Endogenous Production Networks and Supply Chain Disruptions

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Abstract: This paper examines the role of production networks and provides a causal estimate of how supply shocks affect prices and productivity. Using unique firm-level production network data from Turkey, a country with high inflation and expansionary monetary policy, I isolate a supply shock by exploiting the disruption caused by Chinese suppliers due to the lockdown in China. The study finds that firms relying on imports from China raised their prices by 11% and experienced a 24% decrease in labor productivity following the supply chain disruption. To explore the underlying mechanism, I further extend the analysis at the firm-product level and uncover that the effect on labor productivity is primarily driven by the imports of intermediate and capital goods. Guided by these empirical findings, I build a model of endogenous network formation where firms are heterogeneous in terms of their efficiency and the efficiency of their suppliers. The endogeneity of the production network also originates from interdependent choices in the production network. This paper offers a new layer of firm heterogeneity as supply chain selection. Finally, I calibrate the model to analyze the implications of simulated disruptions in the firm's supply chain. Counterfactual supply chains, with disruptions, translate into an increase in aggregate prices while shifting importers from Chinese suppliers to others.

Key Words: Aggregate fluctuations, Disruptions, Firms, Input-Output, Networks, Selection, Shocks, Supply Chains Productivity, Production

JEL codes: E23, E32, F14, L11.

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1 Introduction

Supply chain disruptions are becoming more noticeable with the lockdowns and wars. These types of disruptions, originating in input-output networks, differ from classical aggregate supply shocks as they spread throughout the production networks. It is important to accurately measure the impact of these shocks to for shaping policies. Therefore, this study utilizes a unique dataset of production networks to determine how supply chains impact prices and productivity, providing empirical, theoretical, and quantitative evidence.

This study begins by isolating supply shocks to quantify disruptions in value chains. However, it can be difficult to separate causal evidence through the supply chain because network links between firms are endogenous and may change in response to shocks.[1] To address the problem of endogenous production networks where firms adjust linkages in response to shocks, I develop a novel identification strategy. This paper overcomes the identification challenge by exploiting the disruption from China on Turkish importers during the lockdown. Therefore, this strategy tackles the reflection problem arising from the production network's endogeneity. Additionally, the impact is not related to the demand side, as all importer firms are exposed to identical demand shocks with the same expansionary monetary policy and high inflation. With this strategy, the results show that supply chain disruptions lead to an 11% increase in prices and a 24% decrease in firm efficiency.

The classification of imported products into intermediate, capital, and final categories extends the analysis of supply chains to the product-supplier level to disentangle the mechanism. Our findings show that, for labor productivity, it is crucial to seek low-cost or productive suppliers if imported inputs are intermediate or capital goods. Disruptions in this channel lead to productivity losses, especially for firms that import capital goods from China. In other words, for Turkish firms, labor productivity is mainly driven by investment in capital goods and intermediate goods. As expected, these results reveal no link between labor productivity and the imports of final goods from China. Focusing on product-level estimates also reveals that reconversion from these suppliers cannot be done smoothly if it requires a rearrangement of the production line, particularly for a traditional manufacturing economy like Turkey.

To rationalize these findings, this paper introduces a model of endogenous production networks that takes into account how input-output linkages react to supply chain disruptions. The model is based on the work of Antras (2017) and involves two types of firms: upstream suppliers that create intermediate goods, and downstream

[1] Manski (1993) provides further details on the reflection problem.

firms that produce final goods. The intermediate goods market is perfectly competitive for upstream firms, and these suppliers differ in their efficiencies, as described in Eaton and Kortum (2002). Supplier efficiency is drawn from a Fréchet distribution, where supplier technology varies across countries. The final goods market is monopolistically competitive, and downstream firms in this market are heterogeneous in their core efficiency. These downstream firms draw their efficiency from a Pareto distribution with the same shape and location parameters.

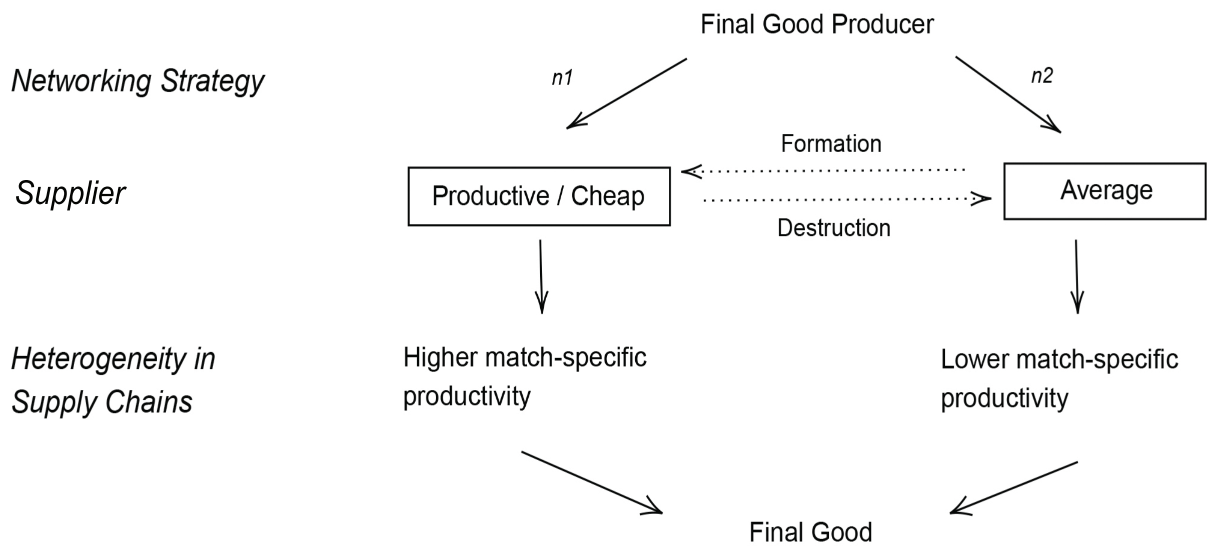


Figure 1: Model Sketch

In the model, firms construct supplier networks by paying fixed costs that are specific to each supplier. As a result, downstream firms must balance the trade-off between choosing a better supplier that offers lower prices but also has higher sourcing costs. This leads to a self-selection mechanism where downstream firms opt for cheaper intermediate inputs. This selection process results in more productive firms being part of more extensive and lower-cost value chains than less productive firms. Additionally, the formation of the production network is endogenous, as each supplier and intermediate choice is interdependent.

When faced with supply chain disruptions, firms experience an increase in fixed costs associated with sourcing from China. As a result of this adverse shock, top firms reduce their reliance on suppliers from China, and the impact of the shock cascades from leading firms to less productive firms. Competition decreases in the domestic market, leading to a weaker selection of firms and less efficiency. Following the disruption, prices increase, and labor productivity falls due to less efficient firms and expensive sourcing.

The quantitative part of the study starts by calibrating the model, and this calibration relies on the domestic production network for the parameters and the simulated method of moments. To calibrate the model, I estimate the sourcing advantage of different countries relative to the domestic suppliers. Based on the estimations, China has the most significant sourcing advantage for Turkish firms.

To simulate the disruption, I impose an increase in the fixed costs of Chinese suppliers exogenously while keeping other variables constant in a counterfactual supply chain. These disruptions lead to a reconfiguration of the supply chain, as firms shift away from China to other sources. In addition, the disruptions also affect prices and importer shares across different countries.

Related Literature: This study contributes to several strands of literature. The first is the literature that questions the role of input-output linkages across sectors as a transmission mechanism (Long and Plosser (1983); Horvath (2000); Shea (2002); Gabaix (2011); Acemoglu et al. (2012); Acemoglu et al. (2016); Grassi (2017); Huneeus (2018); Baqaee and Farhi (2020) Bigio and La'o (2020)). Although these papers emphasize sectoral-level links, more recent papers of this strand demonstrate the role of firm-level production networks in the economy (Di Giovanni et al. (2014); Barrot and Sauvagnat (2016); Mayer et al. (2016); Tintelnot et al. (2018); Di Giovanni et al. (2018); Boehm et al. (2019), Bernard et al. (2019b)). This paper contributes to this literature by underlining how production networks influence firm prices and productivity.

Second, this study builds on emerging literature that investigates the endogenous formation of networks, including Carvalho and Voigtländer (2014), Lim (2018), Oberfield (2018), Acemoglu and Azar (2020), Taschereau-Dumouchel (2020) and Arkolakis et al. (2021). Carvalho and Voigtländer (2014) presents how firms in production networks play a significant role in the diffusion of technology with a new variety of producers, such as semiconductors. By focusing on the variation in size, Lim (2018) illustrates how linkages among firms are endogenously determined, while Oberfield (2018) establishes a matching model for constructing the links between customers and suppliers, where firms can rely on only one intermediate input. Recent work by Acemoglu and Azar (2020) demonstrates how the arrival of new products can lead to the evolution of the production network, which can also be an engine of economic growth. Furthermore, Taschereau-Dumouchel (2020) discusses a firm entry-and-exit model that endogenizes the production network structure. Recently, Arkolakis et al. (2021) underscores the role of geographic proximity in forming connections. This study contributes to existing research by offering an alternative mechanism for the endogeneity of production networks for multiple suppliers, contending that endogeneity originates from a firm's interdependent choices among supply chains.

Third, this work is also related to the literature that examines the mechanism behind production network formation. Bernard et al. (2019a) argues that larger firms can access superior suppliers, and that explain the heterogeneity among firms.[2] Demir et al. (2021), demonstrate that the network formation depends on the quality choices. In contrast to these studies, this paper argues that productivity gains through the supply chain as the primary mechanism behind the formation of these networks. In this regard, it contributes to this literature by suggesting that firms aim to match with better suppliers and build their production networks based on a selection mechanism.

Fourth, the model employed in this paper builds on Antras et al. (2017) multi-country sourcing model where firms select themselves into importing.[3] This model characterizes firms' sourcing decisions across different countries. Following their framework, this paper shows that firms searching for low-cost suppliers and those that can link with superior suppliers can increase their efficiency and reduce costs due to their expansion in supply chains.[4]

Fifth, disruptions in the supply chains also studied in Barrot and Sauvagnat (2016), Boehm et al. (2019), Carvalho et al. (2021) and Lafrogne-Joussier et al. (2022). Barrot and Sauvagnat (2016) shows how customers experience output losses if their suppliers hit by natural disasters. Boehm et al. (2019) documents that the output falls for Japanese affiliates in the U.S. after the East Japanese Earthquake. Using the same experiment, Carvalho et al. (2021) demonstrates that the earthquake affects firms with direct and indirect connections. Further, the propagation of shocks through the network is still significant, even in higher-order indirect linkages. More recently, Lafrogne-Joussier et al. (2022) investigates the impact of early lockdown in China and argues that shock on inputs led to a drop in exports and domestic sales. By contrast with these studies, this paper highlights how these disruptions influence firms' prices and efficiency. This paper is also the first to present the shock propagation based on the type of products in the network[5].

[2] In this respect, Bernard and Zi (2022) argues that random matching across heterogeneous buyers and sellers replicates the sparsity of the production networks.

[3] In addition, Huang et al. (2021) demonstrates global sourcing with buyer-supplier matching frictions.

[4] This study builds on the theoretical literature of heterogeneous firms Melitz (2003) and Melitz and Ottaviano (2008). It follows existing theory to characterize heterogeneous firms' supply-chain decisions. It also relies on Eaton and Kortum (2002) to demonstrate technological differences across firms and follows Halpern et al. (2015) to demonstrate the role of imported inputs productivity by focusing on the proportion of Chinese suppliers in Turkish firms. Similar to Caliendo and Parro (2015), it presents the supply chain heterogeneity in production.

[5] This work is also related to literature that studies supply chains and inflation. Rubbo (2020) reveals that the slope of sectoral Phillips curves decreases in intermediate input shares while productivity fluctuations endogenously deliver a trade-off between inflation and output. For the link between shocks and networks, Baqaee and Farhi (2022) studies a quantitative input-output model of the U.S. economy to gauge the role of supply and demand shocks on inflation. Di Giovanni et al. (2022) decomposes the demand- and supply-side factors underlying the observed inflation and shows how aggregate demand shocks explain the inflation in the United States. This paper contributes to this literature by providing a

Finally, this paper adds to the literature on network effects on firm performance. Alfaro-Urena et al. (2020) illustrates that firms experience gains in their performance after they begin to supply for multinational corporations. Recently, Rachapalli (2021) demonstrates how input-output linkages enrich learning by transforming single-product firms into multi-product firms for the exporters. Unlike these studies, which concentrate on learning through interactions, this paper focuses on the selection mechanism, where firms can increase their cost advantage through the sophistication of their supply chains.

2 Production Network Facts

This part represents facts that motivate the research questions in this paper. It starts by focusing on the linkages between firms and introducing the characteristics of production networks. The objective is to evaluate the interactions across firms using network theory.

Fact 1. *Productive firms have productive supply chains.*

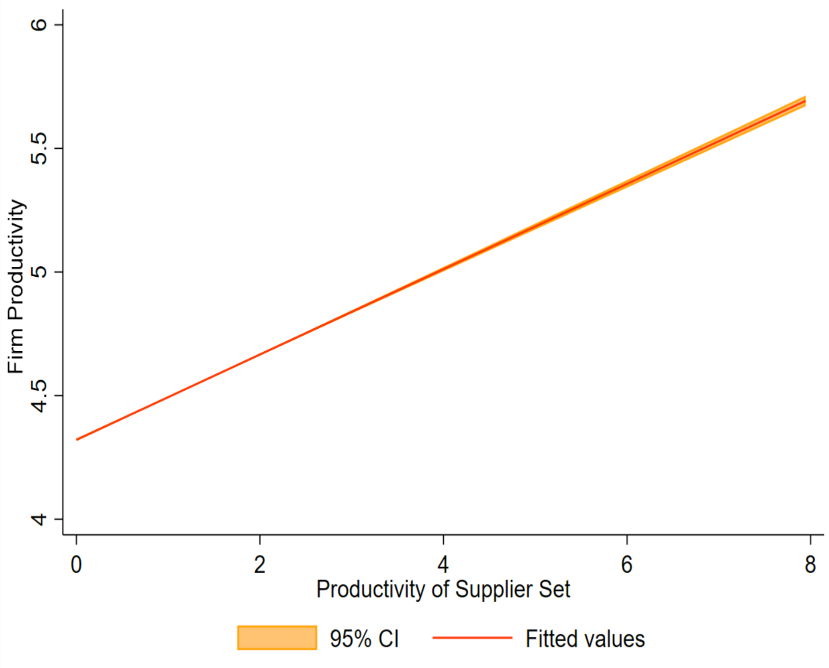


Figure 2: Supplier Set Productivity

Note: The estimation is weighted by the number of employees

The focus is determining whether there is a selection process in forming production networks or if it occurs randomly. To investigate this, I rely on Levinsohn and Petrin

causal estimate for these disruptions at the micro level and exhibiting how the choice of supplier directly affects the firm's price.

(2003) to calculate firms' total factor productivity (TFP) using intermediate inputs as a proxy. Given the productivity at the firm level, I estimate the productivity of the firms' supplier sets[6].

To investigate the presence of productive clusters, Figure 2 is employed. This Figure displays a firm's productivity on the x-axis and its suppliers' productivity on the y-axis, demonstrating how effective firms tend to cluster together within the production network. It also illustrates how effective firms cluster together in the production network. Thus, Figure 2 relies on both the firm's productivity and the mean of its supplier sets' productivity.[7]

Fact 2. *Only a small percentage of firms rely on multiple suppliers.*

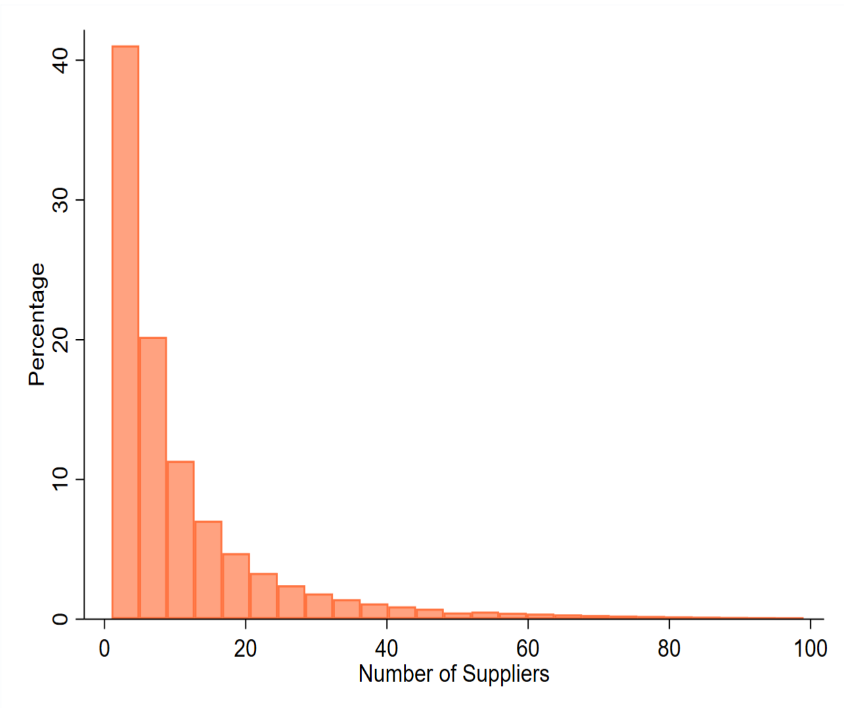


Figure 3: Number of Suppliers per Firm

Note: This figure presents firms with fewer than 100 suppliers.

The initial finding highlights a positive correlation between firms' productivity and their suppliers. Hence, this observation implies that productive firms benefit from

[6]To purchase intermediate inputs, firms rely on production networks consisting of nodes and edges. This study proxies network edges as intermediate input transactions within firms, and each node in a network corresponds to a firm. A production network builds on firm-to-firm transactions in the direction of trade and volume. Also, these transactions determine firms' roles as suppliers and customers over time. Hence, each of these connections assembles a directed and weighted network in which weights are the values of the intermediate input transactions across firms. The goal is to discover how interactions across these production networks change over time and the implications of supply chain dynamics.

[7]This is also weighted by the number of employees.

sourcing intermediate inputs from more efficient suppliers. Accordingly, this can create a layer of diversity among the firms. These observations also suggest that effective clusters within the production network can play a crucial role in firm heterogeneity.

To understand the value chains of firms, another point to consider is their diversification. To this end, the second fact concerns each firm's number of suppliers. Figure 3 shows the number of suppliers on the x-axis and the percentage of firms on the y-axis. The average number of suppliers per firm is 15.17; however, many firms rely on a single supplier. Figure 3 also shows that the distribution of suppliers yields an asymmetric structure.[8]

The second fact suggests that most firms in the production network have a limited suppliers with a skewed distribution, resulting in minimal diversification in the value chain. As shown in Figure 3, more than 10 percent of firms have a single supplier, , while only a small fraction engage with numerous suppliers. This suggests a fixed cost for attaching a new supplier, which varies between firms. This fixed cost may lead some firms to limit themselves to a few suppliers and reduce their diversification across the production network.

These facts reveal three features of the production networks. First, productive firms have productive suppliers. Second, supply chains show a positive correlation between firms' productivity and their suppliers, implying a matching mechanism based on productivity. Third, only a small percentage of firms rely on multiple suppliers. These observations suggest the existence of a selection mechanism in supply chains.

3 Data

This study relies on firm-level datasets of Turkish firms provided by the Turkish Ministry of Industry and Technology. It combines information on VAT statements, balance sheets, imports, exports, and social security records at the firm level spanning from 2006 to 2020. The integration of these datasets relies on the firm identifiers, with industrial classification based on the NACE Rev.2 statistical classification of economic activities, and the territorial units are classified according to NUTS2.

3.0.1 Production Networks

Production networks build on links across firms. This paper utilizes value-added tax statements of each firm to construct the supply chain. When a transaction amount exceeds a tax cut-off, each firm must report its sales to the Ministry of Finance. The lower limit for these transactions is 5000 Turkish liras, corresponding to 260 U.S. dollars.

[8]This includes firms with fewer than 100 suppliers.

Production Network			
# of Transactions	# of Suppliers	# of Customers	# of Years
405.8 mil.	1.94 mil.	2.14 mil.	15

Table 1: Business-to-Business Transactions

Note: This table is based on fifteen years of observations, with 405.8 million transactions between 1.94 million suppliers and 2.14 million customers.

VAT statements contain information about the supplier, buyer, and transaction amount. Each firm in these tax reports corresponds to a node in the production network. This network is established through directed and weighted links where weights correspond to the transaction.

3.0.2 International Trade

Information on firms' imports and exports is based on their customs declarations, which includes details on the product's HS classification, transaction value, and the partner country. Using this information, I expand the domestic production network based on the firm's imports and exports. Table 2 provides the details on the trade dataset.

Imports			
# of Transactions	# of Firms	# of Products (HS6)	# of Years
123.5 mil	235,586	5,837	15
Exports			
# of Transactions	# of Firms	# of Products (HS6)	# of Years
146.4 mil	228,827	5,798	15

Table 2: Customs Declerations

*Notes:*This table is based on fifteen years of observations and includes transactions between importers and exporters, measured in terms of the number of products, with the number of transactions specified.

The final dataset is a panel that includes information on each firm's sector, location, supply chain, balance sheets, and social security records. This dataset covers fifteen years, from 2006 to 2020. All physical units are deflated using the producer price indices for each two-digit industry classification[9].

[9]Producer price indices collected from the Turkish Statistical Institute for each year-sector pair.

4 Supply Chain Disruptions

To identify a causal relationship, I exploit the disruption from Chinese suppliers during the early lockdown.[10] Specifically, I estimate the impact of losing a low-cost supplier on a firm using the disruption of Chinese suppliers. There are three identifying assumptions: First, supply chain disruption can be employed to determine the effects on importers as an exogenous event. Second, firms importing from China and other countries have no differential trends absent the Chinese lockdowns. Third, all importing firms are subject to identical demand shocks. Therefore, the lockdown in China can be employed as a natural experiment to test the implications of supply chain disruptions.

First, the lockdown in China was an exogenous event for all Turkish firms, and thus it can be employed to identify the effect of suppliers. It is also vital to mention that Turkey's manufacturing and other production plants resumed working at standard capacity during the pandemic. Because there were not any restrictions, this way, it is possible to identify the impact of supply chain disruptions on firms.

Second, the identification assumption requires importers from China and other countries to have parallel trends before the event. This ensures that any differences observed after the Chinese lockdown can be attributed to the disruption in supply chain and not to any pre-existing differences between the two groups. The trajectories before the pandemic demonstrate that the parallel trends assumption for the two groups holds, confirming that the causal estimates are unbiased.

Moreover, all firms are exposed to identical demand shocks. As both the control and treatment groups are subject to an expansionary monetary policy and high inflation, price estimates cannot be attributed to changes in demand. Consequently, this methodology isolates the supply shocks to demonstrate that price shifts are directly linked to the firms' suppliers.

Under these identifying assumptions, the following event study estimates the causal impact of the supply chain disruption:

$$y_{i,t,p} = \alpha + \sum_{(j=-4),(j\neq -1)}^{4} \beta_k Disruption_{i,t-j,p} + \mu_i + \lambda_{ht} + \epsilon_{i,t} \tag{1}$$

where $y_{i,t,p}$ is the dependent variable of the price of product p at the HS-6 level that firm i produces in month t. $Disruption_{i,t-j,p}$ is the indicator function that takes a value of one if the firm is an importer from China in 2019 or zero otherwise. This equation includes controls for the firm fixed effect μ_i and the industry-month fixed effect $\lambda_{h,t}$, and

[10]This disruption has serious implications for Turkish firms, as China is Turkey's largest import partner.

$\epsilon_{i,t}$ is the error term[11]. Given that the early Chinese lockdown was in February 2020, the timeline is rearranged, assigning $t = 0$ as the event and $t = -1$ as the baseline.

Employing this lead-lag model has several advantages for assesing the impact of supply-chain disruptions. First, it estimates the cumulative dynamic response to a supply chain disruption, with each point provides the cumulative effect. Second, leads can be used to test the parallel trends assumption by evaluating the output prices of products prior to the Chinese lockdown. It is essential to ensure insignificant coefficients prior to the event to compare similar groups. In this way, causality is associated only with the event. This specification tests the outcomes of the event while allowing for an examination of two groups absent from the event.

For each specification, the following section reports and discusses the outcomes based on the coefficients β_k, which differentiate between firms that import from China and those that do not. The coefficient β_k is plotted for each event study. In graphs, the points indicate the β_k, and dashed lines show 95% confidence intervals.

4.1 Supply Chain Disruptions and Prices

The global rise in prices is linked to disruptions in supply chains. In this section, I present the origins of price increases. When firms cannot reach their existing suppliers, they tend to charge different prices from those kept by their suppliers. Focusing on the output of the treated firms, the estimation shows that prices are sensitive to firm-to-firm links.

The prices are estimated at the firm product level.[12] The quantities are measured in kilograms using customs transaction data. Therefore the prices of each product are matched with producing firms for each month.[13]

Figure 4 shows the results of an event study that examines price changes between control and treated firms, showing how price changes are associated with the supply chains as firms are forced to drop their Chinese suppliers. There are several takeaways from Figure 4. The first point is that the price differences between treated and control groups were insignificant before the lockdown, suggesting that the two groups are comparable. However, the disruption to the networks of the treated firms caused a price difference between the groups, as shown in Figure 4.[14]

The second takeaway is how significant post-trend measures suggest that this isolated supply shock can cause a dramatic price rise. This shock caused a price increase of over ten

[11]Industry for, four-digit NACE Rev.2 classification.

[12]The product is defined for each HS-6 class.

[13]This match is necessary since products can vary in quality. It also controls for single- and multi-product firms.

[14]See Table 3 for the details.

percent, as firms could not reach their low-cost suppliers due to supply chain disruptions.

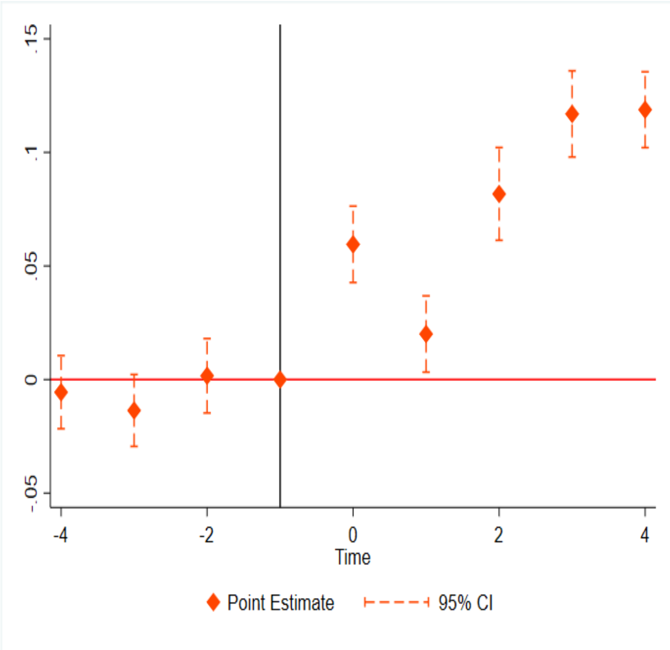


Figure 4: Prices after the Supply Chain Disruption

Notes: This figure plots the estimated coefficients of the event study (early lockdown in China) for each period. The coefficient is normalized to zero at the baseline time $t = -1$. All estimations include four-digit industry month and firm fixed effects.

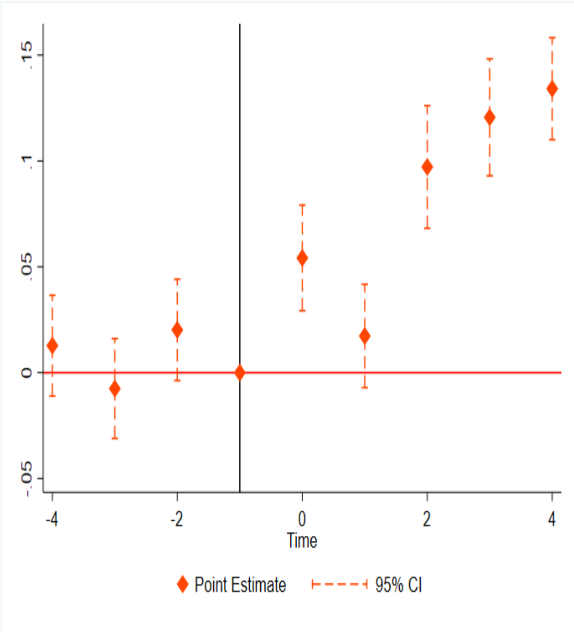
The primary conclusion drawn from this analysis is that disruptions in the production network, even at the micro-level, can reverse the benefits that firms gain through the supply chain. As firms are forced to drop their low-cost suppliers, such as suppliers from China, this disruption translates into higher costs through the production networks. Thus, firms demand higher prices. This mechanism reveals the supply chain's role in the aggregate economy and how supply shocks can generate a cascade of effects through firm-to-firm connections.

Additional robustness checks focus on the industry classification of firms and product classification of the imported input. Product type focuses on the type of trade according to the Broad Economic Categories. Based on HS classification, the exact event study is applied to importers of intermediate goods, capital goods, and final goods from China. The results suggest that the causal estimate is robust to the industry classification of firms and the type of imported goods.

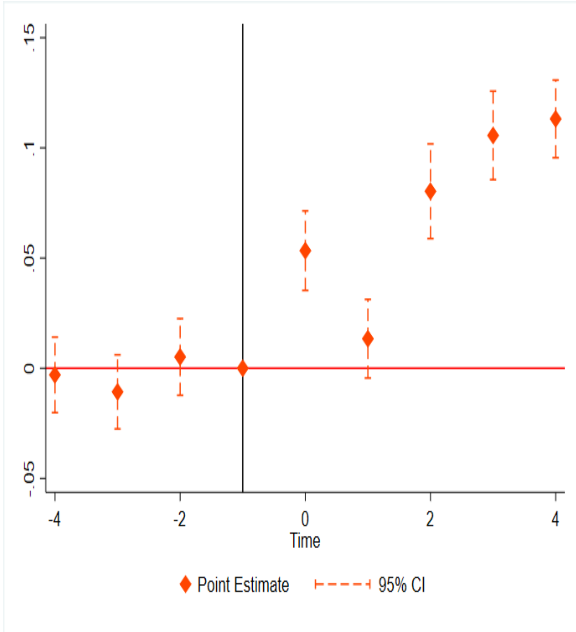
	Industry		BEC Classification		
	All	Manu.	Inter.	Capital	Final
Four months before the Disruption	-0.00554	0.0127	-0.00300	-0.00745	-0.0102
	(0.500)	(0.295)	(0.731)	(0.472)	(0.305)
Three months before the Disruption	-0.0136	-0.00750	-0.00107	-0.0117	-0.0103
	(0.092)	(0.533)	(0.212)	(0.250)	(0.291)
Two months before the Disruption	0.00167	0.0202	0.00514	0.00792	-0.000261
	(0.842)	(0.098)	(0.562)	(0.452)	(0.979)
Disruption	0.0595***	0.0542***	0.0534***	0.0615***	0.0418***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
One month after the Disruption	0.0200*	0.0173	0.0134	0.0169	0.00709
	(0.019)	(0.164)	(0.140)	(0.113)	(0.491)
Two months after the Disruption	0.0817***	0.0972***	0.0803***	0.0749***	0.0956***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Three months after the Disruption	0.117***	0.121***	0.106***	0.117***	0.133***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Four months after the Disruption	0.119***	0.134***	0.113***	0.110***	0.121***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	1131637	510291	1005993	730519	767366
R^2	0.005	0.004	0.005	0.005	0.004
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-month FE	Yes	Yes	Yes	Yes	Yes

Table 3: Event-Study of Prices

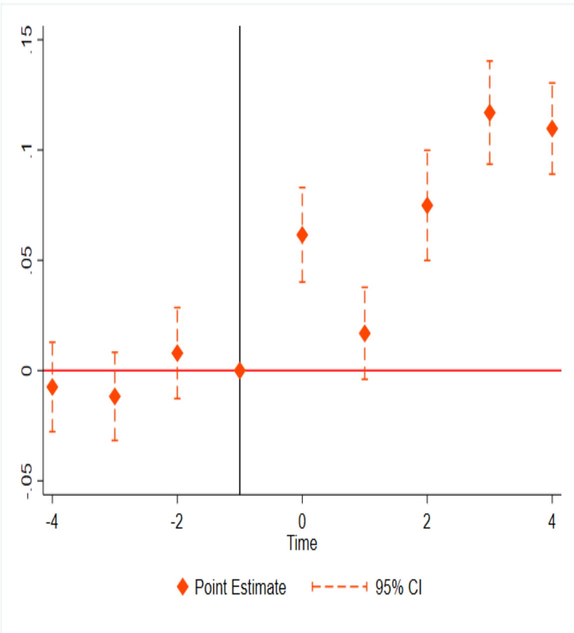
Notes: This table presents the estimated coefficients of the event study for each type of analysis, including controls for firm and industry-month fixed effects. The baseline period of the event study is one month before the event. The first column shows the coefficients for all firms, the second column reports coefficients only for manufacturing firms. The remaining columns report the coefficients of firms that import intermediate, capital, and final goods according to the Broad Economic Categories of the HS-6 products. The p-values are reported in parentheses.



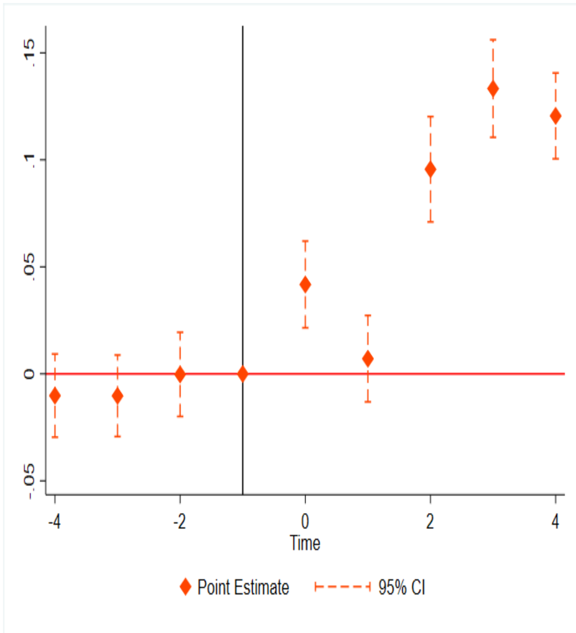
(a) Manufacturing Industry



(b) Intermediate Goods



(c) Capital Goods



(d) Final Goods

Figure 5: Prices after the Lockdown for Different Classifications

Notes: This figure plots the estimated coefficients of the event study for each period for only manufacturing firms, for firms that import intermediate goods, capital goods, and final goods according to the Broad Economic Classifications of the HS6 products. The event is the early lockdown in China. The coefficient is normalized to zero at time $t = -1$. All estimations include four-digit industry-month and firm-fixed effects.

4.2 Supply Chain Disruptions and Firm Efficiency

The findings presented in the previous section demonstrate a causal link between supply chain disruptions and prices. However, in order to understand the impact on production, a deeper analysis is needed. To investigate the production process, this part focuses on the supplier margin and the relationship between suppliers and firm productivity.

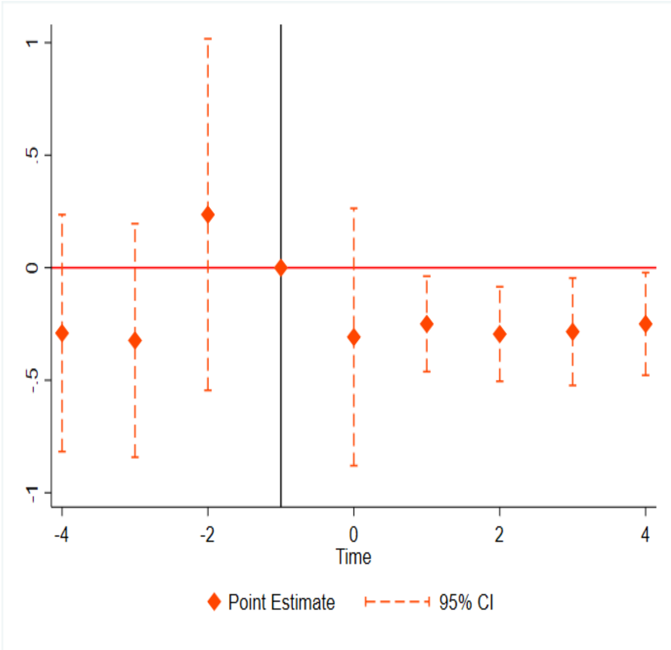


Figure 6: Productivity after the Lockdown

This figure plots the estimated coefficients of the event study for each period. The event is the early lockdown in China. The coefficient is normalized to zero at baseline time $t = -1$. All estimations include four-digit industry-month and firm fixed effects.

To examine how dropping a more productive or low-cost supplier is related to production efficiency, I employ the following regression specification by assessing the firm-level information:

$$y_{i,t} = \alpha + \sum_{(j=-4),(j\neq-1)}^{4} \beta_k Disruption_{i,t-j} + \mu_i + \lambda_{ht} + \epsilon_{i,t} \tag{2}$$

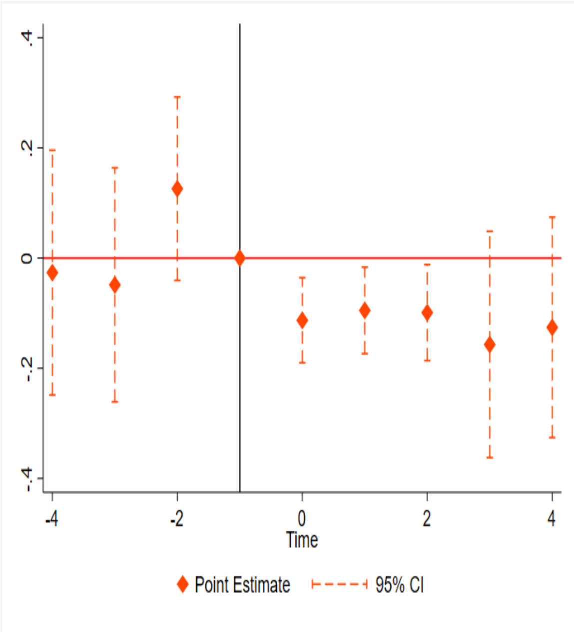
where $y_{i,t}$ is the dependent variable representing firm-level labor productivity.[15] The indicator function takes a value of one for firms that import from China, and zero for firms that do not import from China. The controls are the firm fixed effect μ_i, and the

[15] Labor productivity is defined as sales per labor.

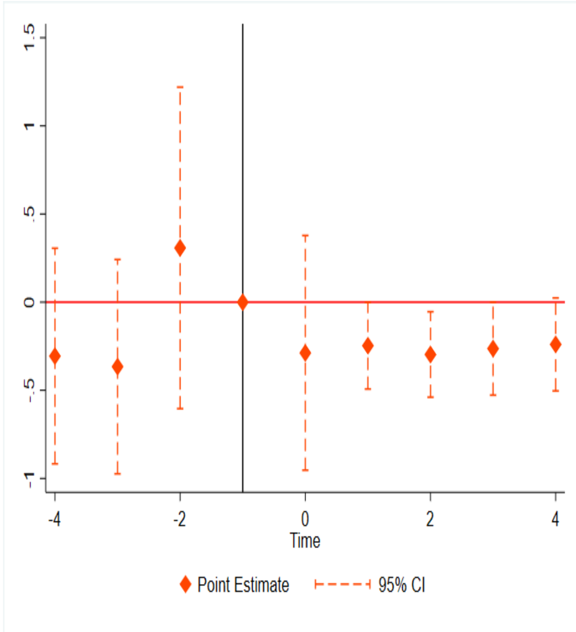
	Industry		BEC Classification		
	All	Manu.	Inter.	Capital	Final
Four months before the Disruption	-0.291	-0.0264	-0.306	-0.598	-0.598
	(0.279)	(0.816)	(0.327)	(0.229)	(0.309)
Three months before the Disruption	-0.323	-0.0486	-0.366	-0.590	-0.546
	(0.222)	(0.654)	(0.238)	(0.231)	(0.355)
Two months before the Disruption	0.236	0.126	0.308	-0.418	-0.302
	(0.553)	(0.138)	(0.509)	(0.399)	(0.609)
Disruption	-0.308	-0.113**	-0.288	-0.520	-0.705
	(0.291)	(0.004)	(0.397)	(0.335)	(0.234)
One month after Disruption	-0.250*	-0.0950*	-0.247*	-0.395*	-0.339
	(0.021)	(0.018)	(0.049)	(0.045)	(0.149)
Two months after Disruption	-0.295**	-0.0990*	-0.297*	-0.424*	-0.326
	(0.006)	(0.026)	(0.016)	(0.030)	(0.161)
Three months after Disruption	-0.284*	-0.157	-0.264*	-0.472*	-0.302
	(0.019)	(0.134)	(0.050)	(0.032)	(0.197)
Four months after Disruption	-0.250*	-0.126	-0.240	-0.443*	-0.317
	(0.032)	(0.218)	(0.075)	(0.037)	(0.175)
Obs.	1266463	550356	1077805	680756	557294
R^2	0.000	0.000	0.000	0.000	0.000
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-month FE	Yes	Yes	Yes	Yes	Yes

Table 4: Event-Study for Productivity

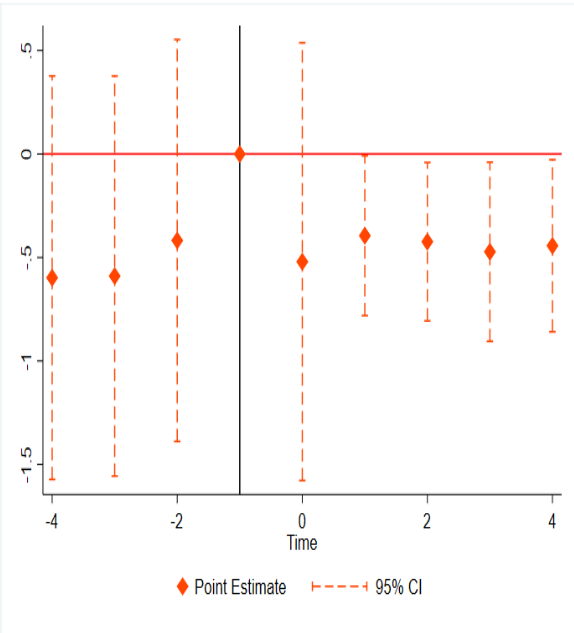
Notes: This table presents the estimated coefficients of the event study for each type of analysis, including controls for firm and industry-month fixed effects. The baseline period of the event study is one month before the event. The first column shows the coefficients for all firms, the second column reports coefficients only for manufacturing firms. The remaining columns report the coefficients of firms that import intermediate, capital, and final goods according to the Broad Economic Categories of the HS-6 products. The p-values are reported in parentheses.



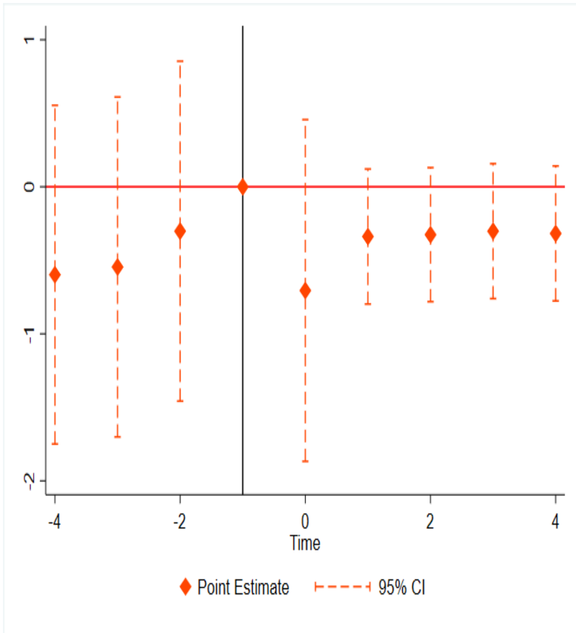
(a) Manufacturing Industry



(b) Intermediate Goods



(c) Capital Goods



(d) Final Goods

Figure 7: Productivity after the Lockdown for Different Categories

Notes: This figure plots the estimated coefficients of the event study for each period for manufacturing firms and for firms importing intermediate goods, capital goods, and final goods according to the Broad Economic Categories of the HS-6 products. The event is the early lockdown in China. The coefficient is normalized to zero at time $t = -1$. All estimations include four-digit industry-month and firm fixed effects.

industry-month fixed effect λ_{ht}, and $\epsilon_{i,t}$ is the error term. The timeline follows the same pattern as the analysis presented in the previous section, using the early lockdown as the event.

The event study shows the trajectory of labor productivity that depends on Chinese suppliers. The results reveal that when firms lose their low-cost intermediate inputs, their labor productivity drops by almost twenty-four percent. This analysis exploits the role of micro firm-level networks by demonstrating that the intermediate inputs from cost-effective suppliers are the main drivers of productivity gains in supply chains.

4.3 Network Origins of Firm Productivity

Understanding the network origins of firm productivity requires interpreting the roles of different types of goods in production. Disentangling the classification of goods according to the Broad Economic Categories also provides insights into the relationship between labor productivity and supplier margins. Table 4 shows how productivity evolves for three types of imported products. First, firms that import machinery from China experience almost a forty-four percent reduction in labor productivity. Second, low-cost intermediate inputs are another crucial input for Turkish firms. Third, there is no significant link between imports of final goods and labor productivity. This distinction between product types is not observed in prices, as anticipated, since price increases are not related to the product type.

All of these results demonstrate the network origins of firm dynamics. It is essential for Turkish firms to obtain low-cost capital and intermediate goods to maintain their efficiency. Once this channel is disrupted, significant losses in productivity occur. These results also reflect the consequences of recent Turkish industrial policies, which aim to promote exports by combining low-cost inputs and relying on Turkey's geographical advantage and customs union with the European Union. However, these policies take low-cost inputs for granted without considering supply chain disruptions, making them unsustainable.

5 Theoretical Framework

A mechanism is required to understand the role of supply chains in the aggregate economy. The preceding section quantifies the role of suppliers at the micro-level. By utilizing the Chinese lockdown as an experiment, the disruption of supplier links resulted in a significant increase in prices and a decline in productivity. Additionally, I highlight the importance of Chinese capital and intermediate goods in efficiency by breaking down the type of imports.

To rationalize these findings, I develop a model of endogenous supplier network formation, where input-output linkages respond to shocks at both intensive and extensive margins. This model of endogenous production networks serves three purposes. Firstly, it illustrates the selection process into supply chains and how firm-to-firm linkages are not established randomly. Secondly, it provides a framework to comprehend the effects of supply chain disruptions. Thirdly, the model enables the running of counterfactuals of supply chains to test the predicted outcomes.

This section provides the micro-foundations of value chains, while considering differences between suppliers, which is an essential layer of firm heterogeneity. Additionally, it explores the consequences of supply chain disruptions at the firm level. To this end, the proposed model builds on Antras et al. (2017) and extends their approach for supply chain disruptions and firm-to-firm settings.

The economy consists of the manufacturing and service sectors. To comprehend how value chains operate, the main focus of this study is on the manufacturing industry. Value chains in this economy rely on two types of firms: upstream and downstream. Upstream firms produce intermediate inputs, while downstream firms use these inputs to produce final goods. Downstream firms depend on the intermediate input bundles purchased from upstream firms to produce their final products.

In this economy, individuals work and consume. These workers supply labor inelastically to earn wages. Their income is divided into two parts, with a constant share of η spent on final goods of the manufacturing sector and the rest spent on services. The service sector is perfectly competitive and uses constant returns to scale technology in labor. Due to the size of the service sector, it restricts the assumption of a minimum wage in the manufacturing sector.

5.1 Preferences

The output of the manufacturing sector is substitutable with constant elasticity equal to σ, which represents the degree of substitutability among different manufacturing sector outputs. Consumers have Dixit-Stiglitz preferences over the output of manufacturing firms:

$$U_i = (\int_{w \in W} q_i(w)^{\frac{(\sigma-1)}{\sigma}} dw)^{\frac{\sigma}{(\sigma-1)}} \tag{3}$$

where w is the variety of goods, W is the set of available manufacturing goods for final consumption, and $\sigma > 1$ represents the elasticity of substitution. The demand for each variety of w

$$q_i(w) = E_i P_i^{\sigma-1} p_i(w)^{-\sigma} \tag{4}$$

where P_i is the standard ideal price index, p_i is the price of good w, and E_i is aggregate spending is in firm i. The market demand of firm i is calculated as

$$B_i = \frac{1}{\sigma}(\frac{\sigma}{\sigma-1})^{1-\sigma} E_i P_i^{\sigma-1} \tag{5}$$

5.2 Production

Firms in the manufacturing sector build up production networks, which consist of two types of firms: upstream and downstream. Upstream firms produce intermediate goods, whereas downstream firms produce final goods.

5.2.1 Upstream Firms

Upstream firms, indexed as j, produce intermediate inputs for downstream firms. These upstream firms are modeled as in Eaton and Kortum (2002), and the intermediate input market is perfectly competitive. For each intermediate input, there are many upstream firms, and the marginal cost of an upstream firm is defined as:

$$\frac{c_j}{z_j(m)} \tag{6}$$

where c_j is the input cost, and $z_j(m)$ is the productivity of upstream firm j. For efficency, these firms draw $z_j(m)$ from the Fréchet distribution as

$$F_j(z) = e^{-T_j z^{\theta}} \tag{7}$$

where T_j is the state of upstream technology. This location parameter differs between suppliers, while all suppliers have the same shape parameter θ.

5.2.2 Selection of Suppliers

Given the factor costs of countries, the main criteria that shape the downstream firms' decisions to source from any supplier are defined as

$$Pr_{ij} = \frac{T_j c_j^{-\theta}}{\Theta_i(\varphi)} \tag{8}$$

where $\Theta_i(\varphi)$ denotes all the available suppliers. This probability shows how downstream firms choose their upstream suppliers from all suppliers. The probability of forming a link to a new supplier is positively influenced by the supplier's productivity and negatively influenced by the supplier's input cost.[16]

5.2.3 Downstream Firms

Downstream firms transform intermediate goods into final goods for consumption in a monopolistically competitive market. Each downstream firm produces its own horizontally differentiated goods, and the number of firms is endogenous. These final good producers differ in terms of core efficiency (φ), as in Melitz (2003). Firms draw their productivity from a Pareto distribution with the same shape and location parameters. The number of downstream producers is determined by sunk entry costs and fixed production costs. Then, the randomness of firm efficiency determines which entrants are above the threshold.

Downstream firms buy bundles of intermediate inputs from upstream firms and convert them into final goods using their heterogeneous productivity. However, to purchase an intermediate input from upstream suppliers, downstream firms must pay a fixed cost of S_{ij}, which can vary between suppliers.[17]

The marginal cost of a downstream firm i with core productivity φ is

$$c_i(\varphi) = \frac{1}{\varphi}\left(\int_0^1 p_j(m,\varphi)^{1-\rho}dm\right)^{\frac{1}{(1-\rho)}} \tag{9}$$

In the equation, φ represents the core productivity of a downstream firm, $p_j(m,\varphi)$ denotes the price of the intermediate or capital goods purchased from upstream supplier j, and m is the input for the producer of the final good with core productivity φ. The price of the intermediate input is equal to the cost of the upstream firm, as these firms operate under the assumption of perfect competition among suppliers. By replacing the intermediate input cost for downstream suppliers i provides the following cost function:

$$c_i(\varphi) = \frac{1}{\varphi}\left(\int_0^1 \left(\frac{c_j}{z_j(m,\varphi)}^{1-\rho}\right) dm\right)^{\frac{1}{(1-\rho)}} \tag{10}$$

The problem faced by the downstream firm i is defined as follows. First, the

[16]Due to the law of large numbers, the probability of downstream firms sourcing from any upstream supplier is the ex-post share of inputs they source from the supplier.

[17]Intermediate inputs are imperfectly substitutable with each other, and the bundle contains a continuum of firm-specific inputs with a symmetric elasticity of substitution ρ.

downstream firm draws potential suppliers. Then, it decides on its upstream suppliers, and finally, the downstream firm makes a production decision. This production decision depends on the marginal cost and the supply chain. According to the model, a unique equilibrium exists, and the market finds the optimal supply chain.[18]

The selection into supply chains originates from the downstream firm's trade-off. Better suppliers quote lower prices for intermediate inputs but are also associated with higher sourcing costs. These differences generate the self-selection of efficient downstream firms into better and low-cost suppliers. Since more productive firms already have a cost advantage, they tend to link with lower-cost suppliers. As firms buy from low-cost suppliers, the density of suppliers shifts from the lower to the upper tail. Hence, the technology varies for each upstream-downstream match. As supplier match-specific productivity rises, downstream firms encounter better draws.[19]

5.2.4 Downstream Price

The price of a final good is determined by the cost of the intermediate or capital m produced by upstream firm j, which is the realization of a random draw $p_j(m)$ with a cumulative distribution function:

$$G_j(m) = Pr\left[p_j(m) \leq p\right] = Pr\left[\frac{c_j}{z_j(m)} \leq p\right] \tag{11}$$

$$G_j(m) = Pr\left[p_j(m) \geq \frac{c_j}{p}\right] = 1 - Pr\left[z_j(m) \geq \frac{c_j}{p}\right] \tag{12}$$

Since $F_j(z) = e^{-T_j z^{\theta}}$, the probability of the price of good m is lower than p:

$$G_j(m) = 1 - e^{-T_i (c_i)^{-\theta} p^{\theta}} \tag{13}$$

Since the distribution of the z_j is known and $p_j(m)$ is available, the price paid by upstream firm i is the realization of the random variable $P_j = min(P_{ij}, j = 1, .., N)$, where $G_j(m)$ is the cumulative distribution function. Then, the price of downstream firm

[18]It is necessary to note that these draws are independent across firms and inputs.

[19]A downstream firm's optimal supply chain strategy depends on T_j and θ. T_j represents the state of technology for an upstream firm j, while θ is the variance of shocks. Thus, firms tend to network with productive suppliers to gain higher match-specific productivity. They also aim to have higher θ with a lower variance of input productivity and higher gains. These two parameters reveal the underlying mechanism of the selection into better value chains. Downstream firms aim to link to more productive suppliers to increase their T_j, thus lowering the cost of production. They diversify by increasing their supplier base and lowering the cost of production, since higher θ reduces the dispersion of pair productivity. As a result, firms can reduce their marginal costs by networking with more productive upstream producers. Each downstream firm wants to source from each low-cost upstream firm, but the gains from the supply chain should exceed the fixed costs of sourcing to achieve profitable links.

i is

$$p_i = \frac{1}{\varphi}\left(\gamma \sum_{j=1}^{N} T_j c_j^{-\theta}\right)^{-\frac{1}{\theta}} \tag{14}$$

where γ is $\left[\Gamma(\frac{\theta+1-\rho}{\theta})\right]^{\frac{\theta}{(1-\rho)}}$.The output price of a downstream firm p_i depends on its core productivity φ, supplier productivity T_j, supplier input costs c_j, and variance of shocks θ. Importantly, it is a decreasing function of more productive or cheaper suppliers, meaning that downstream firms with better suppliers have lower marginal costs.[20]

The intuition behind this is that adding a new productive/low-cost supplier necessarily decreases the marginal cost faced by a firm because forming a new link provides a new draw from the Fréchet distribution. There is a probability that this new supplier can offer better intermediate inputs, or the cost of these intermediate goods may decrease due to increasing competition.

5.3 Endogenous Choice of Links

The problem of the downstream firm is a function of marginal costs that depend on supplier decisions. For downstream firm i, it has the following form:

$$max_{I_{ij}\in\{0,1\}_{j=1}^{N}} \pi_i(\varphi, I_{i1}, .., I_{ij}) = \varphi^{\sigma-1}(\gamma \sum_{j=1}^{N} I_{ij} T_j (c_j)^{-\theta})^{\frac{\sigma-1}{\theta}} B_i - \sum_{j=1}^{N} I_{ij} S_{ij} \tag{15}$$

where I_{ij} is an indicator function that equals one if firm j is part of the supplier network for firm i. B_i represents the residual demand, T_j denotes the supplier's technology, S_{ij} refers to the supplier's fixed cost, and c_j is the input cost of the supplier. The maximization problem suggests that by linking to a new supplier or upgrading to a supplier with lower input costs or higher technology, the marginal cost will decrease. However, an additional linkage or technological upgrade of the supplier comes with a fixed cost S_{ij}.

The solution to this problem is not straightforward, as this function highlights the interdependencies of the supply chain strategy. Additionally, the function is nonlinear and not additively separable, which means that each supplier decision is connected to another. Furthermore, it highlights the endogeneity of the production network and how firms can gain a higher cost advantage by enhancing the technology of their upstream suppliers. Therefore, the endogeneity of the network is due to interdependent supplier choices.

[20]The derivation of the cost function follows Eaton and Kortum (2002) on the derivation of the aggregate price index. The assumption follows Antras et al. (2017) $\theta > \rho - 1$.

This function also displays supermodularity in the core productivity φ of firm i and its supply chain characteristics $\sum_{j=1}^{N} I_{ij} T_j c_j^{-\theta}$. Consequently, more productive firms can gain a cost advantage by expanding their supplier networks. The implications of the model are consistent with the empirical findings since the prices and supplier characteristics are directly linked. By attaching a low-cost supplier, a firm can attain a cost advantage[21]. These properties translate into the following proposition:

Proposition 1. The solution to the choice of the supply chain is non-decreasing in the productivity of the firm φ for each value of I_{ij}.

This proposition suggests that profits increase as the number of suppliers I_{ij} and the productivity of those suppliers T_j increase, while gains decrease with input costs c_j. By reducing supplier costs while keeping demand constant, better suppliers can be obtained. As a result, more productive firms can expand their supply chains to benefit from cheaper intermediate inputs, generating a cost advantage through the sophistication of their supply chains. Therefore, the heterogeneity in production networks determines firm productivity, as firms become more efficient through their advantage in intermediate inputs, For the industry equilibrium, there is a free entry condition and this industry equilibrium is characterized by a fixed point for the market potential.

Hence, building a network depends on the maximization of the nonlinear profit function, which features interdependent possibilities of suppliers. This interdependency of supplier choices endogenizes the network.

5.4 Disruptions in the Network

The proposed model suggests that disruptions in the network can be modeled as an increase in fixed costs. Such shocks can have significant implications for Chinese suppliers, who have a higher likelihood of offering low-cost and efficient intermediate inputs due to lower factor costs. As a result, Turkish firms with higher levels of productivity tend to have a greater share of Chinese suppliers in their value chains. Consequently, these firms are more vulnerable to shocks that originate from disruptions in Chinese inputs.

When disruptions occur, the share of efficient firms that source from China will decrease, as sourcing becomes more challenging. At the same time, less efficient firms may not be able to afford to source from China. Consequently, with the shift in supplier networks, efficient and less efficient firms will share similar production networks. This

[21]The maximization problem leads to one of two cases as complements if ($\frac{(\sigma-1)}{\theta} > 1$) or substitutes if ($\frac{(\sigma-1)}{\theta} < 1$). The empirical results highlight the complementarity of suppliers even at the firm level. In this scenario, the profit function displays increasing differences across the production network, and these entry decisions are complements.

similarity of production networks reduces competition in the Turkish market. As a result, supply chain disruptions reduce labor productivity and raise prices for two reasons: First reason is related to the competition, where the weaker selection in the market is associated with less efficient firms. The second reason is the increase in the costs of intermediate inputs.

6 Structural Estimation

The empirical results highlight the impact of supply chain disruptions. However, due to the endogenous formation of networks, it is econometrically impossible to test the further implications of a supply chain disruption. In this section, I aim to provide a complete picture of the relationship between firms and the value chain by replicating the supply chain disruptions. This part builds a counterfactual supply chain with less accessible Chinese suppliers, which is achieved through higher counterfactual fixed costs to mimic the shock in the value chain.

This section aims to estimate the key parameters by applying the model to the data. To calibrate the model, I rely on micro-level data on the production network and the simulated method of moments, which involves four consecutive steps. The first step starts by calculating the advantage of suppliers in different countries based on imports and domestic intermediate input information to demonstrate how the supplier advantage varies across countries. In the second step, I investigate how firms link with more productive suppliers to calculate the productivity dispersion parameter θ. Due to data limitations, estimations rely upon information from the domestic sample. Therefore, the goal is to analyze the domestic production network to understand how firms shift their purchases toward more productive suppliers. The third step involves estimating the demand elasticity by relying on firm-level markups. Finally, the fourth step computes the fixed costs of suppliers in each exporting country using the simulated method of moments.

The final step requires estimating the fixed cost for each firm-supplier-country link. However, it is not computationally feasible to estimate these costs for all possible suppliers, as each firm decides on a combination of $2^{suppliers}$. To overcome this challenge, I use the algorithm proposed by Jia (2008), as studied in Antras et al. (2017).[22] This study includes countries from which more than 1300 firms actively imported in 2019. This sample consists of thirty-two countries, resulting in 2^{32} possible

[22]Note that the firm's problem involves making interdependent supply chain decisions. Arkolakis and Eckert (2017) has proposed an algorithm that addresses combinatorial discrete choice problems.

choices for each firm.[23]

Parameter	Variable	Source
ε	Sourcing Potential	Microdata
θ	Productivity Dispersion	Microdata
σ	Demand Elasticity	Microdata
φ	Core Productivity	Melitz and Redding (2015)
S_{ij}	Supplier-Country Fixed Cost	SMM

Table 5: Calibration

Notes: This table represents the list of parameters and their sources, microdata refers to the firm-level data between the years 2006 to 2019.

6.1 Sourcing Decisions

The first step involves estimating the supplier advantage of suppliers in different countries by relying on micro-level data. This calculation aims to assess the degree to which importing from a supplier in a specific country is more attractive to Turkish firms than domestic suppliers. Each supplier country advantage is defined as

$$\varepsilon_j = \frac{T_j}{c_j^{\theta}} \tag{16}$$

where T_j represents the supplier's technology, and c_j is the factor cost. Firm-level data enables this calibration to calculate firms' domestic and imported intermediate input purchases. Normalizing a firm's intermediate input purchases provides the supplier advantage of each exporting country as:

$$\frac{X_{ij}}{X_{ii}} = \frac{T_j c_i^{\theta}}{T_i c_j^{\theta}} \tag{17}$$

where X_{ij} represents a firm's imports from country j, and X_{ii} represents the firm's total purchases from the domestic market based on VAT data. By log-linearizing equation 17, the following equation is obtained:

$$logX_{ij} - logX_{ii} = log\varepsilon_j + log\epsilon_j^n \tag{18}$$

where ε_j is the supplier advantage, ϵ_j^n is the firm-country specific shock.

Based on the information on each importing firm, equation 18 is calculated by using OLS to estimate each country's supplier advantage. The advantage is estimated as follows:

[23]The countries included in the analysis are listed in Table 10 in the Appendix.

the dependent variable is the difference between the intermediate input purchase of firm i from country j and the firm's total intermediate purchases from the domestic market. The explanatory variable is the country's advantage, corresponding to the fixed effect.

The supplier advantage of each country is presented in Figure 8. The y-axis displays the supplier advantage, and the x-axis shows the number of firms that import from these countries. Countries with a higher supplier advantage are associated with more importing firms. Based on this relationship, the proxy for supplier advantage does an excellent job of capturing how importing from a certain country is more advantageous than importing from other countries or purchasing from domestic suppliers. China is the most favorable country for most firms. Countries like China, Iran, Germany, and South Korea exhibit a positive supplier advantage for Turkish firms, and as a result, these firms tend to import from these countries instead of relying on Turkish suppliers. In contrast, countries such as Denmark, Canada, and Portugal have a negative supplier advantage compared to domestic inputs.

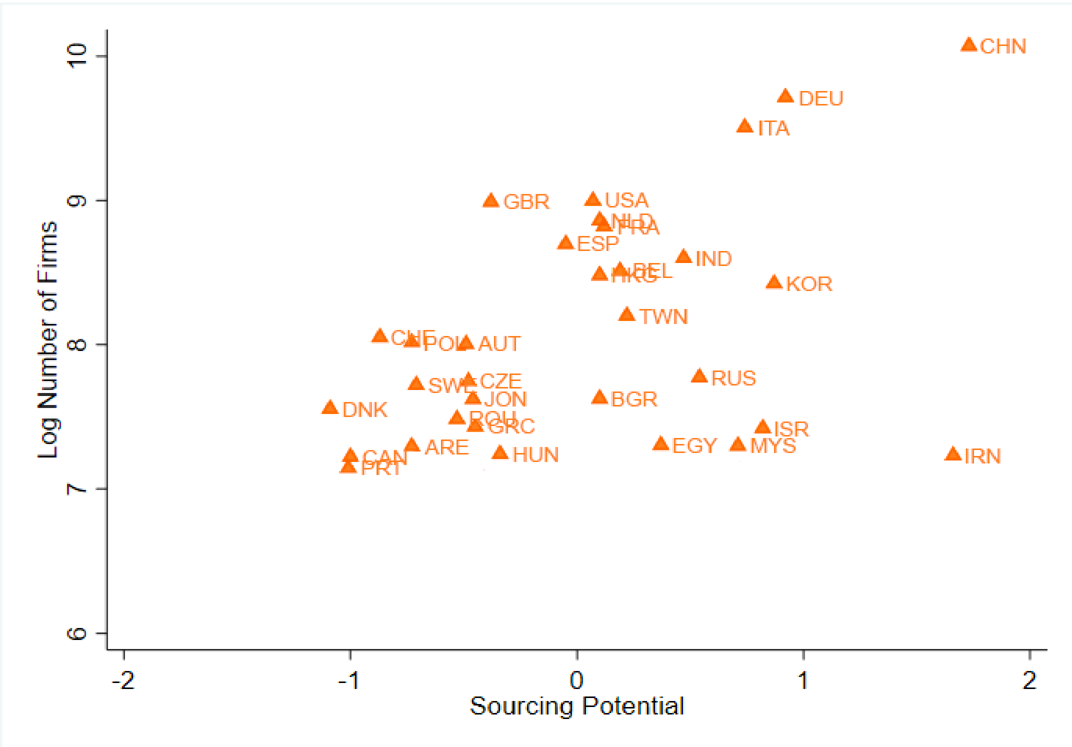


Figure 8: Supplier Advantage

Notes: The figure represents the supplier advantages estimated for various countries, concerning Turkish firms. The x-axis displays the estimated supplier advantages, while the y-axis shows the logarithm of the number of firms.

Most countries, except Iran, tend to have more Turkish partners if they have a higher supplier advantage. In general, the number of importing firms correlates with the supplier advantage, except for Iran. Even though it has the second highest potential, because of the embargo imposed by the United States and the European Union, firms avoid trading to avoid economic sanctions. Thus, the differences and fit shown in Figure 8 suggest that there must be firm-supplier country fixed costs associated with suppliers.

6.2 Productivity Dispersion

The second step aims to estimate the productivity dispersion parameter, denoted as θ, which corresponds to the firm-level trade elasticity. This elasticity reflects the supplier productivity. However, the data does not provide information on import partners' productivity. Instead, information on Turkish suppliers' productivity is available by tracking business-to-business transactions. Therefore, this section examines the relationship between the sourcing potential and supplier productivity at the domestic level. Firstly, the sourcing advantage of each domestic supplier is calculated. Secondly, the objective is to establish a connection between the sourcing advantage of domestic suppliers and their productivity.

The productivity dispersion parameter determines the extent to which firms connect with productive suppliers. Hence, the aim is to predict the dispersion parameter by focusing on suppliers' total factor productivity and other controls affecting the supply chain. Then, the intuition behind this is the estimation of the purchases from effective suppliers by controlling for other proxies, including the supplier and customer fixed effects.

The following analysis relies on domestic suppliers' sourcing potential ε_j. This measure is a function of a supplier's technology, supplier cost, and intermediate input trade. The following estimation projects the sourcing advantage onto proxies for ε_j:

$$log\varepsilon_j = \beta_1 Productivity_j + \beta_2 logdistance_{ij} + \beta_3 logintermediate_{ij} + \lambda_s + \gamma_c \tag{19}$$

where ε_j denotes the sourcing potential, $Productivity_j$ denotes suppliers' total factor productivity, $logdistance_{ij}$ represents the distance (in kilometers) between the buyer's and supplier's cities, $logintermediate_{ij}$ represents the volume of the transaction, λ_s is the supplier dummy, and γ_c is the buyer dummy. The primary interest is in the coefficient of productivity, which indicates how firms' supplier shares are inclined towards more productive suppliers, with other variables serving as controls.

There are several key points to take away from the regression results presented in Table 6.2. First, the productivity dispersion parameter θ is significant at 1.971, indicating that firms tend to prefer suppliers that are more productive. Second, even at the domestic level, distance is a notable factor in sourcing decisions, with a coefficient of -0.288 indicating a negative association with a supplier's advantage. Another important finding is that the supplier advantage increases as trade volume increases across firms,

	Sourcing	Sourcing	Sourcing
Productivity	1.978***	1.971***	1.971***
	(0.000)	(0.000)	(0.000)
Distance	-0.254***	-0.257***	-0.288***
	(0.000)	(0.000)	(0.000)
Intermediate Input	0.003***	0.003***	0.004***
	(0.000)	(0.000)	(0.000)
Obs.	7401908	7401908	7401908
R^2	0.002	0.004	0.010
Supplier FE	Yes	No	Yes
Customer FE	No	Yes	Yes

Table 6: Productivity Dispersion and Sourcing*Notes:* The table displays the coefficients obtained using all buyer-supplier connections at the firm level. The p-values are indicated in parentheses.

although the effect size is small compared to the impact of supplier technology and distance. Taken together, these results suggest that productivity is a critical factor influencing firms' supplier choices.

6.3 Demand Elasticity

The third step estimates the demand elasticity in the model, given monopolistic competition and CES preferences. The demand elasticity can be proxied by the average markup, calculated as the ratio of a firm's gross sales to its total expenditures, including wages, intermediate input purchases, and other reported expenses. Based on the micro-level data, the average markup for Turkish firms is 38% which implies an estimated demand elasticity of 3.93.

The calculation of the demand elasticity and productivity dispersion raises the question of whether intermediate input suppliers are complements or substitutes. This can be determined based on the value of $\frac{\sigma-1}{\theta}$. If the value is greater than one, then suppliers are complements; otherwise, they are substitutes. Using the estimated values of θ of 1.971 and σ of 3.63, the $\frac{\sigma-1}{\theta}$ is 1.34. This suggests that the intermediate inputs used by downstream firms are complements. Moreover, this result indicates increasing differences in downstream firms' maximization problem.

The finding that intermediate input suppliers are complements is consistent with empirical findings, as supply chain disruptions can lead to price increases and productivity reductions when suppliers are lost. This complementarity provides further evidence of supply chain heterogeneity at the firm level.

6.4 Firm-Supplier Country Fixed Costs

The preceding subsection focuses on estimating the model's parameters based on information at the firm level. However, the crucial part of the model is the supplier fixed costs, which vary for each downstream firm and supplier match. To estimate the supplier fixed costs, a simulation-based technique is required. This subsection presents the estimation of firm-supplier fixed costs for each firm using the simulated method of moments.

The estimation begins by simulating firms and comparing their behavior with firm-level data. The focus is on determining firms' supplier choices and how they construct their value chains based on the model predictions. Therefore, the computation of supplier costs starts with supply chain formation, while the last step compares the aggregate moments from the model with the data.

The simulation consists of six consecutive steps. The first step simulates numerous firms that differ in terms of core efficiency. The second step translates the maximization problem based on the firms' supplier choices. The third step computes the supplier set for Turkish firms, consisting of interdependent options among thirty-two countries, including China. The fourth step backs up parameters from the simulation. The fifth step checks the model fit of the simulated data to the actual dataset. The sixth step builds an alternative counterfactual value chain that aims to mirror a disruption in imports from China. The last part compares the implications of this counterfactual supply chain to the actual disruptions documented in the empirical analysis, which presents the impact of a negative shock.

The supplier costs are estimated using the simulated method of moments. First, for downstream firm productivity, ϕ is assumed to vary between firms and to follow the Pareto distribution. Following Melitz and Redding (2015), the productivity of producers of final goods is distributed Pareto, with a shape parameter κ of 4.25. Second, the supplier fixed costs depend on gravity variables, including distance, language, and corruption in the supplier's country. A fixed cost is drawn from a lognormal distribution with a dispersion parameter and scaled as $log\beta_c^f + \beta_d^f logdistance_{ij} + \beta_l^f loglanguage_{ij} + \beta_c^f logcorruption_{ij}$. It is important to note that each firm's core productivity is drawn from the Pareto distribution and other controls from fixed shocks drawn from a standard normal distribution. The algorithm aims to estimate the residual demand B, the coefficient of corruption, distance, language, and the dispersion parameter.

Another critical feature of the simulation is that for each firm, these core productivity draws interact with the fixed cost draws to capture the $z_j(m, \varphi)$, which is the downstream and upstream-matched productivity in the model. However, interdependent preferences among countries require further adjustments to determine how firms decide to form their networks. Firms must choose suppliers and assemble optimal production networks among $2^{suppliers}$. Since information on firm-to-firm links is unavailable for imports, this analysis focuses on firm-to-country links. Hence, the solution requires decisions among 2^{32} countries. However, this estimation is computationally infeasible. Each decision on a supplier depends on other supplier choices, as shown in the previous section. To overcome this problem, the algorithm developed by Jia (2008) is adopted following Antras et al. (2017).

Evaluating supplier choices is required for simulated firms to form the optimal production networks. Since sourcing decisions are interdependent, this analysis creates lower and upper bounds for each firm's decision following Jia (2008). The lower bound begins the iteration with zero suppliers and then attaches a new supplier to the firm if the supplier contributes to the firm's profit. The upper bound starts by including all possible suppliers in the firm's production network, eliminates suppliers, and drops them one by one if the dataset results in a higher profit. The optimal choice of suppliers is determined by the subset between the lower and upper bound.

6.5 Model Fit

To assess the model's predictions, it is necessary to compare the behaviors of the simulated firms with data. Then, the goal is to examine how the simulated firms' import decisions regarding the share of importers among various countries are related to the actual percentage of importers. This part investigates the model's predictions for the moments' targeted fit.[24] Figure 9 presents the first moment, the share of importers by country. According to the fit, the model does an excellent job of replicating the firm dynamics on supplier choices. With this in hand, the following section presents a counterfactual analysis performed to capture the impact of supply chain resilience to understand how firms' sourcing decisions and prices change with an adverse shock to supply chains.

[24] In this analysis, Iran is not included in the sample. As shown in Figure 8, Iran is an outlier due to international sanctions.

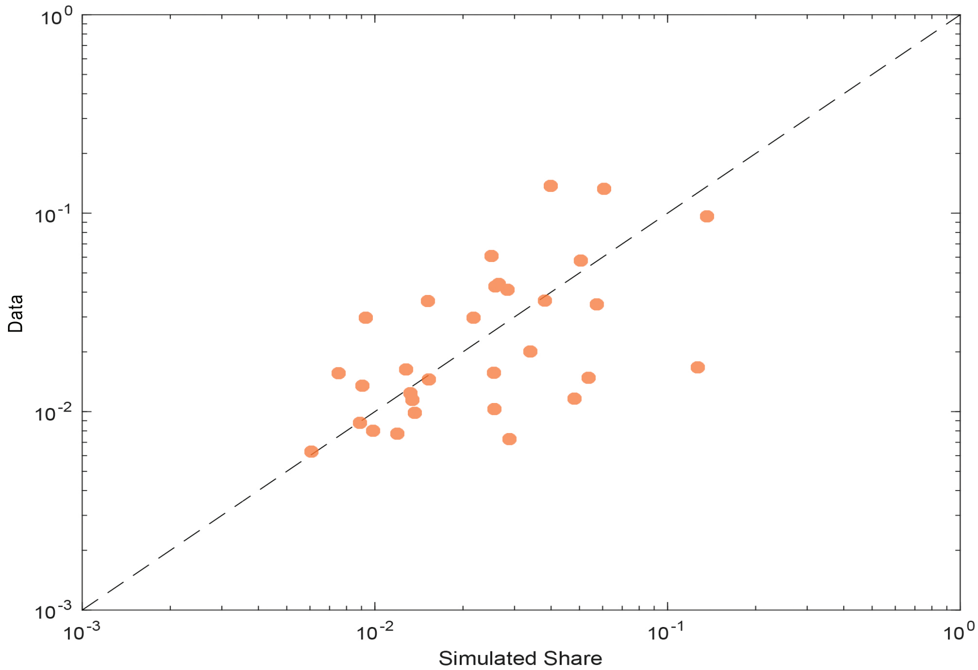


Figure 9: Model Fit

Notes: This figure shows countries' importer shares based on the number of firms. The shares of firms from micro-data are plotted on the y-axis, whereas the simulated percentages are plotted on the x-axis.

7 Counterfactual Scenarios

7.1 Counterfactual Supply Chain

The model focuses on the assumption that each supplier is associated with a fixed cost that varies across countries. In this part, I build counterfactual supply chains where I exogenously impose the same fixed cost to each supplier and compare the results to the baseline prices, share of importers, and percentage of sources to understand how these variables react to changes in their production network. The network modifications impose the fixed costs of China, Greece, Turkey, Taiwan, and the United States on every supplier. Then, it recalculates the number of importers and the share of importers in the counterfactual scenario. The aggregate price index is calculated using the model and equation 5. Resolving the new equilibrium price index leads to different values than the baseline, while firms shift their share based on the type of shock.

The impact of the counterfactual supply chain is presented in Table 7. This table reports the changes associated with various counterfactual scenarios compared to the baseline. Following the changes, not only does the number of importer firms change, but there is also a rearrangement in sourcing decisions across different suppliers. As

	China	Greece	Taiwan	Turkey	US
Price	↑	↓	↑	↓	↑
% of Importers	↓	↑	↓	↑	↓
% of Importers from China	↓	↑	↓	↑	↓
% of Importers from Greece	↓	↓	↓	↑	↓
% of Importers from Taiwan	↑	↑	↑	↑	↑
% of Importers from US	↑	↑	↑	↑	↑

Table 7: Counterfactual Supply Chain *Notes: The table reports price and import shares in the counterfactual scenarios compared to the baseline.*

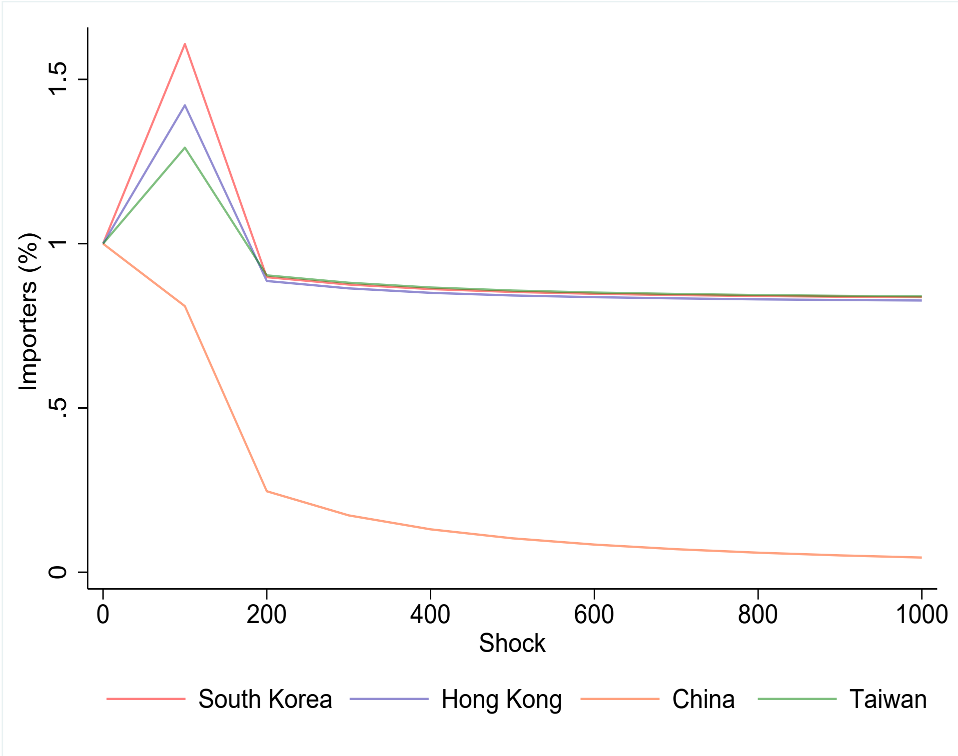
all suppliers exogenously have the same fixed costs as China, prices in Turkey rise, and there is a decrease in the number of importer firms. The share of importers from China decreases as anticipated. Interestingly, firms shift from China to Taiwan and the United States.

Another interesting finding is that the exogenously imposed fixed costs lead to a reconfiguration of the supply chain and affect prices at both the intensive and extensive margins. This demonstrates that production networks and prices of firms are sensitive to supply chain disruptions, but their response depends on the level of the fixed cost.

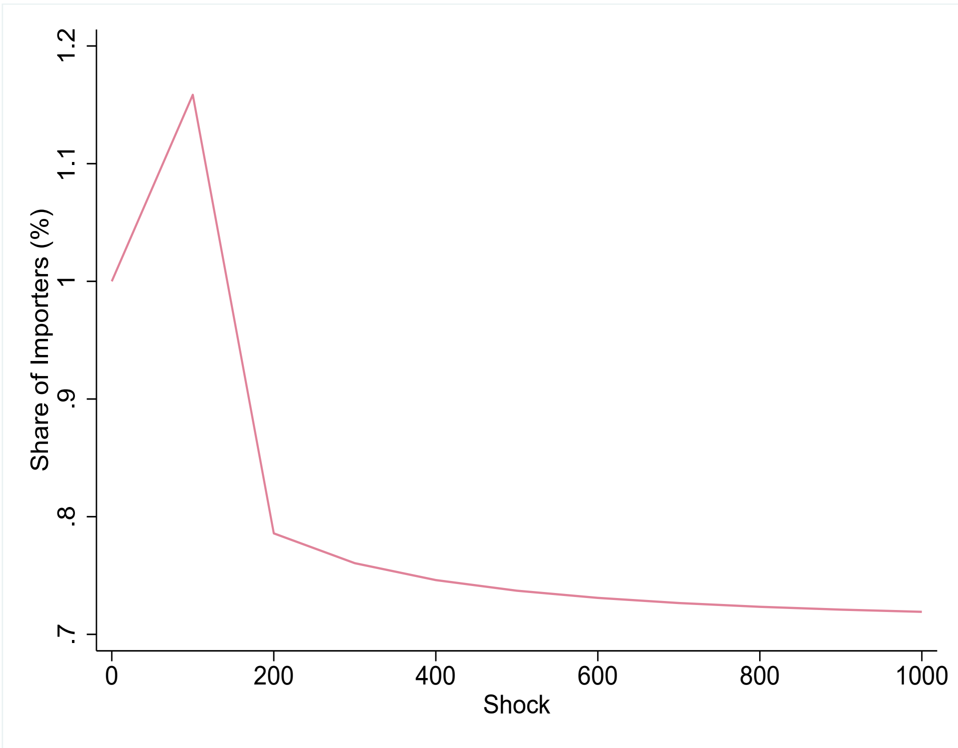
When fixed costs for all suppliers are set to the same level as domestic suppliers, as is the case with Turkey in the counterfactual analysis, more firms begin to import and they increase their sourcing from all countries. As a result, in a counterfactual supply chain with no tariffs, aggregate prices would decline due to increased competition in the domestic market. These findings highlight the importance of considering the heterogeneity of fixed costs and their impact on supply chain resilience and market outcomes.

7.2 Simulated Disruptions

The empirical analysis presented in the first section highlights the importance of firms' supplier choices, focusing on Chinese suppliers. Adverse shocks to production networks can lead to supply chain disruptions that affect firm dynamics. In this analysis, I replicate these disruptions by simulating a negative shock to production networks based on counterfactuals, specifically an exogenous increase in sourcing costs from China while



(a) Share of Importers from China, Hong Kong, South Korea and Taiwan



(b) Share of Importer Firms

Notes: This figure displays the estimated coefficients for both the share of importers from China, Hong Kong, South Korea, and Taiwan and the share of importer firms. The coefficients represent the percentage shares compared to the baseline for each counterfactual scenario. There are ten counterfactual scenarios, starting from a 100 % exogenous increase in fixed costs from Chinese suppliers, increasing by increments of 100 percentage points up to 1000%.

keeping other variables constant. The aim is to investigate the consequences of such an adverse supply chain shock on firm-to-firm linkages and compare the baseline and counterfactual supply chains.

The algorithm estimates the new supply chain by relying on the sourcing decisions of firms that are exposed to an increase in fixed costs for sourcing from China. Therefore, this quantitative analysis tests several counterfactual scenarios that reflect the exogenous fixed cost increases for different percentages, aiming to replicate the variation in disruptions. As the magnitude of the shock increases, firms tend to shift from Chinese suppliers to other countries including Hong Kong, South Korea, and Taiwan. When the fixed costs of Chinese suppliers double, the share of importer firms increases, reflecting the role of China on both direct and indirect Turkish importers. Then, with critical rises in fixed costs, the supply chain becomes more dominated by other countries. However, the share of importers is always different from the baseline scenario.

8 Conclusion

This study contributes to the literature by exhibiting the role of supply chains on prices and productivity. It revisits the gains from trade to underline the role of production networks on firm performance. Through the use of empirical, theoretical, and quantitative evidence, this paper reveals the significant influence of supply chains on firm dynamics.

This study provides empirical evidence that identifies productive clusters in production networks and highlights the tendency of productive firms to have efficient suppliers. To obtain a causal estimate, the study proposes a novel identification strategy that explores the impact of disruptions caused by Chinese suppliers during the lockdown. By isolating this supply shock while keeping the demand constant for all firms, the study provides causal estimates that measure the impact of the shock. The findings indicate that firms facing supply chain disruptions tend to charge higher prices and have lower productivity. The micro-level findings in this study have important policy implications, as supply shocks can cascade through the aggregate economy in granular production networks.[25] Additionally, the analysis at the product level reveals that labor productivity is primarily driven by capital imports from China, while the impact of low-cost final goods on labor productivity is insignificant.

Guided by these findings, this study develops an endogenous production network model, where firms are heterogeneous in their ability to construct production networks. As they expand their networks, they become more productive due to the specific

[25]The appendix provides details on the granularity of the Turkish production network.

productivity gains from using higher-technology and low-cost suppliers. While expanding their networks provides firms with a cost advantage, they also face supplier-specific fixed costs. Firms make decisions on their suppliers among interdependent choices of inputs, demonstrating the endogenous nature of production networks.

One way to interpret the supply chain disruptions is that they increase the fixed costs of suppliers, leading to higher prices and reduced labor productivity for two main reasons. First, there is a rise in the prices of intermediate inputs. Second, weaker selections result from less competitive supplier networks.

The quantitative analysis involves calibrating the model using firm-to-firm networks and the simulated method of moments to investigate the implications of adverse supply chain shocks. To explore the destruction of these links, the study creates a counterfactual supply chain that replicates the impact of fixed costs among different suppliers. The results show that prices react differently to these changes, depending on the origin of the supplier. As the magnitude of shocks increases, firms start replacing Chinese suppliers with suppliers from different countries.

The results of this study provide a new research agenda for evaluating the role of endogenous production networks in firm dynamics. In future research, the proposed framework can be used to understand the role of supply chains in the productivity puzzle, the diffusion of inflation through supply chains, the fragility of global value chains, and to gain insights into the deglobalization trend.

References

Acemoglu, Daron, Ufuk Akcigit, and William Kerr (2016), "Networks and the macroeconomy: An empirical exploration," *Nber macroeconomics annual*, 30, 273–335.

Acemoglu, Daron and Pablo D Azar (2020), "Endogenous production networks," *Econometrica*, 88, 33–82.

Acemoglu, Daron, Vasco M Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi (2012), "The network origins of aggregate fluctuations," *Econometrica*, 80, 1977–2016.

Alfaro-Urena, Alonso, Isabela Manelici, and Jose P Vasquez (2020), "The effects of joining multinational supply chains: New evidence from firm-to-firm linkages," *Available at SSRN 3376129*.

Antras, Pol, Teresa C Fort, and Felix Tintelnot (2017), "The margins of global sourcing: Theory and evidence from us firms," *American Economic Review*, 107, 2514–64.

Arkolakis, Costas and Fabian Eckert (2017), "Combinatorial discrete choice," *Available at SSRN 3455353*.

Arkolakis, Costas, Federico Huneeus, and Yuhei Miyauchi (2021), "Spatial production networks," *Unpublished, Yale University*.

Baqaee, David and Emmanuel Farhi (2022), "Supply and demand in disaggregated Keynesian economies with an application to the covid-19 crisis," *American Economic Review*, 112, 1397–1436.

Baqaee, David Rezza and Emmanuel Farhi (2020), "Productivity and misallocation in general equilibrium," *The Quarterly Journal of Economics*, 135, 105–163.

Barrot, Jean-Noël and Julien Sauvagnat (2016), "Input specificity and the propagation of idiosyncratic shocks in production networks," *The Quarterly Journal of Economics*, 131, 1543–1592.

Bernard, Andrew B, Emmanuel Dhyne, Glenn Magerman, Kalina Manova, and Andreas Moxnes (2019a), "The origins of firm heterogeneity: A production network approach," Tech. rep., National Bureau of Economic Research.

Bernard, Andrew B, Andreas Moxnes, and Yukiko U Saito (2019b), "Production networks, geography, and firm performance," *Journal of Political Economy*, 127, 639–688.

Bernard, Andrew B and Yuan Zi (2022), "Sparse Production Networks," Tech. rep., National Bureau of Economic Research.

Bigio, Saki and Jennifer La'o (2020), "Distortions in production networks," *The Quarterly Journal of Economics*, 135, 2187–2253.

Boehm, Christoph E, Aaron Flaaen, and Nitya Pandalai-Nayar (2019), "Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake," *Review of Economics and Statistics*, 101, 60–75.

Caliendo, Lorenzo and Fernando Parro (2015), "Estimates of the Trade and Welfare Effects of NAFTA," *The Review of Economic Studies*, 82, 1–44.

Carvalho, Vasco M, Makoto Nirei, Yukiko U Saito, and Alireza Tahbaz-Salehi (2021), "Supply chain disruptions: Evidence from the great east japan earthquake," *The Quarterly Journal of Economics*, 136, 1255–1321.

Carvalho, Vasco M and Nico Voigtländer (2014), "Input diffusion and the evolution of production networks," Tech. rep., National Bureau of Economic Research.

Clauset, Aaron, Cosma Rohilla Shalizi, and Mark EJ Newman (2009), "Power-law distributions in empirical data," *SIAM review*, 51, 661–703.

Demir, Banu, Ana Cecilia Fieler, Daniel Xu, and Kelly Kaili Yang (2021), "O-ring production networks," Tech. rep., National Bureau of Economic Research.

Di Giovanni, Julian, ebnem Kalemli-Özcan, Alvaro Silva, and Muhammed A Yildirim (2022), "Global Supply Chain Pressures, International Trade, and Inflation," Tech. rep., National Bureau of Economic Research.

Di Giovanni, Julian, Andrei A Levchenko, and Isabelle Mejean (2014), "Firms, destinations, and aggregate fluctuations," *Econometrica*, 82, 1303–1340.

Di Giovanni, Julian, Andrei A Levchenko, and Isabelle Mejean (2018), "The micro origins of international business-cycle comovement," *American Economic Review*, 108, 82–108.

Eaton, Jonathan and Samuel Kortum (2002), "Technology, geography, and trade," *Econometrica*, 70, 1741–1779.

Gabaix, Xavier (2011), "The granular origins of aggregate fluctuations," *Econometrica*, 79, 733–772.

Grassi, Basile (2017), “Io in io: Size, industrial organization, and the input-output network make a firm structurally important,” *Work. Pap., Bocconi Univ., Milan, Italy*.

Halpern, László, Miklós Koren, and Adam Szeidl (2015), “Imported inputs and productivity,” *American Economic Review*, 105, 3660–3703.

Horvath, Michael (2000), “Sectoral shocks and aggregate fluctuations,” *Journal of Monetary Economics*, 45, 69–106.

Huang, Hanwei, Kalina Manova, and Frank Pisch (2021), “Firm heterogeneity and imperfect competition in global production networks,” in “Allied Social Science Associations 2021 Annual Meeting (ASSA 2021),” .

Huneeus, Federico (2018), “Production network dynamics and the propagation of shocks,” *Graduate thesis, Princeton University, Princeton, NJ*.

Jia, Panle (2008), “What happens when Wal-Mart comes to town: An empirical analysis of the discount retailing industry,” *Econometrica*, 76, 1263–1316.

Lafrogne-Joussier, Raphael, Julien Martin, and Isabelle Mejean (2022), “Supply shocks in supply chains: Evidence from the early lockdown in China,” *IMF Economic Review*, 1–46.

Levinsohn, James and Amil Petrin (2003), “Estimating production functions using inputs to control for unobservables,” *The review of economic studies*, 70, 317–341.

Lim, Kevin (2018), “Firm-to-firm Trade in Sticky Production Networks,” .

Long, John B and Charles I Plosser (1983), “Real business cycles,” *Journal of political Economy*, 91, 39–69.

Lucas, Robert E (1977), “Understanding business cycles,” in “Carnegie-Rochester conference series on public policy,” 5, 7–29, North-Holland.

Manski, Charles F (1993), “Identification of endogenous social effects: The reflection problem,” *The review of economic studies*, 60, 531–542.

Mayer, Thierry, Marc J Melitz, and Gianmarco IP Ottaviano (2016), “Product mix and firm productivity responses to trade competition,” Tech. rep., National Bureau of Economic Research.

Melitz, Marc J (2003), “The impact of trade on intra-industry reallocations and aggregate industry productivity,” *econometrica*, 71, 1695–1725.

Melitz, Marc J and Gianmarco IP Ottaviano (2008), "Market size, trade, and productivity," *The review of economic studies*, 75, 295–316.

Melitz, Marc J and Stephen J Redding (2015), "New trade models, new welfare implications," *American Economic Review*, 105, 1105–46.

Oberfield, Ezra (2018), "A theory of input–output architecture," *Econometrica*, 86, 559–589.

Rachapalli, Swapnika (2021), "Learning between Buyers and Sellers Along the Global Value Chain," Tech. rep., Working Paper.

Rubbo, Elisa (2020), "Networks, Phillips curves, and monetary policy," *manuscript, Harvard University*.

Shea, John (2002), "Complementarities and comovements," *Journal of Money, Credit, and Banking*, 34, 412–433.

Taschereau-Dumouchel, Mathieu (2020), "Cascades and fluctuations in an economy with an endogenous production network," *Available at SSRN 3115854*.

Tintelnot, Felix, Ayumu Ken Kikkawa, Magne Mogstad, and Emmanuel Dhyne (2018), "Trade and domestic production networks," Tech. rep., National Bureau of Economic Research.

Appendix A. Theoretical Appendix

Uniqueness of B_i

The networking of the problem of a firm relies on B_i and exogenous parameters. For this reason, the uniqueness of the market demand among all pairs of different pairs of downstream and upstream firms can be identified.

Since there is a free entry condition, it can be described as f_e

$$f_e = B_i \int_{\varphi_{im(i)}}^{\infty} (\gamma\Theta_i(\varphi)c_j)^{\frac{(\sigma-1)}{\theta}} \varphi^{\sigma-1} dG_i(\varphi) - \int_{\varphi_{im(i)}}^{\infty} \sum_{j\in S_i(\varphi)} S_{ij} dG_i(\varphi) \tag{20}$$

where $j(i)$ is the intermediate input supplier of the least productive firm.

$$(\varphi_{ij(i)})^{\sigma-1} B_i (\gamma T_{j(i)} (\frac{S_{j(m)}}{c_j})^{-\theta})^{\frac{(\sigma-1)}{\theta}} = S_{ij(i)} \tag{21}$$

Taking the derivative of 20 with respect to B_i and replacing by 21 using leads to

$$\int_{\varphi_{ij(i)}}^{\infty} \frac{d(\varphi^{\sigma-1}(\gamma\Theta_i(\varphi))^{\frac{(\sigma-1)}{\theta}} B_i - c_j \sum_{j\in S_i(\varphi)} S_{ij}}{dB_i} dG_{i(\varphi)} > 0 \tag{22}$$

As the firm's supply chain strategy remains constant an increase in market demand will increase the firm i's profits. In this way, the right side of the 20 is monotonically increasing in B_i. Further, as B $\rightarrow \infty$ all firms can source from each upstream firm:

$$B_i(\gamma T_{m(i)}(c_j)^{-\theta})^{\frac{(\sigma-1)}{\theta}} - S_{ij} \tag{23}$$

which goes to infinity.

Proof of Proposition 1

Assume there are two firms with productivities φ_1 and φ_2 where $\varphi_1 > v\varphi_2$. Let the networking strategy of the firms defines as $S_1(\varphi_1)$ and $S_2(\varphi_2)$. For firms that have higher productivity φ_1 to select $S_1(\varphi_1)$ over $S_2(\varphi_2)$ requires profits obtained among these two conditions to be

$$\varphi_1^{\sigma-1}(\gamma\Theta_i S_i(\varphi_1)c_j)^{\frac{\sigma-1}{\theta}} B_i - \sum_{j\in S_i(\varphi_1)} I_{ij}S_{ij} > \varphi_2^{\sigma-1}(\gamma\Theta_i S_i(\varphi_2)c_j)^{\frac{\sigma-1}{\theta}} B_i - \sum_{j\in S_i(\varphi_2)} I_{ij}S_{ij} \tag{24}$$

Further, firms with lower productivity arrange their networking strategy based on the condition

$$\varphi_2^{\sigma-1}(\gamma\Theta_i S_i(\varphi_2)c_j)^{\frac{\sigma-1}{\theta}}B_i - \sum_{j\in S_i(\varphi_2)} I_{ij}S_{ij} > \varphi_1^{\sigma-1}(\gamma\Theta_i S_i(\varphi_1)c_j)^{\frac{\sigma-1}{\theta}}B_i - \sum_{j\in S_i(\varphi_1)} I_{ij}S_{ij} \quad (25)$$

with these two profit functions,

$$[\varphi_1^{\sigma-1} - \varphi_2^{\sigma-1}][(\Theta_i S_i(\varphi_1))^{\frac{\sigma-1}{\theta}} - \Theta_i S_i(\varphi_2))^{\frac{\sigma-1}{\theta}}]\gamma^{\frac{\sigma-1}{\theta}}B_i > 0 \quad (26)$$

Since the productivity of the first firm is larger than the second firm it will imply that networking strategy of the more productive one should be larger than the other. This equation shows that productive firms select into better supply chains.

Technology of the Suppliers

The model in this study builds on the assumption that the technology of the upstream firms that produce intermediate input producers is different. Further, upstream firms draw the value of input productivity from Frèchet distribution. In order to test the validity of this assumption, this part investigates the probability density function of the suppliers from the micro data.

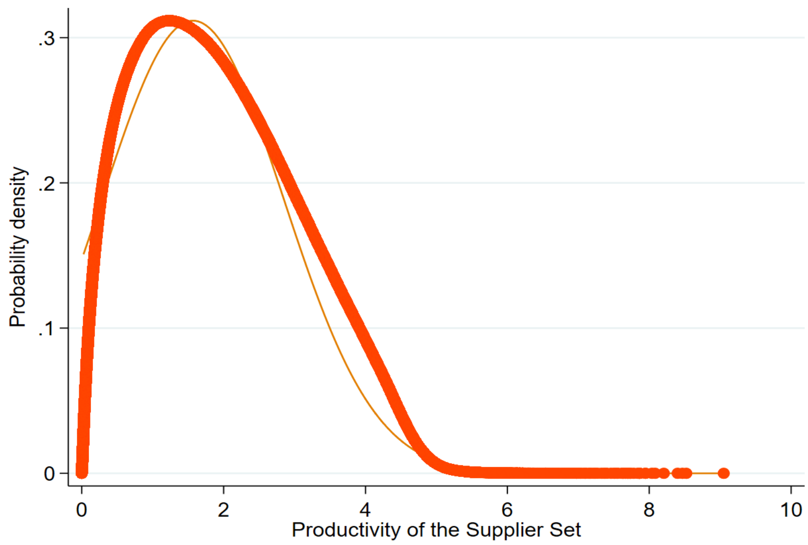


Figure 10: Probability Density Function

Decision to Export

This section expands the model to assess the role of networks in the productivity gains of firms engaging in international trade. Hence, this section provides an alternative perspective that explains the link between productivity and exporting. Firms that decide to export also compete in terms of wages w_i. Following Melitz (2003), firms must pay fixed costs for exporting, and this decision also depends on the supply chain of firm i. According to Eaton and Kortum (2002) exporting depends on a firm's comparative advantage, which is determined in a way similar to that of the supply chain strategy:

$$\beta_{xi} = \frac{T_i(w_i)^{-\theta}}{\Theta_x(\varphi)} \tag{27}$$

where w_i denotes the wages in the country x, and β_{xi} is the supply chain capability of firm i expressed as the terms of the probability of finding a customer. Exporting also depends on the wage levels in different countries. Firm i has the following profit function when its export network is determined endogenously:

$$\begin{aligned} max_{I_{ij}\in\{0,1\}_{j=1}^{N}} \pi_i(\varphi, I_{i1}, .., I_{ij}) = \varphi^{\sigma-1}(\gamma \sum_{j=1}^{N} I_{ij} T_j (c_j)^{-\theta})^{\frac{\sigma-1}{\sigma}} (1 + \sum_{x=1}^{N} \beta_{xi})^{(1+\sigma)} B_i \\ - \sum_{j=1}^{N} [I_{ij} N_{ij}] - \sum_{k=1}^{N} [I_{ki} k_{ki}] \end{aligned} \tag{28}$$

As an extension of the previous result, the cost depends on the productivity of its suppliers and network. Similarly, a firm can sell its output to foreign markets after a fixed-cost investment of k. Thus, the export decision depends on the fixed costs and the comparative productivity advantage. In a general equilibrium, consumers spend a constant share of the manufacturing industry. Given the free entry condition for market demand, a unique market demand exists in the industry equilibrium.

Proposition 2. Reaching to better suppliers leads to exporting[26].

An increase in a firm's productivity results in export participation and a need for better and more suppliers. Moreover, variables that improve a firm's supply chain, such as a reduction in supplier fixed costs with other firms or technological upgrades of an upstream firm, lead to a rise in k_{xi}. These interdependent mechanisms build up selection into domestic and international production networks. In other words, productive firms

[26] Further, a reduction in iceberg costs also leads to participation in exports and improves a firm's sourcing.

become more effective by expanding their customer and supplier networks.

Reducing the fixed costs of suppliers expands the firm's production network by keeping the demand constant. Hence, productive firms can expand their supply chain and select foreign markets. The sophistication of the supply chain enhances firms to become more productive by generating a cost advantage. In this way, heterogeneity in production networks determines firm productivity.

Proof of Proposition 2

The indicator functions of supplier I_{ij} and foreign customer X_{xi} takes values of 0 or 1. The profit function presented as

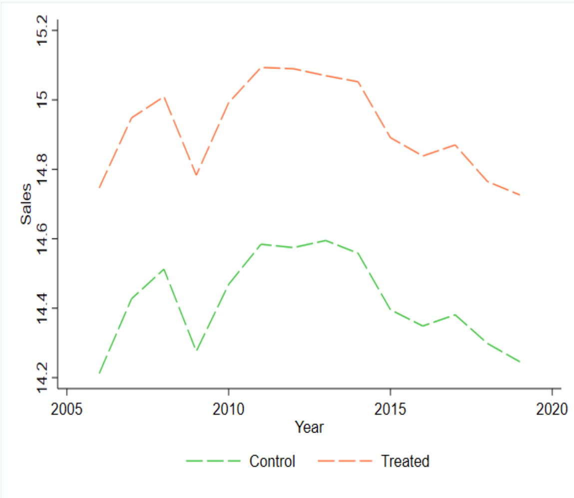
$$\Pi_i(\varphi, I_{i1}, .., I_{ij}) = \varphi^{\sigma-1}(\gamma \sum_{j=1}^{N} I_{ij} T_j (c_j)^{-\theta})^{\frac{\sigma-1}{\sigma}} (1 + \sum_{x=1}^{N} \beta_{xi})^{(1+\sigma)} B_i - \sum I_{ij} S_{ij} - \sum I_{xi} k_{xi} \tag{29}$$

this equation has increasing differences in both I_{ij} and I_{xi}. Further, it also presents increasing differences in I_{xi} and φ. Thus, variables that increase the networking capability $S_i(\varphi)$ such as reduction of networking costs with other firms or increase in the technology of the upstream firm will lead to a rise in I_{xi}. For this reason, firms that increase their supplier network tend to select themselves in foreign markets.

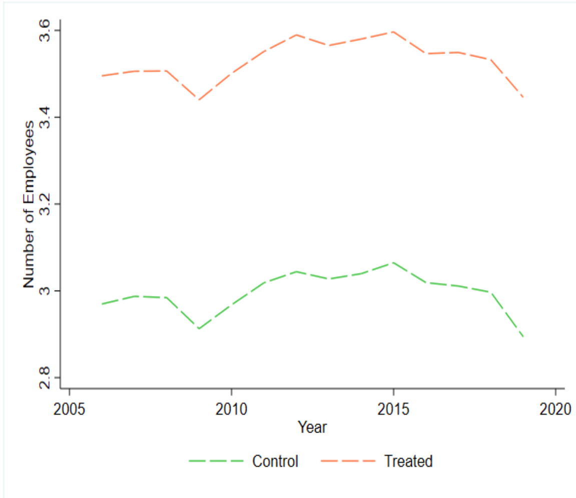
In addition, for the case of complements $(\sigma - 1)/\theta > 1$, if market demand is a constant reduction in supplier costs results in an increase in exports, as the standard trade model suggests. But depending on this profit function, it will also increase the firm's suppliers. As a result, sourcing will increase following the reduction in fixed costs of sourcing since I_{ij} is non-increasing in supplier costs. Hence, the firms which start to export would expand their supply chains. The mechanism behind the exporting and sourcing decisions is to follow more productive firms participating in foreign markets and sophisticating their production network to decrease marginal costs. All in all, productive firms become even more effective by expanding their network.

Appendix B. Empirical Appendix

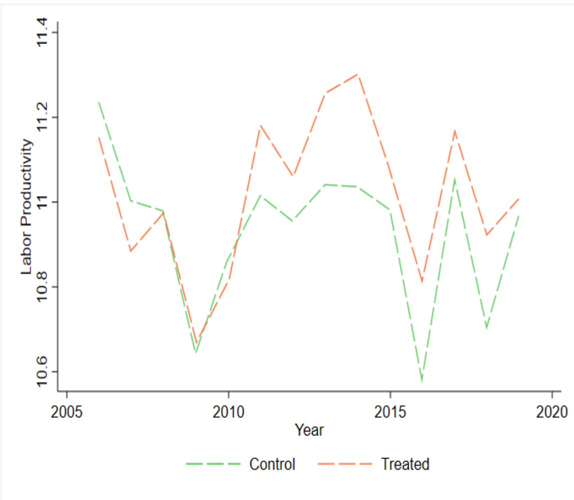
The following graphs examine the pretends of control and treated groups on sales, the number of full-time employees, labor productivity, and total factor productivity to prove that the two groups have parallel trends absent the Chinese lockdown. The mean of these variables, the orange line, refers to firms that import from China, whereas the green line presents the trends for the firms that import from other countries.



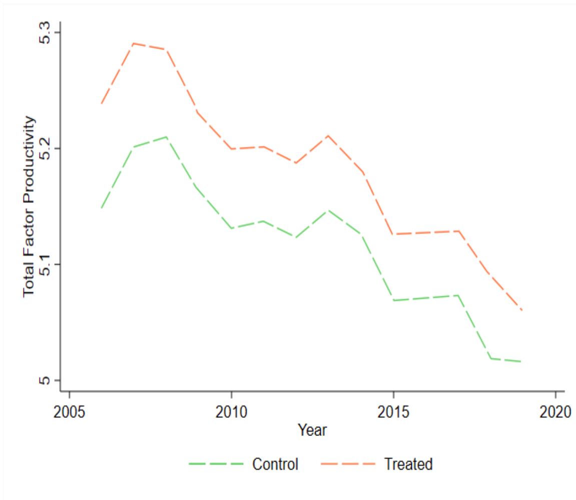
(a) Sales



(b) Number of Full-Time Employees



(c) Labor Productivity



(d) Total Factor Productivity

Figure 11: Pretrends before the Lockdown

Notes: These graphs plot the logarithm of sales and the logarithm of the number of full-time employees for the treated and control groups from 2006 to 2019.

Robustness of the Event

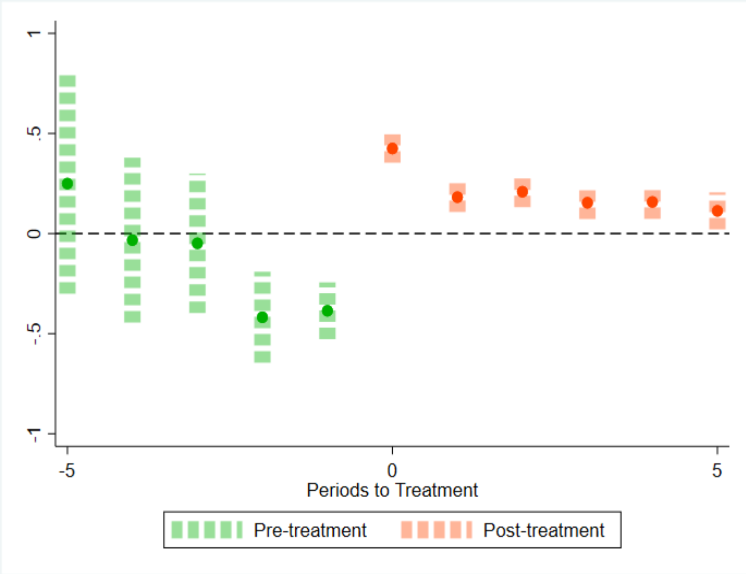
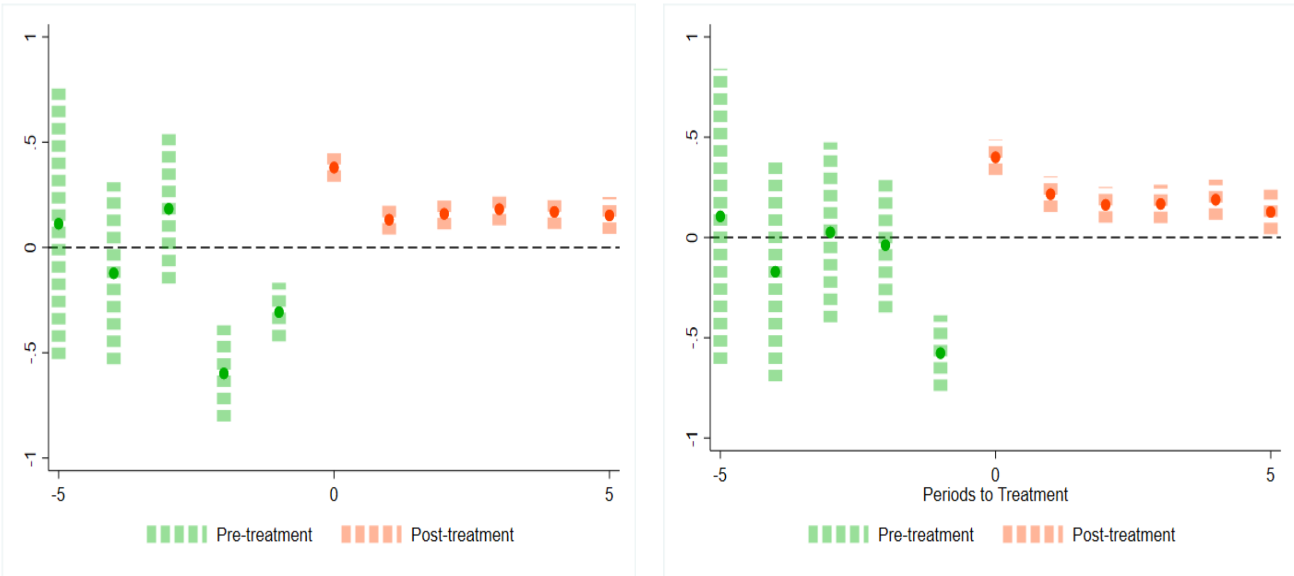


Figure 12: Prices

This figure plots the estimated coefficients of the event study for each period. The event is the early lockdown in China.



(a) Intermediate (b) Capital

Figure 13: Intermediate and Capital Goods

This figure plots the estimated coefficients of the event study for each period. The event is the early lockdown in China.

Appendix C. Structural Appendix

The property of increasing differences in the maximization problem is required to implement this algorithm, which is estimated as $\frac{\sigma-1}{\theta}$ is 1.34. Let $\Pi(N)$ be the maximization problem with a firm's supplier set N of the firm, and let N^* be the optimal solution. The algorithm starts with N^0 suppliers and estimates the sequence as $N^1 = M(N^0)$ and $N^{t+1} = M(N^t)$. Since this problem has increasing differences, it would be $N^1 \geq N^2$. Further, the iteration leads to $N^0 \geq N^1 \geq .... \geq N^x$ as a decreasing sequence. Since N^0 has only k distinct elements with a one-step element, it changes from 1 to 0 in each step. Then, iterating this process provides a convergence within k steps as $N^t = N^{t+1}$, as T is smaller than or equal to K. Let N^u be the convergent vector. In this case, N^u should be the largest element, which provides the firm with highest profit. Thus, N^u is the upper bound for the firm's suppliers. The lower bound N^l follows a similar pattern, starting from zero and iterating with new suppliers. Given the lower bound N^l and upper bound N^u, the estimation focuses on all possible suppliers across these bounds. This way, it delivers the optimal suppliers that maximize the firm's problem.

The simulated method of moments is executed while minimizing the squared percent distances between the model-simulated moments to estimate the parameters. There are two sets of moments. The first moment indicates an importing firm's share in a country that is the percentage of firms importing from China in simulated data $\tilde{m_1}(\delta)$ and the share of importing firms in the actual data for each country $m_1(\delta)$. The second moment captures the percentage of firms with fewer than the average input purchases from the domestic market, which are represented by $\tilde{m_2}(\delta)$ for the simulated firms and $m_2(\delta)$ for the actual number. The parameter estimates obtained from the simulated method of moments are presented in Appendix Table 8 for residual demand and the gravity coefficients associated with the simulated supplier fixed costs

The objective function y is based on the differences in these two moments as follows:

$$\begin{bmatrix} m1 - \tilde{m_1}(\delta) \\ m2 - \tilde{m_2}(\delta) \end{bmatrix} \tag{30}$$

W is the weighting matrix, and the moments are assumed to be weighted equally, corresponding to the identity matrix. For the true parameter value δ^*, it follows the assumption

$$E[\tilde{y}(\delta^*))] = 0 \tag{31}$$

In this case, the simulated method of moments minimizes the following function:

$$\tilde{\delta} = argmin_{\delta}[\tilde{y}(\delta)]^T W[\tilde{y}(\delta)] \tag{32}$$

Estimated Parameters	
Demand	0.222
Distance	2.849
Language	-0.557
Corruption	-0.002

Table 8: SMM Parameters *Notes: This table reports the estimated coefficients for B (residual demand), β_d^f (distance), β_l^f (language) and β_c^f (corruption) by simulated method of moments.*

According to these coefficients, the supplier costs of the firm-country pairs increase with distance, whereas corruption and language have a negative impact. In terms of magnitude, the fixed costs are primarily associated with the distance between a firm and the exporting country. Focusing on language, firms that trade with countries with a common language tend to have lower import fixed costs. The observed corruption effect conflicts with the literature. However, the coefficient is small compared to the others. Therefore, it is not vital for fixed costs.

Simulated Fixed Costs	
Country Level	Firm-Country Level
3.95	96.05

Table 9: Variance Decomposition of the Fixed Costs *Note: This table displays the variance decompositions of the simulated supplier costs at the country and firm-country levels in percentages.*

The variance decomposition of the fixed costs at the country and country-firm levels is presented in Table 9. According to this decomposition, the firm-country level explains 96.05 percent of the fixed costs of different suppliers. Conversely, the country-level variation is negligible, accounting for only 3.95 percent. These results demonstrate that how supply chains can constitute another layer of firm heterogeneity due to firm-country level variation. In line with theoretical discussion and empirical findings, these disparities are irrelevant to countries' characteristics and are mainly driven by firm-supplier matches.

ISO	Country	# of Firms	ISO	Country	# of Firms
CHN	*China*	23654	RUS	*Russia*	2509
DEU	*Germany*	16550	CZE	*Czech Republic*	2376
ITA	*Italy*	13431	SWE	*Sweden*	2316
USA	*United States*	8095	BGR	*Bulgaria*	2255
GBR	*United Kingdom*	8027	JON	*Japan*	2051
NLD	*Netherlands*	7050	DNK	*Denmark*	2047
FRA	*France*	6777	ROU	*Romania*	1913
ESP	*Spain*	6002	GRC	*Greece*	1783
IND	*India*	5447	ISR	*Israel*	1693
BEL	*Belgium*	4984	EGY	*Egypt*	1673
HKG	*Hong Kong*	4831	MYS	*Malaysia*	1488
KOR	*South Korea*	4554	ARE	*United Arab Emirates*	1482
TWN	*Taiwan*	3641	HUN	*Hungary*	1475
CHE	*Switzerland*	3137	IRN	*Iran*	1399
POL	*Poland*	3036	CAN	*Canada*	1386
AUT	Austria	2995	PRT	Portugal	1296

Table 10: Countries in the Quantitative Analysis

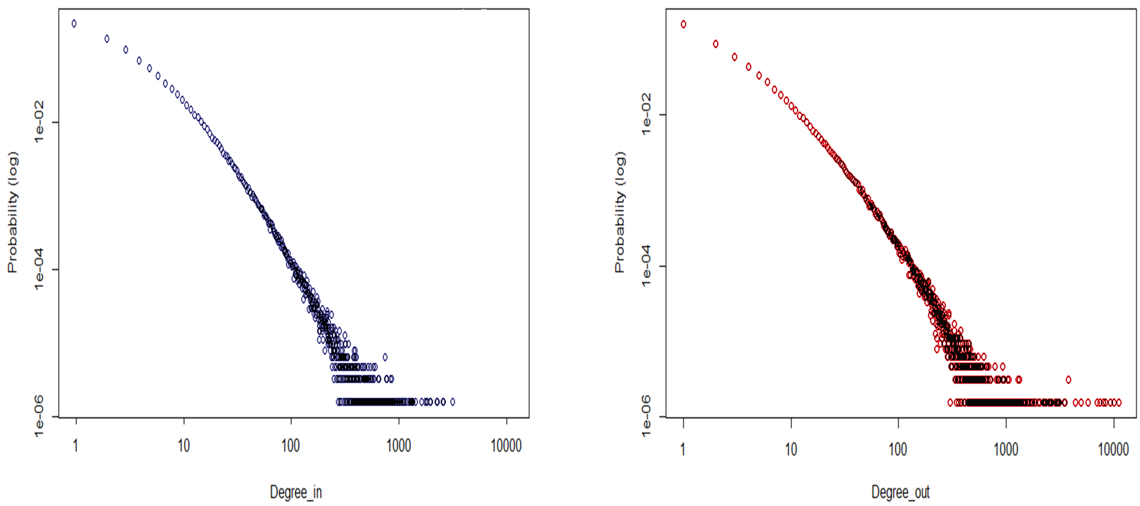
Notes: This table presents the number of importers from different countries in 2019.

Appendix D. Data Appendix

Firm-level Distribution

Weighted in- and out-degree distributions of the firm network follow a power law.

The goal is to discover the variations among firms by concentrating on firms' weighted degree distributions in the supply chain. Then, calculating both weighted in- and out-degree relies on the number and weights a firm has in the production network. Weighted indegree captures a firm's demand depending on the volume of intermediates, whereas weighted out-degree portrays the intermediate input supplied to other firms.



(a) Weighted In-Degree (b) Weighted Out-Degree

Figure 14: Firm-level Weighted Degree Distributions

Figure 14 presents the probability mass function of manufacturing firms' intermediate output supply as a weighted out-degree and input purchase as a weighted in-degree. The distributions of degrees shown in these figures are skewed, revealing the Turkish firm network's asymmetry. The firms located in the right tail of the degree distributions refer to firms with many links, and those found in these fat tails are the superstar firms of the production network. In this type of network structure, if shocks hit those firms in the tails, their impact on the economy will not vanish in the long run.

Shocks to firms with high weighted in- or out-degrees can generate a domino effect through the production network[27]. Based on these graphs, we can argue that the

[27] Lucas (1977)'s standard diversification argument states that idiosyncratic shocks die at the rate of $\sqrt{N}$, as N goes to infinity. Notably, this fact does not apply if the production linkages among firms follow fat-tailed distributions. Both Gabaix (2011) and Acemoglu et al. (2012) present results that shows the

Turkish manufacturing production network is asymmetric at the firm level. These extreme asymmetries in the manufacturing industries are attributable to the firms' presence on the distributions' right tail. As suppliers or purchasers of intermediate inputs, some firms can be "too connected to fail".

In this case, the standard diversification argument does not apply to the production network. Going one step further, there is a need to detect the distribution of both in- and out-degrees of the firm network to comment further. By relying on the Figure 14, the most suitable candidate to fit this data is the power-law distribution (see equation (33)) using the Hill-type MLE estimates of Clauset et al. (2009) with endogenous cutoffs.

Following in the footsteps of Gabaix (2011) and Acemoglu et al. (2012), this part examines the tail parameter ζ, which lies at the heart of the analysis corresponding to asymmetries among firms. For the values of ζ larger than 2, the first two moments are well defined, and the shocks wash out consistent with the standard diversification argument. If the tail parameters are smaller than 1, none of the moments of the distributions are defined. Zipf's law applies if the tail parameter is equal to one, $\zeta = 1$, and the decay rate is proportional to $1/ln(N)$. Still, the variance becomes infinite when $\zeta \in (1, 2]$, and standard diversification fails. Hence, firm-level shocks diffuse to the aggregate economy through network links, and production networks play a fundamental role. Findings in this study underline the sparsity of the Turkish production network by also exhibiting superstar firms' existence as linkages across firms that follow power laws.[28]

$$p_k = ck^{-\zeta} \tag{33}$$

	ζ	**xmin**	**logl**	**Kstat**	**Ksp**	**Obs.**
Outdegree	1.51	0.00	229.24	0.04	0.98	5494103
Indegree	1.60	0.00	367.05	0.04	0.99	5494103

Table 11: Power Law Estimation Notes: For the goodness-of-fit test, the estimation relies on The Kolmogorov-Smirnoff (KS), the table of KS values, and test statistics Ksp evaluated for the power-law distribution.

Table 11 presents the estimated tail parameters for the Turkish production network.

aggregate volatility of output decays slower with the rate of $\frac{1}{N^{1-1/\zeta}}$ with tail parameter ζ. If the tail parameter ζ lies between 1 and 2, then the decay process in volatility is much slower than the proposed rate of $\sqrt{N}$.

[28]As stated in Gabaix (2011), the diversification argument fails if the firm-size distribution exhibits fat-tails that specify the granularity of the economy. Also, Acemoglu et al. (2012) focuses on how idiosyncratic shocks to sectors lead to aggregate fluctuations in the case of a fat-tailed distribution of input-output linkages with specific tail parameters.

From 2006 to 2017, both in- and out-degrees fit power-law distribution[29]. The network structure sustains its asymmetry with very similar tail parameters for the cases of in- and out-degrees. As the tail is concentrated more mass, the production economy is not diversified enough to average out idiosyncratic shocks to firms. This result proves that determining the linkage formation mechanism across firms is essential to understanding the production economy. As a result, these micro shocks associated with the supply chain disruptions propagate through the production network and have aggregate effects.

[29]The values of Ksp smaller than 0.5 state that there is no evidence to support that distribution is not power-law.