Endogenous Production Networks and Supply Chain Disruptions

Nuriye Melisa Bilgin

University of Turin*

Abstract: This paper explores the importance of firm-to-firm linkages and estimates the causal impact of their disruption on firm performance and prices. Using unique monthly firm-level production network data from Turkey, a country with high inflation and an expansionary monetary policy, I isolate the supply shock by exploiting the disruption of Chinese suppliers during the early lockdown. This study shows that firms relying on low-cost and efficient Chinese suppliers initially raised their prices by 9% during the early months of the disruption, and eventually increased prices by 26% in the long term. To explore the underlying mechanism, I track the sourcing patterns of these firms and reveal that supply chain disruptions compelled firms to substitute their Chinese suppliers with domestic suppliers. Guided by these empirical findings, I construct a model of endogenous network formation in which firms select into better value-chains. In the model, firms that rely on imported inputs benefit from additional input-specific productivity depending on the origin of the supplier. Lastly, I calibrate the model to construct counterfactual supply chains to test the impact of exogenous shocks on sourcing strategies. These different counterfactual scenarios illustrate the impact of sourcing strategies on prices.

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

JEL codes: E23, E32, F14, L11.

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1 Introduction

Supply chain disruptions are becoming increasingly prominent due to lockdowns and conflicts. These disruptions, which originate in input-output networks like classical aggregate supply shocks, diffuse through production networks. Accurately measuring the impact of these shocks is essential for designing effective macro and industrial policies. Therefore, this study offers empirical, theoretical, and quantitative evidence on how supply chains affect prices and firm performance.

This study begins by isolating supply shocks to quantify disruptions in value chains. However, separating causal evidence along the supply chain can be challenging because network links between firms are endogenous and may change in response to shocks.[1] To address the issue of endogenous production networks, in which firms adjust linkages in response to shocks, this paper employs a novel identification strategy. This paper overcomes the identification challenge by exploiting the disruption caused by China's lockdown on Turkish importers during the pandemic. This approach provides a novel setting to test the effects on sourcing patterns, effectively addressing the reflection problem that arises from the endogeneity of production networks. Furthermore, this disruption is not about losing an ordinary supplier but rather a cost-effective one, as it originates in China. Importantly, the impact observed is not related to the demand side, as all importer firms faced identical demand shocks due to the same expansionary monetary policy and high inflation.

Using this identification strategy, this paper investigates the short- and long-term impacts of supply-chain disruptions. By implementing this strategy, findings show that supply chain disruptions led to a 9% increase in prices in the short term, and 26% increase in prices in the long term. The findings suggest that these effects endure over time and, notably, grow more pronounced. Analyzing the monthly sourcing strategies through each firm-to-firm linkage reveals that firms typically switch from importing from China to sourcing domestically. This shift results in a 45% increase in the number of domestic suppliers over the long term. However, these findings suggest that this transition in sourcing patterns is not sufficient to sustain the same level of firm performance, highlighting the role of Chinese suppliers on prices and productivity.

To explain these findings, this paper introduces a model of endogenous production networks that examines how input-output connections respond to supply-chain disruptions. Based on the framework developed by Antras (2017), the model consists of two production stages: upstream suppliers producing intermediate goods, and downstream firms manufacturing final goods. Downstream firms face a trade-off

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

between choosing domestic or foreign suppliers. Domestic suppliers provide identical intermediate inputs, while foreign suppliers produce intermediate inputs that vary in technology and costs. Importing intermediate inputs thus offers downstream firms relationship-specific productivity, but also incurs fixed costs depending on the country of origin. This setup allows heterogeneous downstream firms to select into superior suppliers offering both productivity and cost advantages. In this way, the model reveals the underlying mechanism behind the empirical findings and the role of firm-to-firm linkages.[2]

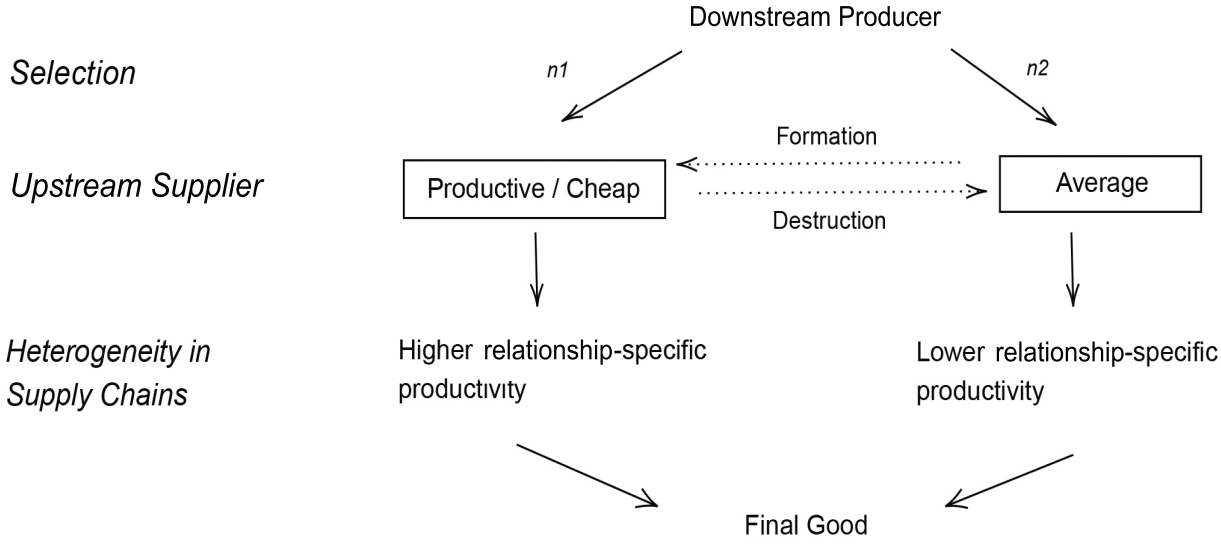


Figure 1: Model Sketch

In the model, firms construct supplier networks by paying fixed costs that are specific to each supplier.[3] This leads to a self-selection mechanism where downstream firms search for cheaper intermediate inputs. 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 due to the loss of Chinese suppliers as top downstream firms share similar supply chains with the less productive ones. This similarity in supply chains leads to weaker firm selection and reduced efficiency. Following the disruption, prices increase, and firm performance falls due to the presence of less efficient firms and the increased cost of sourcing.

[2]This selection process results in more productive firms being part of more extensive and lower-cost value chains with foreign suppliers than less productive firms. Moreover, the formation of the production network is endogenous, as each supplier and intermediate choice is interdependent.

[3]For instance, supply chain disruptions and tariffs can be shocks to these fixed costs for these suppliers.

The quantitative part of this paper 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 rely on the domestic and international production network of each firm to estimate the parameters. With the calibrated model, I build counterfactual supply chains and impose exogenous shocks to mimic the disruptions. Findings reveal that prices and the share of imports react differently to these exogenous shocks. In various simulations, I track the sourcing strategies of firms, showing how their decisions on suppliers and prices respond to different scenarios. These disruptions lead firms to reconfigure their supply chains, shifting their sourcing away from China to other 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); Magerman et al. (2016); Grassi (2017); 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)). For the link between shocks and networks, Baqaee and Farhi (2022) studies a quantitative input-output model of the U.S. economy and demonstrates that adverse supply shocks would lead to higher prices for any network structure. This paper contributes to this literature by underlining how supply shocks in terms of losing a supplier influence firm performance and prices.

Second, this study builds on emerging literature that investigates the endogenous formation of networks, including Carvalho and Voigtländer (2014), Huneeus (2018), Lim (2018), Oberfield (2018), Acemoglu and Azar (2020), Taschereau-Dumouchel (2020), Arkolakis et al. (2023) and Dhyne et al. (2023). 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. Huneeus (2018) shows how firm-to-firm linkages react to firm-specific international trade shocks. 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. (2023) highlights the role of geographic proximity in forming connections and Dhyne et al. (2023) models production networks with fixed costs in which either the buyer or supplier decides to form links. This study contributes to existing research by proposing a novel explanation for the endogeneity of production networks. It shows that the endogenous nature of network originates from interdependent choices among multiple suppliers, each with unique relationship-specific gains.

Third, this paper also investigates the mechanism behind the production network formation. Highlighting the significance of suppliers, Miyauchi et al. (2018) demonstrates that the unexpected bankruptcy of a supplier leads to a gradual match with alternative suppliers and this matching is correlated with the geographic density of suppliers. Studies, including Bernard et al. (2019a), argue that the underlying heterogeneity among firms is related to their accessibility to the larger suppliers.[4] Another aspect involves quality choices in network formation, as demonstrated by Demir et al. (2021). By focusing on production tasks, Eaton et al. (2022) demonstrates how firms choose between performing labor in-house or outsourcing tasks to low-cost suppliers. In contrast to these studies, this paper argues that the primary driver behind sourcing strategies is the pursuit of cost advantages. It contributes to this literature by proposing that the objective is to align with superior suppliers capable of offering cheaper or more productive intermediate inputs. Additionally, sourcing from these superior foreign suppliers is characterized as a selection mechanism.

Fourth, the model employed in this study builds on Antras et al. (2017) multi-country sourcing model that provides insights about the sourcing strategies of the firms. Recently, Acemoglu and Tahbaz-Salehi (2020) show heterogeneity in networks can originate from two types of producers in the economy, where firms can rely on designated suppliers by paying fixed costs. Additionally, Huang et al. (2021) explores sourcing decisions in the context of buyer-seller matching frictions across different countries. Different than the earlier studies, firms in this paper choose to use standard intermediate input or imported intermediate input that can enhance their efficiency and reduce costs through their expanded presence in supply chains.[5]

Fifth, the impact of supply chain disruptions is also studied in Barrot and Sauvagnat (2016), Boehm et al. (2019), Carvalho et al. (2021), Lafrogne-Joussier et al.

[4]In this respect, Bernard and Zi (2022) replicates the sparsity of the production network with random matching across heterogeneous suppliers and buyers.

[5]This extension relies on existing theories to characterize firms' supply chain decisions, drawing on Eaton and Kortum (2002) to show technological disparities among firms. In addition, it builds on the literature of heterogenous firms Melitz (2003). It also follows Halpern et al. (2015) to illustrate the impact of imported input productivity. Similar to Caliendo and Parro (2015), it presents the supply chain heterogeneity in production.

(2022) and Khanna et al. (2022). As natural disasters hit the suppliers, customers experience output losses based on the findings of Barrot and Sauvagnat (2016). In addition, Boehm et al. (2019) documents that Japanese affiliates in the U.S. experienced output losses after the East Japanese Earthquake. Using the same experiment, Carvalho et al. (2021) investigates the impact of this earthquake and exhibits that it has both direct and indirect consequences on the economy. In other words, these disruption shocks propagate through networks and affect higher-order connections in the value chain. More recently, Lafrogne-Joussier et al. (2022) focuses on the impact of the early lockdown in China and shows how this shock on inputs led to a drop in exports and domestic sales. The labor market effects are also investigated by Ulate et al. (2023) while considering a temporary increase in international costs. Following COVID lockdowns in India, Khanna et al. (2022) finds firms dependent on suppliers from districts with stringent lockdown measures tend to have higher separation rates. Di Giovanni et al. (2023) demonstrates that inflationary pressures did not remain contained within national borders, instead they spilled globally through interconnected trade networks. Grossman et al. (2024) show that formation of the supply chains often requires a costly search and partnerships may vary in productivity. The results of this paper align with these findings, indicating that the loss of a supplier cannot be reversed.[6] In contrast to these studies, this paper centers on firm-to-firm linkages and contributes to the literature by revealing how sourcing patterns affect prices. Furthermore, using the COVID-19 shock as a disruption is crucial because it involves a specific type of supplier offering competitive pricing and a wide range of products, unlike disruptions caused by natural disasters or wars.

Finally, this paper builds on the literature that investigates the role of networks on firm performance. More recently, Rachapalli (2021) illustrates how firms learn through the transition from producing single products to multi-products via input-output linkages, particularly for exporter firms. Alfaro-Urena et al. (2022) finds an upsurge in firm productivity as they start to supply for multinational corporations. In contrast to these studies, this paper emphasizes the importance of selection into superior supply chains rather than learning through interactions. In other words, this paper demonstrates that firms with sophisticated supply chains, which can afford superior

[6]On the price effect, this work is also related to the literature that studies supply chains and inflation. Based on the findings of Rubbo (2020), the slope of the sectoral Phillips curves decreases in intermediate input shares while productivity fluctuations endogenously deliver a trade-off between inflation and output. For the United States, Di Giovanni et al. (2022) decomposes the demand- and supply-side factors underlying the observed inflation and presents the link between aggregate demand shocks and productivity. This paper contributes to this literature by providing a causal estimate for these disruptions at the micro-level and exhibiting how the choice of supplier directly affects the firm's price.

suppliers rather than average ones, perform better.

2 Data

The aim of this paper is to track firm performance along with their sourcing patterns by combining several micro-level datasets. The first dataset reports firm-to-firm linkages on a monthly basis. The second dataset contains customs data, tracking monthly exports and imports, including traded products (HS codes) and partner countries. The third dataset covers social security records, detailing the number of workers and wages paid each month. These datasets are provided by the Ministry of Industry and Technology of Turkey and are merged using firm identifiers, with industrial classification following NACE Rev.2 and territorial units classified according to NUTS2.

The final dataset forms a panel that includes information about domestic and international firm linkages and social security records over forty-eight months, from 2019 to 2022. All physical units in this panel, except for exports and imports, are deflated according to producer price indices, allowing for comprehensive tracking of firms' supply chains and performance over time.

2.1 Production Networks

The main interest in this paper is the production networks which are built on links across firms. The domestic firm-to-firm linkages are constructed using the value-added tax statements of each firm, which are required to be reported to the Ministry of Finance for transactions exceeding 5,000 Turkish liras (equivalent to 155 U.S. dollars). Each VAT statement contains the month of the transaction, the identifier of the buyer, the supplier, and the transaction amount. Each firm in these reports represents a node in the production network, with weighted and directed edges. The direction of these edges is determined by the buyer and supplier identifiers, with the transaction amount serving as the edge weight.

2.2 International Trade

The international part of a firm's supply chain is based on customs declarations. These export and import declarations provide monthly information on traded HS products, transaction values, and partner countries. By incorporating this data, the study extends the domestic production network to include the firm's international linkages each month.

3 Production Network Facts

This section begins by presenting the facts about production networks that serve as motivation for the research questions in this paper. It aims to evaluate the interactions among firms using network theory, focusing on the connections between firms and the characteristics of supply chains. The main question in this part is to determine whether there is a selection process in finding linkages or if these chains are established randomly.

To investigate this, I start by calculating the total factor productivity (TFP) of firms by relying on Levinsohn and Petrin (2003) using intermediate inputs as a proxy. With the given productivity at the firm level, I estimate the productivity of each supplier set for a firm.[7] Figure 2 demonstrates the presence of productive clusters where the x-axis presents the firm's productivity and the y-axis shows the productivity of the supplier set. According to this Figure, productive firms cluster within the production network.[8]

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

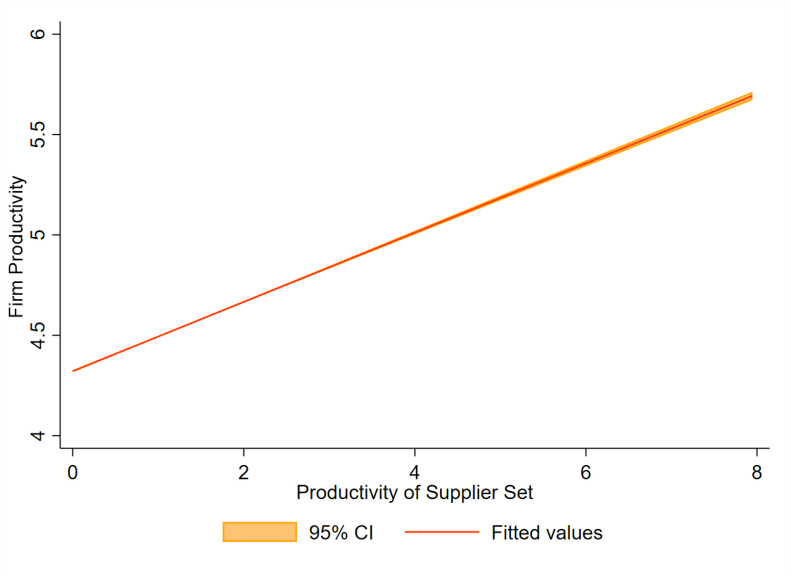


Figure 2: Supplier Set Productivity

The initial finding highlights a positive correlation between firm productivity and their suppliers. This correlation implies that productive firms source their intermediate

[7]Firms rely on production networks that consist of nodes and edges. This study proxies networks as edges as intermediate input transactions within firms, and each node in a network corresponds to a firm. Thus, a production network is constructed based on firm-to-firm transactions, considering the direction of trade and transaction volume. With the supplier and customer identification of the transaction, these connections assemble a weighted and directed network in which weights are the values of the intermediate input transactions among firms. The goal is to discover how these dynamic interactions change over time and the implications of the supply chain disruptions.

[8]Figure 2 is based on both the firm's productivity and the supplier set's productivity and it is weighted by the number of employees.

inputs from more efficient suppliers. It also suggests that productive firms cluster together, and their connections in these clusters can play a crucial role in firm heterogeneity.

Another critical dimension of the nature of these linkages is the diversification. To test how firms diversify their intermediate inputs, the second fact focuses on the number of suppliers for each firm. Figure 3 presents the number of suppliers on the x-axis and the percentage of these firms on the y-axis. As Figure 3 indicates, the majority of firms rely on just one supplier.[9] Furthermore, the distribution of these suppliers is skewed.[10]

The second fact emphasizes the necessity for greater diversification within the value chain, given that the majority of firms in the production network have a limited number of suppliers with a skewed distribution. These extremes include more than ten percent of the firms with a single supplier, while only a tiny fraction engages with numerous suppliers, according to Figure 3. This pattern suggests the presence of fixed costs or barriers when adding new suppliers, which may vary among firms. Hence, due to these fixed costs, firms may limit their production to a few suppliers, thereby reducing their diversification across the production network.

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

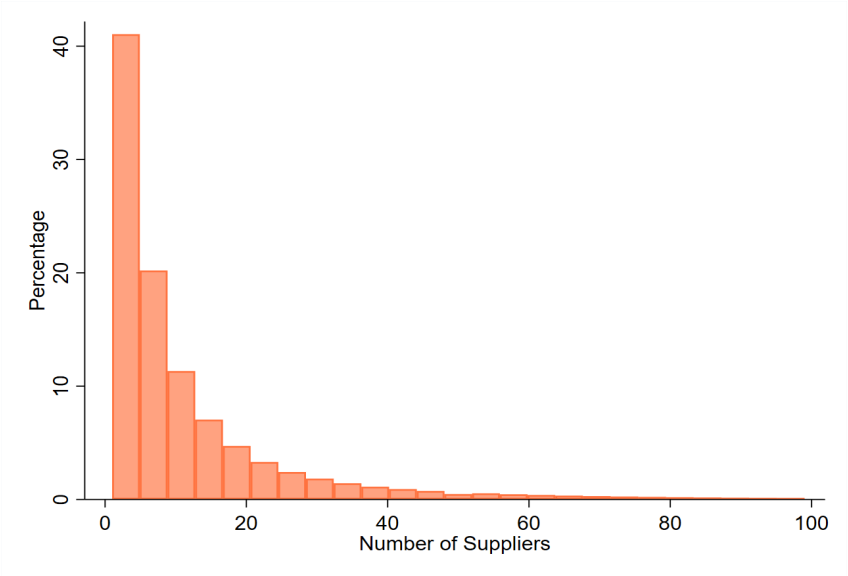


Figure 3: Number of Suppliers per Firm

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

These facts about production networks reveal two critical features. The first is related to the presence of productive clusters, where efficient firms are associated with

[9]The average number of suppliers per firm is 15.17.

[10]This includes firms with less than 100 suppliers.

effective suppliers. This assortative matching is evident in the positive correlation observed between firms' productivity and their suppliers within their supply chains. The second one highlights that only a small percentage of firms rely on multiple suppliers. The limit on the number of suppliers and the assortative matching in productivity suggest a selection mechanism in supply chains.

4 Supply Chain Disruptions

The preceding section emphasizes the significance of suppliers by focusing on firm-to-firm linkages. The goal of this part is to estimate the causal relationship between the choice of suppliers and prices. In order to identify a causal relationship, I exploit the disruption from Chinese suppliers on Turkish firms during the early lockdown.[11] In this way, this study investigates the impact of a supply chain disruption on prices and sourcing patterns.

Specifically, this section explores the impact of losing a low-cost or productive supplier on a firm during this disruption, relying on three key identifying assumptions. The first assumption is that the supply chain disruption due to the early lockdown in China is exogenous for Turkish firms. The second one is that firms importing from China or other countries do not exhibit differential trends absent the Chinese lockdowns. The third assumption is that all firms in this sample are subject to identical demand shocks. By relying on these assumptions, I isolate the impact of this supply shock and utilize the Chinese lockdown as a natural experiment to examine the short- and long-term implications of supply chain disruptions.

The first assumption is that the lockdown in China was an exogenous event and unrelated to the supplier choices of firms in Turkey. Hence, it can be employed to identify the effect of losing a supplier. Another critical point is that manufacturing and other production plants in Turkey resumed working at their standard capacity during the pandemic, without any restrictions on firms. Consequently, this ensures that the outcomes remain unaffected, enabling us to accurately assess the impact of supply chain disruptions on firms.

The second identification assumption requires both treated and control firms, as all importers share the same characteristics before the lockdown. The results indicate that these different groups exhibit parallel trends before the pandemic, which ensures that any differences among the groups following the Chinese lockdown can be attributed to supply chain disruptions. Since there are no pre-existing differences between Chinese

[11] This disruption had critical consequences for Turkish firms, considering that China was Turkey's second largest import partner in 2019.

importers and importers from other countries, the parallel trend assumption for both groups confirms that the results are both causal and unbiased.

The third assumption focuses on isolating supply shocks, considering that 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, difference in price estimates cannot be attributed to the demand side. With this in mind, this methodology isolates the supply shocks to highlight the role of suppliers and sourcing patterns on firm prices.

Under these identifying assumptions, this paper employs the following event study to investigate the causal impact of supply chain disruptions:

$$y_{i,t,p} = \alpha + \sum_{(j=-11),(j\neq -1)}^{20} \beta_k Disruption_i + \mu_i + \lambda_{ht} + \gamma_{kt} + \delta_d + \epsilon_{i,t} \tag{1}$$

$y_{i,t,p}$ represents the dependent variable for the price of product p at the HS-6 level, produced by firm i in month t. $Disruption_i$ is an indicator function that takes a value of one if the firm had any imports from China in 2019, and zero otherwise. This equation also accounts for the firm fixed effect μ_i, the industry-month fixed effect λ_{ht}, the region-month fixed effect γ_{kt}, the destination fixed effect δ_d and $\epsilon_{i,t}$ as the error term.[12] The timeline has been adjusted for the firms, with $t = 0$ corresponding to the Chinese lockdown in February 2020, and $t = -1$ serving as the baseline.[13]

Employing this lead-lag model provides several advantages for assessing the impact of supply chain disruptions. The results demonstrate the cumulative dynamic response in the months following the lockdown, with each point representing the cumulative effect. Additionally, pre-trend coefficients can be employed to test for parallel trends before the disruption. To compare similar groups, it is essential to ensure insignificant coefficients before the event.

For each test, the following section reports the coefficients β_k for each month and discusses how these outcomes diverge between firms that import from China and those import from other countries than China. Each event study plots the points in the graph indicating the coefficients β_k, and dashed lines show 95% confidence intervals.

Another concern related to the lockdown is the difference between the intermediate and long-run effects of losing a supplier. To check whether the supply chain disruption effects persist or disappear in the long run, the empirical analysis documents both short- and long-run implications on prices and sourcing strategies.

[12] Month-industry controls are employed based on four-digit NACE Rev.2 classification.

[13] The leads are specified as eleven months, and lags are specified as twenty months. Twenty months are chosen as the maximum possible lags in this dataset, with February 2020 designated as $t = 0$.

4.1 Supply Chain Disruptions and Prices

Supply chains have a direct impact on prices, and any disruptions in these networks result in price increases on a global scale. In this section, I illustrate the origins of price increases within the value chain. Firms unable to maintain contact with their existing suppliers set different prices compared to those who maintain their supplier relationships. This estimation focuses on output prices and demonstrates the sensitivity of prices to firm-to-firm linkages. The prices are estimated at the firm-level for exporters.[14] Quantities are measured in kilograms using customs data. Additionally, prices for each product are matched with the producing firms for each month.[15]

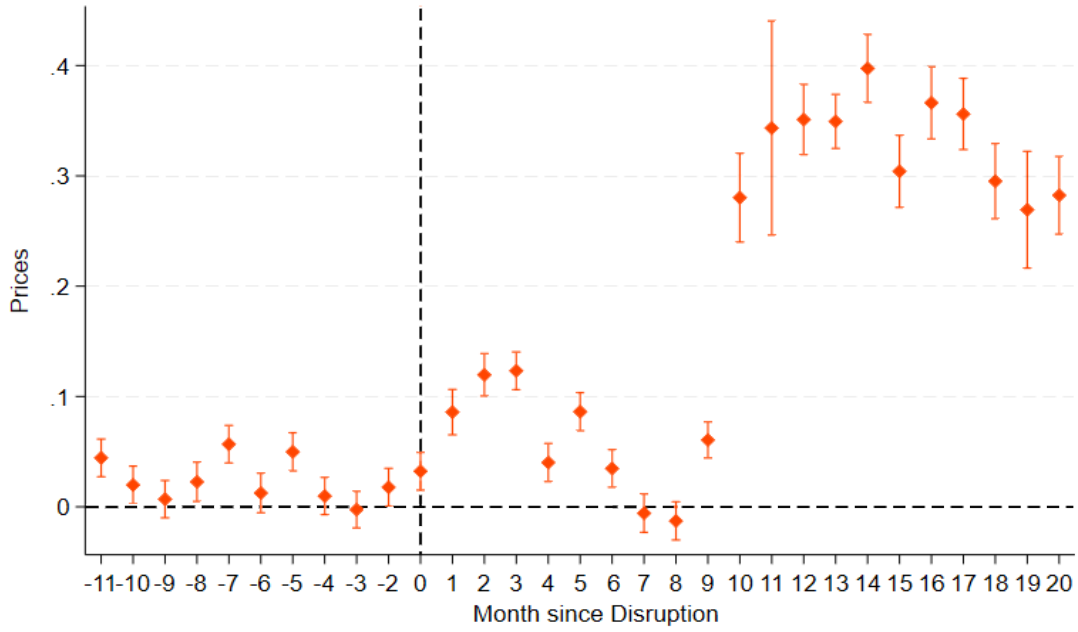


Figure 4: Prices after the Supply Chain Disruption

Notes: This figure displays the estimated coefficients and confidence intervals for each period in an event study using early lockdown in China. The coefficient is normalized to zero at the baseline ($t = -1$), and all estimates account for firm, region-month and four-digit industry-month fixed effects based on 1,936,819 observations.

The event study, displayed in Figure 4, examines price changes among both control and treated firms. This figure demonstrates how price changes are related to the supply chain dynamics, particularly as firms are forced to discontinue their use of Chinese suppliers. Several important insights emerge from Figure 4. Firstly, the two groups exhibit no discernible differences, as indicated by the insignificant pre-trend coefficients.

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

[15]This match is necessary to obtain robust results against quality concerns, and it also controls for single- and multi-product firms.

Consequently, these two groups can be considered comparable and exhibit similar performance prior to the lockdown.

The second takeaway is that the post-trend measures suggest a significant difference between the two groups. Due to this supply shock, treated firms experience a dramatic rise in price levels. According to the estimates, this shock caused a 26.9% increase in prices following the loss of their Chinese suppliers.

Third, the estimates illustrated in Figure 4 show significant spikes after one year. The impact of this supply shock intensifies over time. Losing a supplier is not quickly recoverable, and supply-chain disruptions have lasting effects. Short-term reactions may be constrained, potentially due to inventory adjustments or changes in shipment times. To investigate further, the next section explores the sourcing habits of companies importing from China to examine supplier margins.

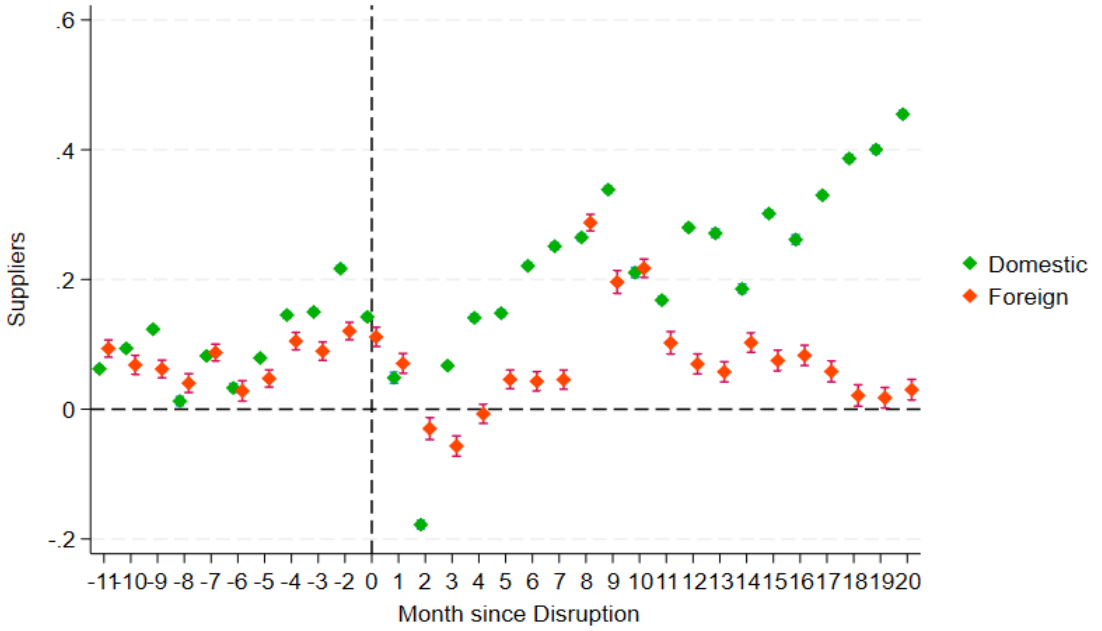
The conclusion drawn from these estimates is that, even at the micro-level, disruptions in value chains can reverse the benefits that firms gain through the supply chain. Since firms cannot purchase their intermediate inputs from their low-cost or productive Chinese suppliers, this change translates into higher costs within the production networks, leading firms to charge higher prices. This exercise reveals the role of firm-to-firm linkages in the aggregate economy and how supply shocks can generate cascade effects through the trade of intermediate goods.[16]

4.2 Supply Chain Disruptions and Sourcing Patterns

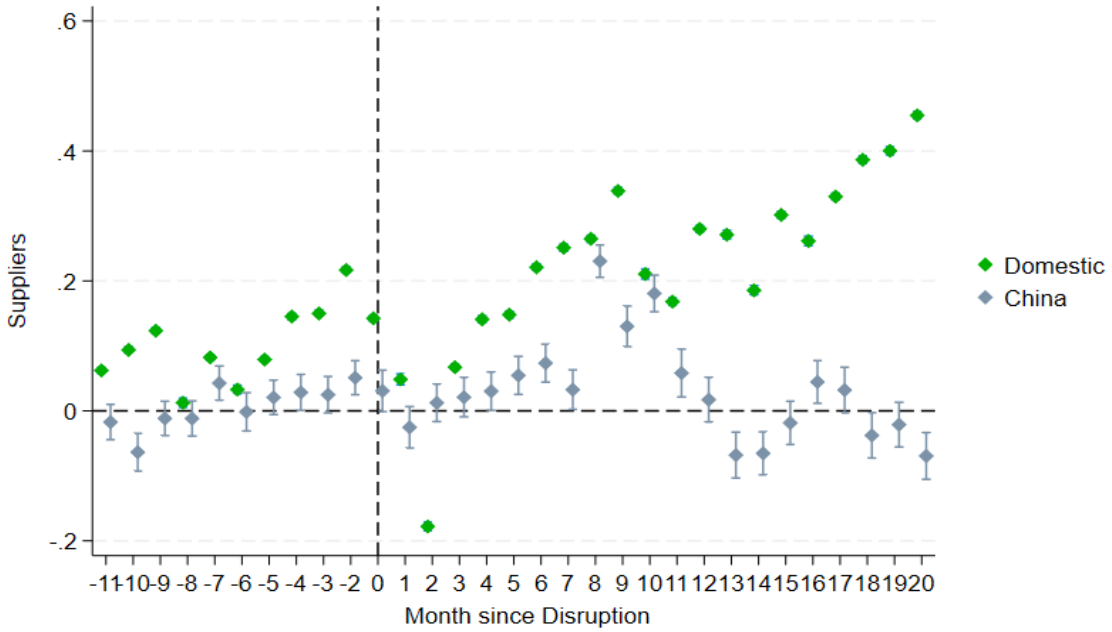
The findings in the previous section demonstrate a causal link between prices and suppliers of a firm. Nevertheless, a more in-depth analysis is required to comprehend the underlying mechanism. It is essential to examine whether the sourcing patterns of Chinese importers have shifted towards domestic suppliers or if these firms have started importing from countries other than China. Therefore, this section explores the impact of supply chain disruptions by focusing on the supplier margin.

To understand how dropping a low-cost supplier is related to production efficiency, this part focuses on the firm-to-firm linkages. Both number of domestic and foreign suppliers of the firm used to track these sourcing patterns. The estimation process follows equation 1, with the dependent variables being the number of domestic and foreign suppliers.

[16]The results are also robust to different types of trade. Focusing solely on intermediate input trade leads to similar estimates, as reported in the Appendix.



(a) Number of Domestic and Foreign Suppliers



(b) Number of Domestic and Chinese Suppliers

Figure 5: Sourcing Patterns

Notes: These figures display the estimated coefficients and confidence intervals for each period in an event study using early lockdown in China. The coefficient is normalized to zero at the baseline ($t = -1$), and all estimates account for firm, region-month and four-digit industry-month fixed effects. The first regression for domestic suppliers is based on 1,157,342 observations, while the second regression for foreign suppliers is based on 415,627 observations and 115,580 for Chinese suppliers.

As the impact of supply chain disruptions persists over time, it is essential to focus on the sourcing strategies of firms in the long run.[17] Interestingly, firms importing from China undergo substantial changes in their sourcing strategies. A notable shift occurred among firms importing from China after twenty months, as depicted in Figure 5. This is evident from a significant 45.5% increase in reliance on domestic suppliers. Conversely, the number of import partners only rose by 3%. Furthermore, Figure 5 highlights the number of Chinese suppliers with the same regression specification. Hence, companies importing from China are actively altering their sourcing strategies, showing a preference for domestic suppliers.[18]

According to these findings, the supply chain disruptions compelled firms to substitute their Chinese suppliers with domestic ones. The shift to domestic sourcing among Chinese importers is reflected in the increased output prices, as shown in the Figure 4. These results highlight the importance of the supplier heterogeneity, even at the micro-level. Furthermore, these estimates demonstrate that firms can exchange one supplier for another but the absence of a low-cost or more productive supplier results in an overall decline in firm performance.

4.3 Alternative Measures

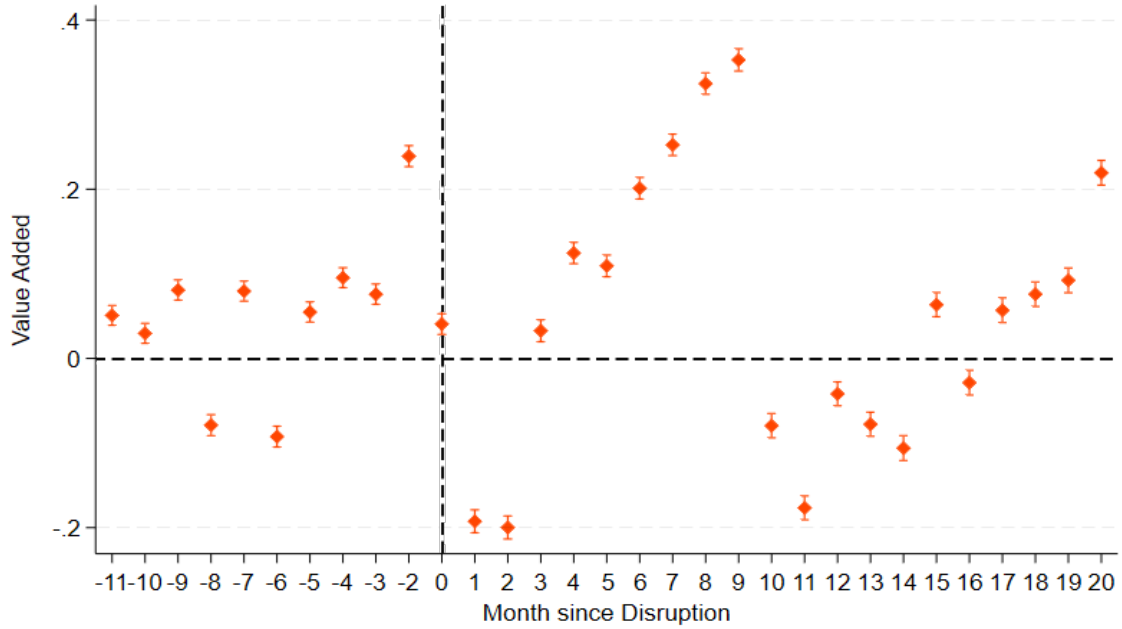
The previous section demonstrates the implications of supply chain disruptions on prices and sourcing patterns. However, as price data is limited to exporting firms, this section shifts focus to include treated firms that do not export, using two alternative measures: value-added and labor productivity. To estimate value-added on a monthly basis, I subtract the intermediate input purchases and wages from the output for each month.[19] Then, to calculate labor productivity, value-added is divided by the number of employees reported each month from the employer-employee database.

According to Figure 6, both value-added and labor productivity follow a similar trajectory. Firms that depend on Chinese suppliers experience a decline in their value-added and labor productivity after ten months. Based on the findings in the previous section, the transition from Chinese to domestic suppliers prompts firms to pursue higher prices, but this shift impacts more than just prices. The treated firms also experience a reduction in their value-added and labor productivity, attributable to the absence of

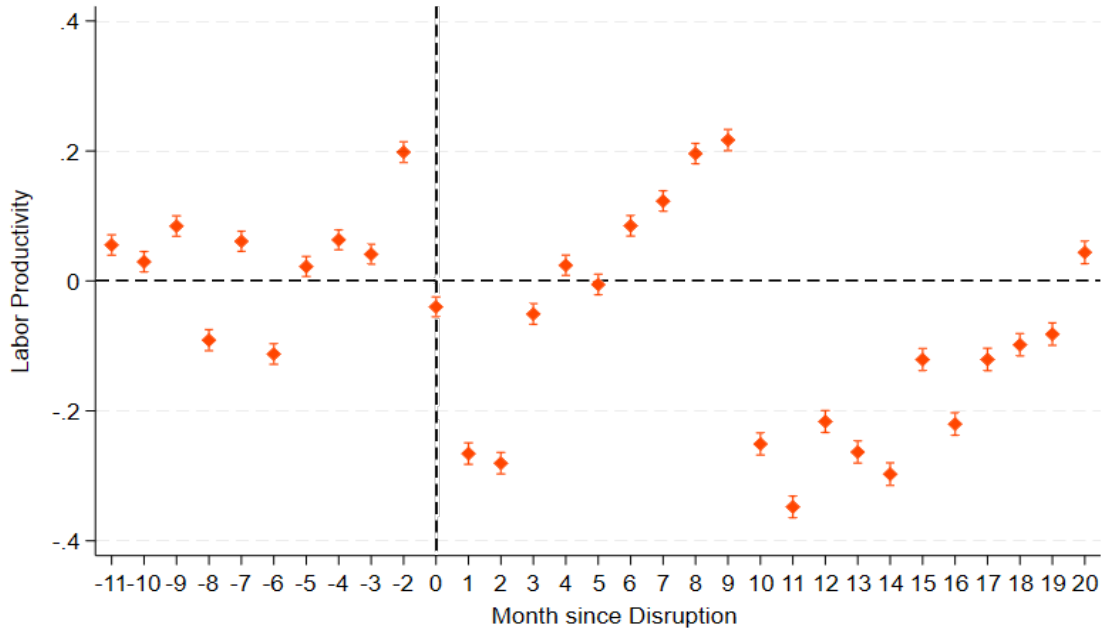
[17] Similarity following the first months might stem from existing inventories or the time needed for post-lockdown shipments.

[18] The Appendix also decomposes the sector and region of the domestic suppliers and underscores that these changes are not due to sectoral or regional differences for the domestic suppliers. Hence, these decompositions provide the robustness of the results.

[19] The intermediate input purchases are the sum of a firm's imports and purchases from the domestic market, whereas output corresponds to the sum of the firm's domestic sales and exports.



(a) Value-added



(b) Labor Productivity

Figure 6: Alternative Measures

Notes: These figures display the estimated coefficients and confidence intervals for each period in an event study using early lockdown in China. The coefficient is normalized to zero at the baseline ($t = -1$), and all estimates account for firm, region-month and four-digit industry-month fixed effects.

low-cost and efficient Chinese suppliers. Therefore, these alternative metrics presents the robustness of results.

5 Theoretical Framework

Empirical evidence underlines the role of supply chains on firm prices and productivity. 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. Further analysis of the sourcing strategy reveals how low-cost and productive sourcing impact firm performance. Nevertheless, a mechanism is required to understand the link between a firm's suppliers and performance.

To rationalize these findings, this section introduces a model of endogenous supplier network formation where input-output linkages adjust to shocks at both intensive and extensive margins with selection. This model of endogenous production networks serves three purposes. First, it illustrates how firms establish their supply chains by choosing among domestic suppliers with identical technologies and foreign suppliers with varying technologies. It also highlights that the formation of firm-to-firm linkages is not random. Second, it offers a framework for understanding the impacts of supply chain disruptions on firms. Third, it enables the construction of counterfactual supply chains to test the predicted outcomes.

In this way, this part illustrates a new aspect of firm heterogeneity as the differences between suppliers to provide the micro-foundations of value chains while exploring 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 to firm-to-firm settings with selection into better suppliers and supply chain disruptions.

The economy consists of two sectors as manufacturing and services. However, the primary focus of this study is on manufacturing, aiming to gain insights into the functioning of value chains. In this economy, value chains hinge on two distinct types of firms: the first type comprises domestic and foreign upstream firms responsible for producing intermediate inputs, while the second type consists of downstream firms that produce final goods. These downstream firms produce final goods while relying on the upstream firms for their intermediate input bundles.

In this economy, individuals engage in both work and consumption. Workers provide labor with inelastic supply in exchange for wages, and their income is divided into two parts. A constant share represented by η is allocated to the purchase of final goods produced by the manufacturing sector. The remainder is spent on services. The service sector operates under perfect competition and utilizes technology with constant returns

to scale in labor.

5.1 Preferences

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

$$U_i = (\int_{w \in W} q_i(w)^{\frac{(\sigma-1)}{\sigma}} dw)^{\frac{\sigma}{(\sigma-1)}} \tag{2}$$

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

$$q_i(w) = E_i P_i^{\sigma-1} p_i(w)^{-\sigma} \tag{3}$$

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

$$B_i = \frac{1}{\sigma}(\frac{\sigma}{\sigma-1})^{1-\sigma} E_i P_i^{\sigma-1} \tag{4}$$

5.2 Production

The production in this economy relies on both upstream and downstream firms. As downstream firms produce final goods, they rely on domestic or foreign upstream firms that manufacture intermediate goods. These links determine the relationship-specific productivity of downstream firms and build up production networks.

Downstream firms can choose to buy their intermediate inputs from both domestic and foreign suppliers. While domestic suppliers offer identical intermediate inputs, foreign suppliers differ in both technology and costs. Additionally, these foreign suppliers are subject to varying fixed costs based on their country of operation.

Downstream firms that can afford these fixed costs rely on the imported intermediate goods and benefit from additional relationship-specific productivity associated with the technology of the foreign supplier. However, there are no additional productivity gains with domestic suppliers. Hence, this establishes a selection mechanism for heterogeneous downstream producers of final goods.

5.2.1 Upstream Firms

There are two types of upstream firms. Domestic upstream firms, indexed with d, provide identical intermediate inputs with the marginal cost of c_d. Foreign upstream firms, indexed as j, produce intermediate goods in a perfectly competitive intermediate input market. These foreign upstream firms are modeled as in Eaton and Kortum (2002). For each imported intermediate input, there are many international upstream firms, and the marginal costs of these upstream firms are defined as

$$\frac{c_j}{z_j(m)} \tag{5}$$

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

$$F_j(z) = e^{-T_j z^{\theta}} \tag{6}$$

where T_j represents the state of upstream technology. This location parameter varies for each supplier, while all suppliers have the same shape parameter θ.

5.2.2 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 core efficiency φ, as in Melitz (2003). Firms draw their productivity from a Pareto distribution with the same shape and location parameters. Sunk entry and fixed production costs determine the number of downstream producers. Then, the randomness of firm efficiency determines which entrants are above the threshold.

These downstream firms leverage their heterogeneous productivity when converting intermediate inputs into final goods. However, the purchase of imported intermediate goods requires downstream firms paying a fixed cost denoted as S_{ij}.[20]

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

$$c_i(\varphi) = \frac{1}{\varphi}\left(\int_0^1 (mp_j + (1-m)p_d)^{1-\rho}\, dm\right)^{\frac{1}{(1-\rho)}} \tag{7}$$

where ρ is the elasticity of subsitution, p_j represents the price of the imported

[20]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.

intermediate goods, p_d is the price of the intermediate goods produced by the domestic suppliers, while m serves as the ratio of imported intermediate inputs for the downstream firm, which also has a core productivity of φ. The price of the intermediate input is equal to the cost of the supplier, a result of perfect competition among all types of upstream firms. Replacing the intermediate input costs with the marginal cost of downstream firm i leads to the following cost function:

$$c_i(\varphi) = \frac{1}{\varphi}\left(\int_0^1 \left(m\frac{c_j}{z_j(m,\varphi)} + (1-m)c_d\right)^{1-\rho} dm\right)^{\frac{1}{(1-\rho)}} \tag{8}$$

Downstream firms face the following problem. First, the downstream firm draws potential suppliers. Then, it selects its share of imported intermediate goods as m, and finally, the downstream firm makes a production decision. These production choices are influenced by both marginal costs and the structure of the supply chain. According to the model, a unique equilibrium exists, and the market finds the optimal supply chain.[21]

The selection into the supply chain is the primary mechanism behind the model and originates from the downstream firm's trade-off. Foreign suppliers can quote lower prices for intermediate inputs, yet they are associated with higher fixed costs to source. Consequently, these disparities among intermediate input producers lead to the self-selection of higher φ downstream firms into relationships with better, more productive, and cost-effective suppliers. Since these productive downstream firms differ in their core productivities and possess cost advantages, they tend to form connections with superior suppliers. Due to relationship-specific productivity gains with better suppliers, the density of suppliers shifts from the lower to the upper tail. Hence, the technology varies for each foreign upstream-downstream match.[22]

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

[22] 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 relationship-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 and differences among foreign suppliers. Downstream firms aim to link with more productive foreign suppliers to increase their T_j, thus lowering the cost of production. They diversify by increasing their supplier base with imports 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 supplying from more productive upstream producers from abroad. 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.

5.2.3 Downstream Price

The final good price depends on the cost of intermediate goods and choices among domestic and foreign suppliers. For the firms that rely on imported inputs, the price p_j is determined as

$$G_j(m) = Pr\left[p_j(m) \leq p\right] = Pr\left[\frac{c_j}{z_j(m)} \leq p\right] \tag{9}$$

$$G_j(m) = Pr\left[p_j(m) \geq \frac{c_j}{p}\right] = 1 - Pr\left[z_j(m) \geq \frac{c_j}{p}\right] \tag{10}$$

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

$$G_j(m) = 1 - e^{-T_i(c_i)^{-\theta} p^{\theta}} \tag{11}$$

Since the distribution of z_j is known and $p_j(m)$ is available, the price paid for the imported intermediates is the realization of the random variable $P_j = min(P_{ij}, j = 1, .., N)$, where $G_j(m)$ is the cumulative distribution function. Hence, the price of imported intermediate input is

$$\left(\gamma \sum_{j=1}^{N} T_j c_j^{-\theta}\right)^{-\frac{1}{\theta}} \tag{12}$$

where γ is $\left[\Gamma(\frac{\theta+1-\rho}{\theta})\right]^{\frac{\theta}{(1-\rho)}}$. The final good price depends on the choices of suppliers and the final good price is estimated as

$$p_i = \frac{1}{\varphi}\left(m\left(\gamma \sum_{j=1}^{N} T_j c_j^{-\theta}\right)^{-\frac{1}{\theta}} + (1-m)\sum_{d=1}^{D} c_d\right) \tag{13}$$

The final good price p_i for the downstream firm depends on its core productivity φ, m as the choices between different types of suppliers, foreign supplier productivity T_j, domestic supplier input costs c_d, foreign supplier input cost c_j and the variance of shocks θ. This price is a decreasing function of more productive and cheaper suppliers, implying that downstream firms with better suppliers have lower marginal costs.[23]

The intuition here is that when a firm adds a new productive or low-cost foreign supplier, it inevitably reduces its marginal cost 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.

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

5.3 Endogenous Choice of Links

The downstream firm makes a production decision based on the marginal costs that are shaped according to the its suppliers. The problem of the downstream firm i has the following form:

$$max_{m\in\{0,1\},I_{ij}\in\{0,1\}_{j=1}^{N}} \pi_i(\varphi, I_{i1}, .., I_{ij}) = \varphi^{\sigma-1}\left(m(\gamma\sum_{j=1}^{N} I_{ij}T_j(c_j)^{-\theta})^{\frac{\sigma-1}{\theta}} + (1-m)\sum_{d=1}^{D} c_d^{\sigma-1}\right)B_i - m\sum_{j=1}^{N} I_{ij}S_{ij} \quad (14)$$

where I_{ij} is the indicator function that takes the value of one if foreign supplier j is part of the production network of firm i. The fixed cost for foreign supplier j is denoted by S_{ij}, and T_j denotes the technology of the foreign supplier, B_i represents the residual demand, c_j is the input cost of the foreign supplier and c_d is the input cost of the domestic supplier. According to this maximization problem, starting to import with lower input costs or higher technology will decrease the marginal costs. However, a supplier-specific fixed cost S_{ij} is required for an additional linkage or technological upgrade.

This function highlights the interdependencies of supply chain strategy, as the solution to this problem is complex. Furthermore, each decision on supplier is interconnected, given that the function is nonlinear and not additively separable. Hence, it underscores the endogeneity of the production network. Firms can achieve a greater cost advantage by enhancing the technology with the foreign upstream suppliers. Consequently, the endogeneity of network arises from the interdependent decisions on suppliers.

The downstream firm's problem also displays supermodularity in the core productivity φ of firm i and its supply chain characteristics $\sum_{j=1}^{N} I_{ij}T_j c_j^{-\theta}$. As a result, a firm can gain a cost advantage by expanding its supplier network. These implications of the model are also consistent with the empirical findings that exhibit a causal link between prices and supplier characteristics. By attaching a low-cost foreign supplier, a firm can gain a cost advantage.[24] These properties translate into the following proposition:

Proposition 1. The solution to the downstream firm's problem ensures that the choice of foreign suppliers $\sum_{j=1}^{N} I_{ij}T_j c_j^{-\theta}$ is nondecreasing in the productivity of the firm φ for each value of I_{ij}.

This proposition suggests that downstream firms can have superior value chains as

[24]Consistent with empirical findings, the model shows that Chinese suppliers often have higher technology and lower factor costs, represented as c_j, compared to domestic suppliers, whose costs are c_d.

they start to import. Consequently, more productive firms select into better supply chains and benefit from cheaper imported intermediate inputs, resulting in a cost advantage driven by the sophistication of their suppliers. Therefore, the heterogeneity in their production networks leads to different production costs. Firms differ and become more efficient through their advantage in intermediate inputs. In the industry equilibrium, there is a free entry condition, and this equilibrium is characterized by a fixed point for the market potential. Hence, the establishment of a supply chain depends on the maximization of the nonlinear profit function, which features interdependent possibilities among the suppliers. This interdependency of supplier choices endogenizes the network.

5.4 Disruptions in the Network

Disruptions in the supply chains can be modeled as shocks to the fixed costs of suppliers. These shocks can have significant implications for Chinese suppliers, who are more likely to offer low-cost and efficient intermediate inputs due to lower factor costs. As studied in the empirical section, Turkish firms with a more significant share of Chinese suppliers in their value chains are more vulnerable to shocks originating from these disruptions.

When disruptions occur, such as pandemic or natural disasters, the fixed costs of suppliers increase, leading to a decrease in the number of firms that source from the affected Chinese suppliers. Simultaneously, less efficient firms may become unable to source from China. Consequently, there is a reduction in the selection into value chains, resulting in productive and unproductive firms sharing similar production networks. This similarity in production networks reduces competition in the Turkish market. As a result, supply chain disruptions lead to a decrease in labor productivity and an increase in prices for two reasons. The first reason is related to 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 role of supply chains. However, due to the endogenous formation of networks, it is econometrically impossible to test additional implications. To address this issue, this section aims to offer a comprehensive understanding of the relationship between firms and value chains by simulating supply chain disruptions. This section constructs counterfactual value chains to replicate shocks and employs additional tests on sourcing patterns.

Structural estimation begins with the estimation of key parameters to apply the model to the data. This calibration involves four steps and relies on micro-level data on the production network and the simulated method of moments. The first step compares firms' imports across different countries while normalizing it with their domestic intermediate usage to illustrate the heterogeneity across different countries. The second step calculates the productivity dispersion parameter, θ, using domestic production network data while exploring the relationship between supplier productivity and intermediate input purchases.[25] The third step involves estimating demand elasticity by examining firm-level markups. Finally, the last step computes the fixed costs of suppliers in each exporting country using the simulated method of moments.

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

Table 1: 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.

Calculating fixed costs requires the estimation of each firm-supplier link. However, each firm must decide among all possible suppliers, resulting in $2^{suppliers}$ combinations, which is computationally infeasible. To address this challenge, this estimation relies on the algorithm proposed by Jia (2008), as explored in Antras et al. (2017).[26] This study limits its analysis to countries that exported to over 1300 firms in 2019. The aim is to create a sample that includes as many customs transactions as possible for a given country to construct a set comparable to domestic sourcing. Consequently, the sample comprises thirty-two countries, leading to a total of 2^{32} possible choices for each firm except domestic suppliers.[27]

6.1 Sourcing Strategy

The first step requires measuring a firm's tendency to source from different countries compared to domestic sourcing. To achieve this, this part estimates the import share of

[25] Due to data limitations, estimation of this parameter relies upon information from domestic sample.

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

[27] For a list of countries included in the analysis, refer to Table 5 in the Appendix. The structural estimation relies on choices among different foreign suppliers for a feasible estimation.

a country j as m_j. 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 import share based on a country j is defined as:

$$m_j = \frac{T_j}{c_j^{\theta}} \tag{15}$$

where T_j represents the productivity and c_j is the factor cost of the supplier country j, and c_d is the factor cost of the domestic supplier. Production network data enables this calibration to calculate and compare the intermediate input purchases from domestic and international markets. Hence, the normalization of intermediate inputs for each exporting country leads to

$$\frac{X_{ij}}{X_{ii}} = \frac{T_j c_i^{\theta}}{c_d} \tag{16}$$

where X_{ii} represents the total purchases from the domestic market based on VAT data, and X_{ij} represents the imports from country j. By log-linearizing equation 16, the following equation is obtained

$$logX_{ij} - logX_{ii} = logm_j + log\epsilon_j^n \tag{17}$$

where m_j is the import share, ϵ_j^n is the firm-country specific shock.

Based on the information on each importing firm, equation 17 is calculated using OLS to estimate the import shares of each country normalized with domestic sourcing. The dependent variable is the difference between the intermediate input purchase from firm i from country j and its total purchases from the domestic production network. Therefore, each fixed effect corresponds to the import share of the respective country.

The m_j as import shares for each country are presented in Figure 7 on the y-axis, while the x-axis represents the number of firms that import from these countries. According to Figure 7, countries with higher m_j are associated with more importing firms. Based on this relationship, this proxy effectively captures the advantage of importing from a specific country over domestic suppliers or other countries when compared to the number of firms on the y-axis.

This figure shows that China is the most favorable country for Turkish firms. Countries like China, Iran, Germany, and South Korea exhibit a positive m_j for Turkish firms. Consequently, firms tend to import from these countries instead of relying on Turkish suppliers. However, this result is only applicable to certain countries. For instance, countries such as Denmark, Canada, and Portugal have a negative import share that is in contrast to domestic inputs.

In general, the number of importing firms correlates with the estimated m_j, except

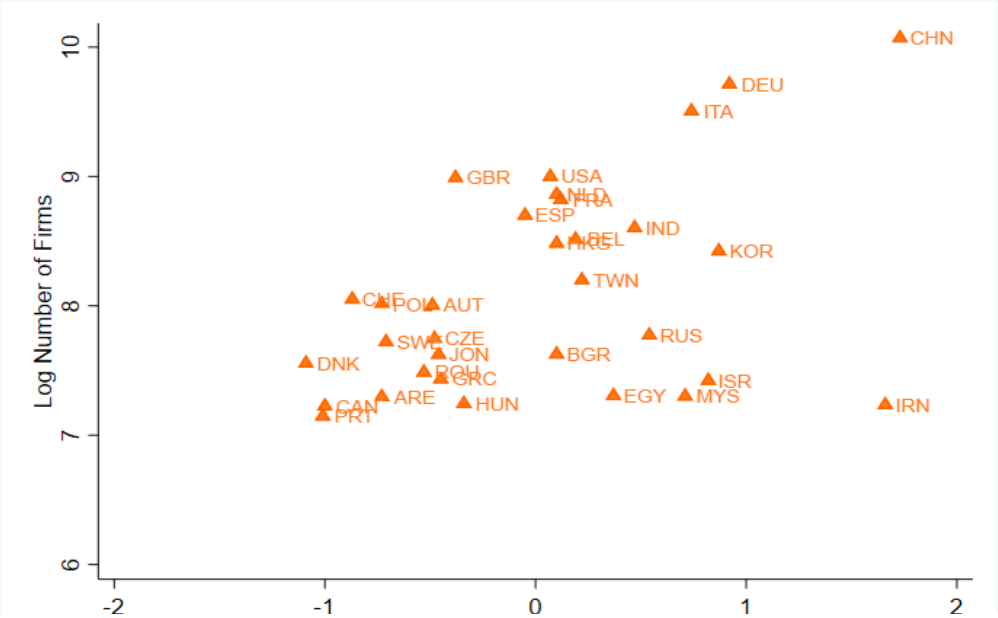


Figure 7: Import Share

Notes: The figure represents the import shares estimated for countries. The x-axis displays the estimated m_j as import share, while the y-axis shows the logarithm of the number of firms.

in the case of Iran. Despite having the second-highest sourcing advantage, firms tend to avoid trading with Iran due to economic sanctions imposed by the United States and the European Union. Therefore, Iran appears as an outlier in Figure 7.

6.2 Productivity Dispersion

One of the critical questions in this paper is the role of supplier technology. In the model, supplier productivity corresponds to the productivity dispersion parameter θ, which represents the firm-level trade elasticity. Domestic production network data enables this study to estimate this parameter because it provides information about the characteristics and productivity of the suppliers. By tracking business-to-business transactions, this part focuses on the relationship between supplier productivity and sourcing patterns in the domestic market.

With this dataset, this part aims to estimate the productivity dispersion parameter to understand the extent to which firms connect with productive suppliers. The intuition behind this estimation is to gain insight into purchases from effective suppliers while considering other controls that affect the supply chain. Firstly, the shares of each domestic supplier is calculated. Secondly, the objective is to examine the link between the sourcing shares and the productivity of the suppliers.

The following analysis relies on the shares of domestic suppliers, denoted as m_d, and its relationship with productivity, location, and intermediate input trade, while

accounting for supplier and customer fixed effects. The estimation presented here projects the shares among domestic suppliers onto proxies for m_d

$$logm_d = \beta_1 Productivity_d + \beta_2 logdistance_{id} + \beta_3 logintermediate_{id} + \lambda_d + \gamma_i \quad (18)$$

where m_d is the share of the domestic supplier among the all domestic suppliers of the firm, $Productivity_d$ is the total factor productivity of the domestic supplier, $logdistance_{id}$ is the logarithm of the distance in kilometers between the cities of the supplier and customer pairs, $logintermediate_{id}$ represents the volume of the transaction, λ_d is the domestic supplier dummy, and γ_i is the buyer dummy.

	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 2: Productivity Dispersion and Sourcing

Notes: The table displays the coefficients obtained using all buyer-supplier connections at the firm level. The p-values are shown in parentheses.

The main interest in this exercise is the β_1, which represents the productivity dispersion parameter. It indicates how sourcing strategy of firms is inclined towards more productive suppliers with the data on domestic supplier productivity, with other variables serving as controls.[28] The regression results are presented in Table 2. Several key takeaways emerge from this regression. The productivity dispersion parameter, θ, is 1.971 and significant, suggesting that firms tend to prefer more productive suppliers. On the contrary, distance remains a notable factor with a coefficient of -0.288,

[28]The calculation of productivity the domestic supplier follows Levinsohn and Petrin (2003) as discussed in the Facts Section.

highlighting the negative association between distance and sourcing strategy. Another important finding is that as trade volume among customer and suppliers increases, firms tend to choose suppliers that they trade more. However, this volume effect is relatively small when compared to the impact of supplier technology and distance. Consequently, these results highlight that productivity is a critical factor in supplier selection.

6.3 Demand Elasticity

The demand elasticity is calculated with the given monopolistic competition and CES preferences in the model. This demand elasticity can be approximated by the average markup, which is the ratio of a firm's gross sales to its total expenditures, including wages, intermediate input purchases, and other expenses. Based on this ratio, the average markup for Turkish firms is 38%, corresponding to the demand elasticity of 3.93.

Calculating demand elasticity and productivity dispersion raises the question of whether the suppliers are complements or substitutes. This distinction can be determined by examining the value of $\frac{\sigma-1}{\theta}$. If this value exceeds one, then suppliers are complements; otherwise, they are substitutes. Plugging in the estimated values, with θ at 1.971 and σ at 3.63, yields a value of $\frac{\sigma-1}{\theta}$ equal to 1.34. This value, being higher than one, suggests that these upstream suppliers for downstream firms are complements. This finding is also consistent with empirical evidence, as supply chain disruptions can lead to price increases and productivity losses due to the complementarity of suppliers. Furthermore, this complementarity provides evidence of supply chain heterogeneity even at the firm level.

6.4 Firm-Supplier Country Fixed Costs

This paper argues that firms select into foreign suppliers associated with varying fixed costs for each supplier. However, estimating this supplier fixed costs requires a simulation-based technique using the estimated model parameters. This section presents the computation of firm-supplier fixed costs using the simulated method of moments.

Calculating these fixed costs begins with simulating firms and comparing their supply chain decisions based on firm-level data. Hence, the focus is on the mechanism of how firms choose their suppliers according to the model predictions. The computation of these costs initiates with the formation of the supply chain, and the final step involves comparing the aggregate moments from the model with the data.

The simulation follows several consecutive steps and simulates numerous firms with varying core efficiencies.[29] The second step translates the maximization problem based

[29]This core efficiency of downstream firms is denoted as ϕ and is assumed to vary among firms.

on the firms' supplier choices. The third step computes the supplier set for Turkish firms, which includes thirty-one interdependent options from various countries, including Chinese suppliers. The final step backs up parameters from the simulation.

Supplier fixed costs depend on gravity variables, including distance, language, and corruption depending on the country of the supplier. These fixed costs are drawn from a lognormal distribution with a dispersion parameter and are scaled as $log\beta_c^f + \beta_d^f log(distance_{ij}) + \beta_l^f log(language_{ij}) + \beta_c^f log(corruption_{ij})$. The algorithm estimates the residual demand, the coefficients of corruption, distance, language, and the dispersion parameter.[30]

Another critical feature of the simulation is the variation in downstream-upstream productivity matches. To construct these matches, each core productivity draw for downstream firms interacted with the fixed cost draws of upstream firms to determine the measure for $z_j(m)$ in the model. Hence, each firm-supplier fixed cost is different due to these interactions. Due to the interdependent choices, firms must select suppliers from among $2^{suppliers}$.[31] Consequently, a simulated firm must make decision about its supply chain among 2^{31} options, representing the countries of suppliers. However, this estimation is not computationally feasible. To address this challenge, this study relies on the algorithm developed by Jia (2008), which was adopted following Antras et al. (2017).[32]

6.5 Model Fit

To assess the model predictions, it is necessary to understand the link between simulated firms and the data. One way to examine this is by computing how import shares of different countries vary among the simulated firms and the actual data. This section investigates the model predictions for the moments.[33] The first moment, the share of importers by country, is presented for both the data and the simulated share for each country in Figure 7.

Following Melitz and Redding (2015), the efficiency of these firms follows the Pareto distribution with a shape parameter of 4.25.

[30] Values are reported in Table 4 in the Appendix.

[31] Since information on firm-to-firm links is unavailable for imports, this analysis focuses on firm-to-country links for fixed costs.

[32] Each simulated firm forms its optimal production networks by selecting its suppliers. Because these sourcing decisions are interdependent, this analysis establishes lower and upper bounds for each firm's decision following Jia (2008). Lower and upper bounds are calculated for each firm. The lower bound begins with zero suppliers and then adds a new supplier only if it contributes to the firm's profits. Conversely, the upper bound assumes that the firm sources from all thirty-two countries and eliminates suppliers to compare the resulting firm profit. With these given lower and upper bounds, the optimal choice of suppliers is determined.

[33] In this analysis, Iran is not included in the sample. As shown in Figure 7, Iran is an outlier due to international sanctions.

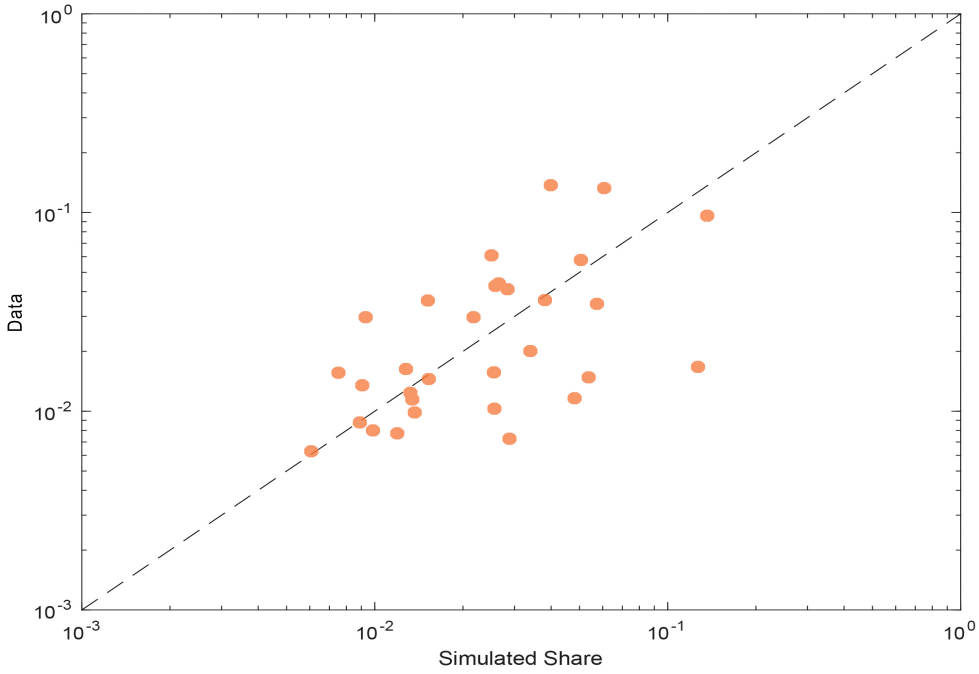


Figure 8: Model Fit

Notes: This graph displays importer shares for various countries. The shares of firms from micro-data are plotted on the y-axis, while the simulated percentages are plotted on the x-axis.

Based on the fit, the model successfully replicates supplier choices. With this fit, the following section constructs counterfactual supply chains to simulate the impact of supply chain resilience on firms in the model. Hence, it is possible to understand how prices and sourcing patterns are associated with various adverse shocks to supply chains.

7 Counterfactual Scenarios

This paper demonstrates the critical implications of disruptions in value chains. This section goes further by constructing counterfactual supply chains involving two scenarios. First, a new value chain is created where all suppliers share the same fixed cost for the sample. Importantly, these costs are exogenously imposed to compare baseline results on prices, number of importers and importer shares to detect the role of sourcing strategies depending on the fixed costs. Hence, it is possible to understand how these variables react to changes in their production networks. The second counterfactual exercise aims to simulate the impact of the pandemic and how supplier selection changes after implementing different fixed costs on Chinese suppliers.

7.1 Counterfactual Supply Chains

The counterfactual supply chains are constructed through network modifications. For each modification, a fixed cost is assumed to be imposed to all possible suppliers of the firm, including domestic and foreign suppliers. There are three counterfactual supply chains in this section. These counterfactual supply chains are constructed by exogenously imposing the same fixed costs of Chinese, Greek, and Turkish suppliers to all possible choices of foreign suppliers.

In this exercise, China is chosen for comparison in order to assess the empirical findings. Greece is specifically chosen as an example to illustrate lower fixed costs for suppliers when compared to China, given that supplier fixed costs are contingent on gravity variables. Subsequently, it recalculates the number of importers, the share of importers from different countries, and the aggregate price index in the counterfactual scenario. The aggregate price index is calculated using equation 4 in the model.

	China	Greece	Turkey
Price	↑	↓	↓
% *of Importers*	↓	↑	↑
% *of Importers from China*	↓	↑	↑
% *of Importers from Greece*	↓	↓	↑
% *of Importers from Taiwan*	↑	↑	↑
% *of Importers from U.S.*	↑	↑	↑

Table 3: Counterfactual Supply Chains

Notes: This table reports how prices, number of importer firms, and share of importers from different countries react to the new fixed costs compared to the baseline scenario.

The impact of these counterfactual supply chains is presented in Table 3. In each case, firms adjust their supplier arrangements in response to the exogenously imposed fixed costs on suppliers. These adjustments lead to changes in the equilibrium price index compared to the baseline. Consequently, the number of importing firms changes, and there is a reconfiguration in sourcing decisions among other suppliers. More interestingly, these responses depend on the source of the shock.

This test represented in Table 3 involves counterfactual supply chains with fixed costs equal to those of Chinese or Greek suppliers. If all fixed fees across all countries

are adjusted to match those in Greece, prices in Turkey would decline. Conversely, aligning them with China has the opposite effect. Moreover, the number of importers demonstrates a similar response to these adjustments. When fixed costs are standardized to those of Greek suppliers for all countries, Turkish firms redirect their imports away from Greece towards other destinations. Conversely, when prices are adjusted to match those in China, firms shift their imports from China and Greece towards Taiwan and the United States. These results also emphasize how firms react differently to varying fixed costs along the value chain.

In the final case, foreign suppliers incur the same costs as suppliers in Turkey. Compared to the baseline, a larger number of firms start importing compared to the baseline. This scenario essentially reflects a supply chain devoid of tariffs. Following this external modification, the aggregate price index in Turkey decreases, prompting firms to boost their imports from a range of countries, such as China, Greece, Taiwan, and the United States.

7.2 Simulated Disruptions

This second counterfactual scenario simulates disruptions, aiming to be compatible with the empirical part and to understand the impact of the pandemic. It focuses on Chinese suppliers while keeping other variables constant. The goal is to mimic the supply chain disruptions and test the effects on supplier selection and results reported in Figures 9 and 10.

Adverse shocks to the costs of Chinese suppliers were implemented by increasing their fixed costs by one hundred percentage points. With the increase in expenses, firms shifted from Chinese suppliers to other countries, including Hong Kong, South Korea, and Taiwan. Furthermore, the share of importing firms initially increased, reflecting China's role in both direct and indirect Turkish imports. However, with a significant rise in costs for Chinese suppliers, the overall share of Turkish importers decreased by almost thirty percentage points compared to the baseline.

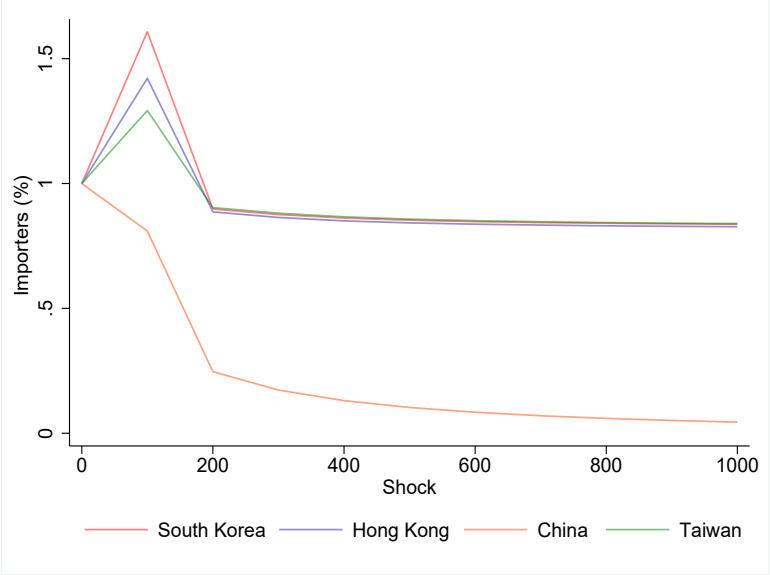
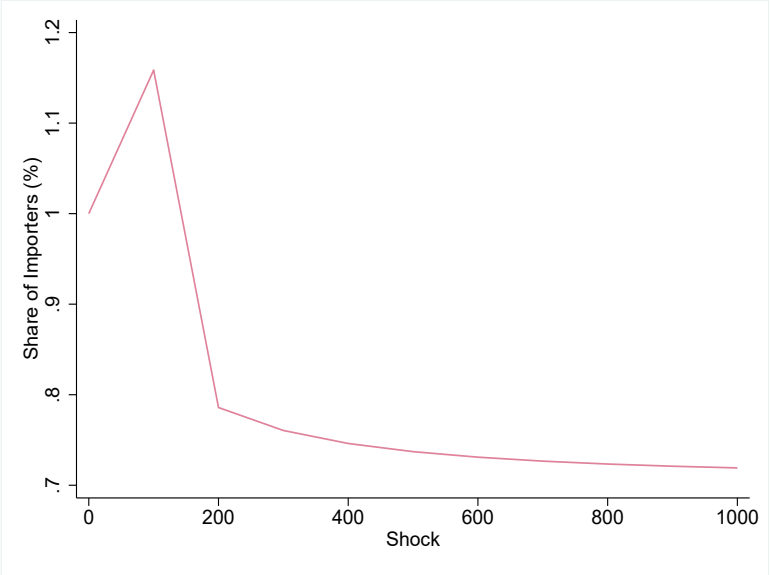


Figure 9: Counterfactual Disruptions: Shifts in Sourcing Strategies

Notes: The coefficients in these figures represent the relative shares compared to baseline estimates. There are ten types of adverse shocks, starting with a 100% exogenous increase in fixed costs for Chinese suppliers.



(a) Share of Importer Firms

Figure 10: Counterfactual Disruptions: Share of Importers

Notes: The coefficients in these figures represent the relative shares compared to baseline estimates. There are ten types of adverse shocks, starting with a 100% exogenous increase in fixed costs for Chinese suppliers.

8 Conclusion

This paper contributes to the literature by presenting the causal impact of supply chain disruptions on prices and sourcing strategies. To achieve this goal, it revisits the gains from trade and suggests a selection mechanism into superior suppliers and complementarity among these suppliers at the firm level. Through empirical, theoretical, and quantitative evidence, this paper reveals the significant influence of sourcing strategies on firm dynamics.

The empirical evidence begins by identifying productive clusters in production networks, highlighting the tendency of productive suppliers to align with more efficient firms. To provide a causal estimate, this study proposes a novel identification strategy that explores the impact of disruptions caused by Chinese suppliers during the lockdown and isolates this supply shock and measure the impact. The findings indicate that firms impacted by supply chain disruptions raise their prices by 26.9% compared to other importers and increase their number of domestic suppliers by 45.5%. Furthermore, the impact of these supply chain disruptions persists over time. The results emphasize that the switch from Chinese suppliers to domestic ones impacts firm performance and highlights the crucial role of suppliers at the micro-level. These results also have critical policy implications, illustrating the importance of supplier heterogeneity in prices and production networks.

To rationalize these findings, this paper develops an endogenous production network model, where firms are heterogeneous regarding their ability to purchase intermediate input from domestic and foreign suppliers. As firms expand their networks, they become more productive due to relationship-specific productivity gains through their imported inputs, but having a foreign supplier is associated with a supplier-specific fixed costs that depends on the country of origin. The decisions regarding their suppliers, made among interdependent choices of sourcing strategies, demonstrate the endogenous nature of production networks. One way to interpret the supply chain disruptions is as an increase in the fixed costs of suppliers, that results in higher prices and a reduction in firm performance.

The quantitative analysis constructs counterfactual supply chains following the calibration of the model using firm-to-firm networks and the simulated method of moments. Counterfactual supply chains are created by exogenously imposing varying fixed costs on suppliers to simulate supply chain disruptions. According to the results, prices and selection mechanisms in networks react differently to these disruptions, depending on the origin of the supplier.

The findings in this paper also carry significant policy implications. In terms of macro

and industrial policies, they illuminate the origins of inflation diffusion through supply chains. Furthermore, by highlighting the impact of supplier heterogeneity on prices, macro policies must take into account the micro origins of inflation and the importance of resilient supply chains for the aggregate economy.

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Appendix A. Theoretical Appendix

Uniqueness of B_i

The problem of downstream firms depends on the residual demand B_i and exogenous parameters, allowing to identify the uniqueness of market demand among all pairs of upstream and downstream firms.

Since there is a free entry condition f_e and let $m = 1$, then f_e can be described as

$$f_e = B_i \int_{\varphi_{im(i)}}^{\infty} (\gamma \Theta_i(\varphi) c_j)^{\frac{(\sigma-1)}{\theta}} \varphi^{\sigma-1} dG_i(\varphi) - \int_{\varphi_{im(i)}}^{\infty} \sum_{j \in S_i(\varphi)} S_{ij} dG_i(\varphi) \tag{19}$$

where $j(i)$ is the upstream firm that supplies intermediate inputs to the least productive firm and Θ_i is the all avaliable suppliers.

$$(\varphi_{ij(i)})^{\sigma-1} B_i (\gamma T_{j(i)} (\frac{S_{j(m)}}{c_j})^{-\theta})^{\frac{(\sigma-1)}{\theta}} = S_{ij(i)} \tag{20}$$

Taking the derivative of the equation 19 with respect to residual demand B_i and replacing by equation 20 leads to

$$\int_{\varphi_{ij(i)}}^{\infty} \frac{d(\varphi^{\sigma-1} (\gamma \Theta_i(\varphi))^{\frac{(\sigma-1)}{\theta}} B_i - c_j \sum_{j \in S_i(\varphi)} S_{ij}}{dB_i} dG_{i(\varphi)} > 0 \tag{21}$$

If the downstream firm keeps the supply chain constant, an increase in the market demand will raise the downstream firm i's profits. Therefore, the right side of the equation 19 monotonically increases with B_i. Moreover, as $B_i \to \infty$, all firms can source from each upstream firm:

$$B_i (\gamma T_{m(i)} (c_j)^{-\theta})^{\frac{(\sigma-1)}{\theta}} - S_{ij} \tag{22}$$

which goes to infinity.

Proof of Proposition 1

Assume two different downstream firms have productivities φ_1 and φ_2 where the first firm is more productive than the second firm. Also, the firms' supply chains are defined as $S_1(\varphi_1)$ and $S_2(\varphi_2)$. The first firm with higher productivity φ_1 choose $S_1(\varphi_1)$ rather than $S_2(\varphi_2)$ requires the profits of two supply chains to be

$$\varphi_1^{\sigma-1}(\gamma\Theta_i S_i(\varphi_1)c_j)^{\frac{\sigma-1}{\theta}}B_i - \sum_{j\in S_i(\varphi_1)} I_{ij}S_{ij} > \varphi_2^{\sigma-1}(\gamma\Theta_i S_i(\varphi_2)c_j)^{\frac{\sigma-1}{\theta}}B_i - \sum_{j\in S_i(\varphi_2)} I_{ij}S_{ij} \quad (23)$$

On the contrary, the second firm that has lower productivity selects its supply chain based on the condition

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

with these two profit functions,

$$[\varphi_1^{\sigma-1} - \varphi_2^{\sigma-1}][\Theta_i S_i(\varphi_1))^{\frac{\sigma-1}{\theta}} - \Theta_i S_i(\varphi_2))^{\frac{\sigma-1}{\theta}}]\gamma^{\frac{\sigma-1}{\theta}}B_i > 0 \quad (25)$$

Since the first firm is more productive than the second one, the supplier set for the more productive firm should be larger. Therefore, this equation represents the selection of superior suppliers by more productive firms.

Technology of the Suppliers

The most crucial assumption in this study is that the technology of upstream suppliers producing intermediate inputs varies. Additionally, these upstream firms draw their productivities from a Frèchet distribution. To test the validity of this assumption, this section relies on microdata to examine the probability density function of supplier productivity by relying on the Ackerberg et al. (2015) and intermediate inputs as a proxy for the estimation of TFP.

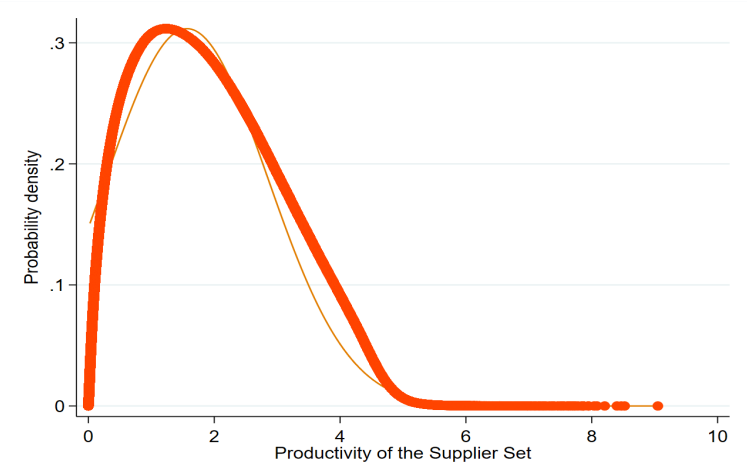
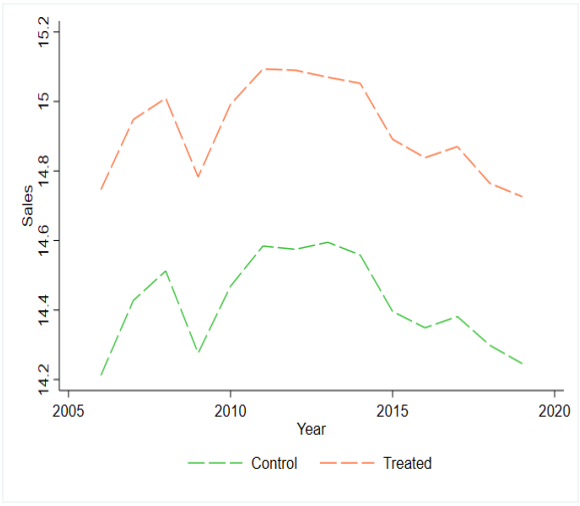


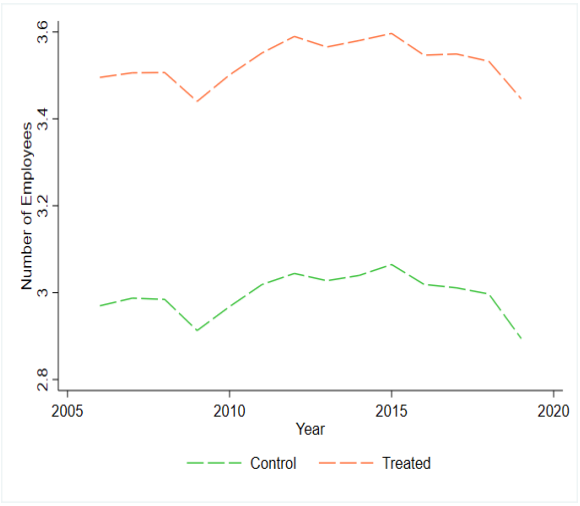
Figure 11: Probability Density Function

Appendix B Empirical Appendix

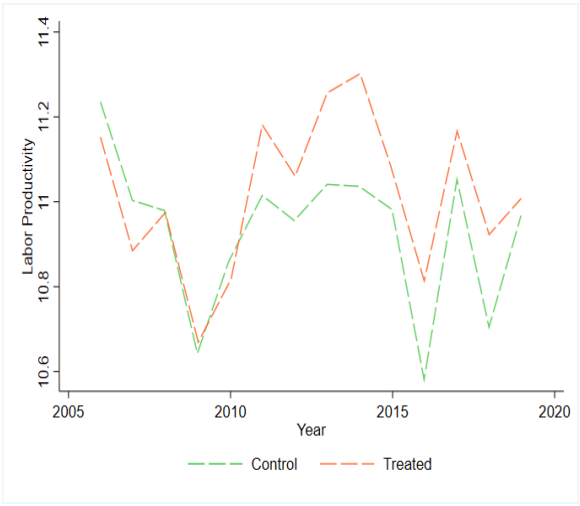
The following graphs examine the pretrends of the control and treated groups from 2006 to 2019. These graphs display the mean of sales, the number of employees, labor productivity, and TFP for each group. The orange line represents firms that import from China, while the green line represents trends for firms that import from other countries. According to these graphs, these groups exhibit parallel trends in the absence of the Chinese lockdown.



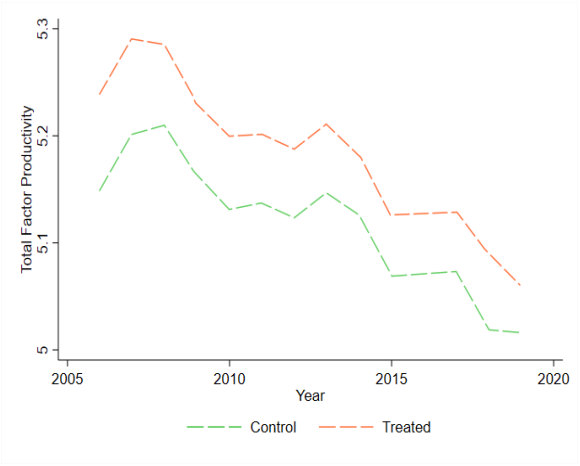
(a) Sales



(b) Number of Full-Time Employees



(c) Labor Productivity



(d) Total Factor Productivity

Figure 12: Pretrends before 2020

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

Robustness of the Estimation Strategy

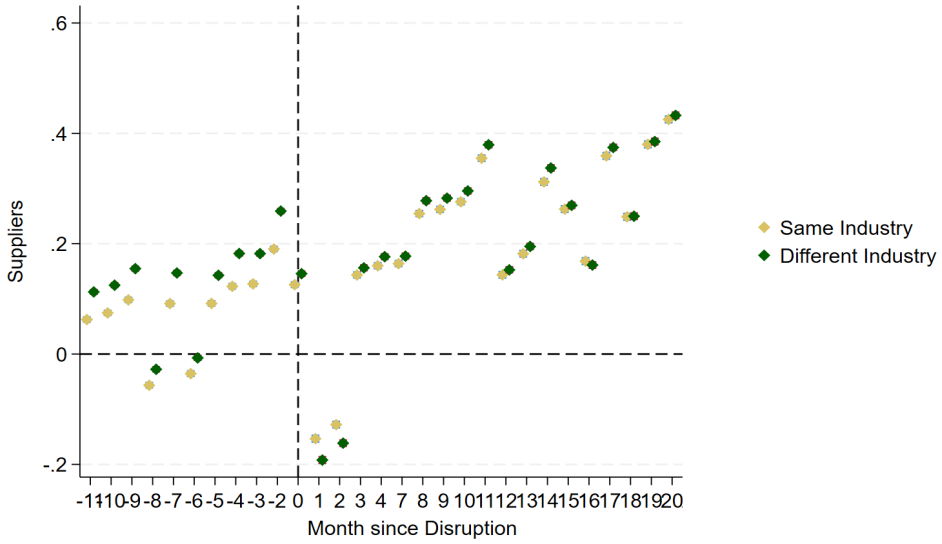


Figure 13: Sector of Domestic Suppliers

Notes: This figure displays the estimated coefficients for the number of domestic suppliers, decomposed according to their two-digit NACE Rev2 sectors, and confidence intervals for each period in an event study using early lockdown in China. The coefficient is normalized to zero at the baseline ($t = -1$), and all estimates account for firm, region-month, and four-digit industry-month fixed effects.

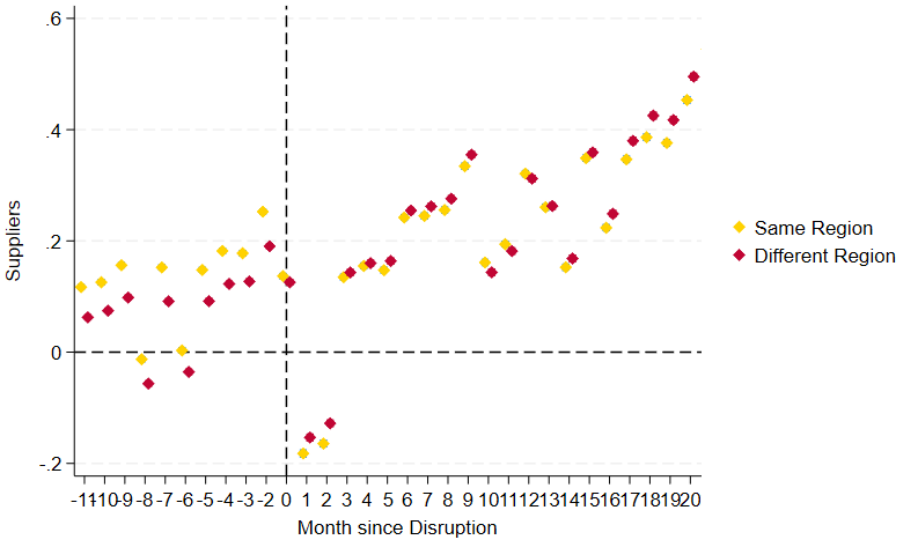


Figure 14: Regions of Domestic Suppliers

Notes: This figure displays the estimated coefficients for the number of domestic suppliers, decomposed according to their NUTS1 regions, and confidence intervals for each period in an event study using early lockdown in China. The coefficient is normalized to zero at the baseline ($t = -1$), and all estimates account for firm, region-month, and four-digit industry-month fixed effects.

Robustness to Broad Economic Category Classification

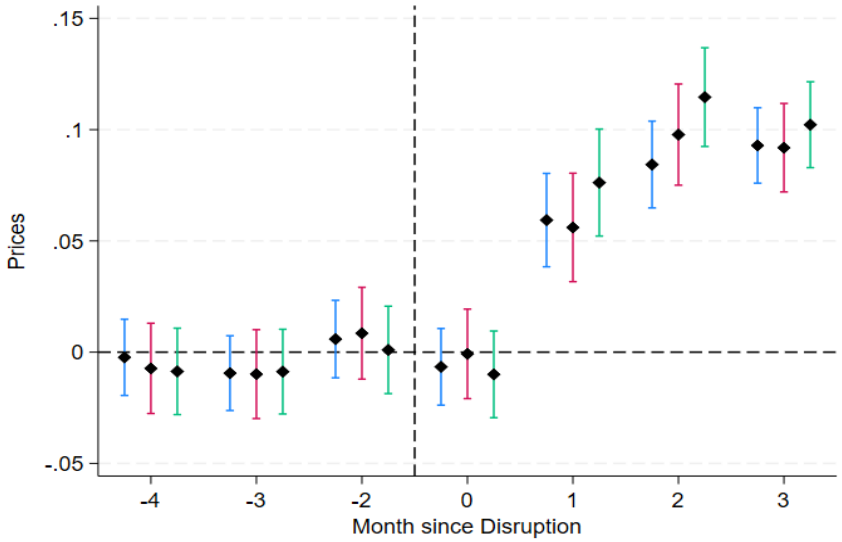


Figure 15: Prices after the Lockdown for Different Classifications

Notes: These figures display the estimated coefficients and confidence intervals for each period in an event study using early lockdown in China. The coefficient is normalized to zero at the baseline ($t = -1$), and all estimates account for firm, destination, region-month and four-digit industry-month fixed effects. The blue confidence interval corresponds to coefficients calculated for intermediate importers from China, the red confidence interval corresponds to importers of capital goods from China, and the green confidence interval demonstrates importers of final goods.

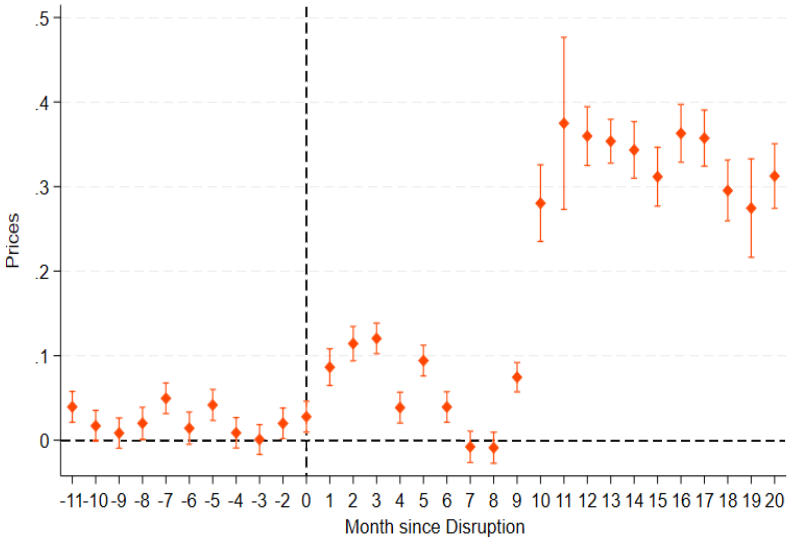


Figure 16: Robustness: Only Intermediate Input Importers

Notes: This figure displays the estimated coefficients for prices and confidence intervals for each period in an event study using early lockdown in China. The coefficient is normalized to zero at the baseline ($t = -1$), and all estimates account for firm, region-month and four-digit industry-month fixed effects.

Appendix C. Structural Appendix

Implementation of this algorithm requires the property of increasing differences in the maximization problem, which is estimated as $\frac{\sigma-1}{\theta} = 1.34$. Let $\Pi(N)$ represent the maximization problem depending on the supplier set N of the firm, and let N^* be the optimal solution. The algorithm initiates with N^0 suppliers and computes the sequence as $N^1 = M(N^0)$ and $N^{t+1} = M(N^t)$. The problem of increasing differences ensures that $N^1 \geq N^2$, and the iteration results in a decreasing sequence: $N^0 \geq N^1 \geq ....\geq N^x$. Since N^0 has only k distinct elements with a one-step element change from 1 to 0 in each step, iterating this process converges within k steps, as $N^t = N^{t+1}$ when T is smaller than or equal to k.

Let N^u be the convergent vector, representing the largest element that yields the highest firm profit and serving as the upper bound for the firm's suppliers. Similarly, N^l starts from zero and iteratively adds new suppliers, establishing the lower bound. With these bounds in place, the estimation considers all potential suppliers within this range to determine the optimal suppliers that maximize the profit.

The aim of the simulated method of moments is to minimize the squared percentage distances. There are two sets of moments. The first moment compares the importer shares in different countries, including the simulated data $\tilde{m_1}(\delta)$ and the share of importers in the actual data for each country $m_1(\delta)$. The second moment compares the percentage of firms that have a lower input share than the average, denoted as $m_2(\delta)$, and simulates them as $\tilde{m_2}(\delta)$. These parameter estimates for residual demand and gravity are reported in Table 4.

The objective function y is based on the differences in these two moments.

$$\begin{bmatrix} m1 - \tilde{m_1}(\delta) \\ m2 - \tilde{m_2}(\delta) \end{bmatrix} \tag{26}$$

The moments are assumed to be weighted equally with W representing the weighting matrix that corresponds to the identity matrix. For the true parameter value δ^*, it follows the assumption

$$E[\tilde{y}(\delta^*))] = 0 \tag{27}$$

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

$$\tilde{\delta} = argmin_{\delta}[\tilde{y}(\delta)]^T W[\tilde{y}(\delta)] \tag{28}$$

The estimated parameters indicate that supplier costs increase with distance, while corruption and a common language have a negative impact. In terms of magnitude,

	Corruption	*Demand*	*Distance*	*Language*
Estimated Parameter	-0.002	0.222	2.849	-0.557

Table 4: 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.

fixed costs are primarily influenced by the distance of the supplier. Regarding language, firms that trade with suppliers with similar languages tend to have lower supplier costs. Interestingly, the corruption parameter conflicts with the literature; however, this coefficient is negligible when compared to other effects.

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 5: Countries in the Quantitative Analysis

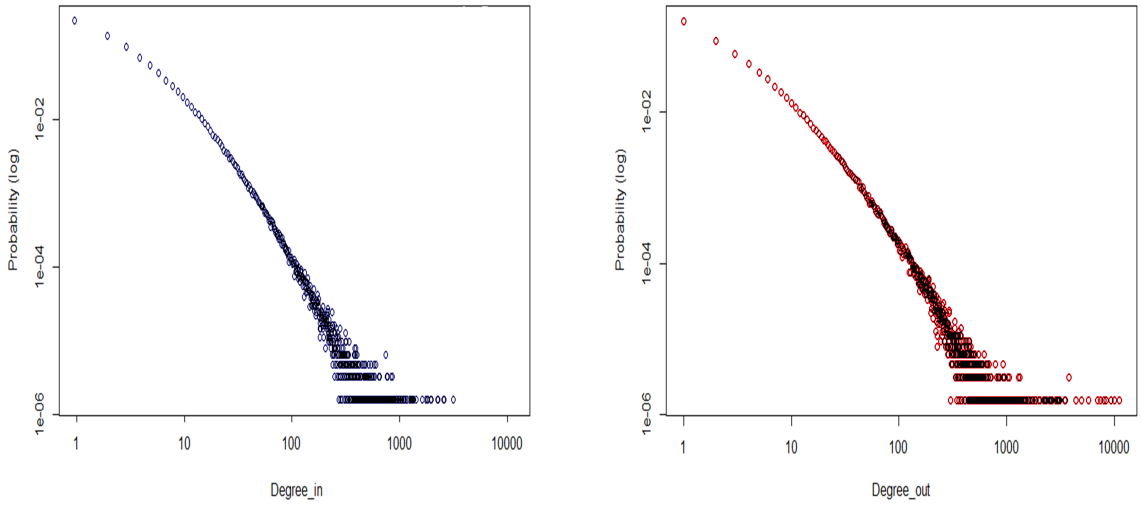
Notes: This table presents the number of importers from different countries in 2019.

Appendix D. Data Appendix

Firm-level Distribution

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

This part investigates the degree distributions in the supply chain, and the calculation of the weighted in- and out-degrees relies on the number and weights in the production network. Figure 17 represents the probability mass function of manufacturing firms. The proxy for the weighted out-degree is sales, while intermediate inputs are used to demonstrate the weighted in-degree. These degree distributions are skewed, reflecting the asymmetry in the supply chain.



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

Figure 17: Firm-level Weighted Degree Distributions

The firms located in the right tail of these 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 these firms in the tails, their impact on the economy will not vanish in the long run. As suppliers or customers of intermediate inputs, some firms can be "too connected to fail". Findings in this study underline the sparsity of the Turkish production network as linkages across firms follow power laws.[34]

$$p_k = ck^{-\zeta} \tag{29}$$

[34] 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.

	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 6: 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.

The estimated tail parameters for the supply chain are shown in Table 6. From 2006 to 2017, both in-degrees and out-degrees follow a power-law distribution. [35] These results highlight how the production economy lacks diversification, resulting in a concentration of mass in the tail. Consequently, micro shocks associated with supply chain disruptions propagate through the production networks and have aggregate effects.

[35] Values of Ksp smaller than 0.5 indicate that there is no evidence to suggest that the distribution is not a power-law.