The Anatomy of Domestic Production Networks: Evidence from Costa Rica*

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Abstract

How are domestic production networks structured, and which features are common across countries? We leverage rich microdata from Costa Rica—specifically, the near-universe of formal firm-to-firm transactions—to document, for the first time, a comprehensive and internally consistent set of facts for a less developed economy. Connections follow power-law distributions and are extremely sparse. The number of connections accounts for roughly 60% of the variance in firms' within-network sales. Distance sharply reduces trade, with about 85% of this effect operating through fewer connections rather than smaller transactions. Domestic supply chains transmit import exposure broadly—most firms source foreign inputs indirectly, with a median share of imports in inputs of about 30%—while export exposure remains concentrated among direct exporters. We compare these patterns with evidence from mostly developed economies such as Belgium and Japan. Despite large differences in development levels, sectoral composition, and trade openness, the qualitative patterns are strikingly similar.

Keywords: domestic production networks, firm-to-firm transaction data, buyer-supplier relationships.

JEL Codes: F14, L14, L25, D85, R15, L52, O54

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1 Introduction

The structure of firm-to-firm production networks determines how idiosyncratic shocks translate into aggregate fluctuations, how international trade affects firms not directly engaged in cross-border trade, and the reach of targeted industrial policies.[1] Establishing empirical regularities of these networks—the distribution of connections, matching patterns, the role of geography, and the extent to which domestic intermediaries transmit international trade exposure—is a necessary first step toward understanding these effects. Yet such regularities remain incompletely documented (Carvalho, 2014; Pichler et al., 2023), particularly in less developed economies.

What does a comprehensive, internally consistent characterization of the domestic production network[2] in a less developed economy reveal? We leverage rich microdata from Costa Rica—specifically, the near-universe of firm-to-firm transactions—to document 16 stylized facts about the domestic production network and compare them descriptively against established facts, mainly from Belgium and Japan—countries that differ markedly in development level, sectoral composition, and trade openness.

Three gaps in the literature motivate our analysis. First, production network facts have been documented in a fragmented way: individual papers typically establish a handful of stylized facts, often using different samples, estimation methods, and time periods.[3] Even for a given country, assembling a comprehensive picture of its production network from prior research requires combining estimates from studies that rely on different methodologies, making it difficult to assess whether the documented features are mutually consistent. Second, the most exhaustive characterizations to date have been conducted for developed countries, specifically Belgium and Japan (Bernard et al., 2019b, 2022). Evidence from less developed countries remains scarce, leaving open whether regularities found in high-income settings extend to economies with different institutional environments, sectoral compositions, and trade openness. Third,

[1] Acemoglu et al. (2012), Magerman et al. (2016), Huneeus (2020), and Demir et al. (2024) study shock transmission through production networks; Carvalho et al. (2021) and C. Fujiy et al. (2025a) examine supply chain disruptions; and Liu (2019) studies industrial policies in production networks.

[2] Throughout the paper, we use "domestic" to refer to within-country firm-to-firm trade, regardless of whether firms are domestically or foreign-owned.

[3] For instance, Bernard et al. (2018, 2019b, 2022) use three different estimators throughout three papers to quantify negative assortativity. Dhyne et al. (2021) and Cardoza et al. (2025) base sample criteria on the number of permanent workers, but Dhyne et al. impose additional restrictions related to fixed assets.

characterizations of global production networks—considering international transactions—do not directly translate into domestic networks, because firms that engage in international trade are systematically more productive (Melitz, 2003). Our data allow us to bridge this divide between domestic and international trade facts. By combining domestic firm-to-firm transaction records with customs declarations and firm-level balance sheets, we can trace how exposure to foreign markets permeates through the domestic production network via supply chain linkages, connecting the literatures on domestic network structure and international trade.

We address these gaps by documenting 16 stylized facts using a unified methodology applied to rich administrative data from Costa Rica. We combine six datasets covering all formal firms and transactions from 2008 to 2019: domestic firm-to-firm transactions, corporate tax returns, social security records, customs declarations, ownership linkages, and a municipality-level distance matrix.[4] Because all facts are estimated on the same sample with the same methodology, they yield an internally coherent characterization of a domestic production network.

Our analysis proceeds in four steps. In the first step, we document distributional properties of firm connections and decompose the sales observed in the firm-to-firm transaction data (hereafter, within-network sales) into extensive and intensive margins. Buyer and seller connections follow power-law distributions with tail exponents ranging from 0.43 to 1.26; networks are sparse, with only 1 in 5,050 potential connections realized. The extensive margin—the number of connections—accounts for 59% of the variance in within-network sales, with an elasticity of 1.02 between the number of buyers and within-network sales. More productive firms have more connections (elasticity of 0.24), and connection survival rates range from 40% for the smallest firms to 75% for the largest. Link creation rates decline with firm size, falling from roughly 40% among small incumbents to 25% among the largest.

In the second step, we characterize how firms match across the degree distribution and how transactions concentrate across partners. Well-connected firms systematically match with less-connected partners—negative degree assortativity—with elasticities of -0.06 for sellers and -0.11 for buyers. Average transaction size declines as sellers gain buyers (elasticity of -0.12), and the top buyer alone accounts for 70% of

[4] The first five administrative datasets have been used to study the effects of multinational companies on firms and workers in Costa Rica (Alfaro-Ureña et al., 2021, 2022, 2025).

within-network sales among firms with fewer than 10 buyers.

In the third step, we estimate gravity-style regressions and decompose the distance effect into extensive and intensive margins. The median connected firm pair is located 21.56 km apart; the distance elasticity of trade is -0.64; and 85% of this effect operates through fewer connections rather than smaller transactions. Using travel time computed from road-network routing—rather than linear distance—we account for the complex geography and uneven infrastructure that characterize developing countries.

In the fourth and final step, we compute direct and total export and import shares using recursive equations that account for indirect trade through domestic intermediaries. Only 5.5% of firms export directly, yet 60.5% reach foreign markets through intermediaries; the median firm's total export share is just 0.04%, while the median total import share is 31.8%. Both direct and total trade shares increase with firm size: direct exporters maintain total export shares around 30% across the size distribution, while non-direct exporters remain below 5%; direct importers exhibit total import shares of 50—58%, while non-direct importers range from 22% to 32%.

We benchmark each set of findings against available evidence from other, mostly developed, countries. Given differences in samples, estimators, variable definitions, and economic structures, we focus on whether qualitative patterns—signs, shapes, and relative magnitudes—are shared across countries, rather than taking quantitative differences at face value. We organize the comparison along three dimensions. First, regarding *network structure and density*, production networks in both developed and developing countries share the same qualitative features: power-law degree distributions, sparsity, and substantial within-sector size dispersion. However, Costa Rica's network is denser than those of larger developed economies—1 in 5,050 potential connections are realized, compared with 1 in 23,000 in Belgium and 1 in 130,000 in Japan—consistent with a smaller economy in which firms face a more limited set of potential partners and consequently form a higher proportion of possible connections. The extensive margin accounts for a similar share of variance across countries (59% in Costa Rica, 53% in Chile), though it is higher than in Ecuador (31%) or India (35%). Second, regarding *matching and dynamics*, negative degree assortativity, declining average transaction sizes as sellers gain partners, and concentrated sales among top buyers are shared features across countries. Quantitatively, degree assortativity is weaker in Costa Rica (buyer elasticity of -0.11) than in Japan (-0.42) or Belgium (-0.18), suggesting a less hierarchical matching structure that may reflect fewer intermediation layers. Link survival rates are higher in Costa Rica (55–75%) than in Chile (38–52%), suggesting greater relationship persistence, potentially due to higher switching costs or thinner partner markets. Third, regarding *trade exposure*, the patterns of direct and indirect trade participation are qualitatively similar across countries. Still, Costa Rica exhibits lower direct export participation (5.5% versus 12% in Belgium) and a much lower median direct plus indirect export share (0.04% versus 3% in Belgium), consistent with a less trade-integrated economy. Import exposure is more comparable: the median direct plus indirect import share is 31.8% in Costa Rica versus 39% in Belgium. A notable finding is that the domestic network transmits import exposure far more effectively than export exposure—a pattern that is more pronounced in Costa Rica than in Belgium, a pattern consistent with smaller firms in a developing economy having fewer direct channels to foreign markets and relying more heavily on domestic intermediaries for imported inputs (Manova et al., 2025). These quantitative differences—a denser network, higher link persistence, and lower trade integration—may partially reflect Costa Rica's development level, though disentangling the roles of economy size, trade policy, and distortions common in less developed economies lies outside the scope of the paper.

Related literature. We contribute to three strands of the literature on production networks. The first strand studies how distance, geography, and the spatial distribution of firms shape firm-to-firm trade (Bernard et al., 2009; Chaney, 2014; Bernard et al., 2019b; Eaton et al., 2023; Miyauchi, 2024; Arkolakis et al., 2025).[5] The second strand examines how firm heterogeneity affects network structure (Bernard et al., 2018; Oberfield, 2018; Acemoglu & Azar, 2020; Bernard et al., 2022). The third strand studies indirect trade exposure through intermediaries (Blaum et al., 2018; Dhyne et al., 2021, 2025).[6]

We differentiate from this literature in three ways. We provide the first comprehensive characterization of a less developed country's domestic production net-

[5] Böken et al. (2024) and C. Fujiy et al. (2025b) show that cultural proximity between firm owners increases the probability of trading.

[6] Blaum et al. (2018) show that heterogeneity in firm import shares and their dispersion complicate the computation of gains from trade based solely on aggregate expenditure data.

work spanning all four dimensions studied in the literature: distributional properties, matching patterns, geography, and indirect trade exposure. While individual facts have been documented in developing country settings—link dynamics in Chile (Huneeus, 2020), network complexity in Ecuador and Hungary (Bacilieri et al., 2025), and network formation in Chile (Arkolakis et al., 2025)—no prior study has systematically documented all these properties in a single economy using a unified methodology. Beyond the value of internal consistency, descriptive comparisons with evidence from other countries are valuable in their own right, as they help identify which qualitative patterns are shared across countries and where differences emerge.[7]

Second, while most of our facts validate patterns previously established in developed economies, several findings are new or substantially extend prior work. We provide, to our knowledge, the first direct empirical evidence consistent with the "star seller" mechanism of Oberfield (2018), evidenced by the positive productivity-connections elasticity of 0.24 for sellers and 0.21 for buyers; and the dispersion ordering in Acemoglu and Azar (2020), whereby the buyer degree distribution exhibits greater tail dispersion than the seller degree distribution. The rank-by-rank concentration of transactions on both sides of the network extends the aggregate concentration patterns documented by Boehm and Sonntag (2023) and Bernard et al. (2022). The decomposition of the distance-trade elasticity into extensive and intensive margins extends Bernard et al. (2011) and Fernandes et al. (2023) to a domestic network setting, and complements Arkolakis et al. (2025) by characterizing the full functional form of each margin across the distribution of distances. The computation of direct and total trade shares through intermediaries, following Dhyne et al. (2021), has not previously been performed for a less developed country. Our results reveal that indirect export exposure is an order of magnitude lower in Costa Rica than in Belgium, whereas indirect import exposure is remarkably similar across the two countries. The remaining facts—degree distributions, sparsity, size dispersion, negative assortativity, gravity, and the size premium of traders—validate patterns documented in developed economies, suggesting these regularities may reflect shared features of firm interactions rather than country-specific phenomena.

[7] A contemporary paper by Bacilieri et al. (2025) analyzes firm-level production networks from the perspective of network complexity; our paper is complementary in that we focus exclusively on domestic networks and document a broader set of patterns, including those pertaining to international trade exposure and the role of geography.

Third, we apply a unified methodology—the same estimator, sample criteria, and fixed effects—across all 16 facts. We characterize the functional form of these relationships using the Cattaneo et al. (2024) estimator, which yields consistent estimates under weaker assumptions than those required by traditional residualized binscatter plots. This methodological consistency across 16 facts facilitates future work seeking to explain subsets of these facts jointly, without concern for internal inconsistencies that could bias estimates. For cross-country comparisons, we note that differences in methodology across studies preclude a clean attribution of quantitative differences in estimates to structural factors versus methodological choices. When qualitative patterns align across countries despite these methodological differences, this suggests that the underlying regularities are robust. Developing harmonized cross-country estimates based on a common methodology applied to multiple countries' data remains an important direction for future research.

The remainder of the paper is organized as follows. Section 2 describes the data and provides descriptive statistics. Section 3 presents the empirical framework. Sections 4—7 document the 16 stylized facts. Section 8 concludes.

2 Data

2.1 Data construction

We rely on a rich combination of administrative datasets that have been used in prior research on the impact of multinational companies on firms and workers in Costa Rica (Alfaro-Ureña et al., 2021, 2022, 2025). We provide a brief overview of these datasets and refer the interested reader to Online Appendix A.1 of Alfaro-Ureña et al. (2022) for a comprehensive description of the data construction and cleaning process.[8]

Firm-to-firm transaction data Since 2008, the Ministry of Finance of Costa Rica has used the D-151 tax form to collect information about the near-universe of formal firm-to-firm input-output relationships in the country. Namely, firms must report the tax identifier of all their sellers and buyers with whom they trade at least 2.5 million Costa Rican colones (around 4,200 U.S. dollars) in a year and the total amount transacted.

[8] Dhyne et al. (2015, 2023a) provide complementary discussions.

This requirement allows cross-checking the reports of buyers and sellers to ensure that firms do not understate income or overstate costs to reduce their corporate income tax liability. Private or public agents that buy or sell goods and services must also file this form, even if they do not pay income tax; otherwise, they are subject to fines for non-compliance. We use these data for 2008–2019 to track the near-universe of firm-to-firm relationships (extensive margin) and annual transaction values (intensive margin). Reporting thresholds as in Costa Rica are common across firm-to-firm transaction datasets: Belgium also applies a minimum reporting threshold, while Japanese credit bureau data cap the number of reported suppliers and buyers at 20 per firm (Bernard et al., 2019b). The Costa Rican threshold is sufficiently low to exclude only marginal one-off transactions or those associated with the smallest firms.[9] The consistency of our network statistics with those from other countries suggests that the observed topology reflects genuine economic structure rather than an artifact of the reporting rule.

Firm-level data Next, we leverage several firm-level datasets to characterize the buyers and sellers observed in firm-to-firm relationships. First, we incorporate variables from the D-101 corporate income tax forms submitted to the Ministry of Finance, which report standard balance-sheet information, including annual sales, input costs, as well as firms' primary four-digit sector and location. We also use panel data from the Costa Rican Social Security Fund on firm-level employment and wage bills. Finally, we draw on Costa Rican customs declarations data on annual firm-level imports and exports.

Shared ownership data Although Form D-101 reports firms' tax ID numbers, it does not indicate whether a firm's owners hold shares in other firms. In practice, multiple Tax IDs may be controlled by a single holding company, or created for administrative purposes. We therefore need to identify shared ownership to group related entities into corporate groups. This step is essential to avoid overstating the number of firms and firm-to-firm transactions within corporate groups. To do so, we use consolidated

[9] Reporting thresholds are particularly relevant for datasets from developing countries, as they bind in either VAT data or other required sources (e.g., corporate income tax returns). They reflect both high informality among small transactions and firms, and governments' efforts to limit reporting requirements. The paper-trail structure of VAT data—which generates third-party cross-reports between trading partners—also creates self-enforcement incentives that improve compliance (Pomeranz, 2015). Wiedemann et al. (2025) use complementary data on informal activity in Kenya to assess how the omission of informality in VAT data affects measures of network density, distance, and trade exposure, illustrating how such data can complement VAT records.

corporate-group identifiers constructed in Alfaro-Ureña et al. (2022), based on data from the Central Bank's national accounts and the Orbis dataset. Throughout the paper, corporate groups are the unit of observation.

Distance and travel time across firms Compared to developed countries, Costa Rica has poor road infrastructure and complex geography, making linear distance unreliable for assessing transport costs. To address this challenge, we constructed a route distance matrix using the coordinates of municipal town halls across Costa Rica. We rely on OpenStreetMap contributors (2023) to calculate distances and travel times of routes, optimizing for travel time rather than distance. Each firm is assigned to the municipality where most of its employees are registered, which typically represents its primary operational location rather than just its administrative headquarters.[10] We assign the distance and travel time between two firms as the route distance and travel time between their respective municipalities' town halls. We further explain the computation algorithm in Appendix D.1.

Analysis sample We focus on firms that employ at least one permanent worker annually, excluding those registered in the "Diplomatic Activities" sector. Appendix Figure A1 summarizes the sample selection process, showing the share of firms retained after each cleaning step for three variables: total sales, within-network sales, and the number of transactions. "Total" denotes all firms filing corporate income tax returns,"Matched" those observed in the transactions dataset, and "Cleaned" those remaining after applying the selection criteria. Our final sample captures 94.3–97.4% of total sales (Appendix Figure A1a), 81.4–87.9% of within-network sales (Appendix Figure A1b), and 78.5–84.8% of transactions (Appendix Figure A1c) in a given year. The analysis sample includes 96,177 firms and 3,839,024 buyer–seller connections.

2.2 Descriptive statistics

We find that in our analysis sample of 96,177 businesses and 3,839,024 connections between buyers and sellers, 46–52% of firms both buy and sell, 13–17% only sell,

[10] The municipality of the firm's headquarters is an alternative option. However, we prefer to use the municipality where the firm conducts most of its activity (as captured by where most of its employees are registered) instead of what might be only a location serving administrative and tax purposes.

and 34–37% only buy. In Appendix Figure A2, we break down these percentages by year. Firms that only engage in buying transactions typically sell to final domestic consumers, buyers outside of Costa Rica, or firms whose annual sales are below the reporting threshold. Conversely, firms that only sell usually import their inputs or keep their annual purchases from local firms below the reporting threshold.

Examining these percentages by sector, we find that upstream sectors (such as Agriculture, Forestry and Fishing, Mining and Quarrying, and Manufacturing) have a higher proportion of firms that both buy and sell. In contrast, downstream sectors, such as Accommodation and Food Services and Education, are predominantly buyers. Appendix Figure A3 illustrates the distribution of each category by sector in 2014.

A few key sectors dominate the Costa Rican economy. In 2014, Wholesale and Retail Trade, Manufacturing, and Financial Activities were the top three contributors, accounting for 62% of total formal-sector sales. Appendix Figure A4 reports the share of firms' total sales across two-digit sectors from 2008 to 2018, shown every two years.

The total sales distribution is positively skewed and heavy-tailed. In 2014, average firm sales are 1.94 million (CPI-deflated) 2014 U.S. dollars, with a standard deviation of 32.31 million. Appendix Table B1 shows substantial variation: average sales peak in 2008 (2.47 million), and reach a low in 2019 (1.81 million). Across all years, median sales are 210 thousand, and firms in the 99^{th} percentile have average sales 648 times larger than those in the lowest decile.

Appendix Table B2 shows that sectoral averages of total sales vary widely. In 2014, firms in the Electricity and Gas sector had the highest average sales (53.70 million 2014 U.S. dollars), while those in the Human Health and Social Work sector had the lowest (0.35 million). Despite this sectoral variation in average firm sales, dispersion is similar: within each sector, the largest firms are several orders of magnitude larger than the sectoral average. Appendix Figure A5 depicts these sectoral patterns.

The distributions of the number of buyers and sellers are also characterized by high dispersion and skewness. Appendix Table B7 shows that the mean firm-level number of buyers in a given year is 11.69, and the standard deviation is 68.38. While the 99^{th}-percentile firm has 158 buyers, the median firm has three. The distribution of the number of sellers per firm is less skewed. Appendix Table B9 shows that the mean is 8.96, and the standard deviation is 23.71. While the 99^{th}-percentile firm has 92 sellers, the median firm has three. In short, the average firm has more buyers than sellers. As with sales, the number of connections has increased over time. Between 2008 and 2019, the average number of buyers rose from 10.47 to 12.09, while the average number of sellers increased from 7.84 to 9.10 (Appendix Tables B7 and B9).

The sectoral distributions of connections differ starkly. Appendix Tables B8 and B10 report key moments for the number of buyers and sellers, respectively. Among sellers, the Electricity and Gas sector exhibits the highest values in 2014, with an average of 150.08 buyers and 2,923 buyers at the 99$^{\text{th}}$ percentile. This sector also records the highest average sales. In contrast, the Agriculture, Forestry, and Fishing sector has the lowest average number of buyers (2.68). Among buyers, Electricity and Gas again stands out, with an average of 49.44 sellers and 711 at the top percentile in 2014, while Human Health and Social Work has the lowest average (3.80).

The distribution of transaction values is heavy-tailed and right-skewed. Appendix Table B11 shows that the average transaction is 39,030 (CPI-deflated) 2014 U.S. dollars—nearly three times the median—with a standard deviation more than twice the mean. Appendix Table B13 reports the distribution of employment, which is also right-skewed. The average firm employs 21.74 workers (standard deviation 215.11), while the median is four and firms at the 99$^{\text{th}}$ percentile employ 305 workers.

Belgium and Costa Rica display notably similar patterns. Using Belgian firm-to-firm data, Bernard et al. (2022) find that, while average firm sales vary widely across sectors, the within-sector size distribution exhibits comparable dispersion throughout; as in Costa Rica, heavy tails are not driven by particular sectors. Relatedly, Dhyne et al. (2015) show, as in our data, that the distribution of buyers per seller is more dispersed than that of sellers per buyer. At the same time, Belgian firms are larger and more connected. The average firm has 135 sellers and 1,021 buyers in Belgium, compared to 8.96 sellers and 11.69 buyers in Costa Rica. Likewise, the 99$^{\text{th}}$ percentiles are higher in Belgium (289 sellers and 393 buyers) than in Costa Rica (92 and 158), consistent with higher average sales.[11] Overall, while Belgian firms are larger and more connected, the qualitative patterns of firm connections are similar across the two countries.

[11] Relative to the median, the distribution of sellers per firm is more right-skewed in Costa Rica: the 99$^{\text{th}}$-percentile firm has roughly 31 times as many sellers as the median firm, compared to about 6 times in Belgium.

3 Empirical strategy

This section outlines our methodology for documenting stylized facts about Costa Rica's production network. We adopt an approach meant to facilitate cross-country comparisons while ensuring internal consistency. This approach is particularly valuable given that Costa Rica is less developed than countries whose production networks have been extensively studied, such as Japan and Belgium.

3.1 Estimation approach

We estimate log–log specifications with four-digit sector fixed effects to recover implied elasticities across the production network. This approach offers two key advantages: it allows for straightforward interpretation in percentage terms and facilitates direct comparison with prior studies. The stylized facts we document reflect cross-sectional properties of firm-to-firm relationships rather than sector-level patterns. Because upstream sectors tend to consist primarily of sellers, while downstream sectors consist of buyers, and because some sectors may disproportionately drive observed correlations, we include four-digit sector fixed effects in all specifications to mitigate these sources of bias.

3.2 Functional form characterization

We go beyond simple elasticities by characterizing the full functional form of bivariate relationships using the semi-linear, covariate-adjusted binscatter estimator of Cattaneo et al. (2024). This approach yields consistent estimates of partial mean effects at average values of the controls and offers clear advantages over existing production network methods. Unlike traditional residualized binscatter plots—which can yield biased estimates under model misspecification—this estimator provides more reliable characterizations of relationships without imposing restrictive functional forms. Previous studies typically rely on kernel-weighted local polynomial regressions or equally spaced 20-bin residualized scatter plots. Cattaneo et al. (2024) show that these approaches produce biased estimates when the true model is non-linear and lack clear interpretability even under strong assumptions.

This methodology delivers three key improvements. First, it allows us to detect nonlinearities that log–log specifications would otherwise mask. Second, it enables systematic comparisons of functional forms across stylized facts. Third, it facilitates cross-country comparisons by isolating methodological artifacts and focusing on underlying economic differences.

For implementation, we select quantile-spaced bins over the support of each explanatory variable to minimize the integrated squared mean error, incorporating covariate adjustment with robust standard errors unless otherwise specified. When the optimal number of bins is computationally infeasible, we reduce it incrementally until estimation becomes feasible.

3.3 Cross-country comparisons

We benchmark our findings from Costa Rica against stylized facts from other countries to assess their external validity. While most existing evidence comes from Belgium and Japan, we also draw on evidence from Chile, Ecuador, Hungary, India, and the United States, spanning a range of development levels and economic structures.

We restrict our comparative analysis to studies using VAT records and commercially collected data, excluding those based on payment systems owing to fundamental differences in data collection procedures. This restriction helps isolate genuine economic differences from methodological variation.

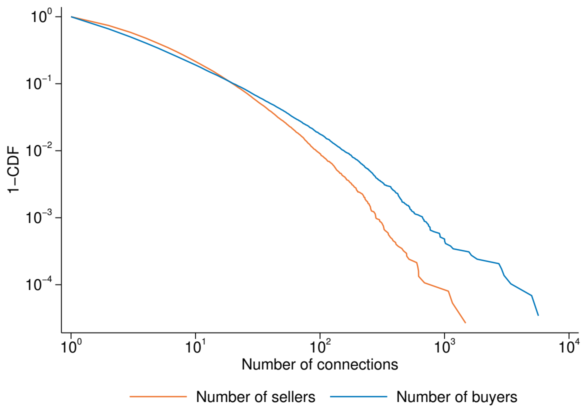
The cross-country similarities we document suggest that the observed patterns reflect intrinsic firm behavior rather than country-specific factors, while also providing indirect validation of the data. To further enhance comparability, future analyses in settings with similar data availability can adopt our consistent sample selection and estimation procedures.

4 Firm heterogeneity in domestic firm-to-firm trade

We first present seven stylized facts on domestic firm-to-firm connections, transaction values and their relationship with firm sales and productivity.

Fact 1. The distributions of the number of buyers and the number of sellers follow a power-law distribution.

Figure 1: Number of sellers and buyers per firm (CCDFs, 2014)



Notes: The figure is the counterpart for Costa Rica to Figure 2 from Bernard et al. (2019b) for Japan. The figure presents the cumulative distribution of the number of sellers and buyers per firm. This figure is based on the 2014 cross-section.

Figure 1 displays the empirical complementary cumulative distribution functions of connections. Both distributions exhibit heavy tails, indicating that most firms maintain few connections while a small minority have extensive networks. Around 50% of firms have fewer than six connections, while only 1% have more than 158. In the upper tail, 0.01% of firms have more than 1,000 suppliers, and 0.1% have more than 1,000 buyers. Appendix C presents the estimation of tail exponents, classification criteria, and cross-country comparisons.

Fact 2. Domestic firm production networks are sparse.

Most buyers and sellers in an economy are not connected. In Costa Rica, only about 1 in 5,050 potential connections is realized (in 2014, among 44,177 active firms, with potential connections defined as all ordered firm pairs with at least one observed link). By comparison, this figure is 1 in 23,000 in Belgium (Dhyne et al., 2015), 1 in 130,000 in Japan (Bernard et al., 2019b), 1 in 2,210 in Ecuador (Bacilieri et al., 2025), and 1 in 13,020 in Hungary (Bacilieri et al., 2025).

Fact 3. The distributions of firm sales, within-network sales and purchases, and buyer-seller connections exhibit substantial dispersion.

There is substantial heterogeneity across firms within sectors. Figure 2 presents the dispersion in six measures of firm size, each demeaned at the four-digit sector level. Figure 2a shows that the distribution of total sales exhibits similar dispersion to that in Appendix Figure A5, despite cross-sector differences. Within sectors, firms up to three orders of magnitude larger than the average coexist with much smaller firms. Appendix Table B2 summarizes these sectoral distributions for 2014. Bernard et al. (2022) document similar patterns in Belgium, with even greater disparities between the largest and average firms.[12] Figure 2b plots the distribution of workers per firm. Within four-digit sectors, employment ranges from one order of magnitude below the sector average to three orders above it. Rossi-Hansberg and Wright (2007) and Garicano et al. (2016) document similar patterns in the United States and France, respectively, showing that full-time employment follows a Pareto distribution.[13]

Figures 2c and 2d show substantial within-sector heterogeneity in within-network sales and purchases. Unlike total firm sales, these measures exclude transactions with final consumers, payments to production factors, and foreign transactions. The pattern observed for total sales persists: firms up to three orders of magnitude larger than the average coexist with much smaller firms. Bernard et al. (2022) document even greater variation in Belgium, with some firms exhibiting within-network sales up to five orders of magnitude above the average.[14]

Figures 2e and 2f illustrate dispersion in the extensive margin—the number of sellers and buyers per firm. Some firms have up to two orders of magnitude more connections than the sector average. Appendix Tables B8 and B10 provide sector-level summaries for 2014. Bernard et al. (2022) document similar patterns in Belgium, albeit with greater variation in the number of buyers. In both countries, the distribution of buyers per firm is more dispersed than that of sellers, consistent with theoretical and empirical findings in production networks (Acemoglu et al., 2012; Acemoglu & Azar, 2020). For additional stylized facts and theoretical discussion, see Appendix C.

[12] Acemoglu et al. (2012) use Input–Output Tables for U.S. sectors (1972 and 2000) to document asymmetric and heavy-tailed sales distributions across seller sectors.

[13] Appendix Tables B13 and B14 summarize the distribution of full-time employment across years and by sector in 2014.

[14] Appendix Tables B4 and B6 summarize the sectoral distributions of within-network sales and purchases.

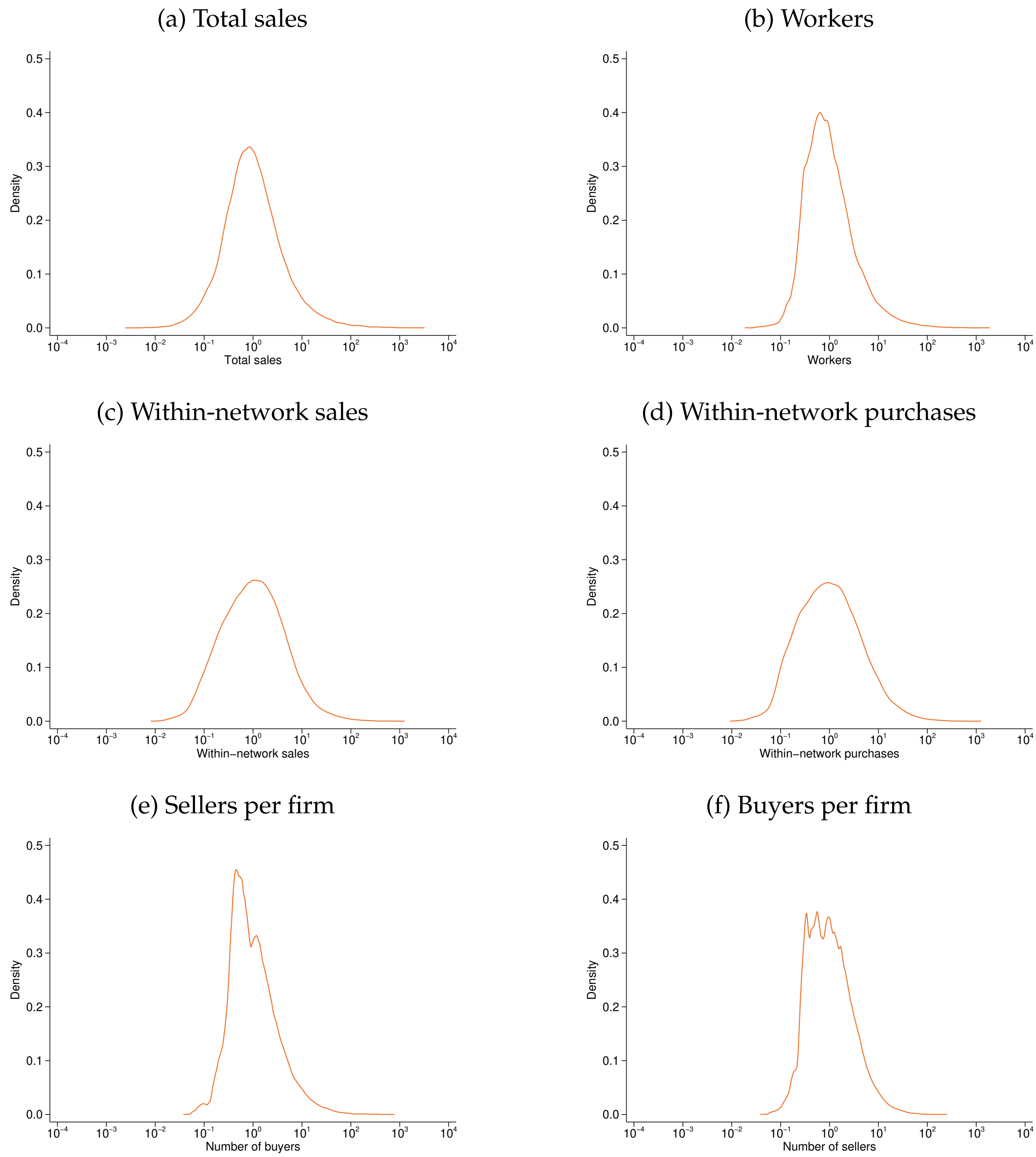


Figure 2: Distribution of firm sales, workers, within-network sales and purchases, number of buyers, and number of sellers (2014)

Notes: This figure is the counterpart for Costa Rica to Figure 1 and 5 from Bernard et al. (2022) for Belgium. We present six measures of firm size. Panel (a) shows the distribution of total sales. Panel (b) shows the distribution of full-time workers per firm. Panel (c) and Panel (d) show the distributions of the within-network sales and purchases, respectively. Finally, Panel (e) and Panel (f) show the distributions for the number of buyers and sellers, respectively. We demeaned all variables at the four-digit sector level. This figure is based on the 2014 cross-section.

Next, we analyze the margins of within-network sales and purchases in Fact 4 and Appendix Fact C2. We adapt the standard export sales decomposition of Bernard et al. (2009) to within-network transactions. Let X_i denote the within-network sales (or purchases) of firm (or sector) i, which can be decomposed as:

$$X_i = \underbrace{\text{\# locations} \cdot \text{\# sectors} \cdot \text{density}}_{\text{number of connections (i.e., number of buyers or sellers)}} \cdot \text{average transaction}, \tag{1}$$

where "# locations" and "# sectors" denote the number of locations[15] and sectors in which firm i has buyers (or sellers), and the "density" term is defined as the ratio of actual connections (buyers or sellers) to the potential number of location–sector combinations.[16] This decomposition separates the extensive margin (number of connections) from the intensive margin (average transaction size), and further decomposes the extensive margin into geographic scope, sectoral scope, and relationship density.

Fact 4. Firm size is strongly correlated with both the number of connections and average transaction size.

(a) Number of connections (b) Average transaction

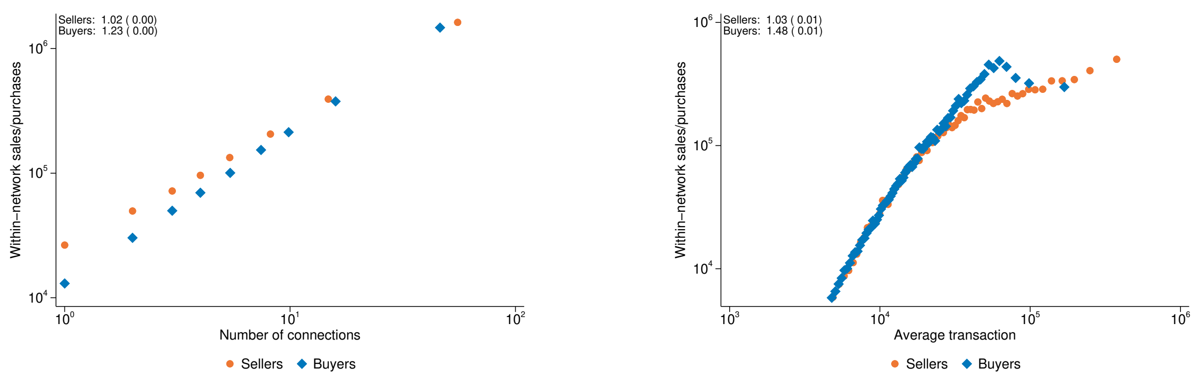


Figure 3: The margins of firm size (2014)

Notes: This figure is the counterpart for Costa Rica to Figure 2A from Bernard et al. (2022) for Belgium. The figure shows a quantile-spaced binned scatter plot of firms' number of connections (average transaction) by within-network sales (purchases), respectively, on a log-log scale. We use the estimator proposed by Cattaneo et al. (2024) and include four-digit sector fixed effects. This figure is based on the 2014 cross-section.

Figure 3a displays the relationship between within-network sales (purchases) and their components on a log–log scale. It focuses on the extensive margin: the correlation between within-network sales and the number of buyers per seller (orange

[15] In Costa Rica, a location corresponds to a municipality; there are 81 municipalities.

[16] Consider a firm with 10 buyers. These buyers may be spread across three municipalities and four sectors. If all municipality–sector combinations were feasible, there would be 12 potential groups; however, the firm connects with 10 buyers across these groups, yielding a concentration ratio of 10/12 = 0.83.

circles), and between within-network purchases and the number of sellers per buyer (blue diamonds). For sales, we estimate an elasticity of 1.02 (s.e. 0.004), implying that a 10% increase in buyers is associated with a 10.2% increase in within-network sales. This aligns with previous findings: Bernard et al. (2022) report a 7.7% effect in Belgium, while Bacilieri et al. (2025) find effects of 8.8% in Ecuador and 10.5% in Hungary. For purchases, we estimate an elasticity of 1.23 (s.e. 0.003), implying that a 10% increase in sellers is associated with a 12.3% increase in within-network purchases, consistent with Bacilieri et al. (2025), who report elasticities of 15.4% and 13.5%.

Figure 3b presents the intensive margin: the relationship between within-network sales and average transaction value (orange circles), and between within-network purchases and average purchase value (blue diamonds). For sales, we estimate an elasticity of 1.03 (s.e. 0.007) with four-digit sector fixed effects, implying that a 10% increase in average transaction value is associated with a 10.3% increase in within-network sales. For purchases, the elasticity is 1.48 (s.e. 0.009), implying that a 10% increase in average purchase value is associated with a 14.8% increase in within-network purchases. These positive correlations are consistent with predictions from random network formation models (Armenter & Koren, 2014; Bernard & Zi, 2022), but cross-country variation in elasticity magnitudes and in the relative importance of intensive versus extensive margins remains unexplained. Unlike the extensive margin, which exhibits constant slopes, the intensive margin shows declining slopes, a pattern that warrants further investigation in future production network models. We decompose the variance contribution of each margin in Appendix Table C2 (see Fact C2).

Fact 5. Firm size is strongly correlated with the geographic and sectoral scope of firm trade.

Figure 4 decomposes the extensive margin from Figure 3a into geographic and sectoral components. Figure 4a shows the relationship between within-network sales and the number of municipalities where buyers are located (orange circles), and between within-network purchases and the number of municipalities where sellers are located (blue diamonds). We estimate elasticities of within-network sales with respect to the number of buyer municipalities of 1.25 (s.e. 0.007), and of within-network pur-

(a) Number of municipalities

(b) Number of four-digit sectors

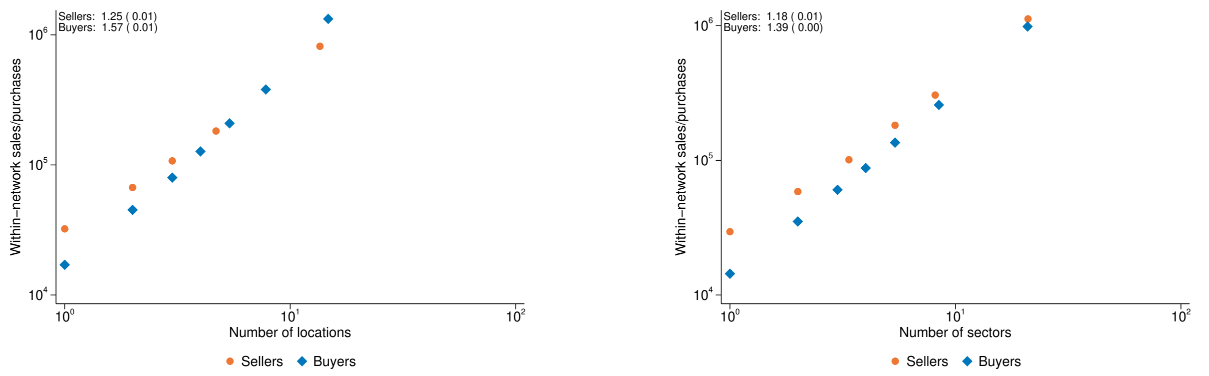


Figure 4: Decomposing the extensive margin of within-network sales (purchases)

Notes: This figure is the counterpart for Costa Rica to Figure 4 from Bernard et al. (2019b) for Japan. These figures document the relationship between the firm's within-network sales (purchases) and the different components of the extensive margin using the 2014 cross-section. In particular, Panel (a) shows the correlation between the number of destination (origin) municipalities and the within-network sales (purchases). Panel (b) features the correlation between the number of buying (selling) sectors and the within-network sales (purchases). The plots correspond to a binned scatter plot with quantile-spaced bins using the estimator proposed by Cattaneo et al. (2024) and include four-digit sector fixed effects.

chases with respect to the number of seller municipalities of 1.57 (s.e. 0.006). Bernard et al. (2019b) report estimates in the reverse direction for Japan, with elasticities of the number of buyer and seller municipalities with respect to firm sales of 0.29 and 0.31, respectively; the corresponding inverse elasticities are 3.45 and 3.23.[17]

Figure 4b shows the relationship between within-network sales and the number of four-digit sectors of buyers (orange circles), and between within-network purchases and the number of four-digit sectors of sellers (blue diamonds). We estimate elasticities of 1.18 (s.e. 0.006) and 1.39 (s.e. 0.004), respectively, controlling for four-digit sector fixed effects. These results indicate that larger firms not only trade with more partners but also connect with partners across more locations and economic sectors.

Fact 6. More productive firms tend to have more connections in the production network.

Figure 5 shows a positive relationship between firm productivity—measured as value added per worker—and the number of connections. The estimated elasticity is 0.24 (s.e. 0.01) for sellers and 0.21 (s.e. 0.01) for buyers. This finding is consistent with Oberfield (2018), which predicts that higher-productivity firms emerge as "star sell-

[17]Differences in magnitude likely reflect variation in sample composition, market definition, and firm size distributions between Japan and Costa Rica.

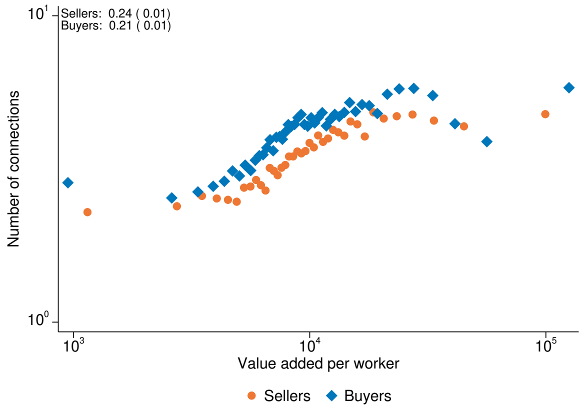


Figure 5: Firm productivity and number of connections (2014)

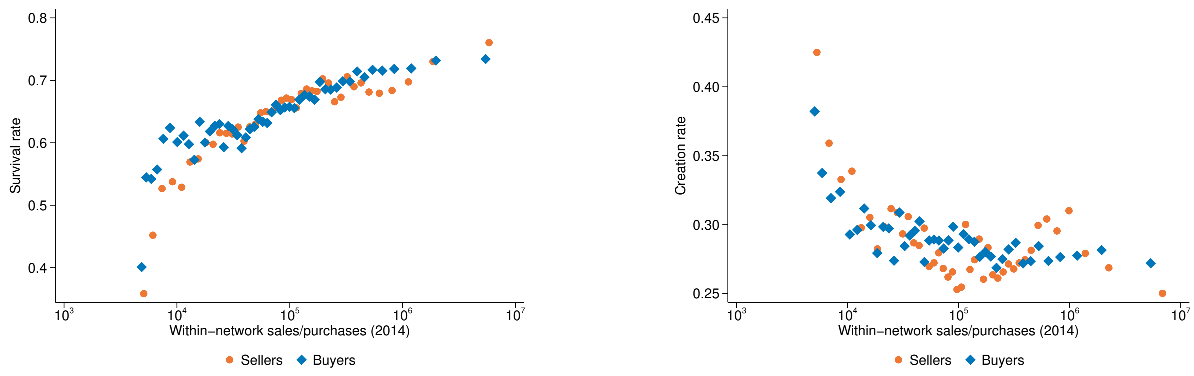
Notes: The figure shows a quantile-spaced binned scatter plot of firm productivity (measured as value added per worker) against number of connections. Orange circles represent sellers with their number of buyers, while blue diamonds represent buyers with their number of seller. Both axes use a logarithmic scale. The plots correspond to quantile-spaced binned scatter estimates using the methodology from Cattaneo et al. (2024). We include four-digit sector fixed effects. Firms with value added to sales ratios higher than one are excluded. The figure is based on the 2014 cross-section.

ers" when intermediate inputs play an important role in production. The mechanism operates through selection: when the elasticity of output with respect to intermediate inputs is high, buyers systematically select lower-cost sellers, generating a skewed distribution of connections even when productivity differences are modest.

Fact 7. The persistence of firm-to-firm connections increases with firm size.

Figure 6a shows that link survival rates—the fraction of connections that persist from one year to the next—increase with firm size, ranging from about 40% for the smallest firms to around 75% for the largest. This pattern holds for both buyer and seller connections. Survival rates in Costa Rica (55–75% overall) exceed those reported by Huneeus (2020) for Chile (38–52%), suggesting potential differences in underlying dynamics across countries. Figure 6b shows a negative and convex relationship between the creation rates of new connections and firm size: the share of new firm-to-firm links declines from about 37% (buyers) and 43% (sellers) to roughly 25% for both as firm size increases. Larger, more established firms form fewer new connections. This pattern is consistent with Huneeus (2020), who finds that in Chile the share of new connections declines from around 50% and 68% for buyers and sellers, respectively, to about 20% for both.

Several mechanisms may account for the observed patterns. A growing theo-



(a) Survival (b) Creation

Figure 6: Creation and survival rates of domestic firm-to-firm links by firm size (2014)

Notes: This figure is the counterpart for Costa Rica to Figure 1 from Huneeus (2020) for Chile. Panel (a) documents the correlation between the year-to-year firm-level survival rate of old firm-to-firm links and the firm-to-firm sales (or purchases). Panel (b) documents the correlation between the year-to-year firm-level creation rate of new firm-to-firm links and the firm-to-firm sales (or purchases). All firm-to-firm links have the same weight. The plots correspond to quantile-spaced binned scatter plots using the estimator proposed by Cattaneo et al. (2024), and we include four-digit sector fixed effects. This figure is based on the firms active in the 2014 and 2015 cross-sections.

retical literature (Chaney, 2014; Boehm et al., 2024; Aekka & Khanna, 2025) identifies relationship-specific investments, contracting frictions, and search costs as central determinants of production network structure—frictions that are generally more binding in less developed economies (Atkin et al., 2024). Testing these mechanisms would require data on relationship duration, switching costs, and contract specificity.

5 Who trades with whom and how much?

Next, we present three stylized facts on matching patterns in firm-to-firm connections and their relationship with within-network transaction values.

Fact 8. Average within-network sales decline as sellers gain more buyers, while average within-network purchases increase as buyers source from more sellers.

Figure 7 shows the relationship between average transaction value and the number of connections. As sellers gain more buyers, they do not deepen relationships with each one; instead, average transaction size[18] declines, with an implied elasticity

[18] We measure average transaction size as the geometric mean of bilateral transaction values across a firm's buyers (or sellers), following Bernard et al. (2019a). Given the heavy right-skew of bilateral transaction values documented in Section 2.2, the geometric mean provides a more robust measure of typical bilateral relationships than the arithmetic mean. This construction also implies that the accounting identity

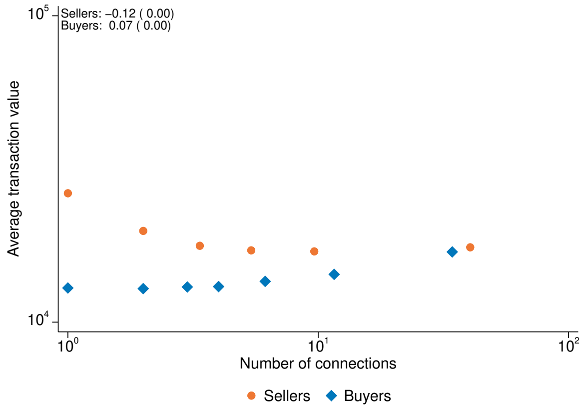


Figure 7: Transaction values and number of connections (2014)

Notes: This figure is the counterpart for Costa Rica to Figure 3 from Bernard et al. (2022) for Belgium. The figure shows a quantile-spaced binned scatter plot of average transaction value against number of connections. Orange circles represent sellers with their number of buyers, while blue diamonds represent buyers with their number of sellers. Both axes use a logarithmic scale. The plots correspond to quantile-spaced binned scatter estimates using the methodology from Cattaneo et al. (2024). We include four-digit sector fixed effects. The figure is based on the 2014 cross-section.

of -0.12. Consequently, sellers with more extensive buyer networks capture smaller shares of each buyer's purchases. This pattern is stronger in Belgium, where Bernard et al. (2022) report an elasticity of -0.23, but absent in Norway, where Bernard and Moxnes (2018) find no significant relationship. Conversely, when buyers add more sellers, they increase their average purchase from each one, with an elasticity of 0.07. Bernard et al. (2019a) further found that as buyers expand their seller base, their median purchase remains stable while the dispersion widens.

These findings reveal a market share puzzle that cannot be explained by bins-and-balls models such as Armenter and Koren (2014) and Bernard and Zi (2022).[19] The difficulty of accounting for these patterns suggests that production network formation is shaped by forces beyond basic firm heterogeneity, pointing to the need for richer models capable of matching these empirical regularities.

Fact 9. The trading partners of more connected firms tend to have fewer connections themselves.

linking the elasticities in Fact 4 and Fact 8 does not apply, as the geometric mean is not equal to total within-network sales divided by the number of buyers.

[19] These models rely on firm heterogeneity to produce random matching and predict that sellers with many buyers should capture larger shares of each buyer's business. Bernard et al. (2022) propose that fixed costs of forming buyer–seller relationships correlated with firm productivity can rationalize this divergence. Bernard and Zi (2022) specifically highlight this pattern as an "instructive statistic" that reveals where standard models fail.

(a) Sellers and buyers of sellers

(b) Buyers and sellers of buyers

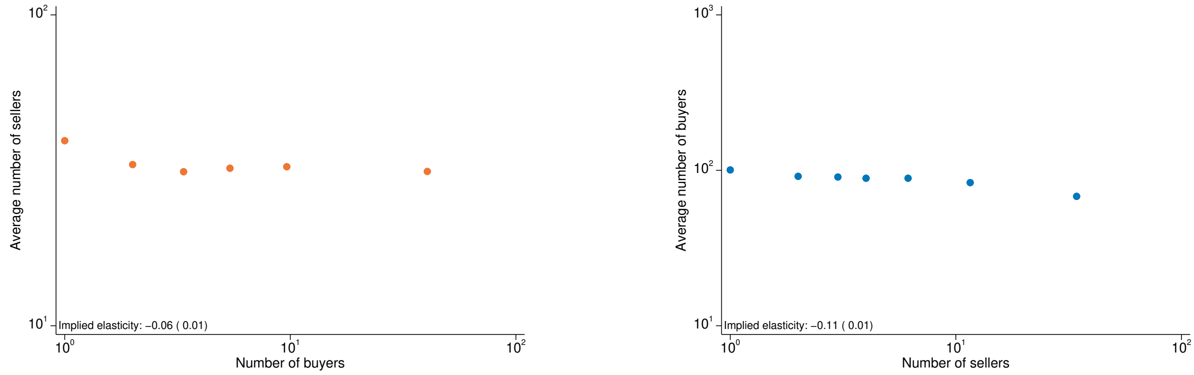


Figure 8: Degree assortativity (2014)

Notes: This figure is the counterpart for Costa Rica to Figure 4 from Bernard et al. (2022) for Belgium. The figure shows a quantile-spaced binned scatter plot of the firm's number of connections compared to their partners. Panel (a) shows the correlation between the seller firm's number of buyers and the geometric average number of sellers of those buyers. Panel (b) shows the correlation between the buyer firm's number of sellers and the geometric average number of buyers of those sellers. We use the estimator proposed by Cattaneo et al. (2024) and include four-digit sector fixed effects. This figure is based on the 2014 cross-section.

A striking feature of production networks is negative degree assortativity: highly connected firms tend to match with less-connected partners. This pattern arises in both buying and selling relationships. Figure 8a illustrates the case for sellers. Sellers with many buyers tend to trade with buyers who, on average, source from fewer sellers. The implied elasticity is -0.06 (s.e. 0.006): a 10% increase in the number of buyers is associated with a 0.6% decrease in the number of sellers among those buyers. Figure 8b shows the corresponding pattern for buyers. The estimated elasticity is -0.11 (s.e. 0.008): a 10% increase in the number of sellers is associated with a 1.1% decrease in the number of buyers among those sellers.

This pattern appears consistently across economies. Japan exhibits stronger negative buyer assortativity with an elasticity of -0.42 (Bernard et al., 2019b). Belgium shows more moderate effects with elasticities of -0.18 for buyers and -0.05 for sellers when controlling for sector (Bernard et al., 2022). In the Dominican Republic, Cardoza et al. (2025) found that buyers with 1% more sellers connect with sellers who have 2.2% fewer buyers on average. Even international trade follows this pattern, with Norwegian customs data showing an elasticity of -0.13 (Bernard et al., 2018).

Fact 10. Top trading partners capture a disproportionate share of transactions.

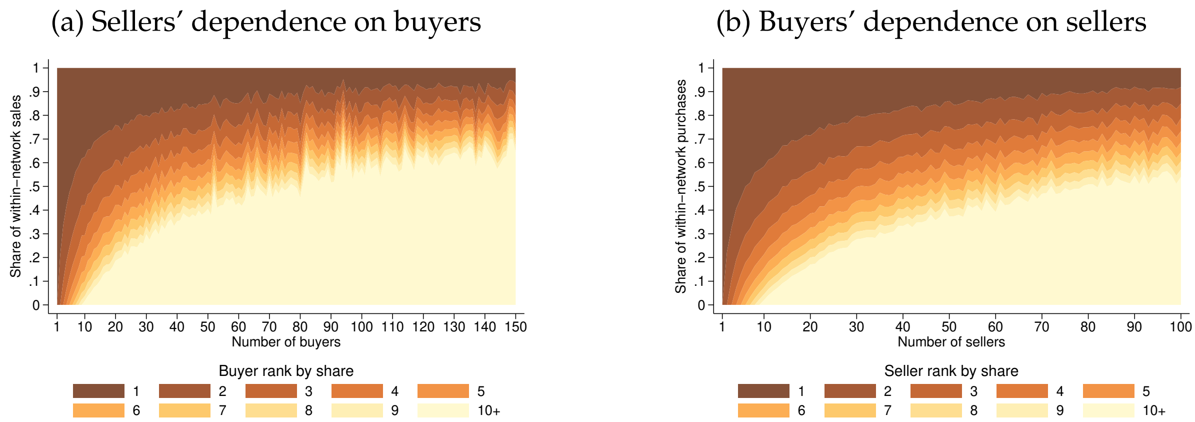


Figure 9: Number of connections and share of transactions (2014)

Notes: This figure illustrates the concentration of transaction shares among ranked trading partners. Panel (a) shows the share of within-network sales accounted for by each buyer rank, with darker colors representing higher-ranked buyers. For each seller with a given number of buyers (x-axis), we compute the weighted average of transaction shares using within-network sales as weights, conditional on firms having that specific number of connections. Panel (b) similarly shows the share of within-network purchases accounted for by each seller rank for buyers with a given number of sellers, using within-network purchases as weights. The figure is based on the 2014 cross-section. We include firms with at least one transaction, excluding observations above the 99th percentile (approximately 150 buyers in panel (a) and 100 sellers in panel (b)).

Figure 9 shows that transaction concentration follows a hierarchical pattern across firms of all sizes, strongest among firms with few connections. Figure 9a illustrates that sellers with fewer than 10 buyers conduct approximately 30% of their within-network sales with their top buyer alone. Although concentration declines as firms add more buyers, it remains substantial: firms with 50 buyers allocate about 15% of sales to their top buyer, while those with 150 buyers still allocate roughly 10%.

The stepped pattern extends throughout the distribution of trading relationships. For any given firm, higher-ranked buyers capture larger shares than lower-ranked ones. This hierarchy persists across firm sizes, though its steepness declines as the number of buyers increases. The top three buyers account for over 30% of within-network sales for firms with fewer than 50 buyers, and even among larger firms, the top buyer alone retains roughly 10%. Concentration thus declines with scale but remains a persistent structural feature. Overall, even as firms expand their buyer base, a small set of key relationships continues to dominate their sales.

Purchasing relationships exhibit the same concentrated structure. Figure 9b shows that firms with around 10 sellers source about 40% of their inputs from their top supplier, rising to over 50% for firms with five or fewer sellers. Although concentration declines as firms expand their seller base, it remains substantial: firms with 50 sellers obtain about 20% of inputs from their top supplier, while those with 100 sellers still source roughly 10%. The top three sellers account for over 30% of purchases for firms with fewer than 50 sellers, and even firms with 100 sellers source about 10% from their top supplier alone. Hierarchical dependence thus declines with scale but persists in both directions of trade.

Transaction concentration is a common feature of production networks across countries, albeit with varying intensity. In the United States, Boehm and Sonntag (2023) document even higher concentration, with the top 10% of buyers accounting for 58.6% of total sales. Bernard et al. (2022) report similar patterns in Belgium, emphasizing the decline in average sales per buyer as firms expand their networks—a pattern consistent with our findings. While concentration declines with network size, relationships with top partners remain disproportionately important.

The pronounced hierarchical structure of firm-to-firm transactions has important implications for shock propagation. When firms rely heavily on a small number of key trading partners, disruptions to these relationships can have disproportionate effects on firm performance and may amplify aggregate fluctuations — a force dampened by diversification across a broader supplier or customer base.

6 How does distance affect domestic firm-to-firm trade?

We next present three facts on the relationship between physical distance between firms and firm-to-firm trade patterns.

Fact 11. Most firm-to-firm connections occur between nearby firms.

Figure 10 illustrates the distribution of geographic distance and travel time between connected firms in Costa Rica. The median distance is 21.56 kilometers, while the mean is 51.29, indicating a right-skewed distribution in which most connections are local and a few long-distance connections raise the average. A similar pattern holds for travel time: the median is 24.00 minutes, compared to a mean of 55.03 minutes.

The weighted distribution (blue line), which weights firm pairs by transaction value, closely resembles the unweighted distribution (orange line). This suggests that, conditional on a link, transaction values vary little with distance, with distance primar-

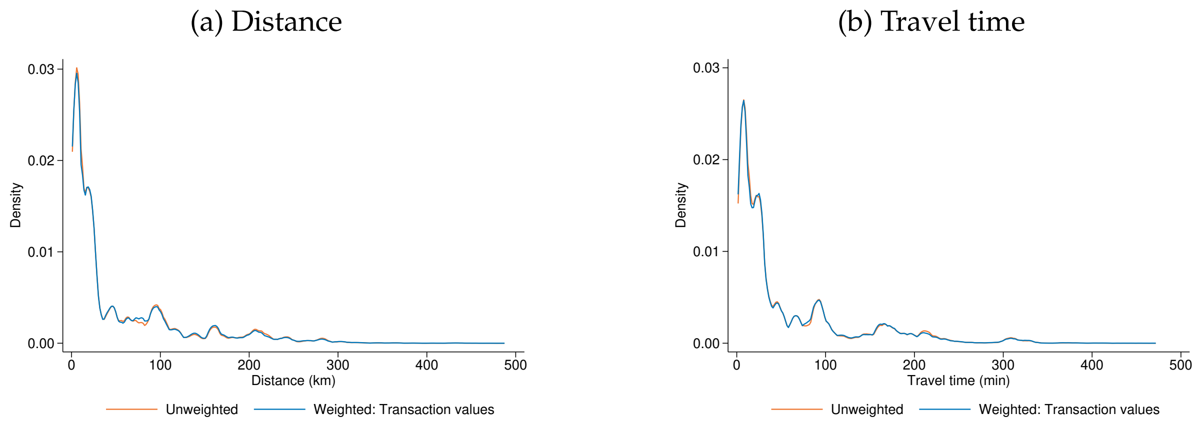


Figure 10: Densities of distance and travel time across buyer-seller pairs (2014)

Notes: This figure is the counterpart for Costa Rica to Figure 6 from Bernard et al. (2019b) for Japan. This figure presents kernel density estimates for the distribution of physical distance (kilometers) and travel time (minutes) between all connected firm pairs in Costa Rica during 2014. The orange line represents the unweighted distribution where each buyer-seller pair receives equal weight. The blue line represents the transaction-weighted distribution where each pair is weighted by their annual transaction value. Distance and travel time are calculated based on the fastest route between the municipalities where firms are located, using OpenStreetMap contributors (2023) data. For firms located in the same municipality, we estimate within-municipality distance following Redding and Venables (2004) as $d_{ii} = \frac{2}{3}\sqrt{\frac{A}{\pi}}$ where A is the geographic area of the municipality in square kilometers. Within-municipality travel times are calculated using the average speed of roads within each municipality, weighted by road length.

ily affecting link formation rather than the size of established relationships. Bernard et al. (2019b) document similar patterns in Japan, where the mean distance between connected firms (172 kilometers) substantially exceeds the median (30 kilometers).

Fact 12. Trade flows between municipalities decline with distance.

Table 1 reports gravity regression results for all municipality pairs in Costa Rica from 2008 to 2019. For each pair, we aggregate the value of all firm-to-firm transactions and estimate gravity models that include origin-year and destination-year fixed effects.

Distance is consistently associated with lower trade flows across all specifications. In the baseline OLS estimates with log-transformed flows, the estimated distance elasticity is -0.95 using route distance (column 1) and -1.03 using travel time (column 2), with each specification including a single distance measure. Poisson Pseudo-Maximum Likelihood (PPML) estimation—which appropriately accounts for zero trade flows—yields slightly smaller but still substantial elasticities of -0.64 for route distance (column 5) and -0.74 for travel time (column 6). The largest absolute elasticities arise when estimating gravity regressions using trade shares with the multinomial Pseudo-Maximum Likelihood (MPML) estimator: -1.03 for route distance (column 9) and -1.13 for travel time (column 10).

Table 1: Gravity regressions

	OLS				PPML				MPML			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
log(Distance)	-0.947		-0.692		-0.644		-0.746		-1.033		-0.766	
	(0.0132)		(0.0163)		(0.0288)		(0.0202)		(0.0161)		(0.0169)	
log(Travel time)		-1.034		-0.762		-0.740		-0.785		-1.133		-0.831
		(0.0146)		(0.0178)		(0.0303)		(0.0203)		(0.0174)		(0.0167)
𝟙[Inter-province]			-0.197	-0.198			-0.0514	-0.110			-0.215	-0.220
			(0.0194)	(0.0192)			(0.0146)	(0.0128)			(0.0306)	(0.0284)
𝟙[Inter-municipality]			-1.446	-1.498			0.361	0.245			-0.913	-1.025
			(0.0428)	(0.0424)			(0.0515)	(0.0548)			(0.0539)	(0.0493)
𝟙[Neighbor]			0.364	0.341			-0.116	-0.0895			0.0888	0.0749
			(0.0256)	(0.0253)			(0.0259)	(0.0247)			(0.0312)	(0.0280)
Fixed effects:												
Origin × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Destination × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.755	0.756	0.762	0.763	0.968	0.969	0.969	0.969	0.287	0.286	0.290	0.291
# dropped observations (zeros)	20,733				0				0			
# observations	$81^2 \times 12$											

Notes: This table presents gravity regression estimates for trade flows between all 81 municipalities in Costa Rica from 2008 to 2019. The dependent variables are: log non-zero trade flows (columns 1-4), total trade flows in levels (columns 5-8), and trade shares (columns 9-12). Distance and travel time measure the length and duration of the fastest route between municipalities' town halls using OpenStreetMap contributors (2023) data. We estimate three types of models: OLS with log-transformed non-zero flows, Poisson Pseudo-Maximum Likelihood (PPML) with trade flows in levels following Santos Silva and Tenreyro (2006), and Multinomial Pseudo-Maximum Likelihood (MPML) with trade shares following Eaton et al. (2013). The augmented specifications (columns 3-4, 7-8, 11-12) include indicators for: whether municipalities are in different provinces (Inter-province), whether trade occurs across municipality boundaries (Inter-municipality), and whether municipalities share a border (Neighbor). All specifications include origin-year and destination-year fixed effects to control for time-varying characteristics of sending and receiving municipalities. Standard errors (in parentheses) are clustered two-way by origin-year and destination-year following Cameron et al. (2011). For OLS models, we report adjusted R^2, while for PPML and MPML models, we report Pseudo R^2 following McFadden (1973), computed as $1 - \frac{\mathcal{L}_{\text{full}}}{\mathcal{L}_{\text{null}}}$, where $\mathcal{L}_{\text{full}}$ is the log-likelihood of the estimated model and $\mathcal{L}_{\text{null}}$ is the log-likelihood of a model with only an intercept; both estimators use the same formula. When two firms are in the same municipality, we compute the distance and travel time following Redding and Venables (2004) as $d_{ii} = \frac{2}{3}\sqrt{\frac{A}{\pi}}$ where A is the geographic area of the municipality in square kilometers.

In the augmented specifications (columns 3-4, 7-8, and 11-12), we include controls for inter-province borders, inter-municipality boundaries, and neighboring status. The inter-province coefficient ranges from -0.05 (column 7) to -0.22 (column 12), indicating relatively modest border effects. By contrast, the inter-municipality and neighboring coefficients vary in sign across estimators. In the OLS and MPML specifications, crossing a municipality boundary is associated with substantially lower trade (coefficients between -0.91 and -1.50), while neighboring status partially offsets this effect (coefficients between 0.07 and 0.36). Under PPML, these signs reverse: the inter-municipality coefficient is positive (0.36 in column 7), while the neighboring coefficient is negative (-0.12 in column 7). This reversal reflects differences in the weighting schemes implicit in each estimator. PPML, estimated in levels, places greater weight on the largest bilateral flows, which tend to occur between nearby municipalities that host major economic centers. By contrast, OLS and MPML—estimated in logs or shares—weight observations more evenly and instead capture the pattern that most cross-boundary pairs trade less than within-municipality pairs. Importantly, even after including these additional controls, distance remains a strong negative correlate of trade. In our baseline PPML specification (column 5), a 10% increase in route distance is associated with a 6.4% decrease in trade flows. This is our preferred specification, following Santos Silva and Tenreyro (2006).

These patterns are consistent with findings from other domestic production networks. Panigrahi (2022) documents similar distance elasticities in India, ranging from -0.22 to -0.71. The reported neighbor coefficients, between 0.25 and 0.56, are comparable to our OLS and MPML estimates. In contrast, Arkolakis et al. (2025) report distance elasticities ranging from -0.52 to -1.43 in Chile.

Fact 13. The number of connections declines with distance and travel time more rapidly than the average transaction value.

Distance is associated with lower trade primarily through a reduction in the number of trading relationships, rather than through changes in the value of existing relationships. Figure 11 decomposes the relationship between distance and trade flows into extensive and intensive margins for municipality pairs from 2008 to 2019.

To decompose the total trade elasticity additively into extensive and intensive margins, we estimate log–log OLS regressions on municipality pairs with positive trade flows. While PPML remains our preferred estimator for the overall magnitude of distance frictions, the log–log specification allows the elasticities of the extensive and intensive margins to sum exactly to the total. Figure 11a shows that total trade between municipalities declines with distance, with elasticities of -0.95 for route distance and -1.03 for travel time. Figure 11b indicates that the number of connections decreases sharply with distance, with elasticities of -0.81 and -0.89, respectively. By contrast, Figure 11c shows that the average transaction value declines much more modestly, with elasticities of -0.13 for distance and -0.15 for travel time.

This decomposition indicates that approximately 85% of the distance effect op-

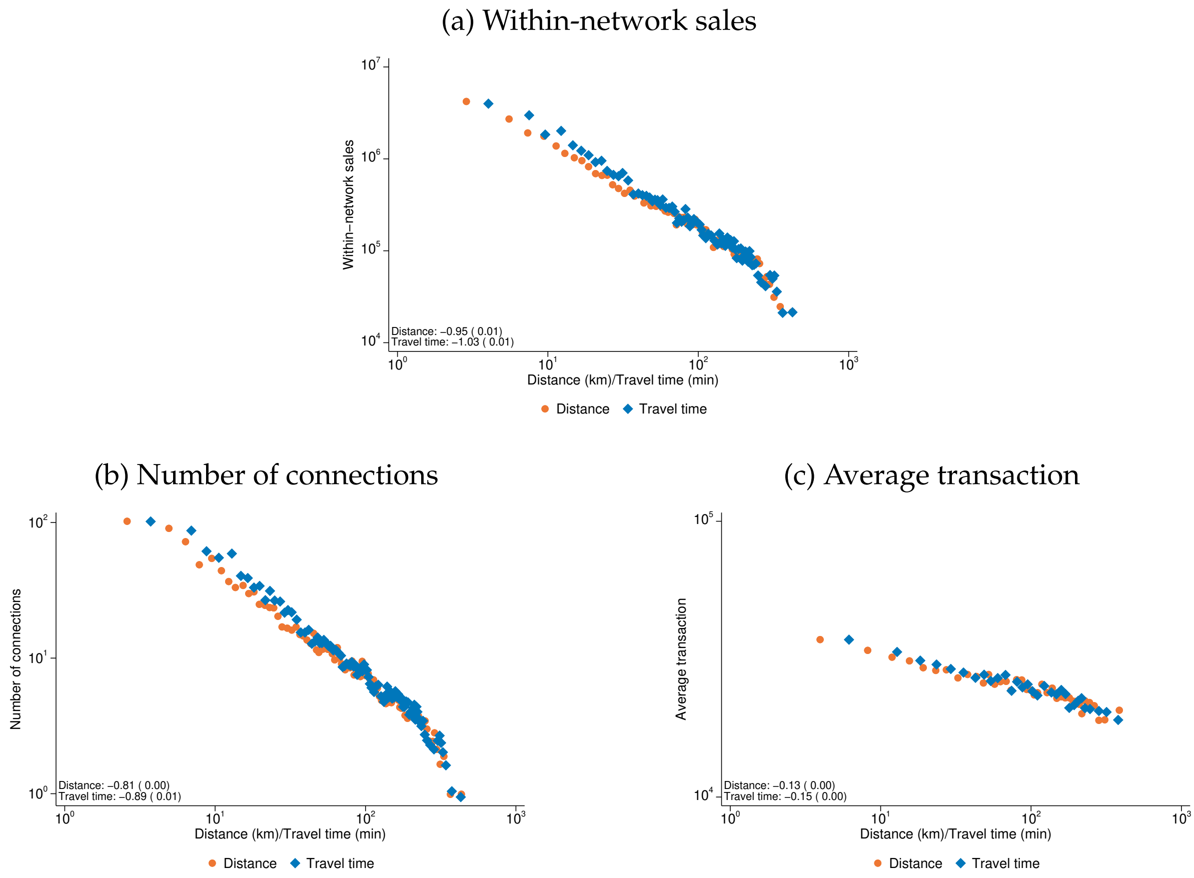


Figure 11: Margins of municipality-level trade (2008-2019)

Notes: This figure decomposes municipality-level trade flows into extensive and intensive margins as functions of distance and travel time. The sample includes all bilateral trade between Costa Rica's 81 municipalities from 2008 to 2019. We use the estimator proposed by Cattaneo et al. (2024). Panel (a) shows the relationship between total bilateral trade flow and distance (orange) or travel time (blue). Panel (b) shows the number of unique firm-to-firm connections between municipality pairs. Panel (c) shows the average value per connection. All plots control for origin municipality-year and destination municipality-year fixed effects, with standard errors clustered at these levels. Elasticity estimates are displayed with standard errors in parentheses. All axes use logarithmic scales. Distance is measured in kilometers and travel time in minutes, calculated as the fastest route between municipalities using OpenStreetMap contributors (2023) data. For firms located in the same municipality, we estimate within-municipality distance following Redding and Venables (2004) as $d_{ii} = \frac{2}{3}\sqrt{\frac{A}{\pi}}$ where A is the geographic area of the municipality in square kilometers.

erates through the extensive margin (fewer connections), with the remaining 15% attributable to the intensive margin (smaller transactions). Firms are much less likely to form connections over longer distances, but conditional on a link existing, transaction values decline only modestly with distance.

This pattern is consistently observed across a range of settings. Bernard et al. (2011) report an elasticity of -1.43 on the extensive margin of U.S. exports, with no significant effect on the intensive margin. Fernandes et al. (2023) document an extensive-margin elasticity of -1.01, while Arkolakis et al. (2025) report elasticities of -0.91 for the extensive margin and -0.52 for the intensive margin in Chile.

One interpretation of the importance of proximity for firm-to-firm connections—particularly along the extensive margin—is that information frictions (Chaney, 2014; Demir et al., 2026) or weak contract enforcement (Boehm & Oberfield, 2020) make it more difficult to identify and trust distant partners. As a result, firms may form links primarily with nearby partners, for whom information is more readily available through local networks and direct observation, and with whom contracts are easier to enforce. An alternative explanation is transportation costs, which are often higher in developing countries (Gonzalez-Navarro et al., 2023). However, it is less clear why transportation costs alone would affect the extensive margin more strongly than the intensive margin.

7 Firm-to-firm trade within and across borders

We next present three stylized facts about the heterogeneous exposure of firms to international trade through direct and indirect purchases from and sales to foreign markets.

Fact 14. Exporter (importer) firms are larger than non-exporter (non-importer) firms.

Firms engaging in international trade face substantial barriers, including fixed costs of market entry (Melitz, 2003; Bernard et al., 2009) and the costs of identifying suitable foreign partners (Aeberhardt et al., 2014; Piveteau, 2021; Fitzgerald et al., 2024). These barriers give rise to a selection effect, whereby predominantly larger and more productive firms participate in direct international trade.

Figure 12 compares the distribution of firm size across foreign trade participa-

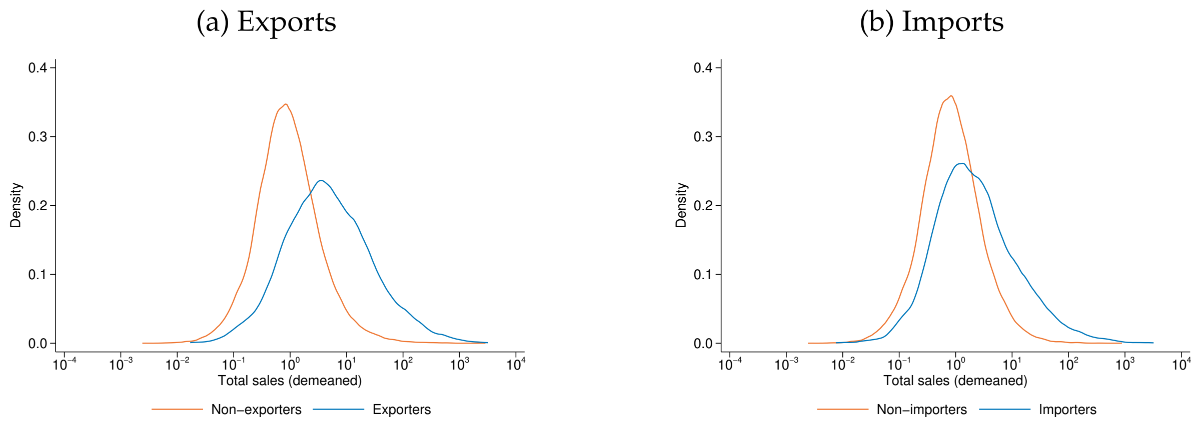


Figure 12: Firm size distribution by participation in foreign trade (2014)

Notes: The figure is the counterpart for Costa Rica to Figure 2a from Blaum et al. (2018) for France. This figure shows kernel density estimates of firm size distributions by international trade participation status using the 2014 cross-section. Panel (a) compares exporter firms (blue line) versus non-exporter firms (orange line), while Panel (b) compares importer firms (blue line) versus non-importer firms (orange line). Firm size is measured as log total sales demeaned by four-digit sector averages. The horizontal axis uses a logarithmic scale. We define exporters as firms with positive exports and importers as firms with positive imports. This figure is based on the 2014 cross-section.

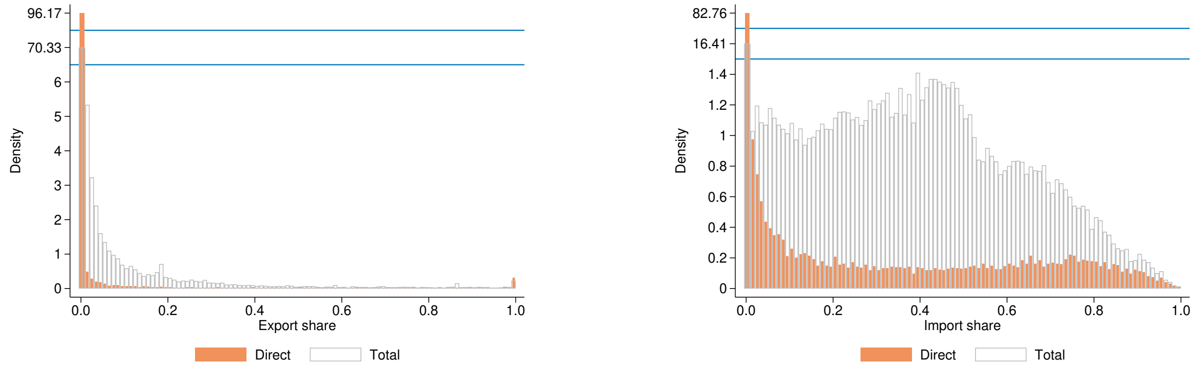
tion statuses, with size defined as total sales demeaned by the four-digit sector average. Figure 12a shows that the distribution for exporters is shifted to the right relative to non-exporters, with less overlap and a fatter right tail. Figure 12b reveals a similar but less pronounced pattern for importers compared to non-importers: the distributions overlap more, although importers still exhibit a fatter right tail. Blaum et al. (2018) document a similar pattern among French manufacturing firms by importing status.

Fact 15. Most firms neither import nor export directly. While many are indirectly exposed to foreign inputs, indirect export intensity remains negligible for most.

While direct participation in international trade is limited, many firms are indirectly connected to global markets through domestic firm-to-firm relationships. To quantify this, we follow Dhyne et al. (2021) and compute total export and import shares using recursive equations that capture both direct and indirect trade exposure:

$$r_{jF}^{\text{Total}} = r_{jF} + \sum_{i \in W_j^D} r_{ji} \underbrace{\left[r_{iF} + \sum_{k \in W_i^D} r_{ik} (r_{kF} + \cdots) \right]}_{r_{iF}^{\text{Total}}}, \tag{2}$$

where r_{jF}^{Total} is the total export share of firm j, r_{jF} is its direct export share, W_j^D de-



(a) Direct and total export share

(b) Direct and total import share

Figure 13: Distributions of direct and total trade across firms (2014)

Notes: This figure is the counterpart for Costa Rica to Figure 1 from Dhyne et al. (2021) for Belgium. This figure shows histograms of direct and total trade shares across firms. Panel (a) presents direct export shares (solid orange bars) and total export shares (gray outlines). Panel (b) presents direct import shares (solid orange bars) and total import shares (gray outlines). Total export shares are computed by solving the recursive equation $r_{jF}^{\text{Total}} = r_{jF} + \sum_{i \in W_j^D} r_{ji} r_{iF}^{\text{Total}}$, where r_{jF} is the direct export share of firm j, W_j^D is the set of domestic buyers, and r_{ji} is the share of j's sales to firm i. Total import shares are computed by solving $s_{Fj}^{\text{Total}} = s_{Fj} + \sum_{i \in Z_j^D} s_{ij} s_{Fi}^{\text{Total}}$, where s_{Fj} is the direct import share of firm j, Z_j^D is the set of domestic sellers, and s_{ij} is the share of j's inputs purchased from firm i. The horizontal blue lines represent scale breaks on the vertical axis, with the top values (96.17 and 82.76) showing the density at zero for direct exports and imports. This figure is based on the 2014 cross-section.

notes its set of domestic buyers, and r_{ji} is the share of j's revenue from sales to firm i. Similarly, for imports:

$$s_{Fj}^{\text{Total}} = s_{Fj} + \sum_{i \in Z_j^D} s_{ij} \underbrace{\left[s_{Fi} + \sum_{k \in Z_i^D} s_{ki} (s_{Fk} + \cdots) \right]}_{s_{Fi}^{\text{Total}}}, \tag{3}$$

where s_{Fj}^{Total} is the total import share of firm j, s_{Fj} is its direct import share, Z_j^D denotes its set of domestic sellers, and s_{ij} is the share of firm j's inputs purchased from firm i. The denominator of the input shares is the sum of the firm's labor costs, purchases from other firms in the country, and direct imports.

Figure 13a highlights sharp differences between direct and total trade participation. Only 5.5% of Costa Rican firms (2,440 out of 44,177) export directly, with 4.4% of all firms exporting less than half of their output. A very small share (0.5%) are highly export-oriented, with export shares above 90%. By contrast, 60.5% of firms have positive total export shares through either direct exports or sales to other exporting firms.

Despite this widespread indirect exposure, export intensity remains low: the median firm's total export share is just 0.04% of sales, with the 75th percentile at 1.8% and the 90th percentile at 13.6%.

These patterns differ from those observed in Belgium. Dhyne et al. (2021) find that 12% of firms export directly, with an additional 75% exporting indirectly. Belgian firms also exhibit higher export intensity, with a median total export share of 3% and a 75th percentile of 17%. Nevertheless, domestic sales remain the primary source of revenue for most firms, even in small open economies such as Costa Rica and Belgium.

Figure 13b shows the distributions of direct and total import shares across firms in Costa Rica. We find that 19.9% of firms import directly, with 13.1% importing less than half their inputs and only 0.6% are heavily import-dependent with import shares above 90%. The reach of indirect importing is substantial—84.9% of firms use foreign inputs directly or indirectly. Unlike exports, the intensity of import exposure is high—the median firm sources 31.8% of its inputs from abroad (directly or indirectly), with the 25th percentile at 8.8% and the 75th percentile at 51.6%.

We find that these patterns are very similar to those in Belgium: 19% of Belgian firms import directly, and nearly all firms use foreign inputs to some extent. The median Belgian firm sources 39% of its inputs from abroad, with the 25th and 75th percentiles at 24% and 55%, respectively. In France, Blaum et al. (2018) document that most manufacturing firms rely predominantly on domestic inputs, with import shares below 10%, although some heavy importers source more than 50% of their inputs from foreign markets. This dispersion in import intensity mirrors our findings for Costa Rica, where the distribution of total import shares varies substantially across firms.

Fact 16. Direct and total export and import shares increase with firm size.

Figure 14 shows how international trade exposure varies with firm size. Both direct and total export shares (Figure 14a) and import shares (Figure 14c) increase with firm size, although the relationship is steeper for imports. When disaggregating by trade participation status (Figures 14b and 14d), these size–exposure relationships appear to be driven primarily by firms that trade directly.

Direct exporters maintain relatively stable total export shares across the size distribution (around 30%), while non-direct exporters exhibit minimal export exposure

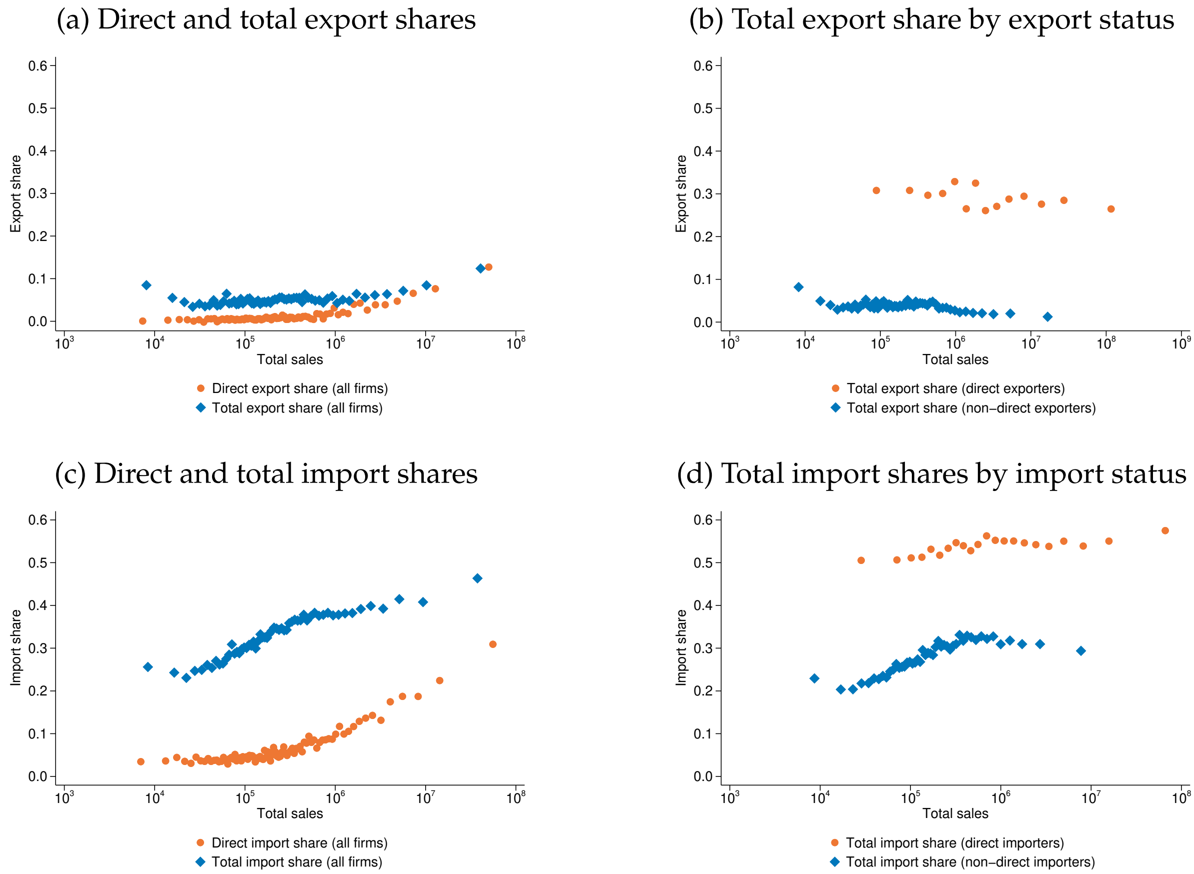


Figure 14: Firm size and direct and total trade shares (2014)

Notes: This figure is the counterpart for Costa Rica to Figure 4 from Dhyne et al. (2021) for Belgium. This figure shows the relationship between firm size and international trade shares. Panel (a) shows direct export shares (orange circles) and total export shares (blue diamonds) by firm size. Panel (b) compares total export shares for direct exporters (orange circles) and non-direct exporters (blue diamonds). Panel (c) shows direct import shares (orange circles) and total import shares (blue diamonds) by firm size. Panel (d) compares total import shares for direct importers (orange circles) and non-direct importers (blue diamonds). All panels use quantile-spaced binned scatter plots using the estimator proposed by Cattaneo et al. (2024), controlling for four-digit sector fixed effects. Total export shares are computed by solving the recursive equation $r_{jF}^{\text{Total}} = r_{jF} + \sum_{i \in W_j^D} r_{ji} r_{iF}^{\text{Total}}$, where r_{jF} is the direct export share of firm j, W_j^D is the set of domestic buyers, and r_{ji} is the share of j's sales to firm i. Total import shares are computed by solving $s_{Fj}^{\text{Total}} = s_{Fj} + \sum_{i \in Z_j^D} s_{ij} s_{Fi}^{\text{Total}}$, where s_{Fj} is the direct import share of firm j, Z_j^D is the set of domestic sellers, and s_{ij} is the share of j's inputs purchased from firm i. The horizontal axis shows firm total sales on a logarithmic scale. This figure is based on the 2014 cross-section.

(consistently below 5%) regardless of size. For imports, direct importers display high total import shares (50–58%) that increase slightly with firm size. In contrast, non-direct importers show a non-monotonic pattern: total import shares rise from 22% to 32% as firm size increases, before declining to 29% among the largest firms.

These patterns partially align with those documented by Dhyne et al. (2021) for Belgium. Unconditionally, both countries show that direct and total trade shares increase with firm size. However, conditional on being a direct exporter, Belgian firms exhibit a steep increase in total export shares with size, whereas in Costa Rica these shares remain nearly flat—suggesting that larger exporters in Costa Rica expand output rather than export intensity. On the import side, Blaum et al. (2018) find that French manufacturing firms maintain roughly constant direct import shares as value added increases, consistent with our finding that direct importers exhibit only a gradual increase in total import exposure with firm size.

The patterns of direct versus indirect trade highlight the importance of firm heterogeneity along multiple dimensions. Models that focus only on direct trade may substantially underestimate firms' exposure to international shocks, while those that do not distinguish between direct and indirect exposure may overstate the vulnerability of firms without direct international linkages.

8 Conclusion

We use rich microdata from Costa Rica and a unified methodology to document 16 stylized facts about the domestic production network and compare them with prior findings, mainly from developed economies such as Belgium and Japan. Because all facts are estimated on the same sample with the same methodology, they provide an internally consistent and comprehensive characterization of the domestic production network—the first of its kind, particularly for a less developed economy.

We find that the domestic production network is sparse—only about 1 in 5,050 potential connections materialize—and outcomes are driven primarily by the extensive margin, which accounts for 59% of the variance in within-network sales. More productive firms have more connections, well-connected firms tend to match with less-connected partners (negative assortativity), and transaction values are highly concentrated among top trading partners. Geographic proximity strongly shapes buyer–seller relationships: the median connected pair is located 22 km apart, with 85% of the distance effect operating through fewer connections rather than smaller transactions.

Direct export participation is rare—only around 5% of firms export—whereas direct import participation is more common, at roughly 20%. Domestic supply chains broaden exposure: nearly 60% (85%) of firms have positive total (direct plus indirect) export (import) shares. However, the intensity of exposure differs markedly. Export exposure remains concentrated among direct exporters, with a median total export share of just 0.04%. By contrast, domestic supply chains extend firms' exposure to imports, with the median firm sourcing nearly one-third of its inputs from abroad.

We compare our findings with those from other, primarily developed, economies. Methodological differences, along with other plausibly relevant differences in economy size, trade policy, and the burden of distortions, preclude a direct interpretation of quantitative differences. Nonetheless, the qualitative patterns we uncover—power-law distributions, sparsity, the dominance of the extensive margin, strong gravity effects, and broad transmission of trade exposure—appear consistently across otherwise dissimilar countries. This suggests that these regularities reflect common features of firm-to-firm interactions rather than country-specific phenomena.

Our findings provide empirical benchmarks for future research on production networks, particularly in less developed economies where evidence remains scarce. The observed sparsity, assortativity, and the role of the extensive margin underscore the need for models of endogenous network formation, in which buyer–seller relationships emerge under firm heterogeneity and relationship-specific costs (Oberfield, 2018; Dhyne et al., 2023b; Arkolakis et al., 2025). A related strand of the literature examines how network structure shapes market power, with a focus on bilateral bargaining, surplus division, and the role of network position (Alviarez et al., 2025; Huang et al., 2025). Our findings on transaction concentration and the breadth of trade exposure further reinforce the relevance of this line of research.

Finally, our findings highlight the importance of accurate production network measurement. We contribute to the global effort advocated by Pichler et al. (2023) — harnessing granular supply-chain data to support rigorous network analysis and evidence-based policymaking — by providing harmonized estimates for Costa Rica.

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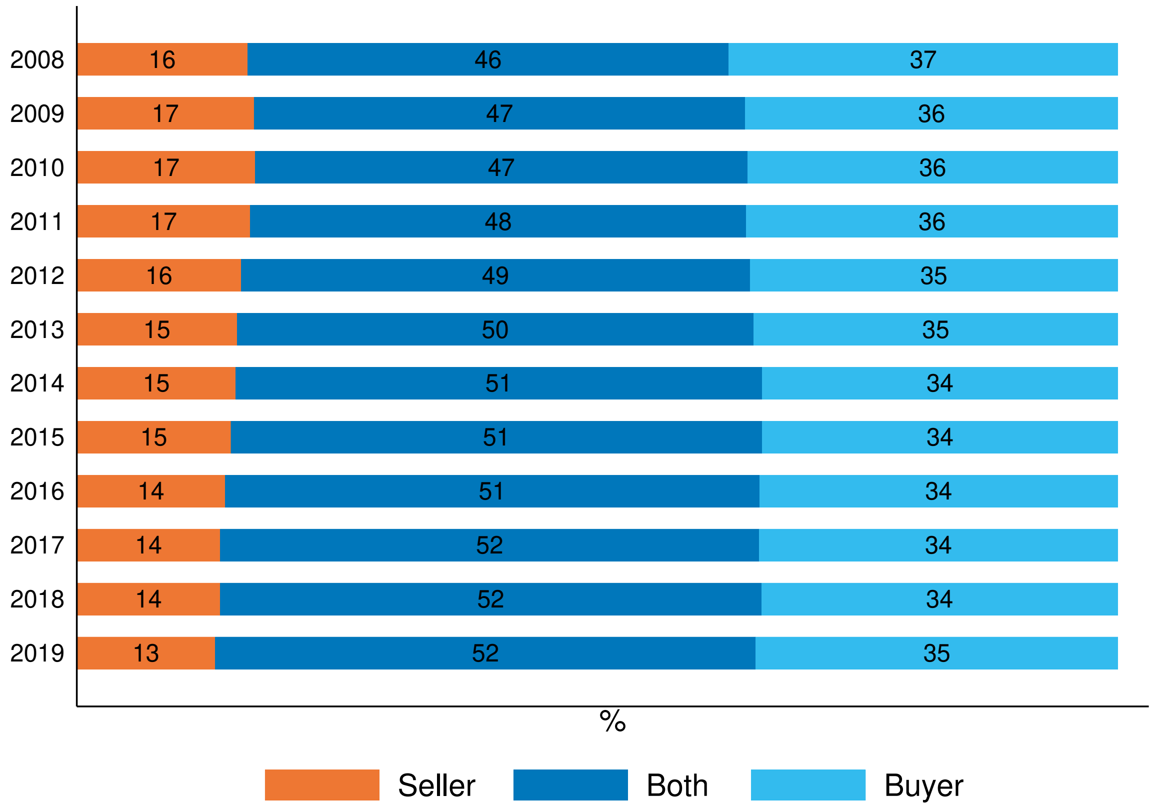
Appendices

Appendix A Figures

Figure A1: Percentage of sample retention after each cleaning step

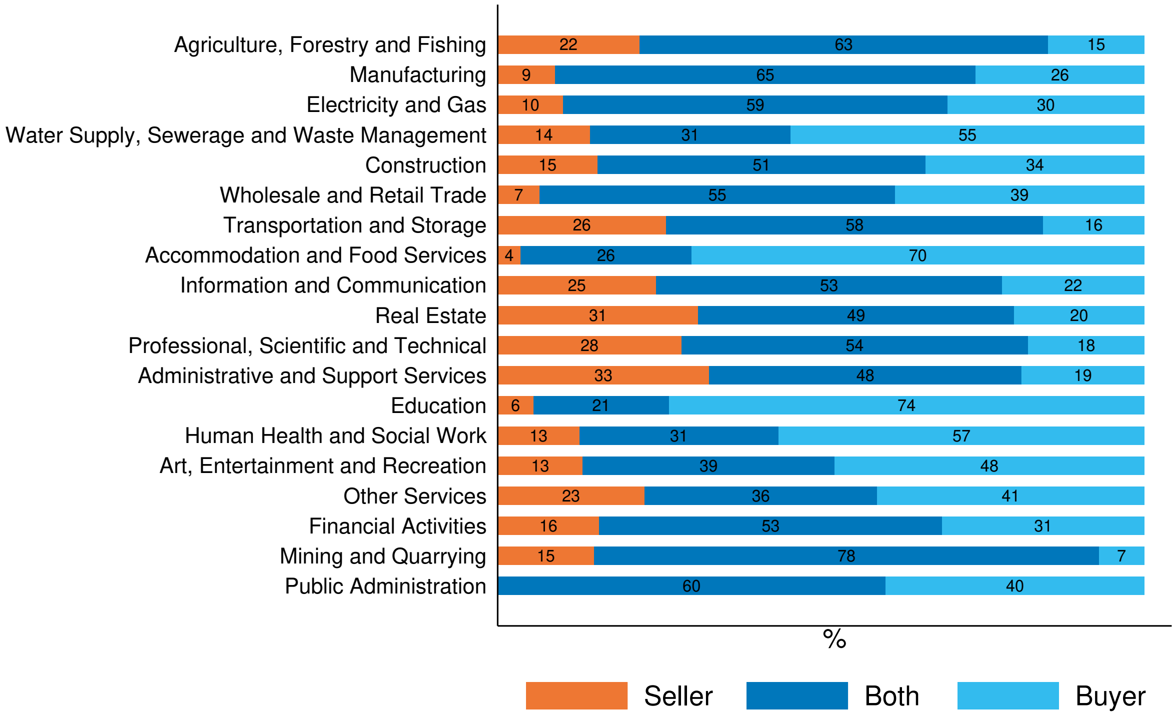
Notes: This figure shows the percentage of firms retained after each cleaning step in each year explained in Section 2.1 considering three size measures: total sales, network sales (i.e., the sum of sales transaction values in a year), and the number of transactions sellers made. The "Total" bars represent the universe of firms that file the Corporate Income Tax form, while the "Matched" bars refer to the firms present in the transactions data set. The "Cleaned" bars refer to the remaining firms after applying the sample selection criteria.

Figure A2: Share of seller and buyer firms across years



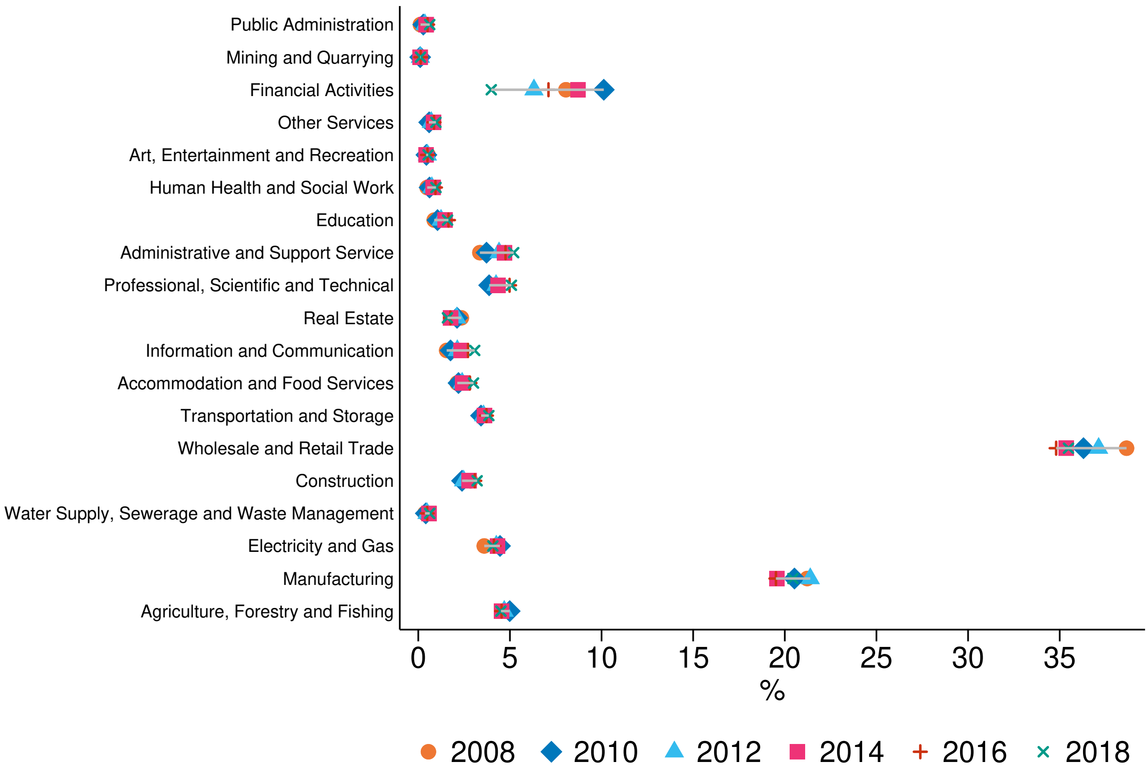
Notes: This figure presents the percentage of firms that engage in buying and selling activities with other firms in the Costa Rican production network after the cleaning process described in Section 2.1. We present this percentage for every year in our sample.

Figure A3: Share of seller and buyer firms by sector (2014)



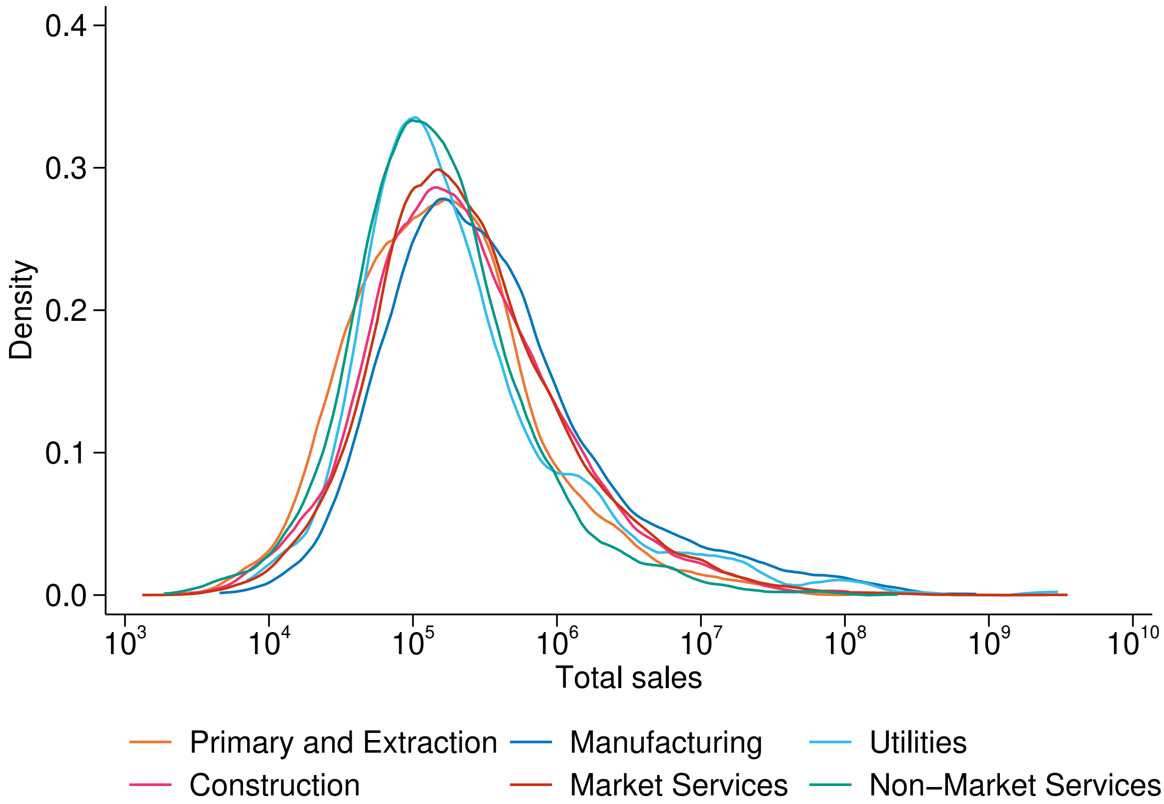
Notes: This figure presents the percentage of firms that engage in buying and selling activities with other firms in the Costa Rican production network after the cleaning process explained in Section 2.1 by sector. We present these percentages in the 2014 cross-section.

Figure A4: Percentage of total sales by sector across years



Notes: This figure presents the share of the sum of total sales by sector out of the sum of the total sales in the formal Costa Rican economy. We consider the firms in the production network after the cleaning process described in Section 2.1. We present the 2008, 2010, 2012, 2014, 2016, and 2018 shares.

Figure A5: Firm sales distribution by sector (2014)



Notes: This figure plots the densities of firms' total sales conditional on the firm's sector. We classify sectors into broad categories (see table B16 for the grouping of sectors into these broad categories). This figure is based on the 2014 cross-section.

Appendix B Tables

Table B1: Firm sales by year (million U.S. dollars, CPI-deflated to 2014 U.S. dollars)

Year	N	Mean	St Dev	10th	25th	50th	75th	90th	95th	99th
2008	32,247	2.47	37.04	0.05	0.10	0.24	0.71	2.40	5.77	31.69
2009	34,171	2.12	32.67	0.04	0.09	0.21	0.61	2.05	4.84	26.36
2010	36,332	2.26	38.07	0.04	0.09	0.21	0.62	2.10	4.98	27.42
2011	39,230	2.17	34.82	0.04	0.09	0.21	0.61	2.05	4.80	26.47
2012	41,443	2.11	32.55	0.04	0.09	0.21	0.60	2.01	4.76	26.23
2013	42,869	2.07	32.17	0.04	0.09	0.21	0.59	1.97	4.62	26.51
2014	44,177	1.94	32.31	0.04	0.08	0.19	0.53	1.79	4.21	24.07
2015	45,205	1.89	26.33	0.04	0.09	0.20	0.56	1.84	4.37	25.00
2016	46,600	1.91	26.94	0.04	0.09	0.21	0.57	1.84	4.35	25.12
2017	47,260	1.82	25.18	0.04	0.09	0.20	0.55	1.82	4.24	24.16
2018	47,899	1.82	25.75	0.04	0.09	0.20	0.55	1.81	4.16	24.44
2019	47,687	1.81	25.70	0.04	0.09	0.20	0.55	1.79	4.14	24.43
Pooled	96,177	2.01	30.62	0.04	0.09	0.21	0.58	1.94	4.55	25.92

Notes: This table presents summary statistics on total sales for firms in Costa Rica for each year in our sample period (and pooled across all years). We report the number of firms each year, while the last row reports the number of unique firms used to compute the pooled statistics. The included summary statistics are the sample average, standard deviation, and percentiles from the 10^{th} to the 99^{th}.

Table B2: Firm sales by sector (2014, million U.S. dollars, CPI-deflated to 2014 U.S. dollars)

Sector	N	Mean	St Dev	10th	25th	50th	75th	90th	95th	99th
Agriculture, Forestry and Fishing	3,362	1.16	12.01	0.03	0.06	0.15	0.37	1.09	2.49	15.70
Manufacturing	4,001	4.19	26.09	0.05	0.11	0.27	0.82	3.82	13.34	91.72
Electricity and Gas	69	53.70	364.04	0.09	0.15	0.47	5.24	24.96	86.07	1,043.12
Water Supply, Sewerage and Waste Management	364	1.37	13.74	0.04	0.07	0.13	0.33	1.17	2.27	13.30
Construction	2,187	1.09	5.02	0.04	0.08	0.20	0.57	1.71	3.59	15.00
Wholesale and Retail Trade	12,336	2.45	39.09	0.06	0.13	0.30	0.83	2.70	5.92	23.90
Transportation and Storage	2,859	1.08	5.68	0.04	0.08	0.17	0.47	1.69	3.50	16.93
Accommodation and Food Services	3,848	0.54	3.41	0.04	0.08	0.14	0.30	0.70	1.25	5.61
Information and Communication	950	2.11	10.96	0.05	0.10	0.27	0.88	2.51	6.32	35.65
Real Estate	1,443	1.05	8.83	0.03	0.05	0.10	0.28	0.90	2.41	23.34
Professional, Scientific and Technical	4,221	0.88	8.26	0.03	0.06	0.14	0.34	0.92	1.79	12.16
Administrative and Support Services	2,319	1.74	7.81	0.03	0.08	0.21	0.72	2.40	6.00	35.68
Education	955	1.31	8.76	0.06	0.13	0.28	0.67	1.80	4.14	12.53
Human Health and Social Work	1,983	0.35	2.23	0.03	0.05	0.10	0.22	0.49	0.90	2.75
Art, Entertainment and Recreation	570	0.64	1.99	0.04	0.06	0.14	0.32	1.06	2.73	11.44
Other Services	1,458	0.48	3.04	0.03	0.06	0.11	0.25	0.57	0.97	6.64
Financial Activities	701	10.64	139.86	0.03	0.08	0.24	0.97	5.86	13.27	123.41
Mining and Quarrying	114	0.83	1.40	0.05	0.13	0.33	0.88	2.23	3.29	6.42
Public Administration	35	10.75	20.19	0.21	0.50	2.54	7.16	28.37	53.54	82.95
Pooled	44,177	1.94	32.31	0.04	0.08	0.19	0.53	1.79	4.21	24.07

Notes: This table presents summary statistics on the total sales of firms in Costa Rica for the 2014 cross-section. We report the number of firms in this cross-section by their sector. These summary statistics are the sample average, standard deviation, and percentiles from the 10^{th} to the 99^{th}. The statistics are presented across all sectors and separately by broad group sector.

Table B3: Within-network sales (million U.S. dollars, CPI-deflated to 2014 U.S. dollars)

Year	N	Mean	St Dev	10th	25th	50th	75th	90th	95th	99th
2008	20,194	0.41	2.02	0.01	0.03	0.09	0.26	0.69	1.38	5.58
2009	21,945	0.37	1.90	0.01	0.03	0.08	0.23	0.60	1.22	5.03
2010	23,408	0.38	2.09	0.01	0.03	0.08	0.24	0.63	1.26	5.39
2011	25,229	0.41	2.34	0.01	0.03	0.09	0.25	0.67	1.32	5.76
2012	26,795	0.43	2.64	0.01	0.03	0.09	0.26	0.69	1.39	5.78
2013	27,872	0.44	2.75	0.01	0.03	0.09	0.27	0.70	1.42	5.97
2014	29,080	0.41	2.60	0.01	0.03	0.08	0.25	0.67	1.34	5.44
2015	29,761	0.46	2.88	0.01	0.03	0.09	0.27	0.76	1.48	5.96
2016	30,565	0.48	3.05	0.01	0.03	0.09	0.29	0.80	1.58	6.25
2017	30,976	0.49	3.15	0.01	0.03	0.09	0.29	0.79	1.57	6.44
2018	31,501	0.56	3.58	0.01	0.03	0.09	0.30	0.95	1.85	7.62
2019	31,105	0.55	3.50	0.01	0.02	0.08	0.28	0.92	1.93	7.78
Pooled	64,745	0.46	2.83	0.01	0.03	0.09	0.27	0.75	1.50	6.15

Notes: This table presents summary statistics on within-network sales in Costa Rica across the years (and pooled across all years). We report the number of seller firms each year, while the last row reports the number of unique firms used to compute the pooled statistics. The included summary statistics are the sample average, standard deviation, and percentiles from the 10^{th} to the 99^{th}.

Table B4: Within-network sales by sector (2014, million U.S. dollars, CPI-deflated to 2014 U.S. dollars)

Sector	N	Mean	St Dev	10th	25th	50th	75th	90th	95th	99th
Agriculture, Forestry and Fishing	2,862	0.17	0.29	0.01	0.03	0.09	0.23	0.41	0.52	1.19
Manufacturing	2,958	0.75	4.01	0.01	0.04	0.12	0.40	1.17	2.82	12.07
Electricity and Gas	48	4.56	21.40	0.02	0.06	0.20	0.92	4.78	13.45	87.08
Water Supply, Sewerage and Waste Management	165	0.27	0.57	0.01	0.03	0.10	0.27	0.50	0.97	3.28
Construction	1,448	0.19	0.32	0.01	0.03	0.09	0.24	0.46	0.70	1.21
Wholesale and Retail Trade	7,579	0.63	3.11	0.01	0.03	0.10	0.37	1.20	2.40	8.24
Transportation and Storage	2,412	0.32	0.93	0.02	0.04	0.10	0.25	0.60	1.16	4.62
Accommodation and Food Services	1,153	0.14	0.42	0.01	0.01	0.03	0.11	0.29	0.57	1.88
Information and Communication	741	0.42	1.66	0.01	0.04	0.10	0.32	0.74	1.31	5.08
Real Estate	1,152	0.24	1.03	0.01	0.02	0.05	0.14	0.37	0.83	3.14
Professional, Scientific and Technical	3,462	0.22	0.88	0.01	0.03	0.07	0.20	0.46	0.76	2.08
Administrative and Support Services	1,878	0.38	1.10	0.01	0.04	0.10	0.30	0.77	1.41	5.42
Education	253	0.13	0.31	0.01	0.01	0.02	0.09	0.36	0.70	1.39
Human Health and Social Work	862	0.07	0.20	0.01	0.01	0.02	0.06	0.15	0.24	0.81
Art, Entertainment and Recreation	297	0.16	0.42	0.01	0.02	0.04	0.14	0.36	0.62	2.55
Other Services	856	0.12	0.57	0.01	0.02	0.05	0.11	0.22	0.38	0.98
Financial Activities	482	1.16	8.88	0.01	0.03	0.08	0.27	0.68	2.42	15.47
Mining and Quarrying	106	0.38	0.49	0.03	0.06	0.21	0.44	1.06	1.54	2.07
Public Administration	21	0.71	1.22	0.01	0.03	0.08	0.45	2.71	3.31	3.67
Pooled	29,080	0.41	2.60	0.01	0.03	0.08	0.25	0.67	1.34	5.44

Notes: This table presents summary statistics on within-network sales in Costa Rica for the 2014 cross-section. We report the number of seller firms in this cross-section by their sector. These summary statistics are the sample average, standard deviation, and percentiles from the 10^{th} to the 99^{th}. The statistics are presented across all sectors and separately by sector.

Table B5: Within-network purchases (million U.S. dollars, CPI-deflated to 2014 U.S. dollars)

Year	N	Mean	St Dev	10th	25th	50th	75th	90th	95th	99th
2008	26,959	0.31	1.19	0.01	0.02	0.07	0.23	0.61	1.16	3.99
2009	28,357	0.28	1.15	0.01	0.02	0.07	0.21	0.55	1.05	3.71
2010	30,105	0.30	1.30	0.01	0.02	0.07	0.21	0.57	1.11	3.90
2011	32,693	0.32	1.52	0.01	0.02	0.07	0.22	0.60	1.17	4.44
2012	34,904	0.33	1.63	0.01	0.02	0.07	0.22	0.61	1.19	4.45
2013	36,274	0.34	1.68	0.01	0.02	0.07	0.22	0.62	1.21	4.66
2014	37,433	0.32	1.65	0.01	0.02	0.06	0.20	0.58	1.16	4.53
2015	38,519	0.35	1.86	0.01	0.02	0.06	0.21	0.63	1.26	4.96
2016	39,964	0.37	2.06	0.01	0.02	0.06	0.21	0.65	1.30	5.35
2017	40,750	0.37	2.02	0.01	0.02	0.06	0.20	0.65	1.31	5.37
2018	41,308	0.43	2.56	0.01	0.02	0.06	0.20	0.68	1.49	6.77
2019	41,351	0.41	2.70	0.01	0.02	0.05	0.18	0.63	1.43	6.68
Pooled	86,301	0.35	1.90	0.01	0.02	0.06	0.21	0.62	1.24	4.91

Notes: This table presents summary statistics on within-network purchases in Costa Rica across the years (and pooled across all years). We report the number of buyer firms each year, while the last row reports the number of observations used to compute the pooled statistics with the whole sample. The included summary statistics are the sample average, standard deviation, and percentiles from the 10^{th} to the 99^{th}.

Table B6: Within-network purchases by sector (2014, million U.S. dollars, CPI-deflated to 2014 U.S. dollars)

Sector	N	Mean	St Dev	10th	25th	50th	75th	90th	95th	99th
Agriculture, Forestry and Fishing	2,624	0.29	1.42	0.01	0.02	0.06	0.18	0.51	1.06	3.85
Manufacturing	3,645	0.63	3.22	0.01	0.03	0.09	0.32	1.03	2.66	9.35
Electricity and Gas	62	2.68	12.03	0.02	0.06	0.20	1.09	3.48	9.27	44.00
Water Supply, Sewerage and Waste Management	312	0.21	1.46	0.01	0.01	0.02	0.08	0.28	0.64	2.36
Construction	1,849	0.34	1.17	0.01	0.02	0.06	0.23	0.71	1.51	4.96
Wholesale and Retail Trade	11,530	0.37	1.58	0.01	0.03	0.09	0.29	0.72	1.35	4.47
Transportation and Storage	2,114	0.26	0.69	0.01	0.02	0.05	0.20	0.63	1.14	2.88
Accommodation and Food Services	3,710	0.17	0.68	0.01	0.02	0.05	0.12	0.28	0.50	2.05
Information and Communication	717	0.27	0.99	0.01	0.02	0.04	0.15	0.52	0.85	5.07
Real Estate	995	0.26	1.29	0.01	0.01	0.04	0.13	0.41	0.90	4.25
Professional, Scientific and Technical	3,021	0.17	0.63	0.01	0.01	0.04	0.11	0.33	0.62	2.73
Administrative and Support Services	1,560	0.35	1.03	0.01	0.02	0.05	0.24	0.81	1.63	5.34
Education	902	0.22	1.11	0.01	0.02	0.06	0.15	0.38	0.66	2.37
Human Health and Social Work	1,732	0.09	0.55	0.01	0.01	0.02	0.06	0.15	0.28	0.73
Art, Entertainment and Recreation	495	0.17	0.46	0.01	0.01	0.04	0.10	0.34	0.72	2.69
Other Services	1,127	0.09	0.28	0.01	0.01	0.02	0.06	0.20	0.38	1.24
Financial Activities	591	0.83	3.00	0.01	0.03	0.09	0.37	1.53	3.54	14.70
Mining and Quarrying	97	0.27	0.36	0.02	0.03	0.12	0.38	0.82	1.15	1.38
Public Administration	35	1.43	2.41	0.02	0.06	0.57	1.60	3.76	5.85	9.92
Pooled	37,433	0.32	1.65	0.01	0.02	0.06	0.20	0.58	1.16	4.53

Notes: This table presents summary statistics on within-network purchases in Costa Rica for the 2014 cross-section. We report the number of buyer firms in this cross-section by their sector. These summary statistics are the sample average, standard deviation, and percentiles from the 10^{th} to the 99^{th}. The statistics are presented across all sectors and separately by broad group sector.

Table B7: Number of buyers per firm by year

Year	N	Mean	St Dev	10th	25th	50th	75th	90th	95th	99th
2008	20,194	10.47	44.87	1	1	2	6	19	38	142
2009	21,945	10.63	48.40	1	1	2	6	19	39	145
2010	23,408	10.60	52.44	1	1	2	6	18	38	149
2011	25,229	10.95	56.56	1	1	2	6	19	39	154
2012	26,795	11.32	67.86	1	1	2	6	19	39	155
2013	27,872	11.54	69.29	1	1	2	7	19	39	158
2014	29,080	11.71	70.55	1	1	2	7	20	40	155
2015	29,761	12.10	73.69	1	1	3	7	21	42	161
2016	30,565	12.44	75.11	1	1	3	7	21	42	167
2017	30,976	12.60	77.90	1	1	3	7	21	43	169
2018	31,501	12.63	78.39	1	1	3	7	21	43	172
2019	31,105	12.09	76.24	1	1	3	7	21	41	160
Pooled	64,745	11.69	68.38	1	1	3	7	20	40	158

Notes: This table presents summary statistics on the number of buyers for firms in Costa Rica in our sample period (and pooled across all years). We report the number of seller firms each year, while the last row reports the number of unique firms used to compute the pooled statistics. The pooled sample contains firms that reported selling to other firms at least once between 2008 and 2019. The included summary statistics are the sample average, standard deviation, and percentiles from the 10^{th} to the 99^{th}.

Table B8: Number of buyers per firm by the seller firm's sector (2014)

Sector	N	Mean	St Dev	10th	25th	50th	75th	90th	95th	99th
Agriculture, Forestry and Fishing	2,862	2.68	4.37	1	1	2	3	5	8	17
Manufacturing	2,958	18.23	76.52	1	2	4	11	31	71	250
Electricity and Gas	48	150.08	726.60	1	2	6	16	155	447	2,923
Water Supply, Sewerage and Waste Management	165	7.44	18.33	1	1	2	6	13	23	119
Construction	1,448	3.06	4.80	1	1	2	3	6	9	19
Wholesale and Retail Trade	7,579	19.95	76.81	1	2	4	14	42	78	253
Transportation and Storage	2,412	7.78	24.54	1	1	2	5	14	27	111
Accommodation and Food Services	1,153	5.30	13.61	1	1	2	4	11	20	55
Information and Communication	741	13.28	50.11	1	1	4	10	22	44	184
Real Estate	1,152	6.47	26.94	1	1	2	4	10	20	81
Professional, Scientific and Technical	3,462	6.41	23.86	1	1	3	6	13	19	56
Administrative and Support Services	1,878	9.25	26.32	1	1	3	7	19	37	117
Education	253	6.17	12.64	1	1	1	4	15	32	65
Human Health and Social Work	862	2.94	7.75	1	1	1	2	5	8	26
Art, Entertainment and Recreation	297	5.25	9.92	1	1	2	5	10	24	54
Other Services	856	4.53	26.86	1	1	2	4	7	12	31
Financial Activities	482	36.04	308.31	1	1	2	4	18	54	440
Mining and Quarrying	106	10.54	13.16	1	2	5	15	26	40	58
Public Administration	21	17.48	30.16	1	1	5	14	50	91	105
Pooled	29,080	11.71	70.55	1	1	2	7	20	40	155

Notes: This table presents summary statistics on the number of buyers for firms in Costa Rica for the 2014 cross-section. We report the number of seller firms in this cross-section by their sector. These summary statistics are the sample average, standard deviation, and percentiles from the 10^{th} to the 99^{th}. The statistics are presented across all sectors and separately by the seller firm's broad group sector.

Table B9: Number of sellers per firm by year

Year	N	Mean	St Dev	10th	25th	50th	75th	90th	95th	99th
2008	26,959	7.84	19.21	1	1	3	7	17	29	79
2009	28,357	8.22	20.49	1	1	3	8	18	30	82
2010	30,105	8.24	21.31	1	1	3	7	18	30	81
2011	32,693	8.45	23.19	1	1	3	8	18	31	86
2012	34,904	8.69	23.78	1	1	3	8	19	32	88
2013	36,274	8.86	24.05	1	1	3	8	19	32	90
2014	37,433	9.10	24.59	1	1	3	8	19	33	93
2015	38,519	9.35	24.97	1	1	3	8	20	34	96
2016	39,964	9.52	25.42	1	2	3	8	20	35	98
2017	40,750	9.58	25.42	1	2	3	8	20	35	100
2018	41,308	9.63	25.17	1	2	3	9	21	36	100
2019	41,351	9.10	23.10	1	2	3	8	20	34	92
Pooled	86,301	8.96	23.71	1	1	3	8	19	33	92

Notes: This table presents summary statistics on the number of sellers for firms in Costa Rica across the years (and pooled across all years). We report the number of buyer firms each year, while the last row reports the number of unique firms used to compute the pooled statistics. The pooled sample contains firms that reported buying from other firms at least once between 2008 and 2019. The included summary statistics are the sample average, standard deviation, and percentiles from the 10^{th} to the 99^{th}.

Table B10: Number of sellers per firm by the buyer firm's sector (2014)

Sector	N	Mean	St Dev	10th	25th	50th	75th	90th	95th	99th
Agriculture, forestry and fishing	2,624	6.81	20.76	1	1	3	6	14	24	72
Manufacturing	3,645	15.07	41.05	1	2	5	11	28	61	196
Electricity and Gas	62	49.44	190.16	1	3	8	22	81	191	711
Water Supply, Sewerage and Waste Management	312	6.02	26.80	1	1	2	4	9	19	43
Construction	1,849	9.28	20.72	1	1	3	9	21	36	96
Wholesale and Retail Trade	11,530	10.64	22.23	1	2	5	11	25	38	84
Transportation and Storage	2,114	7.12	14.25	1	1	3	7	17	27	68
Accommodation and Food Services	3,710	6.38	14.06	1	2	3	7	12	20	50
Information and Communication	717	7.55	21.69	1	1	3	6	15	24	86
Real Estate	995	6.72	20.97	1	1	2	5	13	23	83
Professional, Scientific and Technical	3,021	5.82	12.87	1	1	2	5	12	21	60
Administrative and Support Services	1,560	10.45	21.43	1	1	3	9	25	49	104
Education	902	8.00	27.08	1	1	3	7	14	24	69
Human Health and Social Work	1,732	3.80	11.55	1	1	2	4	7	11	24
Art, Entertainment and Recreation	495	6.32	13.74	1	1	2	5	13	27	75
Other Services	1,127	4.27	8.75	1	1	2	4	8	14	53
Financial Activities	591	18.36	48.20	1	2	4	13	38	78	262
Mining and Quarrying	97	8.40	10.10	1	2	4	10	22	33	38
Public Administration	35	35.63	49.47	2	4	13	46	82	133	205
Pooled	37,433	9.10	24.59	1	1	3	8	19	33	93

Notes: This table presents summary statistics on the number of sellers for firms in Costa Rica for the 2014 cross-section. We report the number of buyer firms in this cross-section by the broad group sector of the buyer firm. These summary statistics are the sample average, standard deviation, and percentiles from the 10^{th} to the 99^{th}. The statistics are presented across all sectors and separately by broad group sector.

Table B11: Firm-to-firm transaction values by year (thousand U.S. dollars, CPI-deflated to 2014 U.S. dollars)

Year	N	Mean	St Dev	10th	25th	50th	75th	90th	95th	99th
2008	211,475	39.38	55.54	7.34	9.76	17.73	41.36	96.82	158.85	295.16
2009	233,170	34.43	49.40	6.58	8.69	15.44	35.44	83.77	139.18	265.65
2010	248,060	36.32	53.71	6.84	9.01	16.01	36.46	87.86	147.41	291.76
2011	276,197	37.72	57.06	6.76	8.96	16.16	37.68	91.66	154.60	310.77
2012	303,333	37.77	59.77	6.49	8.61	15.54	36.73	91.24	156.88	328.20
2013	321,545	38.11	63.10	6.32	8.40	15.16	36.01	90.92	158.84	351.85
2014	340,497	35.38	62.03	5.51	7.35	13.39	32.20	83.74	149.05	350.55
2015	359,976	37.73	70.34	5.55	7.42	13.62	33.08	87.04	159.01	397.84
2016	380,344	38.91	78.36	5.41	7.24	13.27	32.45	87.10	162.33	445.72
2017	390,450	38.70	79.17	5.16	6.91	12.73	31.53	86.68	166.57	447.69
2018	397,864	44.42	119.13	4.96	6.66	12.28	30.73	88.26	175.11	624.84
2019	376,113	45.57	141.00	4.69	6.24	11.49	28.92	84.26	170.96	672.03
Pooled	3,839,024	39.03	82.67	5.77	7.73	14.06	33.88	88.12	158.39	379.10

Notes: This table presents summary statistics on the transaction values of firms in Costa Rica in our sample period (and pooled across all years). We report the number of transactions observed each year, while the last row reports the number of transactions observed between 2008 and 2019 used to compute the pooled statistics. The included summary statistics are the sample average, standard deviation, and percentiles from the 10^{th} to the 99^{th}.

Table B12: Firm-to-firm transaction values by seller firm's sector (2014, thousand U.S. dollars, CPI-deflated to 2014 U.S. dollars)

Sector	N	Mean	St Dev	10th	25th	50th	75th	90th	95th	99th
Agriculture, Forestry and Fishing	7,666	65.21	96.16	6.30	9.91	22.73	71.48	192.57	300.75	450.94
Manufacturing	53,936	41.07	70.27	5.55	7.55	14.46	37.76	104.30	185.28	381.25
Electricity and Gas	7,204	30.36	58.16	5.29	6.66	11.04	24.42	67.83	126.90	344.64
Water Supply, Sewerage and Waste Management	1,228	35.94	61.20	5.53	7.28	12.49	33.52	90.12	154.70	309.29
Construction	4,430	62.68	89.21	6.23	10.41	25.30	73.15	176.43	272.68	429.09
Wholesale and Retail Trade	151,172	31.41	55.49	5.44	7.12	12.56	28.81	70.81	124.40	316.91
Transportation and Storage	18,771	40.92	69.28	5.62	7.69	14.74	38.84	100.96	179.10	382.13
Accommodation and Food Services	6,110	26.68	46.84	5.39	6.85	11.44	25.13	57.48	97.58	259.40
Information and Communication	9,844	31.26	57.45	5.38	6.91	11.92	27.54	68.76	126.92	324.28
Real Estate	7,454	36.62	58.21	6.04	8.83	16.73	35.76	84.51	142.78	322.53
Professional, Scientific and Technical	22,198	34.74	58.93	5.61	7.59	14.16	32.89	80.87	142.46	334.67
Administrative and Support Services	17,377	41.15	68.46	5.77	8.17	16.21	38.99	99.50	178.88	378.81
Education	1,562	21.53	38.82	5.39	6.97	10.69	19.64	37.69	70.48	214.56
Human Health and Social Work	2,531	24.44	43.20	5.37	6.86	10.47	21.22	52.57	92.94	224.61
Art, Entertainment and Recreation	1,560	31.23	56.74	5.44	7.10	12.40	27.64	68.98	127.56	345.09
Other Services	3,879	26.78	46.81	5.26	6.62	11.14	24.34	60.77	105.51	246.19
Financial Activities	17,371	32.21	59.19	5.40	6.99	12.10	28.02	73.19	131.88	334.30
Mining and Quarrying	1,117	36.49	61.58	5.74	8.09	15.82	35.00	82.14	147.13	371.15
Public Administration	367	40.53	72.68	5.52	7.03	15.52	37.22	96.62	178.41	384.32
Pooled	340,497	35.38	62.03	5.51	7.35	13.39	32.20	83.74	149.05	350.55

Notes: This table presents summary statistics on the transaction values of firms in Costa Rica for the 2014 cross-section. We report the number of transactions in this cross-section by the sector of the seller firm. These summary statistics are the sample average, standard deviation, and percentiles from the 10^{th} to the 99^{th}. The statistics are presented across all sectors and separately by broad group sector.

Table B13: Firm-level employment by year

Year	N	Mean	St Dev	10th	25th	50th	75th	90th	95th	99th
2008	32,247	24.68	223.01	1	2	4	11	31	66	356
2009	34,171	22.95	229.72	1	2	4	10	28	60	324
2010	36,332	22.25	229.49	1	2	4	9	27	58	318
2011	39,230	21.48	224.61	1	2	4	9	26	55	305
2012	41,443	21.38	221.92	1	2	4	9	26	55	304
2013	42,869	21.19	217.45	1	2	4	9	26	54	296
2014	44,177	21.06	213.07	1	2	4	9	26	54	291
2015	45,205	20.91	204.81	1	2	4	9	26	54	289
2016	46,600	21.06	202.07	1	2	4	9	25	54	290
2017	47,260	21.38	201.65	1	2	4	9	26	54	292
2018	47,899	21.83	211.69	1	2	4	9	26	55	302
2019	47,687	21.88	211.46	1	2	4	9	26	55	305
Pooled	96,177	21.74	215.11	1	2	4	9	26	56	305

Notes: This table presents summary statistics on firm-level employment in Costa Rica in our sample period (and pooled across all years). We report the number of workers per firm each year, while the last row reports the number of unique firms used to compute the pooled statistics. The included summary statistics are the sample average, standard deviation, and percentiles from the 10^{th} to the 99^{th}.

Table B14: Firm-level employment by sector (2014)

Sector	N	Mean	St Dev	10th	25th	50th	75th	90th	95th	99th
Agriculture, Forestry and Fishing	3,362	26.17	314.04	1	2	3	8	23	51	376
Manufacturing	4,001	37.78	168.78	1	2	5	15	52	131	708
Electricity and Gas	69	449.17	3,363.97	2	2	7	32	76	375	9,365
Water Supply, Sewerage and Waste Management	364	18.38	195.48	1	2	3	6	14	30	133
Construction	2,187	15.43	50.18	1	2	4	11	29	54	187
Wholesale and Retail Trade	12,336	13.38	129.77	1	2	4	8	20	36	137
Transportation and Storage	2,859	14.85	65.86	1	2	3	7	25	56	237
Accommodation and Food Services	3,848	13.11	67.08	1	2	4	8	19	37	147
Information and Communication	950	24.92	91.10	1	2	5	15	45	86	402
Real Estate	1,443	9.84	69.42	1	2	3	5	12	24	139
Professional, Scientific and Technical	4,221	12.79	115.94	1	1	3	6	17	32	141
Administrative and Support Services	2,319	46.71	184.17	1	2	6	22	82	177	754
Education	955	47.63	401.67	1	2	5	21	58	125	423
Human Health and Social Work	1,983	7.76	48.81	1	1	2	4	10	19	59
Art, Entertainment and Recreation	570	13.88	38.27	1	2	3	9	28	59	196
Other Services	1,458	20.44	255.49	1	2	3	6	13	26	194
Financial Activities	701	70.77	387.34	1	2	5	19	69	191	1,213
Mining and Quarrying	114	9.23	12.27	1	2	5	13	25	30	65
Public Administration	35	119.88	195.91	4	7	69	124	268	546	814
Pooled	44,177	21.06	213.07	1	2	4	9	26	54	291

Notes: This table presents summary statistics on firm-level employment in Costa Rica for the 2014 cross-section. We report sample statistics on the number of workers by firm's sector. These summary statistics are the sample average, standard deviation, and percentiles from the 10^{th} to the 99^{th}. The statistics are presented across all sectors and separately by broad group sector.

Table B15: Direct and total (direct + indirect) trade shares (2014)

	N	Mean	St Dev	10th	25th	50th	75th	90th	95th	99th
Direct export shares (r_{jF})	44,177	0.01	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.59
Total export shares (r_{jF}^{Total})	44,177	0.05	0.18	0.00	0.00	0.00	0.02	0.14	0.29	0.88
Direct import shares (s_{Fj})	44,177	0.07	0.19	0.00	0.00	0.00	0.00	0.26	0.63	0.86
Total import shares (s_{Fj}^{Total})	44,177	0.33	0.26	0.00	0.09	0.32	0.52	0.70	0.78	0.90

Notes: This table presents summary statistics on the direct and total (direct + indirect) export and import shares in Costa Rica for the 2014 cross-section. We report the number of firms in the cross-section. These summary statistics are the sample average, standard deviation, and percentiles from the 10^{th} to the 99^{th}. Total export shares are computed by solving the recursive equation $r_{jF}^{\text{Total}} = r_{jF} + \sum_{i \in W_j^D} r_{ji} r_{iF}^{\text{Total}}$, where r_{jF} is the direct export share of firm j, W_j^D is the set of domestic buyers, and r_{ji} is the share of j's sales to firm i. Total import shares are computed by solving $s_{Fj}^{\text{Total}} = s_{Fj} + \sum_{i \in Z_j^D} s_{ij} s_{Fi}^{\text{Total}}$, where s_{Fj} is the direct import share of firm j, Z_j^D is the set of domestic sellers, and s_{ij} is the share of j's inputs purchased from firm i.

Table B16: Concordance table between different levels of sectoral aggregation

Sector in this paper	Sector in Bernard et al. (2022)
Agriculture, Forestry and Fishing	Primary and extraction
Mining and Quarrying	Primary and extraction
Manufacturing	Manufacturing
Electricity and Gas	Utilities
Water Supply, Sewerage and Waste Management	Utilities
Construction	Construction
Wholesale and Retail Trade	Market services
Transportation and Storage	Market services
Accommodation and Food Services	Market services
Information and Communication	Market services
Financial Activities	Market services
Real Estate	Market services
Professional, Scientific and Technical	Market services
Administrative and Support Services	Market services
Public Administration	Non-market services
Education	Non-market services
Human Health and Social Work	Non-market services
Art, Entertainment and Recreation	Non-market services
Other Services	Non-market services
Activities of Extraterritorial Organizations and Bodies	-
Activities of Households as Employers and for Own Use	-

Notes: This table is an adaptation of Table 1 from the Online Appendix of Bernard et al. (2022).

Appendix C Additional stylized facts

Fact C1. The distributions of the number of buyers and sellers follow a power-law distribution.

Table C1: Tail exponent of the number of connections distributions (2014)

	MLE (1)		Hill (2)		Moments (3)		Kernel-type (4)	
	κ	ξ	κ	ξ	κ	ξ	κ	ξ
Number of buyers	265	0.622	27,862	1.258	178	0.609	15,042	0.929
Number of sellers	2,667	0.665	36	0.432	27,852	0.667	16,092	0.612

Notes: This table presents the tail exponent estimates $\hat{\xi}$, and the optimal number of order statistics $\hat{\kappa}$ for the EVT estimators, i.e., the data points used in the estimation, for the distributions of the number of buyers and the number of sellers. Column (1) presents the MLE estimator for pure Pareto tails proposed by Clauset et al. (2009). The estimator returns estimates $\hat{\gamma}$ of γ and report $\hat{\xi} = \frac{1}{\hat{\gamma}-1}$. Columns (2)-(4) show the results from the double-bootstrap extreme value estimators proposed by Voitalov et al. (2019): Hill, Moments, and Kernel, respectively. The estimation was performed using the 2014 cross-section.

Figure 1 displays the empirical complementary cumulative distribution functions (CCDFs) of these connections on log–log scales. Both distributions exhibit heavy tails: most firms maintain relatively few connections, while a small minority have extensive networks. This is consistent with findings by Acemoglu et al. (2012) and Bernard et al. (2019), who also document power-law distributions in production networks. Networks generated by power-law distributions with finite means but divergent second moments are commonly classified as scale-free. Such network structures are widespread across disciplines, including biology, economics, transportation, and geology (Voitalov et al., 2019).

Scale-free networks exhibit several notable properties in the context of production networks, including robustness to firm entry and exit, high clustering of production linkages, ultrasmall-world behavior (short paths between distant firms despite sparse direct connections), and correlations between the numbers of buyers and sellers. Identifying the precise data-generating distribution is therefore crucial for understanding the dynamics of production networks.

Appendix Table C1 reports tail exponent estimates based on 2014 data. For the distribution of the number of buyers, the extreme value index $\hat{\xi}$ ranges from 0.622 to 1.258 across estimators. For sellers, the estimates range from 0.432 to 0.667. We classify both distributions as power laws. For buyers, all three EVT estimators yield $\hat{\xi} > \frac{1}{2}$, satisfying the condition for a divergent second moment. For sellers, the Hill estimator yields $\hat{\xi} < \frac{1}{2}$, so we classify the seller distribution as a power law without a divergent second moment.

The buyer distribution is more dispersed than the seller distribution, consistent with Acemoglu and Azar (2020), who predict greater dispersion in outdegrees than indegrees. Our findings are also in line with evidence from other countries: Bacilieri et al. (2025) report extreme value indices of 0.629 (0.704) for buyers and 0.420 (0.372) for sellers in Ecuador (Hungary), while Bernard et al. (2019) find indices of 0.730 for buyers and 0.685 for sellers in Japan.[i] Using OLS, Cardoza et al. (2025) obtain higher values—2.326 for buyers and 3.333 for sellers.[ii]

Fact C2. As sales and purchases are aggregated from the firm to the sector level, the average transaction value with buyers or sellers becomes more important in explaining the variation in within-network sales and purchases.

We use OLS to decompose the variation in log X_i — the within-network sales (purchases) of a firm (sector) i— into the four log components as described in Equation 1. We implement this decomposition at the firm level, as well as at the four- and two-digit sector levels.

Table C2 presents this decomposition. Panel A (B) reports the decomposition of the variance in total sales (purchases). At the firm level, the extensive margin accounts for approximately 59% (63%) of the variance in within-network sales (purchases). The number of locations is particularly important, explaining about 40% (43%) of the variance. These results highlight the importance of the spatial reach of firms' buyer and seller networks in Costa Rica. The intensive margin becomes more important than the extensive margin at the sector level. When firm-level sales or purchases are aggregated to two-digit sectors, the intensive margin explains 44–53% of the variance in X_i. As estimates become noisier with aggregation, we cannot rule out that the intensive margin

[i] Data truncation in Bernard et al. (2019) may lead to overestimation of shape parameters by excluding poorly connected firms. See Chaney (2022), who shows in a replication of Chaney (2018) that the estimated Pareto shape parameter λ of the firm size distribution for French exporters increases monotonically as the lower size threshold rises.

[ii] The upward bias in these estimates may arise from the OLS estimator imposing a pure Pareto distribution over the entire distribution, rather than focusing on tail behavior.

dominates the extensive margin at the two-digit sector level for sales in the firm-to-firm transaction data, given the 95% confidence intervals.

Table C2: Margins of trade (2014)

	Number of connections			Average	Number of
	Locations	Sectors 4-D	Density	transaction	observations
	(1)	(2)	(3)	(4)	(5)
Panel A: Within-network sales					
Firms	40.4%	45.1%	-27.0%	41.4%	28,069
	(0.2%)	(0.3%)	(0.2%)	(0.3%)	
Sectors 4-D	45.8%	55.1%	-26.3%	25.4%	356
	(1.1%)	(1.2%)	(1.5%)	(1.7%)	
Sectors 2-D	6.6%	19.1%	28.6%	45.6%	20
	(2.3%)	(3.6%)	(1.9%)	(4.5%)	
Panel B: Within-network purchases					
Firms	42.6%	53.0%	-32.5%	36.9%	36,455
	(0.2%)	(0.2%)	(0.2%)	(0.2%)	
Sectors 4-D	43.0%	50.9%	-25.0%	31.3%	368
	(0.1%)	(1.0%)	(1.3%)	(0.8%)	
Sectors 2-D	3.9%	17.4%	24.0%	54.7%	20
	(1.2%)	(3.7%)	(1.7%)	(4.0%)	

Notes: This table is the counterpart for Costa Rica to Table A.2 from Huneeus (2020). We decompose trade margins at the firm and sector levels into the extensive (number of connections) and intensive (average transaction) margins using the OLS estimator, following Bernard et al. (2009). Panel (A) decomposes the within-network sales, while Panel (B) decomposes the within-network purchases. We separate the extensive margin into three subcomponents: column (1) reports the contribution of the number of locations, i.e., municipalities, of the buyers (sellers), column (2) the number of four-digit sectors of the buyers (sellers), and column (3) the density of connections with buyers (sellers) by their sector and location. Column (4) reports the share of variance explained by the intensive margin (the average transaction with buyers and sellers, respectively). Column (5) reports the number of observations used in each decomposition. We report the standard errors in parentheses below the point estimate. We include four-digit sector fixed effects in the firms' decomposition. This table is based on the 2014 cross-section.

Our findings are consistent with the existing literature. For comparison, Huneeus (2020) finds that, at the firm level, the extensive margin explains 53% (54%) of the variance in sales (purchases), while Fernandes et al. (2023) report that the extensive margin accounts for 60% of the variance among exporters across 50 countries. In contrast, Bacilieri et al. (2025) find that the extensive margin explains about 31% and 36% of the variance in within-network sales, and Panigrahi (2022) reports a share of 35% across five Indian states. We echo the insight of Huneeus (2020) that, when aiming to understand variation in firm size, reliance on sector-level input–output tables can lead to misleading conclusions about the relative importance of the extensive and intensive margins of trade.

Appendix D Additional methodological details

Appendix D.1 Geographic distance calculation methodology

We compute optimal routes using Dijkstra's algorithm, implemented via the OSMnx Python package (Boeing, 2017), to identify the fastest paths between locations. Edge weights correspond to travel time, so the optimization targets minimum travel time rather than distance. Distance and travel time are then measured as the length and duration of the resulting optimal path, respectively. The road network includes highways classified by OpenStreetMap contributors (2023) as primary, secondary, tertiary, trunk, and residential roads.

For intra-municipal distances, where firms are located within the same municipality, we adopt the formula in Redding and Venables (2004). Specifically, we calculate the distance d_{ii} for a municipality i as $d_{ii} = \frac{2}{3}\sqrt{\frac{A}{\pi}}$, where A denotes the geographic area of the municipality in square kilometers. We compute the average speed within a municipality as the length-weighted average speed across all road segments. Travel time is then calculated as the ratio of distance to speed.

To validate our approach, we compare our calculated travel times with those from the Google Maps API and find close agreement across the entire distribution.

Appendix D.2 Power-law distribution estimation

Power-law distributions Following Voitalov et al. (2019), we characterize these distributions as Regularly Varying Distributions (RVDs). A distribution is regularly varying if its Complementary Cumulative Distribution Function (CCDF) satisfies:

$$\bar{F}(k) = \ell(k)k^{-\alpha}, \tag{C1}$$

where $\alpha > 0$, and $\ell(k)$ is a slowly varying function. A function $\ell(x)$ is considered slowly varying if

$$\lim_{x\to\infty} \frac{\ell(tx)}{\ell(x)} = 1,$$

for any $t > 0$. The RVDs encompass all distributions with Probability Density Functions (PDFs) of the form:

$$P(k) = \ell(k)k^{-\gamma}. \tag{C2}$$

These distributions exhibit power-law behavior in their tails while potentially taking arbitrary shapes at smaller degrees. Specifically, they can assume any form for degrees $k < K$ below a fixed threshold $K > 0$. The number of data points beyond this threshold is termed the number of order statistics κ.

Estimating the parameters Estimating the tail exponent requires selecting both an appropriate order statistic and an estimator. We employ four estimators proposed in the literature:[iii]

First, we apply the Maximum Likelihood Estimator (MLE) described by Clauset et al. (2009) to estimate γ from equation (C2). This approach selects the threshold by minimizing the Kolmogorov-Smirnov distance between estimated and empirical CCDFs. We then convert these estimates using equation (C4) below.

Second, following Voitalov et al. (2019), we estimate the extreme value index ξ of the Generalized Extreme Value Distribution (GEVD) directly, rather than estimating the PDF or CCDF tail exponents γ and α directly; these are then recovered via equation (C4). According to extreme value theory, the asymptotic distribution of the normalized maximum of i.i.d. random variables, if it exists, is the GEVD parametrized by $\xi \in \mathbb{R}$, with CDF:

$$F(x) = \begin{cases} e^{-(1+\xi x)^{-\frac{1}{\xi}}} & \text{if } \xi \neq 0, \\ e^{-x} & \text{otherwise.} \end{cases} \tag{C3}$$

The class of Extreme Value Distributions consists of three subclasses—Fréchet ($\xi > 0$), Gumbel ($\xi = 0$), and Weibull ($\xi < 0$)—with regularly varying distributions belonging to the Maximum Domain of Attraction (MDA) of the Fréchet distribution. The tail exponents γ and α relate to the extreme value index ξ via

$$\xi = \frac{1}{\alpha} = \frac{1}{\gamma - 1}. \tag{C4}$$

Voitalov et al. (2019) present three consistent, stable, and efficient estimators for ξ: Hill, moments, and kernel estimators.[iv] The optimal threshold κ is determined using

[iii] We thank François Lafond for suggesting this approach to estimate the tail exponents. The packages to apply these estimators Clauset et al. (2009) and Voitalov et al. (2019) can be found in https://github.com/jeffalstott/powerlaw (Alstott et al., 2014) and https://github.com/mu373/tailestim.

[iv] The estimators considered by Voitalov et al. (2019) and Clauset et al. (2009) are consistent under the

the double bootstrap method, which applies two consistent estimators to bootstrap samples, estimating ξ for every possible value of κ and selecting κ^* that minimizes the mean squared error between the estimated and true values of ξ. Since the true ξ is unknown, the two estimators applied to subsamples of different sizes serve as a proxy: their disagreement across values of κ approximates the true MSE, exploiting the fact that both estimators converge to the true ξ. Intuitively, small values of κ produce high-variance estimates because they use too few tail observations, while large values introduce bias from the slowly varying function $\ell(k)$; the double bootstrap balances this tradeoff automatically.

Evaluating the fitting of the data to the power-law distribution Voitalov et al. (2019) propose classifying networks based on extreme value estimator results:[v] (1) not power-law distributions if at least one estimate is $\hat{\xi} \leq 0$; (2) hardly power-law distributions if all the estimates are positive ($\hat{\xi} > 0$) and at least one estimate is $\hat{\xi} \leq \frac{1}{4}$; (3) power-law distributions with a divergent second moment, all the estimates are $\hat{\xi} > \frac{1}{2}$; and (4) other power-law distributions.

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assumption that they are applied to i.i.d. samples from a regularly varying distribution, which is not a testable assumption in this context.

[v] RVDs are not subject to hypothesis testing due to being part of the nonparametric class of distributions with infinite degrees of freedom attributable to the slowly varying function $\ell(k)$.

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