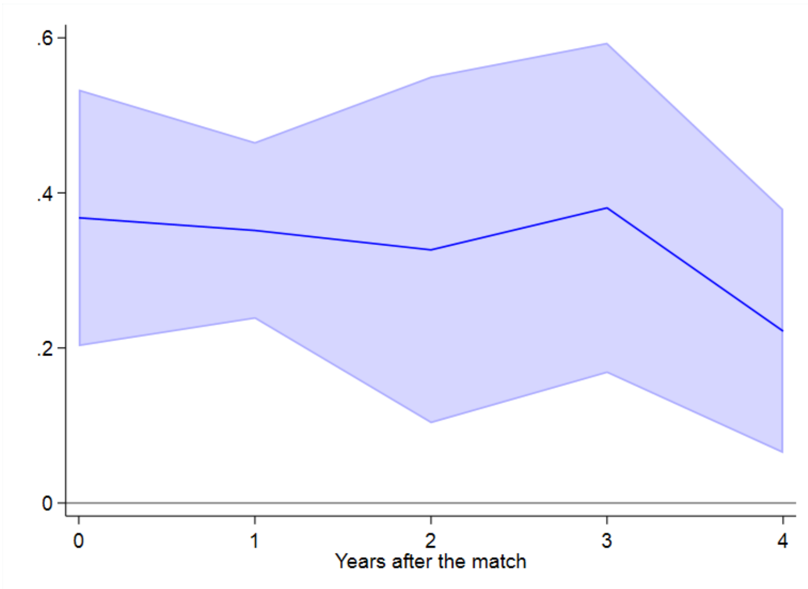
6.2 Information Frictions

Finally, we consider the role that selection and information frictions might play in explaining our findings, in particular the tendency for workers to move to buyers or suppliers of their previous employer. 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

[17] In Section 4.3 we do not distinguish between hiring from buyer or supplier. However, the results hold if we focus exclusively on any of the two.

Figure 4: Persistence of Productivity Growth After Hiring from Key Suppliers

(Percent)



Notes: The line denotes the point estimate of the increase in productivity growth between T and $T+K$ relative to $T-1$, for firms that hired workers from a key supplier (measured in terms of that supplier's weight in the firm's purchases) in $T-1$. The shaded area denotes the 90 percent confidence interval computed with standard errors clustered at the municipality level.

workers in the buyers or suppliers of their current employer. In addition, '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 (Burks et al., 2015). 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), it seems possible that such frictions explain in part why workers tend to get hired by buyers and suppliers. That said, information frictions alone cannot explain why firms start purchasing more from their suppliers after having hired workers from them. Neither they can easily explain why firms and coworkers learn more from workers coming from buyers or suppliers.

Though we have limited approaches to directly test the importance of information frictions and referrals, we evaluate its importance by considering the role of ex-coworkers (following Glitz (2017)) in explaining which firms workers move to. Social networks are an important source of information on job availability, and coworkers are an important part of people's social networks. We therefore follow the approach in section 3, but focusing on firm pairs that never saw an employee moving from one to the other between 2012 and 2016, as these firms are less likely to have used referrals for hiring. We then look at the worker flows between 2016 and 2017 as a function of trading between firms in 2016. We therefore limit the role of ex-coworkers in explaining our findings. The results in Table 2 show that the share of workers who move to a buyer/supplier is lower in the data (11.5 percent) and also under the random allocation (1.3 percent), with an odds ratio of 10. Though limited in scope, these results suggest that ex-coworker networks can't explain away our main findings.

7 Conclusion

In this paper we use a unique dataset on the universe of permanent formal employer-employee relationships in the Dominican Republic, together with VAT 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 also common in large as well as smaller firms, in firms that experienced large layoffs, in firms that cease to have permanent employees, and to excluding firms that have previous or current coworkers in their workforce.

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.

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A1 A Description of the Domestic Production Network

In this appendix we present some key stylized facts about the domestic production network of the Dominican Republic. We start with an overview of the supplier-buyer connections, then we look at the employer-employee network, and finally we relate the stylized facts to data on firms' turnover.

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.[18]

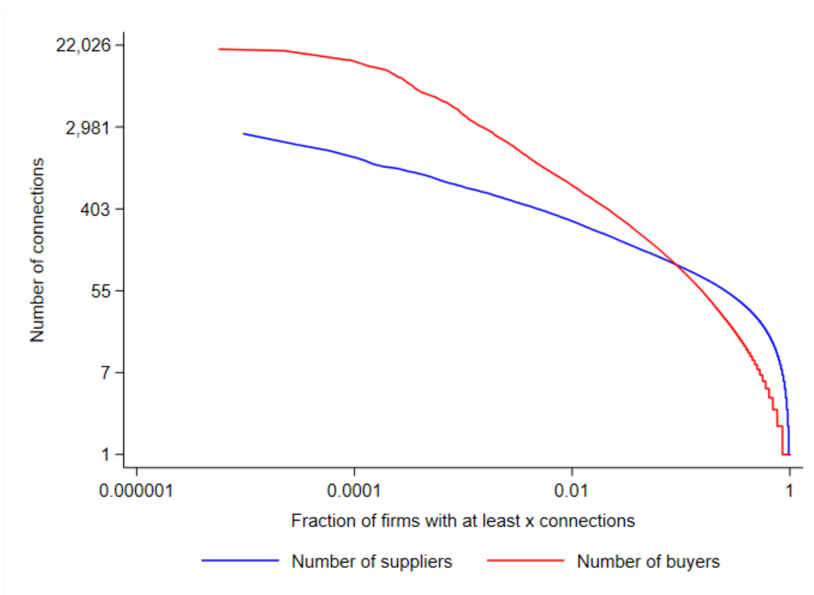
We now take a look at the degree of assortativity between buyers and suppliers. That is, in the case of suppliers, we count the number of buyers for each supplier and we relate

[18]The parameters estimated for the Pareto distributions of per-firm suppliers and per-firm customers are -0.30 and -0.43, respectively. These estimates are more negative for Costa Rica in Alfaro-Urena et al. (2018), -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.

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

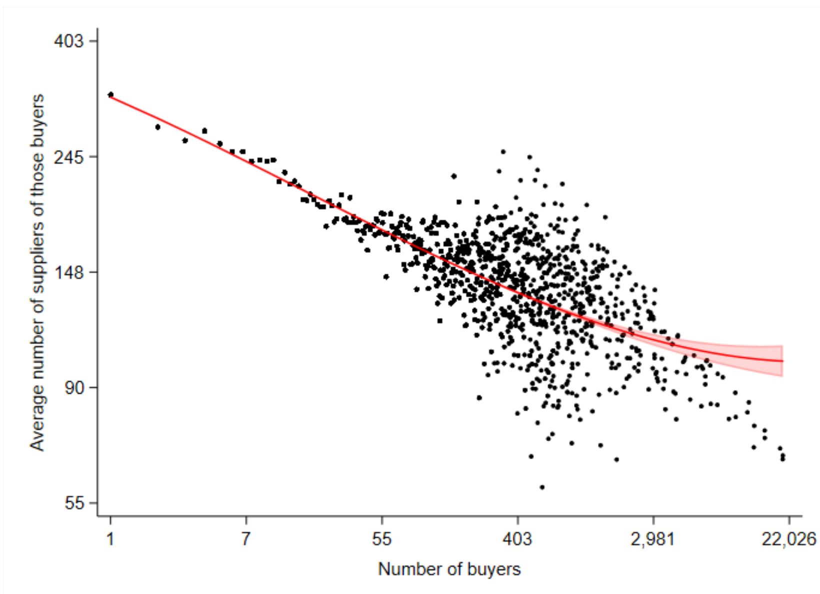
Figure A1: Number of Firms and Number of Connections, 2017



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.

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 coefficient 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.[19]

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

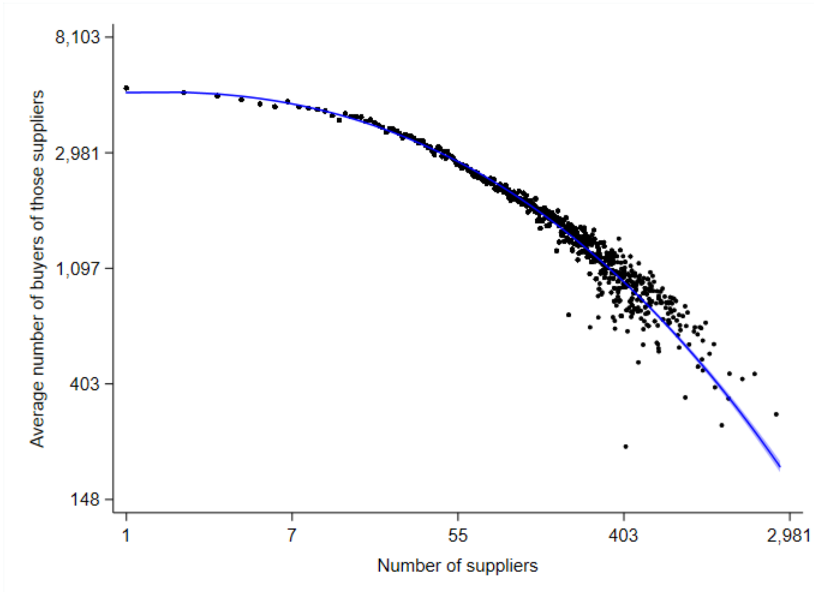


Notes: A third degree polynomial regression of the log of the number of suppliers for each buyer on the log of the average number of buyers for those suppliers is used to generate the figure. The shaded areas denote the 95 percent confidence intervals.

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 coefficient 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 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.

[19]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.

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, area 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.

A1.2 Workers

We now turn to the employer-employee network. Table A3 shows that since 2012 the number of workers per firm fluctuated between 45 and 50, with an average standard deviation of 268 workers. In 2017, the average firm 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 firm had only 11 workers and one fourth of the firms in the sample had a maximum of 5 workers. Most of the workers were concentrated in the firms at the top one percent of the distribution, which had a

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

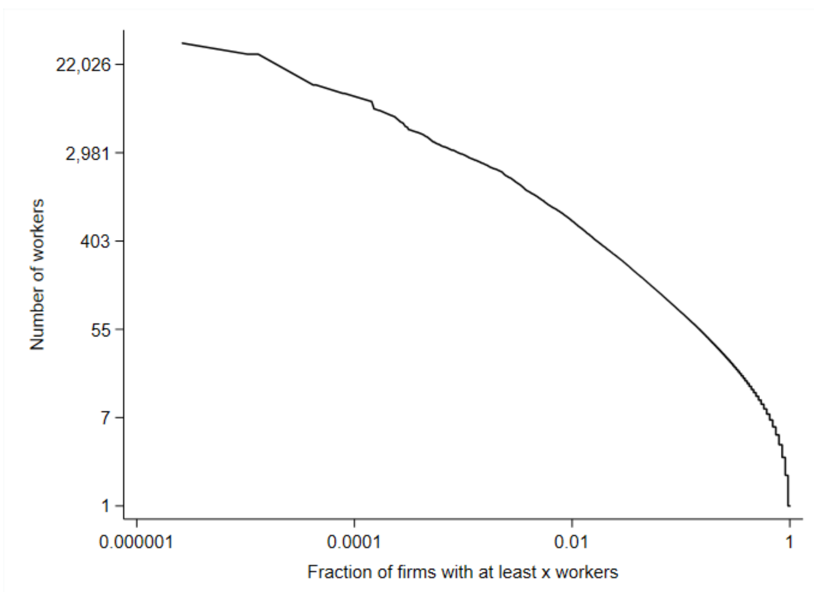
minimum of 608 employees.

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 confirms that a very large portion of firms have only a few workers and that only a few firms employ a lot of workers. For example, 3.8 percent of the firms in the sample had one single employee, compared with one tenth of 1 percent of the firms with over 2,800 workers.[20]

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



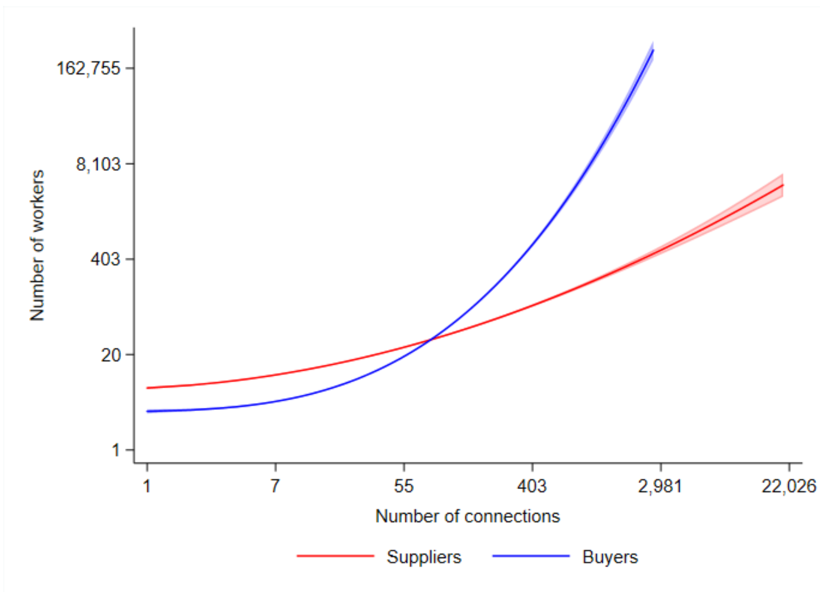
Notes: The figure shows the inverse of the cumulative distribution functions of the number of workers per firm.

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

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

to be positive relationship, suggesting that firms with a larger number of connections are also the ones employing a larger number of people. The coefficient 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.

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

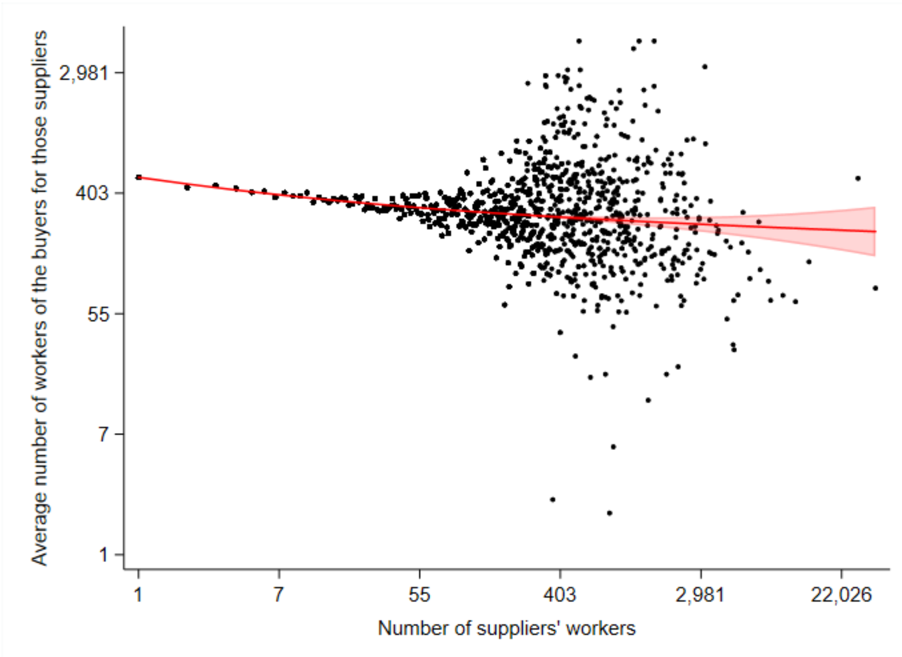


Notes: A third degree polynomial regression of the log of firm workers on the log of the number of connections is used to generate the figure. The shaded areas denote the 95 percent confidence intervals.

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

The evidence for buyers confirms 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 work-

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

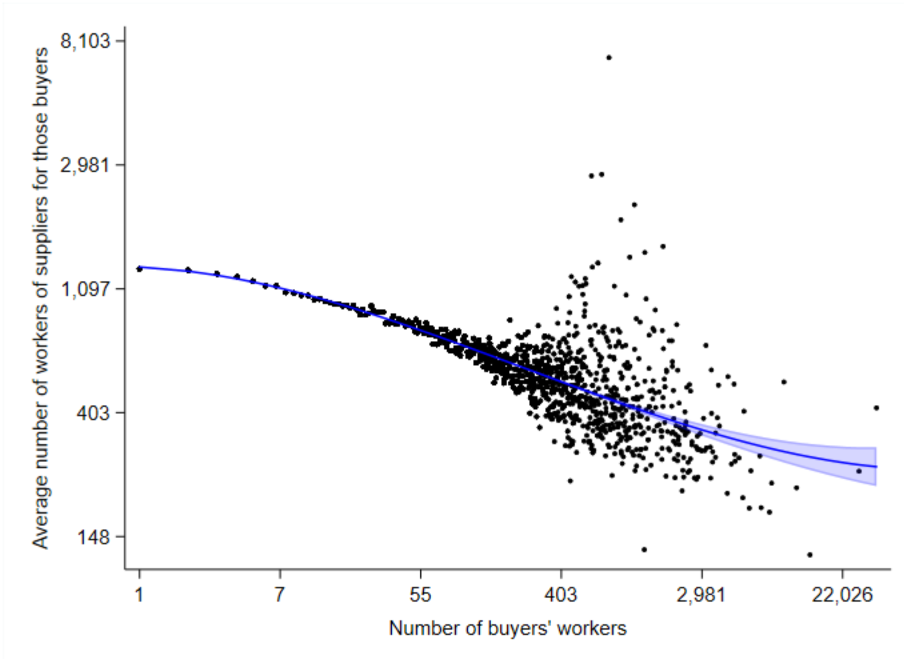


Source: Source: Authors' calculations.
Notes: A third degree polynomial regression of the log of the number of workers of suppliers on the log of the average number of workers of the buyers for those suppliers is used to generate the figure. The shaded areas denote the 95 percent confidence intervals.

force buy from suppliers employ only a few people. The coefficient 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 figures 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 firms per sector in 2017. The sectors that employ most workers, on average, are "finance and insurance" with 658 workers and manufacturing 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 firm 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 firm in the sector. Using the same metric, the least concentrated sector appears to be "education", where the firms in the top one percent of the distribution employ 6.6 times the the amount of workers employed by the average firm, respectively.

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 figure. The shaded areas denote the 95 percent confidence intervals.

A1.3 Sales

We finally look at firms' sales. Table A5 shows that since 2012 domestic sales increased by 7.6 percent reaching US$28.6 billion in 2017. However, as new firms 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 firms in the sample registered relatively low sales. For instance, in 2017, one fourth of the firms in the sample sold less than US$0.01 million. The top one percent of the firms 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 firms in the sample remained broadly unchanged, while the decline took place for other firms.

In Figure A8, we explore if the firms with the largest sales are also the ones with the largest number of connections, either suppliers or buyers. We find 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. Interestingly, the figure

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

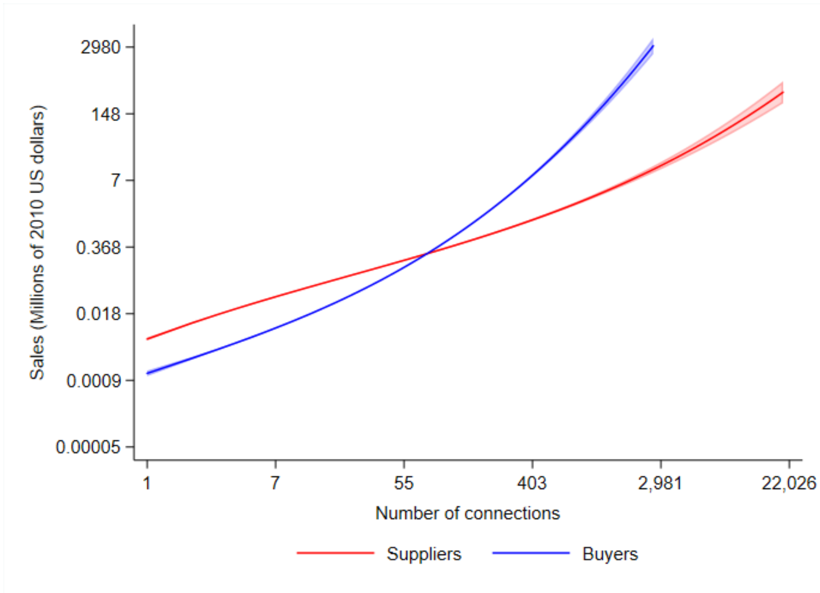
Sector	Mean	St. Dev.	10th	25th	50th	75th	90th	99th
Agriculture, hunting, and forestry	71	160	3	6	17	64	177	766
Construction	32	113	2	5	11	26	67	333
Education	31	41	4	9	18	36	71	206
Finance and insurance	658	1597	4	12	72	394	2154	7782
Health	53	125	3	5	12	39	135	590
Hotels and restaurants	79	293	4	8	17	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

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

shows that the slope of the curves becomes steeper for larger numbers of connections, indicating disproportionally higher sales for those firms with a lot of connections.

Figure A8: Sales and Number of Connections, 2017

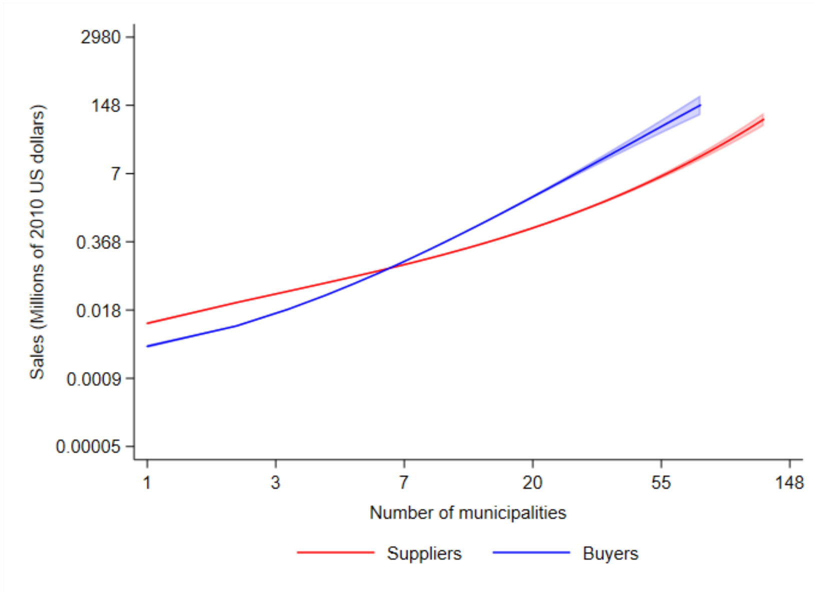


Notes: A third degree polynomial regression of the log of firm sales on the log of the number of connections is used to generate the figure. The shaded areas denote the 95 percent confidence intervals.

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.

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 figure. The shaded areas denote the 95 percent confidence intervals.

We now look at sales heterogeneity across sectors. As shown in Table Table A6, sales are largely concentrated in two sectors, "manufacturin" 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 firms by sector in 2017. The sector recording the largest sales by firm is "finance and insurance", with an average by firm of US$8.2 million. This is much larger than in any other sector. Specifically, this is 2.7 times larger than the sales for the average firm in the "manufacturing" sector (the sector with the second largest average sales by firm) and about 8 times larger than the sales for the "agriculture, hunting, and forestry" sector (the sector with the third largest average sales by firm). Across almost all sectors, sales are concentrated in a very few firms. Firms in the top one percent of the "finance and insurance" sector, for example, registered sales for US$132 million, which is about 17 times the sales for the average firms.

Table A8 shows the distribution of transactions between suppliers and buyers across sectors in 2017. The largest average transaction took 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, how-

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

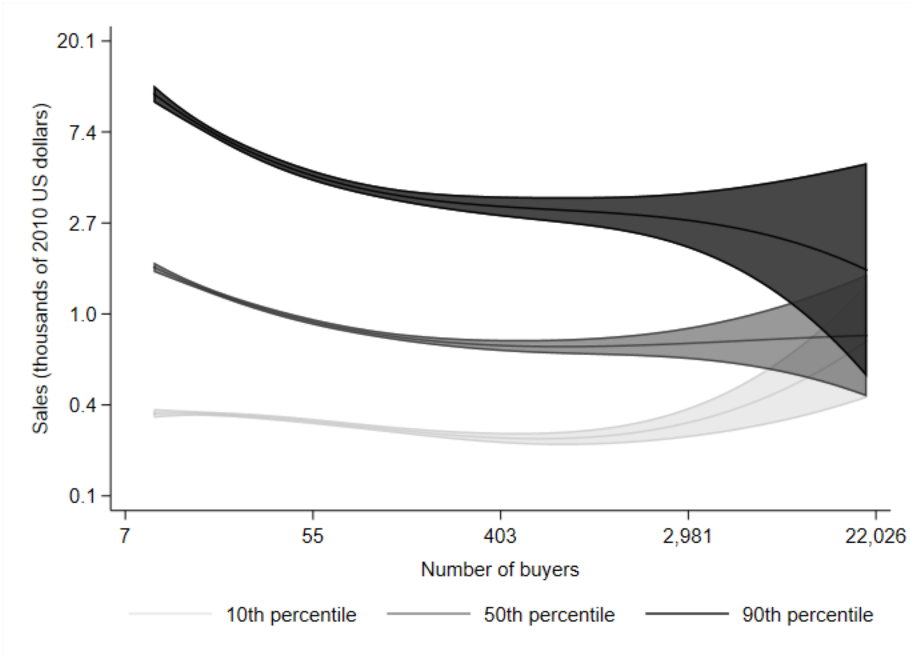
Sector	2012	2013	2014	2015	2016	2017	Total
Agriculture, hunting, and forestry	2.2	2.5	2.4	2.6	2.7	2.7	2.5
Construction	3.5	3.3	3.1	3.9	4.2	4.1	3.7
Education	0.0	0.0	0.0	0.1	0.1	0.1	0.1
Finance and insurance	3.4	3.3	3.2	3.6	3.7	3.8	3.5
Health	0.5	0.7	0.9	1.3	1.4	1.3	1.1
Hotels and restaurants	1.1	1.0	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 deflated 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 figure. Regressions are run for the 10th, 50th, and 90th percentiles. The shaded areas denote the 95 percent confidence intervals.

ever, 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.

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 deflated with the US producer price index.

A2 Alternative Productivity Specifications

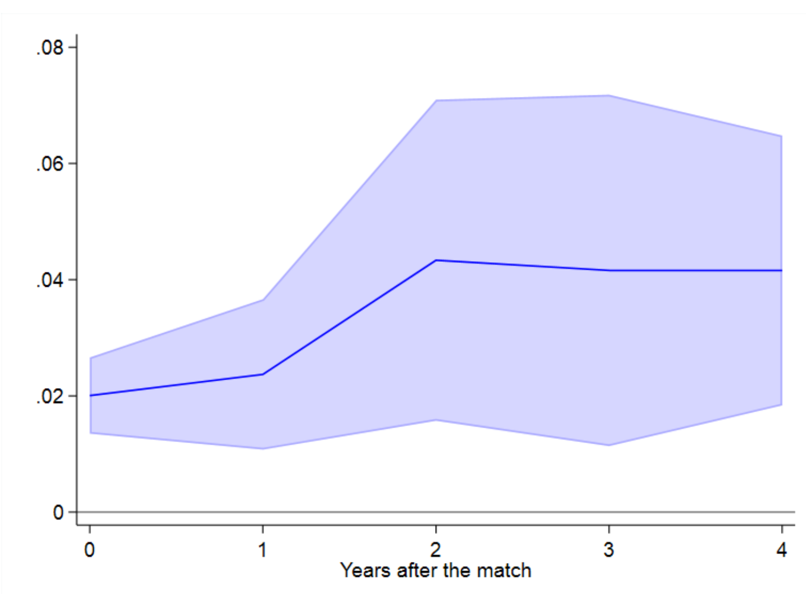
In this Appendix we present some alternative specifications to investigate the relationship between worker movements along the production network and productivity growth. First, we modify equation (11) by substituting the dependent variable with the productivity level. That is, rather than considering changes in productivity between year $t-1$ and year $t+k$ conditional on productivity at $t-1$, we consider the level of productivity in $t+k$ conditional on productivity at $t-1$. This is to ensure that the results are not driven by a mechanical correlation between the productivity level and the dependent variable of equation (11). We therefore estimate the following equation:

$$prod_{d,t+k} = \phi_{o,k} + \rho_k \cdot prod_{d,t-1} + \beta_k TF_{d,o,t-1} + \gamma X_{d,o,t-1} + \delta_k X_{w,t-1} + \eta_{w,d,o,k} \tag{16}$$

We present the estimates of β_k in Figure A11. These confirm the findings discussed in Section 4.3: firms that hire workers from their buyer and supplier are not only more productive to start with, but also become more productive after the new hire, conditional on the initial productivity level.

Figure A11: Persistence of the Productivity Impact—Alternative Specification

(Percent)



Notes: The line denotes the point estimate of the productivity in year $T+k$, conditional on the productivity in year $T-1$, for firms that hired workers from a buyer or supplier in $T-1$. The shaded area denotes the 90 percent confidence interval, with standard errors clustered at the municipality level.

We also estimate the specification in Section 5.2 about knowledge spillovers using productivity level rather than productivity growth as a dependent variable. The (unreported) results confirm that positive productivity spillovers are larger when firms hire workers of highly productive buyers or suppliers.

We then move to estimate firm-level—rather than worker-level—regressions.[21] That is, for each horizon k, we estimate the regression:

$$\Delta prod_{i,t+k} = \rho_k \cdot prod_{i,t-1} + \beta_k HN_{i,t-1} + \delta_k X_{i,t-1} + \eta_{i,t,k} \tag{17}$$

where i is a firm that hired at least one worker from another firm and $HN_{i,t-1}$ is the share of new hires that came from connected firms.[22] $X_{i,t-1}$ is a set of firm-level controls including the calendar year, firm industry, location, size (measured as the number of permanent employees), and the number of new hires. We weight each firm-year observation by the number of new hires. As we have a short panel, we do not include firm fixed effects as it may lead to a substantial bias (Nickell, 1981).

The results in Figure A12 confirm the conclusions of Section 4.3: firms that successfully hire from buyers or suppliers experience a significantly stronger productivity growth, and this additional growth persists over time. We find similar results if we focus on firms which hired only one worker during the year.

We finally turn to estimate the productivity gains arising from knowledge spillovers at the firm level with the following specification:

$$\Delta prod_{i,t+k} = \rho_k \cdot prod_{i,t-1} + \beta_k HN_{i,t-1} + \tau_k gap_{i,t-1} + \psi_k gapconnected_{i,t-1} + \delta_k X_{i,t-1} + \eta_{i,t,k} \tag{18}$$

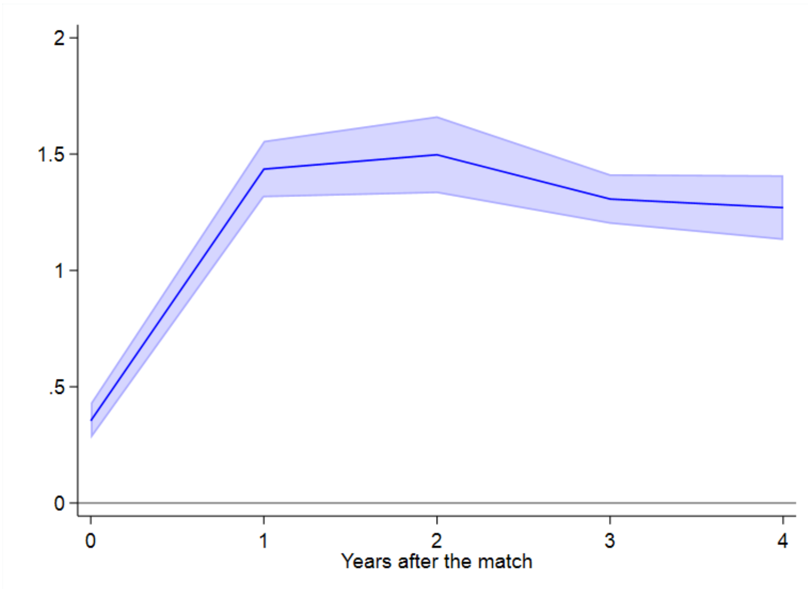
which differs from the one in equation (17) as we now include the terms $gap_{i,t-1}$ and $gapconnected_{i,t-1}$. For each worker who changes employer between two years, we estimate the productivity gap as the difference between the productivity of the old versus the new firm, with minimum value zero. The variable $gap_{i,t-1}$ is equal to the average gap across all the new hires who moved to firm i between $t-1$ and t. The variable $gapconnected_{i,t-1}$, instead, is the average gap across all the workers who moved to firm i and that were working for one of i's buyers or suppliers during the previous year. This is zero if no workers were hired from a connected firm.

Figure A13 shows the coefficient estimates for ψ_k, which capture the additional knowledge spillovers owing to workers movements along the production networks. The results confirm the findings of Section 5.2: firms learn more by hiring workers from more productive firms when they hire from buyers or suppliers. These additional knowledge

[21]The magnitudes of the coefficients in firm- and worker-level regressions are not directly comparable.
[22]We do not consider new hires who were not permanent workers of another firm in the previous year.

Figure A12: Persistence of Productivity Growth—Firm-Level Regressions

(Percent)

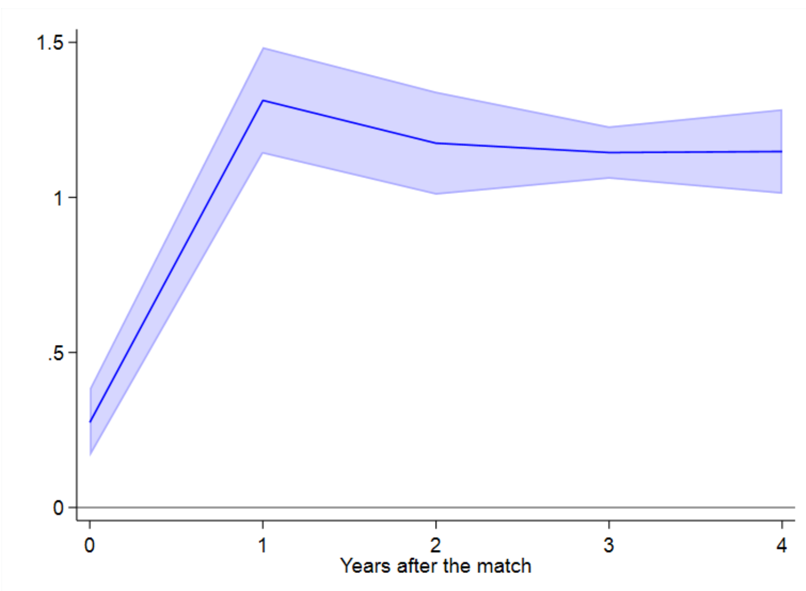


Notes: The line denotes the point estimate of the productivity in year, conditional on the productivity in year $T-1$, for firms that hired workers from a buyer or supplier in $T-1$. The shaded area denotes the 90 percent confidence interval, with standard errors clustered at the municipality level.

spillovers are also persistent.

Figure A13: Persistence of Productivity Growth—Firm-Level Regressions

(Percent)



Notes: The line denotes the point estimate of the productivity in year, conditional on the productivity in year $T-1$, for firms that hired workers from a buyer or supplier in $T-1$. The shaded area denotes the 90 percent confidence interval, with standard errors clustered at the municipality level.