Imperfect Competition and the Transmission of Shocks: The Network Matters*

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This paper studies the aggregate implications of the firm-to-firm production network structure. Using a dataset on all domestic transactions between Belgian firms, we establish two facts: firms charge higher markups if they have higher input shares within their customers, and firms experience larger churn of suppliers if they face a larger reduction in foreign goods' prices. Motivated by these two facts, we build a model where firms compete as oligopolies to supply inputs to each customer and where firms optimally choose their suppliers. The network structure becomes irrelevant in a benchmark case where we impose perfect competition and hold the network fixed. In this case, firm-level variables are sufficient to compute the welfare response to a large fall in import prices. Allowing for oligopolistic competition generates two counteracting forces within supplier-customer pairs. A supplier raises its markup to a customer when its costs decline, but it reduces the markup if other firms supplying the same customer receive the shock. Further, allowing for endogenous networks amplifies the impact of the shock as firms begin importing and begin sourcing from other firms exposed to the import shock. Due to the omission of these dynamics, the aggregate response in the benchmark case is less than one quarter of those in the full estimated model.

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1 Introduction

Does the structure of the firm-to-firm production network affect how the economy responds to shocks in the aggregate? Results from Hulten (1978) imply that the network structure is irrelevant up to a first order approximation in an efficient and closed economy. Under perfect competition and fixed network structures, firm-level variables such as firms' total sales, are sufficient in evaluating how aggregate variables respond to firm-level shocks. Due to this theoretical result and the scarcity of data on firm-to-firm transactions, the literature has widely assumed away the possibility that the network structure matters, or assumed network structures in which firm-level information is sufficient to work with.

In this paper, we analyze a detailed administrative dataset on all domestic firm-to-firm transactions in Belgium and establish two novel facts. First, firms charge higher average markups when they have larger input shares within their customers. This holds even after controlling for the firms' sectoral market shares. In addition, the variations in our metric of average input share within the customer firms are more important in predicting firms' profitability than those of the commonly used metric of sectoral market share. These results suggest that in addition to the *firm-level* market share within the sector, the firm's pairwise input shares to each customer capture the *pair-level* pricing power that the firm has to each of its customers. Second, we evaluate how firms alter linkages in response to an exogenous reduction in import prices. We borrow insights from Autor, Dorn, and Hanson (2013) and Hummels, Jørgensen, Munch, and Xiang (2014) and take the increase in firms' imports from China in the 2000s as a trade shock. We find that the more exposed the firms are to the import supply shocks, the more churn they have in their suppliers.

Motivated by these facts, we build a model that has two key departures from perfect competition and fixed network structures. The first departure is oligopolistic competition in firm-to-firm trade where firms charge different markups to each customer firm. The relative size of the supplier in the total input sourcing of each customer becomes the relevant determinant of the supplier's markup on that transaction. This is in contrast with a setting in which firms' sectoral market shares determine their firm-level market power. The second departure is endogenous network formation, where firms face fixed costs and optimally choose which firms to supply from.

Our model presents a network irrelevance result in the benchmark case where we shut down both oligopolistic competition and endogenous networks. In addition to perfect competition and fixed networks, this benchmark case imposes strong restrictions: exports are in terms of composite final goods, and there is common substitutability across goods in technology and preference. In this case, shocks still transmit to other firms along the production chain. But firm-level variables such as firms' total sales and their direct exposure to the shock, become sufficient statistics for evaluating global changes in the aggregate variables.

We model oligopolistic competition with a nested CES structure as in Atkeson and Burstein (2008). Rather than the more conventional implementation where a firm's share in the sector's purchases determine its elasticity and markup, in our model a firm charges a higher markup to a customer when its share in that customer's purchases is larger. This departure leads to two counteracting effects on aggregate variables. First, variable markups imply there will be an incomplete pass-through from a supplier's input price reduction to its output price reduction since the supplier will increase its markup, what we call the "attenuation effect." Second, the other suppliers that sell goods to the same customer will reduce their markups in face of increased competition, what we call the "pro-competitive effect."

We model endogenous network formation as firms choosing which set of suppliers to source from. They additionally decide whether to import and/or export. Each linkage requires payment of a fixed cost and firms maximize their net profits given other firms' sourcing decisions and prices. Upon a reduction in foreign price, firms can start to directly import from abroad. They can additionally source from firms whose goods have become relatively cheaper. These will amplify the aggregate response to the foreign price reduction as the input costs of firms that changed suppliers discretely drop.

Guided by our model, we estimate the CES parameters so that the firm-level average markups – averages of the model implied markups on sales to other producers and to the final consumer – provide best fit of those implied from the data. We then study how the aggregate price index and welfare respond to the reduction in a foreign good's price. We start by analyzing the predictions from the benchmark case where the network structure is irrelevant. We then investigate how adding oligopolistic competition and endogenous networks alter aggregate predictions.

When evaluating the model with oligopolistic competition and fixed networks, we compute the changes in the aggregate price index using the observed input shares and the estimated CES parameters following a technique developed by Dekle, Eaton, and Kortum (2007). We find that oligopolistic competition in firm-to-firm trade slightly attenuates movements in the aggregate price index. The magnitudes of the net effects are small because the attenuation and pro-competitive effects largely cancel each other out in each customer firm's input market. Nevertheless, we analytically characterize the magnitudes of the two and their net effects. We demonstrate that a measure of the firm's exposure to the shock, either directly or indirectly through its suppliers, can help us understand whether the firm faces higher or lower markups on average. Moreover, we argue that the nature of the shock is also key in determining the magnitudes of the net effects. The shock of foreign price reduction hitting all the importers produces small net attenuation effect. But if the same price reduction hits only a single importer, the magnitudes of the net attenuation effects become much larger.

For the analysis of the model with endogenous networks, we rely on simulations of the estimated model. We use a model with a smaller set of firms, since simulating an endogenous network with the number of firms observed in the data is computationally infeasible. Even so, we find that endogenous networks significantly amplify aggregate responses.

Overall, the benchmark case can capture less than a quarter of aggregate responses that are implied by our estimated full model. The differences in aggregate responses are mostly driven by firms switching from non-importers to importers. In addition, we also find that oligopolistic competition in firm-to-firm trade makes a quantitative difference in aggregate responses through its interaction with endogenous networks. In our model, oligopolistic competition means that firms face a greater degree of double marginalization compared to a case where firms engage in monopolistic competition. Firms face higher markups in each transaction, and they accumulate throughout the firm-to-firm network. Higher input costs alter firms' decisions in choosing their suppliers.

This paper is closely related to the growing body of literature that studies aggregate outcomes beyond the network irrelevance result of Hulten (1978). Baqaee (2014) theoretically shows that extensive margins of firm entry and exit can amplify idiosyncratic shocks. Baqaee and Farhi (2017) analyze the importance of second order effects of firm-level TFP shocks. They emphasize the roles of substitutability across inputs, returns to scale, factor reallocation, and structure of the network.[1] While they focus on second order effects in an economy without market frictions, we focus on how market frictions produce different aggregate outcomes in response to large shocks. We specifically focus on two deviations from the efficient economy, which we find to be relevant in the data: oligopolistic competition in firm-to-firm trade and endogenous networks.

We build on the literature that focuses on the aggregate implications of oligopolistic competition. Grassi (2016) develops a model in which firms engage in oligopolistic competition in an economy with sectoral input-output linkages and studies the contribution of firm-level shocks on the aggregate dynamics.[2] Effects similar to our attenuation and pro-competitive effects are studied extensively in other contexts. For example, Feenstra, Gagnon, and Knetter (1996) study how the degree of price pass-through varies with the firm's export market share. Amiti, Itskhoki, and Konings (2017) study how firms prices respond to changes in the prices of their competitors. Atkeson and Burstein (2008) focus on incomplete price pass-through to explain deviations of international relative prices from relative PPP.[3] All these papers analyze oligopolistic competition where firms compete with others within the same sector, implying that the firm's market power is captured by its market share in its sector.[4] In contrast to these papers, we propose a novel view on competition between firms. Instead of the *firm-level* market share within the sector being the determinant of the firm's market power, we suggest that the *pair-level* input shares across its customers are the relevant metrics for the firm's ability to charge markups.

This paper is also related to papers that study the aggregate implications of firms changing sup-

[1]For other papers that investigate the effects beyond the network irrelevance result, see Altinoglu (2015), Liu (2016), and Bigio and La'o (2017) for models where firms face financial constraints, and Pasten, Schoenle, and Weber (2017) for models with price rigidities.

[2]As in Grassi (2016), we focus on strategic complementarities across suppliers in the style of Atkeson and Burstein (2008). See Krugman (1979), Ottaviano, Tabuchi, and Thisse (2002), Melitz and Ottaviano (2008) and Zhelobodko, Kokovin, Parenti, and Thisse (2012) for imperfect competition where complementarities arise from the demand side.

[3]See Neiman (2011) for a similar model of variable markups that allows for arm's length and intra-firm transactions.

[4]There are also cases in which aggregate volatilities can be captured by the distribution of market shares. See for example Gabaix (2011), where the Herfindahl-Hirschman Index (HHI) is the main metric that captures aggregate volatility.

pliers. For example, Lim (2015) points out the importance of extensive margins in firm-to-firm relationships.[5] Tintelnot, Kikkawa, Mogstad, and Dhyne (2017) empirically show that shocks to a firm's actual suppliers and customers transmit to the firm itself even after controlling for shocks that affect the firm's potential suppliers and customers. This suggests that there are rigidities in firm-to-firm relationships, which also motivates our model where firms pay fixed costs when choosing suppliers.[6] They also build a tractable model of endogenous network formation. Unlike ours, their model relies on the assumption that firms do not obtain profits from firm-to-firm trade, and the resulting network is constrained to be acyclic.

This paper also contributes to a recently growing literature on how shocks transmit through the production network. Carvalho, Nirei, Saito, and Tahbaz-Salehi (2014) and Boehm, Pandalai-Nayar, and Flaaen (2016) have found that shocks to suppliers transmit to firms by looking at firms that sourced from Japanese firms impacted by the 2011 Tohoku earthquake. Barrot and Sauvagnat (2016) have also found shock transmission through production linkages by looking at firms sourcing from firms located in places hit by natural disasters in the US. In the context of sector-to-sector linkages, Acemoglu, Akcigit, and Kerr (2015a) study the propagation of demand and supply shocks.[7] In this paper, shocks on firms indeed transmit to other firms along the production chain. Our main result is that the structure of the production network matters in the aggregate because the magnitudes of these network effects cannot be solely captured by firm-level observables.

Finally, our paper is related to the considerable literature on micro shocks translating to aggregate movements. Firm- or sector-level shocks may not wash out when evaluating aggregate fluctuations if the firm- or sector-level size distributions are fat-tailed (Gabaix, 2011; Carvalho and Gabaix, 2013) or if the input-output structures are asymmetric (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012).[8] In particular, Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) show that the economies with different input-output structures may produce different aggregate output volatilities in response to the same sector-level shocks.[9] As aforementioned, we focus on exact changes in response to large shocks instead of the variance of the changes. In a Cobb-Douglas model that builds

[5]Other papers that focus on the formation of domestic firm-to-firm relationships include Bernard, Moxnes, and Saito (2016) and Oberfield (2017).

[6]One of the findings of Tintelnot, Kikkawa, Mogstad, and Dhyne (2017) is that firms increase their scale in response to positive import shocks to their suppliers, as well as to themselves. Papers that study the effects of import shocks on firms include Gopinath and Neiman (2014), Halpern, Koren, and Szeidl (2015), Magyari (2016), Antras, Fort, and Tintelnot (2017) and Furusawa, Inui, Ito, and Tang (2017).

[7]These network effects are also studied in other contexts and have found to generate instabilities in the system as a whole. For example, Scheinkman and Woodford (1994) point out that small independent shocks to different firms can lead to instability of the system through their nonlinear interactions. Elliott, Golub, and Jackson (2014) and Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015b) study the stability of financial networks.

[8]Di Giovanni, Levchenko, and Mejean (2014) and Magerman, De Bruyne, Dhyne, and Van Hove (2016) study the two potential sources of aggregate fluctuations together. Yeh (2016) points out that large firms tend to be less volatile, leading to mitigated effects of fat-tailed firm size distributions in the aggregate.

[9]Other papers that study the importance of micro shocks on aggregate volatility include Jovanovic (1987), Durlauf (1993), Bak, Chen, Scheinkman, and Woodford (1993), Horvath (1998), Horvath (2000), Carvalho (2010), Foerster, Sarte, and Watson (2011), Di Giovanni, Levchenko, and Mejean (2014), Stella (2015), Atalay (2017), and Acemoglu, Ozdaglar, and Tahbaz-Salehi (2017).

on Long and Plosser (1983), the irrelevance of the network structure still holds when one focuses on the changes in aggregate variables.

This paper proceeds as follows. Section 2 describes the data. We also provide two pieces of descriptive evidence. First, we show that firms' input shares across suppliers are skewed, and the variation in input shares are not entirely driven by firm-level components. Second, we show that there is large churn in supplier-customer relationships. Section 3 establishes the two empirical facts: suppliers charge higher markups if their input shares to customers are higher and firms alter suppliers in response to shocks. Section 4 outlines the model and presents the network irrelevance result in the benchmark case. Section 5 estimates the parameters of the model, and Section 6 conducts counterfactual analysis where a reduction in foreign price is taken as the shock. Finally, Section 7 concludes.

2 Data and descriptive evidence

In this section we start by introducing our main data sources. We then provide descriptive evidence that activities at the pair-level cannot be fully captured by firm-level components alone, and that there is a large churn in supplier-customer relationships.

2.1 NBB B2B dataset

Our main dataset is the National Bank of Belgium (NBB) Business-to-Business (B2B) transactions database, which is a panel of VAT-id to VAT-id transactions among the universe of Belgian VAT-ids over years 2002-2014. As explained in detail in Dhyne, Magerman, and Rubinova (2015), all enterprises in Belgium are assigned unique VAT-ids and are required to report total yearly sales to other VAT-ids that are larger than 250 Euro. We also make use of the VAT declarations, in which we observe their total sales and total purchases. In addition, we merge the datasets with the annual account filings and the international trade dataset. From the annual accounts we observe the primary sector of each VAT-id (NACE Rev. 2, 4-digit), total sales, labor cost, ownership relations to other VAT-id's, location (ZIP code), and other variables that are standard in the annual accounts. In the international trade dataset we observe the values of imports and exports of goods at the VAT-country-product (CN 8-digit)-year level.

One firm can have multiple VAT-ids. In our paper, we focus on the effect of inter-firm pricing and inter-firm linkage formations on the aggregate variables. The nature of these pricing and linkage formation decisions may be different from those at the within-firm level. Thus we aggregate VAT-ids up to the firm-level using ownership filings in the annual accounts and foreign ownership filings in the Balance of Payments survey. In the Balance of Payments survey, we observe for each VAT-id the name and the country of the foreign firm that owns at least 10 percent of the shares, along with the associated ownership share. We group all VAT-ids into firms if they are linked with more than or equal to 50% of ownership, or if they share the same foreign parent firm that holds more than or equal to 50% of their shares. See Appendix A.1 for further details.

2.2 Sample selection

For our sample of the analysis, we select private and non-financial sector Belgian firms that report positive labor cost. Following De Loecker, Fuss, and Van Biesebroeck (2014), we select firms that report tangible assets of more than 100 Euro and positive total assets for at least one year throughout our sample period. Table 1 describes the coverage of our selected sample compared to the Belgian aggregate statistics.[10]

In the table, one can see that our selected sample covers the aggregate statistics well. However, note that the total sales in our sample turn out to be larger than those in the aggregate statistics. The differences can be explained by the fact that the output values in the aggregate statistics sum up value added for trade intermediaries instead of their gross output, hence the smaller numbers in the aggregate statistics.

Table 1: Coverage of selected sample

Year	Private, non-financial		Imports	Exports	Selected sample				
	GDP	Output			Count	V.A.	Sales	Imports	Exports
2002	149	411	210	229	122,460	123	586	179	189
2007	192	546	300	314	136,370	157	757	280	269
2012	212	626	342	347	139,605	170	829	296	295

Notes: All numbers except for Count are in terms of billion Euro in current prices. Belgian GDP and output are for all private and non-financial sectors. Data for Belgian aggregate statistics are from Eurostat. Value added is the sum of value added reported in the annual accounts. Total sales in our selected sample are larger total output in the aggregate statistics because the output values in the aggregate statistics sum up value added for trade intermediaries instead of their gross output.

2.3 Descriptive evidence

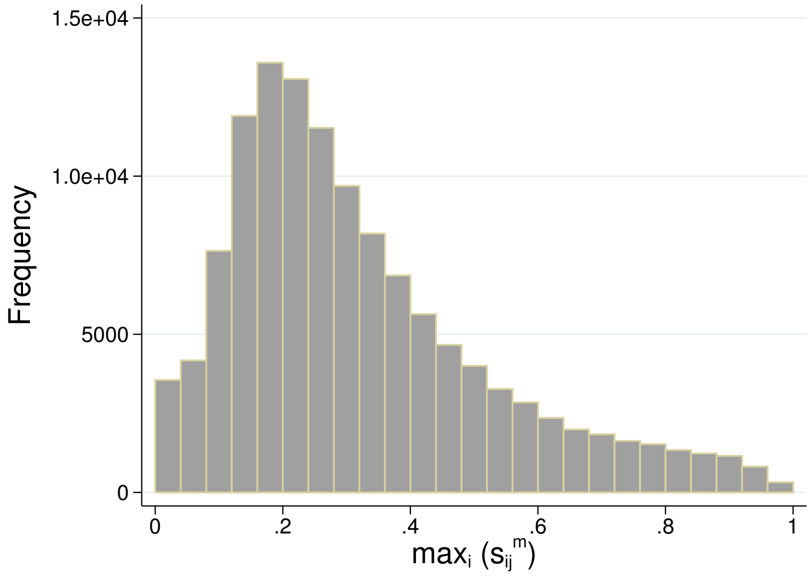
In this section, we provide descriptive evidence that motivate our empirical analysis in Section 3. We first show that firms' input shares across suppliers are skewed, and then that the variation in pairwise input shares is not entirely driven by firm-level components. Finally, we show that there is large churn in supplier-customer relationships.

[10] In Appendix A.2, we also report the coverage of the full sample constructed in Dhyne, Magerman, and Rubinova (2015). There we also provide aggregate statistics of the B2B dataset and some descriptive statistics of the production network.

Skewed input shares across suppliers

Figure 1 plots a histogram for the input shares of the largest suppliers for all customer firms in 2012 that have more than 10 suppliers. The input share of the largest supplier for the median firm in this figure is 27%.

Figure 1: Input shares of the largest suppliers



Notes: s_{ij}^m is defined as firm i's goods share among firm j's input purchases from other Belgian firms and abroad. The above histogram shows the distribution of $\max_i \left(s_{ij}^m\right)$, which is the maximum value of s_{ij}^m for each customer firm j in 2012 that has more than 10 suppliers. The median value is 0.27.

Together with the fact that the median firm has 28 suppliers, it indicates that suppliers' input shares are highly skewed throughout the economy. For each customer, few suppliers tend to account for most of its input purchases. In Appendix A.3 we present a histogram of the Herfindahl-Hirschman Index (HHI) of s_{ij}^m for the same set of firms with at least 10 suppliers. We find that 50% of firms have a HHI above 0.15. 26% of firms have a HHI above 0.25%.

Pairwise components are driving the variations in input shares

However, high skewness in input shares may simply be caused by firm-level components. For example, one may argue that the skewness of input shares across suppliers is coming from the skewness in the suppliers' productivity distribution. If that is indeed the case, one would expect that a firm with a high input share on a particular customer would also be one with high total sales. To investigate this further, we compute for each firm the rank correlation between its suppliers' input shares and their total sales.

Consider the firm on the left of Figure 2. This firm is purchasing goods worth 10, 5, and 1 Euro from its three suppliers, a, b, and c, respectively. The three suppliers' total sales are 100, 50, and 10

Euro. The ordering of the firm's suppliers according to the input shares aligns with the ordering of their total sales. Thus, the rank correlation for the firm is 1. One the other hand, consider the firm on the right of the figure. The transaction values are identical to the firm on the left, but the three suppliers' total sales are 10, 50, and 100 Euro, respectively. Here the ordering of the two are opposite, so the rank correlation for the firm is -1.

Figure 2: Example for computing rank correlations

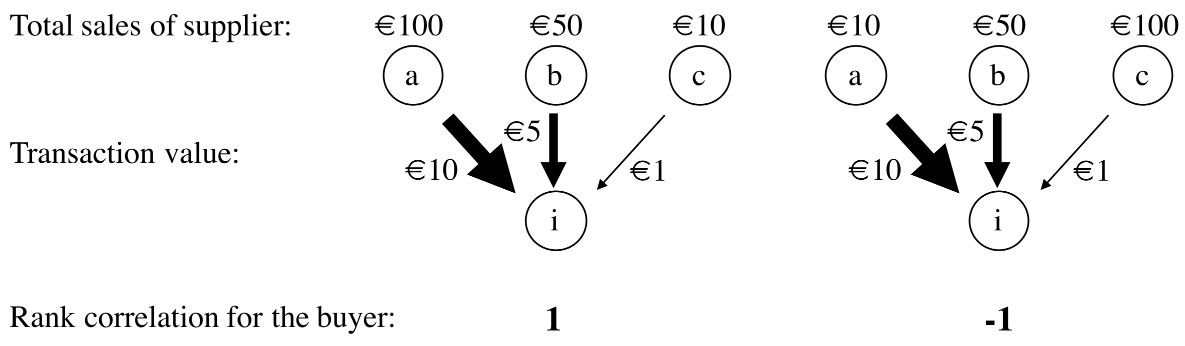
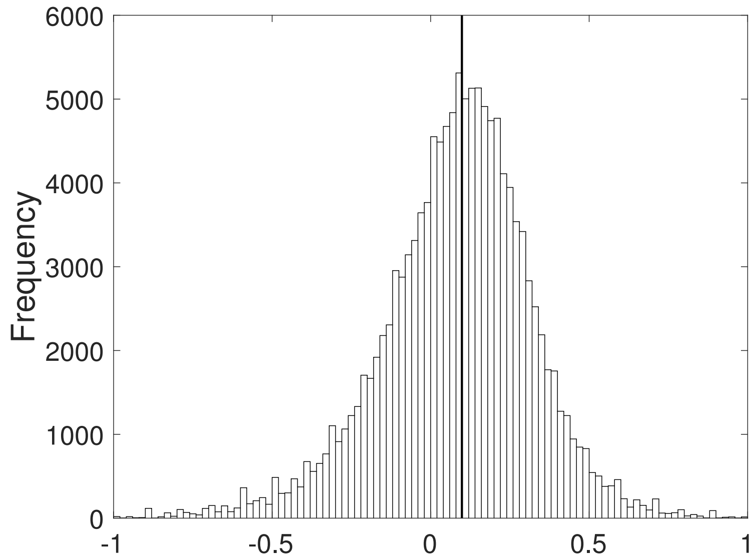


Figure 3 displays the histogram of the correlation coefficients. The median firm's coefficient is around 0.10. 35% of firms have correlation coefficients that are zero or negative. This result indicates that a firm with high input share on a particular customer is not necessarily large.[11] It illustrates that pairwise match components play a large role in firm-to-firm trade in addition to firm-level components.

Figure 3: Histogram of rank correlation of suppliers' input shares and total sales



Notes: This figure shows a histogram of Spearman's rank correlation coefficients between s^m_{ij} and TotalSales_i for suppliers of j for all j with 5 or more suppliers. The vertical line depicts the median correlation coefficient of 0.10.

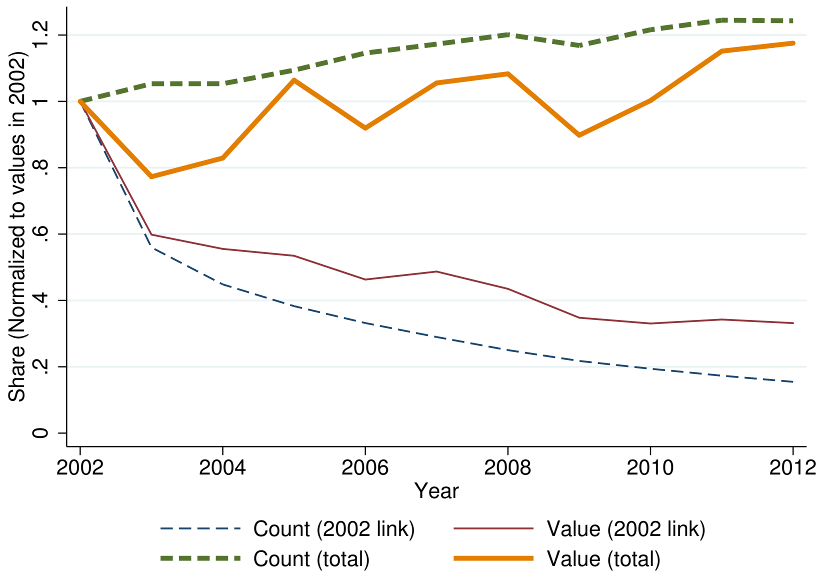
[11]This becomes the case if the distributions of firms' output shares to each customer are skewed. In Appendix A.4 we provide a figure analogous to Figure 1, but for output shares. The output shares are indeed skewed, where more than 20% of the output of a median firm goes to its largest customer.

Indeed, in Figure 3 we plot the unconditional rank correlations which do not take into account the difference in the goods produced by suppliers. The low correlations in the figure may come from the fact that a supplier's good is heavily used in firms from one sector, but not from firms in others. In Appendix A.5 we take into account this heterogeneity of input compositions across sector-to-sector relationships. We calculate the rank correlations for each firm, but now for each group of suppliers in each sector. Even after conditioning the analysis within each of the sector-to-sector relationships, we see the same pattern as in Figure 3. We also show in Appendix A.5 that the results are qualitatively the same when we use the Pearson correlations instead of the rank correlations.

Large churn in supplier-customer relationships

We also see that there is a large churn in supplier-customer relationships. Figure 4 plots the share of firm-to-firm links present in 2002 that survived through 2012. It also depicts the evolution of total firm-to-firm links in terms of both numbers and values. One can see that there is substantial churn in the linkages: less than 40% of the links that were present in 2002 were still there in 2012 in terms of the values. In terms of pure numbers, linkage survival decreases to less than 20% in 10 years.

Figure 4: Evolution of firm-to-firm links



The evidence of this section confirms that pairwise patch components play a large role in firm-to-firm networks and that there is a large churn in linkages. In the next section, we establish the two facts that motivate our model.

3 Motivating empirical results

In this section we establish two empirical facts that will motivate our model in Section 4: firms charge higher average markups when they have higher input shares within their customers, and firms change their suppliers in response to an exogenous reduction in prices of imports.

Markups positively associated with input shares within customers

We start by exploring the relationship between firm-level markups and firms' average input shares within their customers. We ask if the two are positively associated with each other, even after controlling for firm-level sectoral market shares. A positive relationship suggests that firms' market power contains pair-level components that come from each individual customer in addition to firm-level components that are captured by sectoral market shares.

Firm-level markups, $\mu_{i,t}$, are measured as the ratios of firms' total sales over variable costs (sum of goods purchases and labor costs). Firm-level sectoral market shares, $\text{SctrMktShare}_{i,t}$, are computed at the NACE 4-digit level. This measure captures firms' market power in models that feature oligopolistic competition in which firms' output is aggregated at the sectoral level.

We also construct a measure that captures the input shares firms have within their customers. For each supplier-customer pair, we can compute the share of sales from the supplier firm i to the customer firm j out of j's total input purchases: $s^m_{ij} = \frac{\text{Sales}_{ij}}{\text{InputPurchases}_j}$. Using these pairwise input shares, we compute firm i's weighted average input shares to its customers at year t, as

$$\begin{aligned}
\overline{s^m_{i\cdot,t}} &= \sum_{j\in W_{i,t}} \frac{\text{InputPurchases}_{j,t}}{\sum_{k\in W_{i,t}} \text{InputPurchases}_{k,t}} s^m_{ij,t} \\
&= \frac{\sum_{j\in W_{i,t}} \text{Sales}_{ij,t}}{\sum_{j\in W_{i,t}} \text{InputPurchases}_{j,t}},
\end{aligned}$$

where $W_{i,t}$ is the set of i's customers at year t. Total input purchases are assigned as weights for each customer firm.

With these variables, we run the following regression:

$$\mu_{i,t} = \beta\,\text{SctrMktShare}_{i,t} + \gamma\,\overline{s^m_{i\cdot,t}} + \varphi\,X_{i,t} + \delta_t + \epsilon_{i,t}, \tag{1}$$

where firm-level controls and year fixed effects are included.

Table 2 reports the results. The specification of the first column includes sector fixed effects, and the specifications of the second and the third columns include firm fixed effects. First, in all specifications we see a positive relationship between markups and firm-level market shares. This is not surprising, as it may be because of the mechanical relationship between both variables. The numerators in both variables are firms' total sales. For example, the result on the third column indicates that within each firm, an increase of one standard deviation in the firm's market share is associated with an increase of around 6.9 percentage points in the firm's markup.

However, even after controlling for firms' market shares, the coefficients on the firms' average input shares to customers are positive. The third column indicates that within each firm a single standard deviation increase in average input shares to customers leads to around an increase of 17 percentage points in the firm's markup. This positive correlation indicates that firms have greater ability to charge markups if they have higher shares within their customers' inputs.

The relative size of the two coefficients is also worth discussing. Across all specifications, we see much larger coefficients on the average input shares compared to those on the firm-level market shares. In addition, we show in Table 11 in Appendix B.1 that the R-squared increases more when adding the average input shares on the RHS, as opposed to adding the firm-level market shares. These results indicate that the variations in the average input shares within customers' inputs are more important for firms' ability to charge markups than the variations in the sectoral market shares.

Table 2: Firm-level markups and input shares

	Firm-level markups		
	(1)	(2)	(3)
$\text{SctrMktShare}_{i,t}$ (4-digit)	0.0929***	0.0430***	0.0686***
	(0.00928)	(0.00963)	(0.0129)
Average input share $\overline{s^m_{i\cdot,t}}$	0.298***	0.182***	0.173***
	(0.0130)	(0.00938)	(0.00925)
N	1099496	1089209	1070602
Year FE	Yes	Yes	Yes
Sector FE (4-digit)	Yes	No	No
Firm FE	No	Yes	Yes
Controls	Yes	No	Yes
R2	0.0994	0.619	0.625

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. The coefficients are X-standardized. Standard errors are clustered at the NACE 2-digit-year level. Controls include firms' indegree, outdegree, employment, total assets, and age.

The result of the positive correlation between markups μ_i and average input shares $\overline{s^m_{i\cdot,t}}$ is robust under different average measures of $\overline{s^m_{i\cdot,t}}$: either taking simple averages or taking median values. It is also robust when using other measures of pairwise input shares. For example, instead of using s^m_{ij} we use s_{ij}, which is the firm i's sales share in j's total variable inputs (goods purchases plus labor costs). Another alternative share we use is the supplier's sales share among the customer's inputs that are classified as the same goods as the supplier's, either at the 2-digit or 4-digit level. We report the results of other robustness checks in Appendix B.1.[12]

[12]The positive correlation is also robust to alternative markup measures. The measure of markups we use is consistent with the model we construct in Section 4, which is static and features CRS production technology. Firms might also use additional factors, such as capital inputs, and production technology may differ across sectors. Given these possibilities,

Larger churn in suppliers when exposed to larger reduction in input prices

As shown in Section 2.3, there is a large churn in supplier-customer relationships. The median firm has a churn of around 20% of its suppliers annually, in terms of values. Here we show that in addition to random changes, there is a systematic relationship between churn of suppliers and an exogenous shock to import opportunities from abroad. We take the reduction in prices of Chinese imported goods throughout the 2000s as the shock. Belgian imports from China more than doubled in the 2000s after its accession to the WTO. We interpret this as a decrease in the prices of Chinese goods available in the international market over the same period.[13]

We regress changes in firms' share of continuing and added suppliers on firms' increase in Chinese sourcing over the periods:

$$\Delta Y_i = \beta \Delta CS_i + \gamma X_{i,t_0} + \delta_{s(i)} + \epsilon_i, \tag{2}$$

where ΔY_i denotes the shares of continuing and added suppliers scaled by the values at the initial period.[14] ΔCS_i denotes the increase in Chinese sourcing scaled by the total input value of the firm at the initial period.

$$\Delta CS_i = \frac{\Delta V_{China,i}}{\text{TotalInput}_{i,t_0}}.$$

We add sector fixed effects and firm-level controls at the initial period.

The OLS regression of equation (2) is subject to an endogeneity issue. Increases in Chinese sourcing may be triggered by factors that also affect firm activities, including decisions on which firms to source from. To capture the increase in firms' Chinese imports driven by factors exogenous to firms, we instrument firms' increase in Chinese sourcing using changes in Chinese exports to eight non-European developed countries.[15] The instrument for ΔCS_i becomes

$$\Delta IV_i = \sum_k \frac{V_{ALL,i,k,t_0}}{\text{TotalInput}_{i,t_0}} \Delta \frac{V_{China,Rich,k}}{V_{World,Rich,k}}, \tag{3}$$

where k represents products at the NACE 4-digit level. We first construct a sectoral measure of the increase in Chinese exports to the developed countries by taking the changes in Chinese goods' share in the developed countries' imports ($\Delta \frac{V_{China,Rich,k}}{V_{World,Rich,k}}$). We then convert product level measures into firm-level measures by using firm specific weights for each product ($\frac{V_{ALL,i,k,t_0}}{\text{TotalInput}_{i,t_0}}$). The weights measure firm i's exposure to sector k goods at the initial period by taking the ratio of the sum of product k inputs

we show positive correlation under alternative measures of firm-level markups following De Loecker and Warzynski (2012). See Appendix B.2 for details.

[13] In Appendix A.7 we compare Chinese imports to Belgium with imports from other countries to Belgium and show that the rapid increase in imports was not common with regard to other countries.

[14] For example, consider a firm with 10 suppliers that dropped 3 and added 5, resulting in 12 suppliers. The share of continuing suppliers (in numbers) is calculated as 7/10, and the share of added suppliers (in numbers) is calculated as 5/10.

[15] Australia, Canada, Chile, Japan, Korea, New Zealand, the UK, and the USA.

over the total inputs.

The idea of the instrument is similar to that of Autor, Dorn, and Hanson (2013). Differently, we use the change in Chinese goods' share in developed countries' imports as the product level measure that captures the increase in Chinese exports to developed countries. Instead of simply taking the growth rate of Chinese exports, this way we can remove the demand effects that increased developed countries' growth in imports from developing countries as a whole.

Our instrument is also at the firm-level, with variation coming from across firms that are within sectors. Similar to that of Bartik (1991), the instrument is valid if the variations in firms' initial exposure to each product are not correlated with unobservable firm-level characteristics that may affect firms' domestic sourcing decisions.

Table 3 reports both the first and second stage results when the changes in suppliers are computed in terms of values. The first and second columns of Panel A represent the second stage results where the LHS variables are the shares of continuing and added suppliers. The third and the fourth columns of Panel A decompose the effect of the added suppliers. Out of the firms that were added, the third column shows the shares which were incumbent, meaning firms that existed in the initial period. The fourth column displays the shares which were newly born.[16] All variables are computed as average yearly changes over the sample period. Panel B reports the first stage results. We see that the first stage coefficient is positive and statistically significant.

Table 3: First and second stage results

Panel A: Second stage result					Panel B: First stage result	
	Changes in suppliers (in terms of value)					
	(1) Continuing suppliers	(2) Added suppliers	(3) Added suppliers: Incumbent firms	(4) Added suppliers: New firms		(1) ΔCS
ΔCS	-0.128^{***}	0.110^{***}	0.0973^{***}	0.0128^{***}	ΔIV	0.00370^{***}
	(0.0283)	(0.0334)	(0.0316)	(0.00366)		(0.000649)
N	56146	56146	56146	56146	R2	0.0255
Controls	Yes	Yes	Yes	Yes	F Stat	32.48

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. The coefficients of the second stage results are X-standardized. Controls include firm age and employment size in 2002 with sector fixed effects (NACE 2-digit) and geographic fixed effects (NUTS 3). The same controls are used in the first stage results. ΔCS is the firm's average yearly increase of Chinese imports from 2002 to 2012 scaled by its total inputs in 2002. ΔCS is instrumented by the weighted sum of the sectoral change in Chinese goods' share in developed countries' total imports from 2002 to 2012. Standard errors are clustered at the NACE 2-digit-NUTS 3 level.

The results first suggest that firms experience greater churn in suppliers when the price of imported goods' is further reduced. A one standard deviation increase in the change of Chinese sourcing leads to firms dropping around 13% of domestic suppliers on a yearly basis. The same shock also

[16] As the variables are computed as average yearly changes, the coefficients of the third and fourth columns need not exactly add up to the coefficients in the second columns.

leads to firms adding around 11% of domestic suppliers. Given that the median firm loses around 19% and adds around 25% of suppliers in terms of value on a yearly basis, the magnitudes of churn induced by the import supply shock are significant. The results also show that the additions of links mostly come from the rewiring of links among existing firms, and not from firms that entered the market.[17]

We reported the results for the changes in suppliers in terms of values, but the same features remain robust when conducting the same analysis in terms of numbers.[18] In addition, we find qualitatively the same results when we analyze the changes in customers. We report these results in Appendix B.3 in addition to their OLS results and first stage results.

4 Model

In the previous section, we established two empirical facts: firms charge higher markups when they have higher input shares within their customers, and firms alter linkages in response to shocks. These facts motivate a model of a small open economy where firms engage in oligopolistic competition within each customer's inputs, and where firms optimally choose suppliers. In this section, we set up the model and define the equilibrium. Then we turn to a special case of the model and present a network irrelevance result.

There are representative households inelastically supplying a fixed amount of labor. There is a homogeneous goods sector under perfect competition. These goods are also freely traded, and enables us to pin down wages. In the heterogeneous goods sector, there are a fixed number of domestic firms each producing a differentiated good. Labor, goods from other domestic firms, and/or imported goods are used for production. Firms sell their goods to final consumption, to other firms, and/or abroad.

We treat firms to be infinitesimal in the final demand market and assume monopolistic competition. On the other hand, we assume oligopolistic competition in firm-to-firm trade, which generates pairwise markups. Lastly, firms make decisions on their sourcing sets (including whether to import), and their exporting decisions.

4.1 Preference

There is a mass of representative households each providing one unit of labor. Households have Cobb-Douglas preference on the goods from the homogenous goods sector, Y, and on the goods from the heterogeneous goods sector. Within the heterogeneous goods sector, the representative household

[17] The coefficients for the added suppliers which were entrants are small relative to the coefficients on the total added suppliers. However, the ratios are large compared to how much new entrants account for in the aggregate economy. In our sample period, new entrants account for around 3% of the total sales in the total economy, where our regression results imply that entrants account for around 12% of firms that were added as suppliers.

[18] The results are also qualitatively robust when using variables in terms of yearly changes with additional year fixed effects, instead of average yearly changes over 2002 to 2012.

has a CES preference over all firms' goods with substitution parameter σ. We assume that goods are substitutes, thus $\sigma > 1$. We also assume that households do not directly consume foreign goods in the heterogeneous goods sector. The household's preference is denoted as

$$U = \left(\sum_{i \in \Omega} \beta_{iH} q_{iH}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\alpha\sigma}{\sigma-1}} Y^{1-\alpha}, \tag{4}$$

where Ω denotes the set of domestic firms in the heterogeneous goods sector and α is the Cobb-Douglas share on the heterogeneous goods sector. q_{iH} denotes the quantity of goods that firm i sells to the household. Given the price that i charges to the household, p_{iH} , q_{iH} can be written as

$$q_{iH} = \beta_{iH}^{\sigma} \frac{p_{iH}^{-\sigma}}{P^{1-\sigma}} \alpha E, \tag{5}$$

where E denotes the aggregate expenditure. P denotes the price index of the heterogeneous goods sector:

$$P = \left(\sum_{i \in \Omega} \beta_{iH}^{\sigma} p_{iH}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}. \tag{6}$$

The price index of the aggregate economy, $\tilde{P}$, is a Cobb-Douglas aggregate of P and the price of the homogeneous good, p_y: $\tilde{P} = \left(\alpha^{\alpha} (1-\alpha)^{1-\alpha}\right)^{-1} P^{\alpha} p_y^{1-\alpha}$.

We model demand from abroad to have the same structure as the domestic household. Let I_{iF} be an indicator of whether firm i is an exporter or not. Given a price that i charges on exported goods, p_{iF}, export quantity, q_{iF}, can be written as

$$q_{iF} = p_{iF}^{-\sigma} D^{*}, \tag{7}$$

where D^{*} is the exogenous demand shifter from abroad.

4.2 Technology and market structure

Each firm in the heterogeneous goods sector produces a single differentiated good. In addition to labor inputs, they purchase goods from other firms and/or imported goods as intermediate goods. On the output side, they sell their goods to other domestic firms and/or export, at the same time selling directly to final demand. We treat firms to be infinitesimal in the final demand market and assume monopolistic competition. Thus firms charge constant markups on their goods when selling to the final consumer. We also assume that firms apply the same markups when exporting.

When firms sell goods to other domestic firms, the assumption of infinitesimal suppliers for each customer is not consistent with the data. Firms tend to have highly concentrated input share distributions, where a handful of top supplier firms account for the majority of firms' goods purchases. Moreover, in Section 3, we found that firms charge higher markups when they have higher input shares to customers. Thus we assume oligopolistic competition in firm-to-firm trade, where firms charge different markups to different customers depending on the shares they have in their customers' goods purchases. In doing so, we take the framework of Atkeson and Burstein (2008) and apply to firms' pricing decisions in firm-to-firm trade.

Motivated by the findings in Section 3, we also model firms to optimally make domestic sourcing decisions as well as importing and exporting decisions. We assume that firms pay fixed costs in order to supply from another domestic firm, and also for importing and exporting.[19]

We first lay out the firms' problem given the production network in Section 4.2.1. Then we describe the endogenous formation of the production network in Section 4.2.2.

4.2.1 Production given network

Let Z_i be firm i's set of domestic suppliers, and let I_{iF} and I_{Fi} be indicators for the exporting and importing status of firm i. In this subsection we take these as given.

Firms in the homogeneous goods sector produce goods with a linear technology with respect to labor:

$$y = l^Y. \tag{8}$$

Firms in the heterogeneous goods sector have a CES production function over the labor inputs and intermediate goods bundle. The intermediate goods bundle itself is a CES bundle of goods from the firms' suppliers and foreign goods. We denote the elasticity of substitution across labor inputs and the intermediate goods bundle to be η, and the substitution parameter across firms' goods and imported goods to be ρ. We assume both parameters to be above one: $\rho, \eta > 1$.[20]

The implied unit cost of firm i becomes

$$c_i = \phi_i^{-1} \left(\omega_l^\eta w^{1-\eta} + \omega_m^\eta p_{mi}^{1-\eta}\right)^{\frac{1}{1-\eta}}, \tag{9}$$

where ϕ_i is i's core productivity. ω_l and ω_m denote CES weights in the production function on labor and intermediate goods. w denotes wage, and p_{mi} is the firm specific price index of intermediate goods. p_{mi} varies with firms' sourcing strategy Z_i and I_{Fi}:

$$p_{mi} = \left(\sum_{j\in Z_i} \alpha_{ji}^\rho p_{ji}^{1-\rho} + I_{Fi}\alpha_{Fi}^\rho p_F^{1-\rho}\right)^{\frac{1}{1-\rho}}. \tag{10}$$

The term p_{ji} denotes the price that firm j charges for its goods when selling to firm i. p_F denotes the

[19] We take this approach because we see a positive relationship between firms' sales to domestic final demand and their number of domestic suppliers, as reported in Appendix A.8. These size advantages for firms with larger number of domestic suppliers are suggestive of fixed costs associated with domestic sourcing.

[20] When we estimate both ρ and η in Section 5.1, we do not impose any restrictions concerning the relative magnitudes of ρ and η. We find the point estimate of ρ to be larger than that of η, meaning that firms' goods are more substitutable with each other than with labor.

exogenous price of the foreign good. The terms α_{ji} and α_{Fi} reflect how salient goods from firm j and foreign are as inputs for firm i.

Before discussing the market structures of the final demand market and of the firm-to-firm markets, let us derive the firms' shares on inputs implied by the above CES structures. The share of firm i's variable costs spent on labor, s_{li}, is:

$$s_{li} = \frac{\omega_l^{\eta} w^{1-\eta}}{c_i^{1-\eta} \phi_i^{1-\eta}}. \tag{11}$$

The intermediate goods' share, s_{mi}, becomes

$$\begin{aligned} s_{mi} &= 1 - s_{li} \\ &= \frac{\omega_m^{\eta} p_{mi}^{1-\eta}}{c_i^{1-\eta} \phi_i^{1-\eta}}. \end{aligned} \tag{12}$$

Among i's variable costs spent on intermediate goods, the share of firm j's good, s^m_{ji}, and the share of foreign goods, s^m_{Fi}, are:

$$\begin{aligned} s^m_{ji} &= \alpha^{\rho}_{ji} \frac{p_{ji}^{1-\rho}}{p_{mi}^{1-\rho}} \\ s^m_{Fi} &= I_{Fi} \alpha^{\rho}_{Fi} \frac{p_F^{1-\rho}}{p_{mi}^{1-\rho}}. \end{aligned} \tag{13}$$

Analogously, we can write s_{ji} and s_{Fi} as the shares of j's goods and foreign goods, out of i's total variable costs: $s_{ji} = s^m_{ji} s_{mi}$ and $s_{Fi} = s^m_{Fi} s_{mi}$.

We assume monopolistic competition for firms in the heterogeneous goods sector when they sell to final demand. Firms charge a constant markup over marginal cost. We assume the same when firms export:

$$p_{iH} = p_{iF} = \frac{\sigma}{\sigma - 1} c_i. \tag{14}$$

We introduce oligopolistic competition in firm-to-firm trade in the following way. When selling to firm j, firm i sets price p_{ij} that maximizes variable profits by taking as given prices of j's other suppliers and j's unit cost and output, c_j and q_j. Solving the firm's profit maximization problem yields the following price:

$$\begin{aligned} p_{ij} &= \frac{\varepsilon_{ij}}{\varepsilon_{ij} - 1} c_i \\ \varepsilon_{ij} &= \rho \left(1 - s^m_{ij}\right) + \eta s^m_{ij}. \end{aligned} \tag{15}$$

The markup firm i charges on firm j depends on the input share that i's goods have in j's intermediate goods, s^m_{ij}. If a supplier has an infinitesimally small share in the customer's intermediate goods bundle ($s^m_{ij} \to 0$), then all the competition the supplier engages in is with the other suppliers that share the same customer. Then the price converges to what we obtain when assuming monopolistic competition: a constant markup of $\frac{\rho}{\rho-1}$. As the supplier's input share on the customer increases, then not only does the supplier engage in competition with the other suppliers, but also with the labor input that the customer firm employs. Thus, the elasticity of demand that the supplier faces, ε_{ij}, is a weighted average of ρ and η with the weight on η being s^m_{ij}. When the supplier is the only firm supplying the customer ($s^m_{ij} \to 1$), the markup converges to $\frac{\eta}{\eta-1}$. The intuition of how pairwise markups depend on pairwise shares are identical to what is described in Atkeson and Burstein (2008). The difference is that here the relevant shares and markups are defined for each supplier-customer pair.

As mentioned above, we assume that the supplier takes as given the customer's unit cost and output. A plausible alternative would be to assume that the supplier firm internalizes the change in demand for the customer's good when deciding on its price. In that case, the supplier needs to know the output composition of the customer firm to infer the elasticity of demand that it is facing. As firms are not likely to observe the flow of goods that are far from itself in the production chain, we find our assumption to be reasonable.[21]

We assume Bertrand competition as our baseline case. One can alternatively assume firms engage in Cournot competition, where firms set quantity q_{ij} to maximize variable profits. In that case, the demand elasticity that firm i faces, ε_{ij}, becomes a weighted harmonic mean of the two CES parameters ρ and η: $\varepsilon_{ij} = \left(\frac{1}{\rho}\left(1 - s^m_{ij}\right) + \frac{1}{\eta} s^m_{ij}\right)^{-1}$. As we show in Section 5.1, the estimates of the CES parameters are not affected much by this alternate specification.

Finally, let us describe firms' output. A firm sells its goods to households, abroad (if the firm is an exporter), and also to other domestic firms. Therefore we have

$$q_i = q_{iH} + q_{iF} + \sum_{j \in W_i} \alpha^{\rho}_{ij} \frac{p^{-\rho}_{ij}}{p^{1-\rho}_{mj}} s_{mj} c_j q_j, \tag{16}$$

where W_i is the set of i's customers.

[21] This assumption that firms have incomplete information about firms that are far from itself in the production chain is similar to that considered by Antràs and de Gortari (2017). In Appendix D.2 we discuss in detail the optimal prices that firms charge their customers under alternative assumptions. When a firm internalizes the effect of its price on the demand for the customer's goods, the markup it charges not only depends on s^m_{ij} but also on quantities that the customer sells to other firms and the quantities that it sells to final demand. One can also assume that firms take as given a constant demand elasticity that firms assume their customers face. In this case, if one assumes that the value of this demand elasticity is η, the pricing equation collapses to that of equation (15).

4.2.2 Formation of the production network

Let us now describe how firms make their decisions on sourcing and participation in international trade. In our model, customer firms pay fixed costs to form links with suppliers. Firm i pays a random firm-specific fixed cost, f_{Di}, when supplying from a domestic supplier. Analogously, when the firm decides to import or export, it has to pay random firm-specific fixed costs of f_{Fi} and f_{iF}, respectively. All fixed costs are in terms of labor.

The firm maximizes its variable profits net of these fixed costs by choosing the set of domestic suppliers, Z_i, and importing/exporting statuses, I_{Fi} and I_{iF}. The variable profits of firm i come from sales to final demand, exports, and sales to other domestic firms. Taking as given others' sourcing strategies and participation decisions in international trade, the variable profit of i is a function of its own sourcing strategies and importing/exporting statuses:

$$\begin{aligned}\pi_i^{var}\left(Z_i, I_{Fi}, I_{iF}\right) =& \frac{1}{\sigma}\underbrace{\beta_{iH}^{\sigma}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} c_i\left(Z_i, I_{Fi}\right)^{1-\sigma}\frac{\alpha E}{P^{1-\sigma}}}_{\text{Sales to HH}} + I_{iF}\frac{1}{\sigma}\underbrace{\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} c_i\left(Z_i, I_{Fi}\right)^{1-\sigma} D^*}_{\text{Exports}} \\ &+ \sum_j \frac{1}{\varepsilon_{ij}}\underbrace{\alpha_{ij}^{\rho} p_{ij}\left(Z_i, I_{Fi}\right)^{1-\rho}\frac{s_{mj}c_j q_j}{p_{mj}^{1-\rho}}}_{\text{Sales to } j}. \end{aligned} \tag{17}$$

The total profit of the firm becomes variable profits net of fixed costs.

$$\pi_i\left(Z_i, I_{Fi}, I_{iF}\right) = \pi_i^{var}\left(Z_i, I_{Fi}, I_{iF}\right) - \sum_{j\in Z_i} w f_{Di} - I_{Fi} w f_{Fi} - I_{iF} w f_{iF}. \tag{18}$$

Thus the firm's problem becomes

$$\max_{Z_i, I_{Fi}, I_{iF}} \pi_i\left(Z_i, I_{Fi}, I_{iF}\right). \tag{19}$$

It is important to note that we do not assume firm pair-specific fixed costs for domestic sourcing. Our assumption of fixed costs for domestic sourcing, f_{Di}, is i specific, which implies that given its importing and exporting decisions, a firm only has to evaluate N different sourcing sets for its domestic suppliers: no sourcing, only from the firm with the lowest unit cost, from two firms with the lowest unit costs, and so on. This substantially reduces the number of evaluations, from 2^{N-1} to N.[22] At the same time, the model predicts a strict pecking order in the sourcing strategies. The set of customers of a firm with the most outdegree includes the set of customers of a firm with the second most outdegree, and so on.

[22]This assumption is similar to that of Blaum, Lelarge, and Peters (2016), where they assume firms' importing fixed costs vary across firms but common across sourcing countries.

4.3 Equilibrium

Here we close the model and describe the equilibrium. We assume that the profits firms make are distributed back to the households. We also assume that labor is mobile across homogeneous and heterogeneous goods sectors, and that both sectors are active both at home and abroad. We take the homogeneous good's price as the numeraire, and since markets in the homogeneous goods sector are perfectly competitive, wages can be taken as given in that sector. We also assume balanced trade. The household's budget constraint becomes

$$E = wL + \sum_{i\in\Omega} \pi_i, \tag{20}$$

where L denotes the mass of households. Trade balance and labor market clearing conditions are the following:

$$[\text{TB}]:0 = \underbrace{\sum_{i\in\Omega} I_{iF} p_{iH}^{1-\sigma} D^*}_{\text{Hetero. exports}} - \underbrace{\sum_{i\in\Omega} I_{Fi} s_{Fi} c_i q_i}_{\text{Hetero. imports}} + \underbrace{wl^Y - (1-\alpha)E}_{\text{Net exports of homog.}} \tag{21}$$

$$[\text{LMC}]:wL = \sum_{i\in\Omega} s_{li} c_i q_i + \sum_{i\in\Omega}\left(\sum_{j\in Z_i} wf_{Di} + I_{Fi} wf_{Fi} + I_{iF} wf_{iF}\right) + wl^Y, \tag{22}$$

where l^Y is the domestic labor allocated to the production of homogeneous goods.[23]

Let us first characterize the equilibrium under a fixed network structure.

Definition 1 (Equilibrium under a fixed network)**.** Take as given foreign demand D^* and foreign price p_F. Assume that the total amount of labor associated with the fixed costs is less than the total supply of labor L. An equilibrium for the model where the production network and firms' participation in international trade are exogenous and fixed is a set of variables $\{w, P, E, q_i, l^Y\}$ that satisfy equations (5)-(7), (9)-(16), (18), and (20)-(22).

Under a fixed network and given wages, one can find prices by solving for the fixed-point problem of firm-level unit costs, c_i, from equations (9), (10), (13) and (15). After backing out all the pairwise shares and prices, including the aggregate price index P, one can then solve for the fixed point of aggregate expenditure, E, from equations (5), (7), (16), (18), and (20).

Let us now turn to the equilibrium with endogenous network formation. We cannot rule out the potential multiplicity of the equilibrium that arises from firms' problem described in equation (19). Suppose that a firm guesses it will face high unit cost and thus face less demand for its good. Then it would expect less variable profits, and as a result it would not source from many suppliers. Then

[23] The assumption of both sectors being active in both countries are crucial, as without it the trade balance condition would not hold.

the firm will indeed end up having high unit costs. Conversely, if a firm guesses it will have low unit cost, then the guess will be realized by the firm sourcing from many firms.

Given this potential multiplicity, we focus on a particular equilibrium following Atkeson and Burstein (2008) and Edmond, Midrigan, and Xu (2015). We focus on an equilibrium that results from firms sequentially making sourcing and international trade participation decisions. We order firms in terms of productivity, and let the most productive firm in the economy make domestic sourcing and importing/exporting decisions. Taking the first firm's decisions as given, the second most productive firm makes its own decisions, and so on.[24] We essentially solve a large fixed-point problem of the production network, where all firms choose the optimal domestic sourcing and international trade participation decisions, taking as given the decisions of other firms. The resulting equilibrium is a pairwise stable equilibrium, where no firm has an incentive to drop its existing supplier or an incentive to add new suppliers.[25]

Note that in each evaluation of the network structure, we solve the equilibrium described by Definition 1. Firms set prices that maximize variable profits, taking as given the network structure. Consistent with the concept of "Nash-in-Nash" equilibrium (Collard-Wexler, Gowrisankaran, and Lee, 2016), we do not allow firms to consider alternations in linkages when setting prices.

Lastly, we highlight some differences in the approach we take for endogenous network formation compared to Tintelnot, Kikkawa, Mogstad, and Dhyne (2017). In their framework, firms are sorted so that they can only supply from the firms previous in the ordering. This results in an acyclic network, where there exists at least one ordering of firms so that all directed edges face one direction. Additionally, they assume that firms do not charge markups when selling to other domestic firms. This makes the network formation problem more tractable, as firms' profits are not affected by the sourcing decisions of the firms downstream in the ordering.

Our paper puts emphasis on imperfect competition in firm-to-firm trade, and one of our main focuses is on pairwise variable markups in firm-to-firm trade. Thus we employ another approach that focuses on an equilibrium arising from sequential decision making. The resulting networks we obtain are not confined to ones that are acyclic. Since the sourcing decision of a firm is affected by those of other firms (subsequent in the ordering) through the changes in its profit, the fixed-point problem of the network we solve remains computationally demanding.

[24] We find that altering this ordering has little impact on the aggregate variables. Similar to what is discussed in Edmond, Midrigan, and Xu (2015), the differences in the networks across the orderings come from differences in decisions on sourcing from marginal suppliers, which have little impact in the aggregate variables.

[25] We describe the computational algorithm for the network formation in Appendix C. Existence of such equilibrium is not theoretically guaranteed. However, we find that the network generally converges to a fixed point in the numerical analysis.

4.4 Network irrelevance under the benchmark case

Let us now consider the network irrelevance results under special cases in the model. Consider the change in price index and welfare, given an exogenous change in foreign price. The following proposition and lemma demonstrate that under certain assumptions, firm-level variables are sufficient in computing aggregate responses. These results resemble that of Hulten (1978) and of Baqaee and Farhi (2017), but focus on global changes in a setup with international trade. Following Dekle, Eaton, and Kortum (2007), let the change in variable x from the pre-shock equilibrium x to the post-shock equilibrium x' be $\hat{x} = x'/x$.

Assumption 1. *Only composite final consumption goods are exported.*

Assumption 2. *Preferences and technologies have common CES parameters, $\sigma = \eta = \rho$.*

Assumption 3. *Goods are competitively priced, $p_i = c_i\ \forall i \in \Omega$.*

Assumption 4. *The domestic firm-to-firm network is exogenous and fixed.*

Proposition 1 (Network irrelevance with a common CES parameter)**.** *Suppose that Assumptions 1-4 hold. Denote $\tilde{\sigma}$ as the common CES parameter from Assumption 2. Then the change in aggregate price index in the heterogeneous goods sector, $\hat{P}$, can be expressed as*

$$\hat{P}^{1-\tilde{\sigma}} = \sum_{i \in \Omega} \frac{p_i q_i}{\alpha E + Exports} \left(s_{li} + s_{Fi} \hat{p}_F^{1-\tilde{\sigma}} \right), \tag{23}$$

and the change in aggregate welfare, $\hat{U}$, can be expressed as:

$$\hat{U} = \left(\sum_{i \in \Omega} \frac{p_i q_i}{\alpha E + Exports} \left(s_{li} + s_{Fi} \hat{p}_F^{1-\tilde{\sigma}} \right) \right)^{\frac{-\alpha}{1-\tilde{\sigma}}}. \tag{24}$$

Proof. See Appendix D.3. □

This result shows that under these assumptions, one does not need any information on how firms are linked with other firms in evaluating aggregate changes. Firms' direct exposure to the shock are captured by firms' foreign input shares, s_{Fi}. The importance of each firm in the production network is captured by the Domar (1961) weight, $\frac{p_i q_i}{\alpha E + \text{Exports}}$. These two firm-level variables are the sufficient statistics when one is interested in how the aggregate price index and welfare respond to a foreign price change.

However, in order to compute the changes in price index and welfare, one needs to know the value of $\tilde{\sigma}$ in addition to the firm-level observables. In the following lemma, we impose a stronger assumption in preference and technologies and obtain a network irrelevance result where aggregate changes can be computed solely by firm-level observables.

Assumption 5. *Assume Cobb-Douglas functions in preferences and technologies, $\sigma = \eta = \rho = 1$.*

Lemma 1 (Network irrelevance under the benchmark case)**.** *Suppose that Assumptions 1, 3, 4, and 5 hold. Then the change in aggregate price index in the heterogeneous goods sector, $\hat{P}$, can be expressed as*

$$\ln \hat{P} = \sum_{i \in \Omega} \frac{p_i q_i}{\alpha E + Exports} s_{Fi} \ln \hat{p}_F, \tag{25}$$

and the change in aggregate welfare, $\hat{U}$, can be expressed as:

$$\ln \hat{U} = -\alpha \sum_{i \in \Omega} \frac{p_i q_i}{\alpha E + Exports} s_{Fi} \ln \hat{p}_F. \tag{26}$$

Under the Cobb-Douglas assumption in both preference and technology, one obtains a log-linear expression where aggregate movements are essentially the weighted sum of shocks that hit each firm. As the necessary variables are all observables in standard datasets, we use this case in Lemma 1 as the benchmark case in the counterfactual analysis and characterize the produced differences in the predictions between the benchmark case and the full model. We will also discuss predictions from the case in Proposition 1 under various values of $\tilde{\sigma}$.

Let us now discuss the assumptions. First, it is worth noting that the four assumptions in both Proposition 1 and Lemma 1 work as sufficient conditions in obtaining the network irrelevance result. In both Proposition 1 and Lemma 1, instead of having firms export their differentiated goods separately abroad, we assume that goods from all firms are bundled up to a composite final good, and that they are either consumed by the domestic households or exported abroad (Assumption 1).[26] By treating the exports of firms in the same way as their sales to final demand, we can use aggregate consumption and aggregate exports as the denominator of the Domar weights.

At first sight Assumptions 3 and 4 may not seem consistent with Assumption 2 in Proposition 1, where one usually assumes monopolistic competition in a CES demand framework. One can interpret this combination of assumptions in terms of the following. Consider an economy where firms are endowed with production technologies that also specify which other firms and countries to buy from, thus fixing the production network. And when there is another identical firm ready to enter the market and take over production, firms charge a competitive price.

In Proposition 1, one might conjecture that relaxing Assumption 3 and having constant and common markups in firm-to-firm trade would still produce the network irrelevance result. It turns out that it is not the case. As we show in detail in Appendix D.4, we obtain equation (23) because firms' Domar weights, which capture the importance of firms as suppliers of goods, coincides with a measure of firms' importance as consumers of goods. This is only possible when Assumption 3 holds.

[26] One can alternatively interpret this assumption as all firms in the heterogeneous goods sector either export or do not export at all.

5 Estimation

There are three sets of parameters that we estimate separately. First is the set of CES parameters in the preference and production functions: $\{\eta, \rho, \sigma\}$. The second set governs the distribution of productivities. The third is the set of parameters that determine fixed costs of forming domestic links and fixed costs of participating in international trade. We describe the estimation procedures for the three sets of parameters in the following subsections.

5.1 Estimating the CES parameters

We estimate the CES parameters $\{\eta, \rho, \sigma\}$ by exploiting the firm-to-firm shares that we observe in the data. Recall that in equation (15) pairwise markups $\mu_{ij} = \frac{\varepsilon_{ij}}{\varepsilon_{ij}-1}$ are functions of parameters $\{\eta, \rho\}$ and observables s^m_{ij}. We have also assumed that markups firms charge on goods to domestic households and on exported goods, μ_{iH}, are $\frac{\sigma}{\sigma-1}$.

In our static model, a firm's input cost equals its sum of sales, each deflated by the destination-wise markups:

$$c_i q_i = \sum_j \frac{V_{ij}}{\mu_{ij}} + \frac{V_{iH}}{\mu_{iH}} + \frac{V_{iF}}{\mu_{iH}}. \tag{27}$$

We observe the input costs $c_i q_i$ and firms' destination-wise sales: sales to firm j, V_{ij}, sales to households, V_{iH}, and exports, V_{iF}.[27] Using these observables, we estimate the CES parameters $\{\sigma, \rho, \eta\}$ by minimizing the Euclidian distance between both sides of equation (27):

$$\min_{\eta,\rho,\sigma} \sum_i \left[c_i q_i - \left(\sum_j \frac{V_{ij}}{\mu_{ij}} + \frac{V_{iH}}{\mu_{iH}} + \frac{V_{iF}}{\mu_{iH}} \right) \right]^2 . \tag{28}$$

Since firms' markups to final demand, μ_{iH}, are constants $\frac{\sigma}{\sigma-1}$, the variations in the ratio of firms' sales to final demand ($V_{iH} + V_{iF}$) over firms' total inputs ($c_i q_i$) pins down the value of σ. Firm-to-firm markups, μ_{ij}, are functions of pair specific shares, s^m_{ij}, and two parameters, ρ and η. Thus the ratio of firm-to-firm sales $\left(V_{ij}\right)$ over suppliers' input costs ($c_i q_i$) and the input shares $\left(s^m_{ij}\right)$ jointly determine the value of the two parameters.[28]

The underlying assumption of this estimation procedure is that there are measurement errors in firms' labor costs, which is a component of $c_i q_i$. We assume that these errors are not correlated with the RHS variables of equation (27). The parameters are identified under this assumption, since firms' labor costs only appear on the LHS as one component of supplier i's total inputs and not in the RHS

[27] We compute variable input costs $c_i q_i$ by summing up firms' labor costs, purchases from other domestic firms, and imports. We assume that labor costs in our data are variable costs, as distinguishing fixed costs from variable costs is impossible.

[28] Edmond, Midrigan, and Xu (2015) use a similar procedure with sectoral market shares to infer one of the CES parameters in models with variable markups.

variables. Table 4 reports the estimation results.[29]

Table 4: Estimated values for $\{\eta, \rho, \sigma\}$

	η	ρ	$\frac{\sigma}{\sigma-1}$
Estimate	1.27	2.78	1.25
s.e.	1.07	0.31	0.05
	η (Labor and goods)	ρ (Firm's goods in production)	σ (Firms' goods in consumption)
Implied value	1.27	2.78	4.99

Notes: Standard errors are based on 100 bootstrap samples drawn with replacement.

We find that in the production function, the substitution parameter across labor and goods, is 1.27. Within intermediate goods, the substitution parameter across goods from different firms and imported goods is 2.78. In the preference function, we find that the substitution parameter across goods is 4.99. The estimated values fall in plausible ranges. With a sectoral layer in the production function, the survey of Anderson and van Wincoop (2004) finds that the elasticity of substitution across goods in the production function within sectors to be in the range of 5 to 10. As we do not have a sectoral layer, it is plausible that our estimate of ρ is smaller.[30]

Robustness

In our model, firms engage in Bertrand competition in firm-to-firm trade. In an alternate specification we assume that firms engage in Cournot competition, which leads to a different formula for pairwise markups μ_{ij}:

$$p_{ij} = \frac{\varepsilon_{ij}}{\varepsilon_{ij} - 1} c_i$$
$$\varepsilon_{ij} = \left(\frac{1}{\rho} \left(1 - s_{ij}^m \right) + \frac{1}{\eta} s_{ij}^m \right)^{-1}.$$

In Appendix E.2 we estimate the three parameters under this setup, and we find similar estimates.[31]

Our estimates for the three parameters are also not affected when one assumes oligopolistic competition in the final goods market. This is because for most firms, shares in the final goods consumption are infinitesimal, which validates our assumption of monopolistic competition.

[29] To illustrate the fit of the model under the estimated parameters, in Appendix E.1 we provide the distribution of errors at the firm level, i.e., the difference between the LHS and RHS of equation (27).

[30] Our approach of estimating CES parameters is different from that of other papers that estimate substitution parameters at higher frequencies. For example Boehm, Pandalai-Nayar, and Flaaen (2016), Barrot and Sauvagnat (2016), and Atalay (2017) find much lower estimates in the production function parameters. In contrast, we estimate CES parameters using implied markup levels.

[31] In another alternative setup, we estimate ρ and σ by assuming constant markups in firm-to-firm trade, where firms charge $p_{ij} = \frac{\rho}{\rho-1} c_i$. Here we also obtain similar estimates, where the estimated value of ρ is slightly smaller than what we estimate here. The results are reported in Appendix E.3.

Finally, it is worth pointing out that we do not have capital goods in our model. We sum firms' total labor costs, purchases from other domestic firms, and imported goods in our measurement of firms' total inputs, $c_i q_i$. Missing capital inputs will lower our measurement of $c_i q_i$. If the degree of capital intensity is correlated with the firm's sales, then it violates our assumption of uncorrelated errors. To accommodate this potential issue, we take into account firms' capital inputs in two alternative ways. First, we uniformly scale up labor costs of firms by assuming a common labor-to-capital share. Second, we compute firm-level capital costs from the annual accounts data. As the results in Appendix E.4 reveal, we find similar estimates in both cases.

5.2 Estimating the productivity distribution

We then recover the productivity distribution from the identity equation implied by the model:

$$\ln \phi_i = \frac{1}{\sigma - 1} \ln V_{iH} + \frac{1}{\eta - 1} \ln s_{li} + \ln \left(\frac{\sigma}{\sigma - 1} \omega_l^{\frac{-\eta}{\eta - 1}} P^{-1} \alpha^{\frac{-1}{\sigma - 1}} E^{\frac{-1}{\sigma - 1}} \right). \tag{29}$$

Equation (29) implies that the log productivity of a firm can be recovered up to a scale, from firms' sales to households, V_{iH}, and from firms' labor input shares, s_{li}. We assume that the productivity distribution is log-normal, and we estimate the dispersion parameter to be 2.44.

Note that the firm's sales to households and firm's labor share both determine the firm's productivity. Since we assume constant markups in firms' sales to final demand, the variation in firms' sales to households reflects the variation in firms' unit costs. However, the variation in unit costs is not driven by the variation in firms' productivity alone.

A firm may have low unit cost simply because its core productivity is high, but it might also be buying cheap goods from other firms. Therefore, we need to control for the effects that come from firms' sourcing strategies. Notice from equation (11) that the variation in firms' labor share comes only from firms' sourcing strategies, as we assume that wage is common across firms. In order to pin down the variation in firms' core productivity, equation (29) controls for firms' labor share in addition to firms' sales to final demand.

5.3 Estimating the fixed cost distributions

The remaining parameters in need of estimation govern the fixed cost distributions. We assume that firms' fixed costs for sourcing from a domestic supplier, f_{Di}, are drawn from a common distribution, $F_D(\cdot)$. Firms' fixed costs for importing and exporting, f_{Fi} and f_{iF}, are drawn from the common distributions $F_{IM}(\cdot)$ and $F_{EX}(\cdot)$. We additionally assume that the three distributions are log-normal, independent from each other, and that they have a common dispersion parameter Φ^{disp}. We estimate the three scale parameters Φ_D^{scale}, Φ_{IM}^{scale}, and Φ_{EX}^{scale}, along with the common dispersion parameter Φ^{disp} via simulated methods of moments.

When running model simulations under endogenous networks, we additionally assume that the saliency terms in preference and production functions, $\left\{\beta_{iH}, \alpha_{ij}, \alpha_{Fi}\right\}$, to be equal to 1. We also calibrate the rest of the parameters. We set the production weights on labor inputs and goods inputs, ω_l and ω_m, to be 0.3 and 0.7, respectively, to match the average labor input share of 0.34 in our sample. The Cobb-Douglas share in the preference function on the heterogeneous goods sector α is set to 0.55 to match the aggregate share of the private and non-financial sectors in Belgium. We set the foreign demand D^* to be 10^{14} so that it matches the average export share for exporting firms' output of 0.2. Analogously, we set foreign price p_F to be 5 so that it matches the average imported goods' share for importing firms' inputs of 0.31. Finally, we set L to be 10^{10}.

For determining the three scale parameters of domestic sourcing, importing and exporting, we use the aggregate shares of firms that are sourcing from at least one domestic firm, m_{dom}, shares of firms that are importing, m_{imp}, and shares of firms that are exporting, m_{exp}, as moments. We use the correlation between domestic indegrees and outdegrees of firms, m_{cor}, to infer the dispersion parameter in the fixed costs. The intuition is as follows. Suppose that the dispersion parameter is zero. Then all firms draw a common number for the domestic fixed costs. In that case, the most productive firm will be the firm that sources from the most firms, and it will also be the firm that sources to the most firms. Thus, the correlation between indegrees and outdegrees becomes one. As the dispersion parameter increases from zero, it will no longer be the case that the most productive firm is the firm that sources from the most firms, and the correlation decreases. In all, we have four moments to identify four parameters.

Let us denote δ as the set of four moments, $\left\{\Phi_D^{scale}, \Phi_{IM}^{scale}, \Phi_{EX}^{scale}, \Phi^{disp}\right\}$, and the vector of four moments generated by the model as $\hat{m}(\delta)$. Given δ, we can calculate the difference between the moments generated by the model and the moments from the data:

$$\hat{y}(\delta) = m - \hat{m}(\delta) = \begin{bmatrix} m_{dom} - \hat{m}_{dom} \\ m_{imp} - \hat{m}_{imp} \\ m_{exp} - \hat{m}_{exp} \\ m_{cor} - \hat{m}_{cor} \end{bmatrix}.$$

We assume that the following moment condition holds at the true parameter values δ_0:

$$E\left[\hat{y}(\delta_0)\right] = 0.$$

Therefore, we estimate δ by solving the following minimization problem

$$\min_{\delta} \left[\hat{y}(\delta)\right]' \boldsymbol{W} \left[\hat{y}(\delta)\right],$$

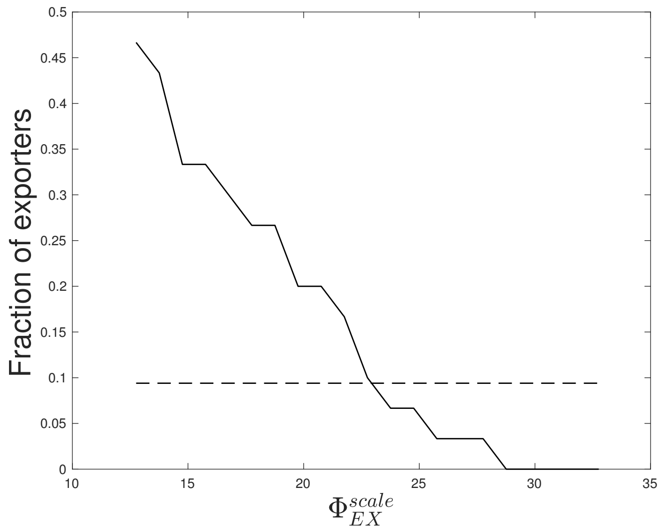
where $\boldsymbol{W}$ is a weighting matrix.[32] We report the estimated values in Table 5, as well as the standard errors from a bootstrap method. In the bootstrap method, we draw a different set of firms with different productivities each time.

Table 5: Estimated values for the fixed cost parameters

	Φ_D^{scale}	Φ_{IM}^{scale}	Φ_{EX}^{scale}	Φ^{disp}
Estimate	2.37	21.10	22.76	6.10
s.e.	0.38	0.28	0.33	0.56

We provide local identification for the four parameters, which we display for Φ_{EX}^{scale} in Figure 5 as an example. Fixing other parameters, one can see that as the scale parameter for exporting fixed costs increases, less firms become exporters. This monotonic relationship determines the value of the parameter. We display this local identification for the other parameters in Appendix E.5.

Figure 5: Local identification of Φ_{EX}^{scale}



Notes: On the x-axis we plot Φ_{EX}^{scale}, the scale parameter for the distribution of fixed costs for exporting, which we vary while fixing all other parameters to their estimated values. On the y-axis we plot the share of exporters. The horizontal line indicates the observed value in the data. The monotonic relationship determines the value of Φ_{EX}^{scale}.

Finally, we note that due to computational limitations, we can only simulate the economy with a limited number of firms. Our problem of endogenous network formation is arguably complex. One has to solve a large fixed-point problem of a cyclic network where, within each network, one has to solve another fixed-point problem of pairwise prices and shares. In our estimation, we simulate the economy with 30 firms.

One may argue that 30 firms may not be able to entirely capture the effects of firm-to-firm trade on the aggregate movements. In Appendix G, we build a variant of our model adjusted to represent one single manufacturing sector where we focus on firm-to-firm trade within the sector. In this sector,

[32] In practice, we weight the moments equally.

the top 30 firms account for almost all the sales and firm-to-firm trade. We argue that the results from the counterfactual exercise under this partial equilibrium model are qualitatively the same as what we will show in Section 6.

5.4 Model fit

Table 6 reports the model fit for targeted and non-targeted moments under the estimated parameters. One can see that the model does well in fitting the targeted statistics. As for the non-targeted moments, the model succeeds in predicting positive correlations between firms' sales and indegrees/outdegrees. It also succeeds in generating a weak negative assortativity in the network: a negative correlation between suppliers' sales and customers' sales. Finally, the last three rows report the model fit in terms of matching the distributions of pairwise input shares, which dictate the level of markups. The model seems to suitably match the magnitudes of the median and the 25th percentile. The model fails to match the right tail of the input share distribution. However, the pairwise markups derived in equation (15) are increasing and convex in the pairwise input shares under the estimated parameters of ρ and η. Therefore, there is little difference in the level of markups in the region where input shares are close to zero.

Table 6: Targeted and non-targeted moments

Panel A: Targeted moments		
	Data	Model
Fraction of firms sourcing from domestic firms	0.98	0.97
Fraction of importers	0.15	0.17
Fraction of exporters	0.09	0.10
Corr(Indeg, Outdeg)	0.65	0.65
Panel B: Non-targeted moments		
	Data	Model
Corr(Sales, Indeg)	0.48	0.24
Corr(Sales, Outdeg)	0.51	0.33
Corr(Sales_i, Sales_j)	-0.02	-0.06
25th percentile s_{ij}^m	3.1×10^{-4}	3.0×10^{-4}
Median s_{ij}^m	1.8×10^{-3}	3.4×10^{-3}
75th percentile s_{ij}^m	8.2×10^{-3}	4.5×10^{-2}

6 Counterfactual analysis

We conduct counterfactual analysis with the model parameters that we have recovered in the previous section. In particular, we focus on an exogenous reduction in a foreign good's price, p_F, and analyze how it affects aggregate variables, such as price index and welfare. We start with the results from the benchmark case where the network structure is irrelevant. We then add market frictions one by one, and finally present the results from the full model.

In the first subsection, we do counterfactual analysis where the network is fixed. We analyze the predictions from the benchmark case then add monopolistic competition in firm-to-firm trade, and then finally add oligopolistic competition. In all three cases, we use the firm-to-firm network that we observe in the data, along with the estimated CES parameters from Section 5.1. In the next subsection, we add endogenous networks. Here we switch to the estimated full model and conduct model simulations. Finally, in the last subsection, we consider the model with a common CES parameter that features a network irrelevance result (described in Proposition 1). We do so by evaluating aggregate changes under different values of the common CES parameter.

6.1 Under fixed network

We characterize the differences in aggregate predictions made by models with a fixed network. We focus on the movements in the aggregate price index. First, we consider the predictions from the benchmark case. We have shown in equation (25) of Lemma 1 that given the change in the foreign good's price, $\hat{p}_F$, the change in the aggregate price index, $\hat{P}$, can be solely determined from firm-level variables. The aggregate price index falls more in response to a reduction in the foreign good's price if firms that have larger sales have higher exposure to foreign goods.

In the second case, we add constant markups in firm-to-firm trade and compare the movements in the aggregate price index with those from the benchmark case. In this second case we relax Assumptions 1, 3, and 5. Instead we assume CES structures in preference and technology, using the estimated parameters for σ, ρ, and η. In this case, the fall in the aggregate price index becomes even larger. Firms and households now face CES substitution parameters that are larger than one, and are able to shift their expenditures more towards goods that became relatively cheaper. This contributes to larger movements in the aggregate price.

For the third case, we consider firms charging variable markups in firm-to-firm trade. When one adds variable markups, there are two counteracting forces that push the aggregate price index in the opposite directions: the attenuation effect and the pro-competitive effect.

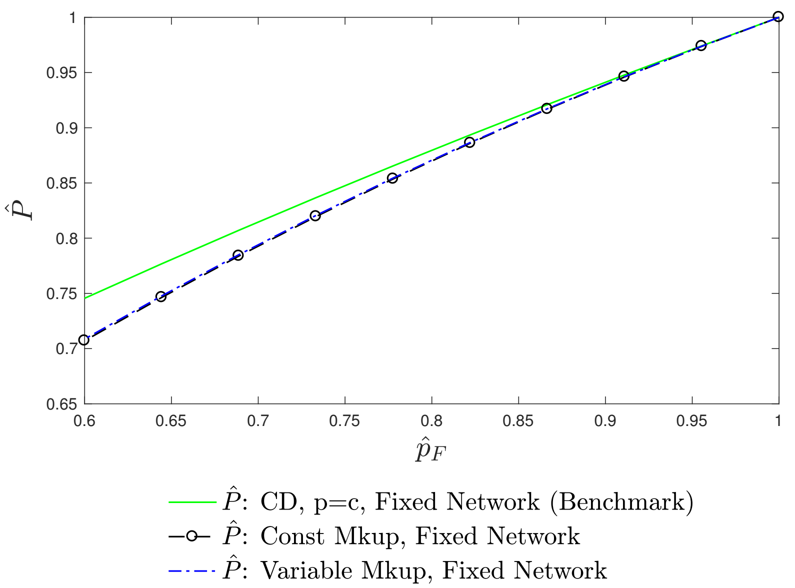
Consider a firm facing a price reduction in one of its inputs. In the constant markup case, the firm's output prices go down proportionally to the input's share in the firm's total inputs. However, in the variable markup case, the firm will increase its markups as it enjoys larger shares in its customers' inputs. This attenuation effect leads to incomplete price pass-through and reduces the aggregate movement in the price index. On the other hand, the other firms that sell goods to the same customer may also receive positive cost shocks. In that case, the firm reduces its markup in the face of increased competition. This pro-competitive effect leads to larger movements in the aggregate price index. Overall, the net effect on the movements in the aggregate price index can either be positive or negative.

In both the constant markup case and the variable markup case, following a technique developed by Dekle, Eaton, and Kortum (2007), we can compute the change in the aggregate price index using the observed input shares and the estimated CES parameters. In Appendix D.5 we present the system of equations for the changes in firms' unit costs and pairwise markups.

We display the results in Figure 6. The first line in the figure displays the change in price index computed using equation (25) in the benchmark case.[33] As the foreign good's price falls (as $\hat{p}_F$ moves from right to left), the aggregate price index falls. In the benchmark case, 40% reduction in the foreign good's price ($\hat{p}_F = 0.6$) leads to a drop in the aggregate price of about 25%.[34] In the second case, we indeed see a larger reduction in the aggregate price index. With higher substitutability across goods, the price index now falls by around 30% when $\hat{p}_F$ is 0.6.

Adding pairwise variable markups does not seem to make significant changes in the movements of aggregate prices, as one cannot visually distinguish the third line in Figure 6 from the second line. As aforementioned, the two counteracting forces cancel each other out. But in the aggregate, the third line in Figure 6 is slightly above the second, indicating that the attenuation effect weakly dominates the pro-competitive effect.

Figure 6: $\hat{P}$ under the fixed network



[33] This prediction exhibits nonlinearity as the $\hat{P}$ is computed for global changes. In Appendix F.1 we also provide predictions for the first order approximated changes, as considered in Hulten (1978).

[34] Under the estimated value of $\rho = 2.78$ and fixed demand, $\hat{p}_F = 0.6$ corresponds to an increase in import value of around 150%. Chinese imports to Belgium have also increased by around the same amount in the 2000s. Accordingly, we consider foreign price shocks between $\hat{p}_F = 1$ and $\hat{p}_F = 0.6$, treating $\hat{p}_F = 0.6$ as the largest possible shock to the economy.

Characterizing the attenuation and pro-competitive effects

Even though the net effects turn out to be small, it is worth exploring the underlying mechanisms. To characterize the two effects of adding variable markups, we work with the system of cost changes that are approximated at the first order. In the case where firms charge constant markups, the system of equations for the first order approximated changes in prices given $\frac{\mathrm{d}p_F}{p_F}$ and parameters are as follows:

$$\frac{\mathrm{d}c_i}{c_i} = \sum_{j\in Z_i} s_{ji}\frac{\mathrm{d}c_j}{c_j} + s_{Fi}\frac{\mathrm{d}p_F}{p_F}. \tag{30}$$

And in the case where firms charge pairwise variable markups in firm-to-firm trade where the network is fixed, the system of first order changes in prices is expressed in equations (31), (32), and (34). The changes in firms' unit costs are now affected by the changes in the unit costs of their suppliers and also the changes in the markups they charge:

$$\frac{\mathrm{d}c_i}{c_i} = \sum_{j\in Z_i} s_{ji}\left(\frac{\mathrm{d}\mu_{ji}}{\mu_{ji}} + \frac{\mathrm{d}c_j}{c_j}\right) + s_{Fi}\frac{\mathrm{d}p_F}{p_F}, \tag{31}$$

where

$$\frac{\mathrm{d}\mu_{ji}}{\mu_{ji}} = \underbrace{-\Gamma_{ji}\frac{\mathrm{d}c_j}{c_j}}_{\text{attenuation effect}} + \underbrace{\Gamma_{ji}\frac{\mathrm{d}p_{\not{j}i}}{p_{\not{j}i}}}_{\text{pro-competitive effect}}. \tag{32}$$

The term Γ_{ji} represents the elasticity of the markup μ_{ji} with respect to the supplier's cost c_j:

$$\begin{aligned}\Gamma_{ji} &= -\frac{\partial\mu_{ji}}{\partial c_j}\frac{c_j}{\mu_{ji}} \\ &= \frac{\Upsilon_{ji}\left(1-s^m_{ji}\right)}{1-\Upsilon_{ji}s^m_{ji}},\end{aligned} \tag{33}$$

where

$$\Upsilon_{ji} = \frac{\left(\rho-\varepsilon_{ji}\right)(\rho-1)}{\left(\varepsilon_{ji}-1\right)\varepsilon_{ji} + \left(\rho-\varepsilon_{ji}\right)(\rho-1)}. \tag{34}$$

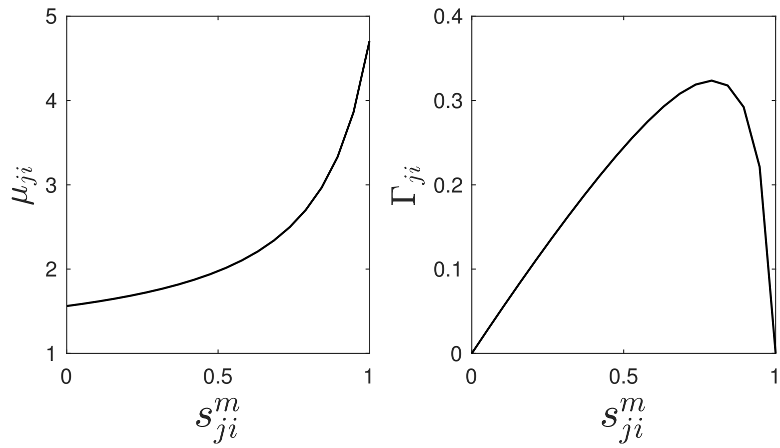
The term $\frac{\mathrm{d}p_{\not{j}i}}{p_{\not{j}i}}$ represents the average price change from suppliers other than j:

$$\frac{\mathrm{d}p_{\not{j}i}}{p_{\not{j}i}} = \frac{\sum_{k\in Z_i, k\neq j} s^m_{ki}\left(\frac{\mathrm{d}\mu_{ki}}{\mu_{ki}} + \frac{\mathrm{d}c_k}{c_k}\right) + s^m_{Fi}\frac{\mathrm{d}p_F}{p_F}}{1-s^m_{ji}}. \tag{35}$$

The term $\frac{\mathrm{d}\mu_{ji}}{\mu_{ji}}$ in equation (31) captures the additional effect that firm j has on firm i's unit cost by adding variable markups. $\frac{\mathrm{d}\mu_{ji}}{\mu_{ji}}$ can be decomposed into two. The first term in equation (32) captures the attenuation effect, since reduction in j's cost leads to an increase in markup μ_{ji}. On the other hand, the second term in equation (32) says that the markup μ_{ji} is also affected by i's other suppliers besides j. If the prices of other suppliers and imported goods decline on average, then μ_{ji} decreases.

The magnitudes of both effects are governed by two components. First, the term Γ_{ji}, which is the elasticity of markup with respect to the supplier's cost, governs the maximum possible magnitudes of the two. As one can see in Figure 7, markup μ_{ji} is increasing and convex with respect to the input share s^m_{ji}. And when the input share converges to either 0 or 1, the markup converges to a constant, making the elasticity Γ_{ji} converge to 0. The elasticity displays a hump shape with respect to s^m_{ji} and is largest when the share is around 0.8. This allows both attenuation and pro-competitive effects to be large. However, the magnitudes of the two effects are also affected by how much shock the supplier or the other suppliers received. For example, even if the input share for a specific pair is in the region where the elasticity Γ_{ji} is large, if the supplier's cost did not decrease at all, there will be no attenuation effect. The degrees of cost reductions by the suppliers govern the degree of attenuation effects within the same values of input shares. Likewise, the average degrees of price changes by other suppliers determine the degree of pro-competitive effects within the same value of input shares.[35]

Figure 7: Markup μ_{ji} and elasticity Γ_{ji} with respect to input share s^m_{ji}



Notes: The figure plots the pairwise markup, μ_{ji}, and elasticity of μ_{ji} with respect to c_j, Γ_{ji}, in equation (32), as a function of s^m_{ji}. We use the parameter values of $\rho = 2.78$ and $\eta = 1.27$.

Characterizing the net effects

We now characterize the aggregate magnitudes of the two effects in a similar fashion, by computing the first order approximations of the changes in aggregate prices. We decompose the aggregate price change into three, as shown in equation (36):

[35] In Appendix F.2 we plot these pairwise attenuation and pro-competitive effects with respect to input shares. We also show that the degree to which suppliers and the other suppliers received the shock are correlated with a measure capturing the exposure of firms to foreign goods, both directly and indirectly through their suppliers.

$$\frac{\mathrm{d}P}{P} = \sum_i s_{iH} \left(\sum_{j \in Z_i} s_{ji} \frac{\mathrm{d}c_j}{c_j} + s_{Fi} \frac{\mathrm{d}p_F}{p_F} \right) + \sum_i s_{iH} s_{mi} \sum_{j \in Z_i} s_{ji}^m \frac{\mathrm{d}\mu_{ji}}{\mu_{ji}}. \tag{36}$$

The first line represents the effects that are present in the constant markup case: firms' cost changes come from their direct exposures to foreign price change, and their exposure to each supplier's cost change. The second line represents captures the aggregate effects of the net changes in individual markups. The term $\sum_{j \in Z_i} s_{ji}^m \frac{\mathrm{d}\mu_{ji}}{\mu_{ji}}$ captures the average movements of markups that firm i faces, each weighted by the input share for each supplier.[36]

To help understand which firm faces higher markups from its suppliers and which firm faces reductions in markups, in Figure 8 we plot firms' average change in markups $\sum_{j \in Z_i} s_{ji}^m \left(\hat{\mu}_{ji} - 1 \right)$ against a measure that captures firms' *indirect* exposure to foreign goods, $s_{Fi}^{Indirect}$. We first construct the measure of "total foreign input share", s_{Fi}^{Total}, that captures firm i's exposure to foreign inputs by summing up its direct exposure, and its suppliers' exposure, and so on:[37]

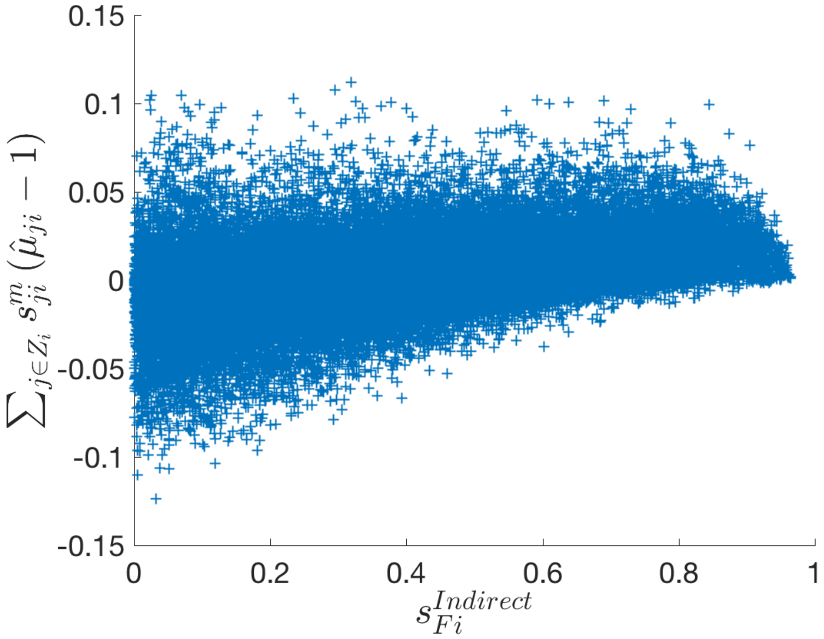
$$s_{Fi}^{Total} = s_{Fi} + \sum_{k \in Z_i} s_{ki} s_{Fk}^{Total}.$$

We then subtract firms' direct exposure to foreign inputs: $s_{Fi}^{Indirect} = s_{Fi}^{Total} - s_{Fi}$. One can see that there is a positive correlation between the two measures. Consider a firm with high value of $s_{Fi}^{Indirect}$, which supplier with high input share is highly exposed to foreign imports. In this case the attenuation effect dominates the pro-competitive effect, as the supplier with high input share raises its markup charged to the firm.

[36] The sum of the change in markups, $\sum_i s_{iH} s_{mi} \sum_{j \in Z_i} s_{ji}^m \frac{\mathrm{d}\mu_{ji}}{\mu_{ji}}$, can be decomposed into two components: the sum of the attenuation effects, $-\sum_i s_{iH} s_{mi} \sum_{j \in Z_i} s_{ji}^m \Gamma_{ji} \frac{\mathrm{d}c_j}{c_j}$, and the sum of the pro-competitive effects, $\sum_i s_{iH} s_{mi} \sum_{j \in Z_i} s_{ji}^m \Gamma_{ji} \frac{\mathrm{d}p_{\not{f}i}}{p_{\not{f}i}}$. In Appendix F.3 we plot the three components of the change in the aggregate price index. Though the net aggregate effect is small, the aggregate attenuation effect and pro-competitive effect are non-negligible in magnitude. In addition, in Appendix F.4 we characterize the magnitudes of average attenuation and pro-competitive effects at the firm-level using the HHI of input shares.

[37] s_{Fi}^{Total} is defined by Tintelnot, Kikkawa, Mogstad, and Dhyne (2017), and there is a one-to-one mapping between $\frac{\mathrm{d}c_j}{c_j}$ and s_{Fj}^{Total} under the benchmark case of our model.

Figure 8: Average change in markups and $s_{Fi}^{Indirect}$



Notes: The figure plots $\sum_{j \in Z_i} s_{ji}^m \left(\hat{\mu}_{ji} - 1\right)$ upon $\hat{p}_F = 0.6$, against firms' indirect exposure to foreign goods, $s_{Fi}^{Indirect}$.

The nature of the shock also matters in explaining the correlation between $\sum_{j \in Z_i} s_{ji}^m \left(\hat{\mu}_{ji} - 1\right)$ and $s_{Fi}^{Indirect}$. The shock we are focusing on here affects all the importers (accounting for around 15% of all firms) directly, and many other firms at the same time. The median value of the total foreign input share, s_{Fi}^{Total}, is around 41%. The shock being large scale, it is plausible to imagine that many firms have multiple suppliers which experience roughly the same degree of cost reductions. In these cases, both attenuation and pro-competitive effects tend to cancel each other out.

To illustrate this point, in Appendix F.5 we study an alternative shock where we hit only one importer with the foreign price reduction. We demonstrate that the positive correlation between the average movements in markups and firms' indirect exposure to the shock is much stronger. Moreover, in this case the net aggregate effects of adding variable markups are much larger. The differences in the changes in aggregate price index under constant markups and under variable markups are around 0.5% when considering the shock that hit all importers. But when considering the shock that hit a single importer, then the differences in the $\hat{P}$ becomes around 3% to 5%.[38]

6.2 Under endogenous networks

In this section we additionally consider cases where firms are allowed to change their sourcing sets and status for importing/exporting. In doing so, we depart from the firm-to-firm trade data and con-

[38]The net effect on the aggregate price index also depends on the underlying CES parameters. In Appendix F.6 we illustrate how different values of ρ and η affect the markup elasticities Γ_{ji}'s and, in turn, impact the aggregate effects on $\hat{P}$.

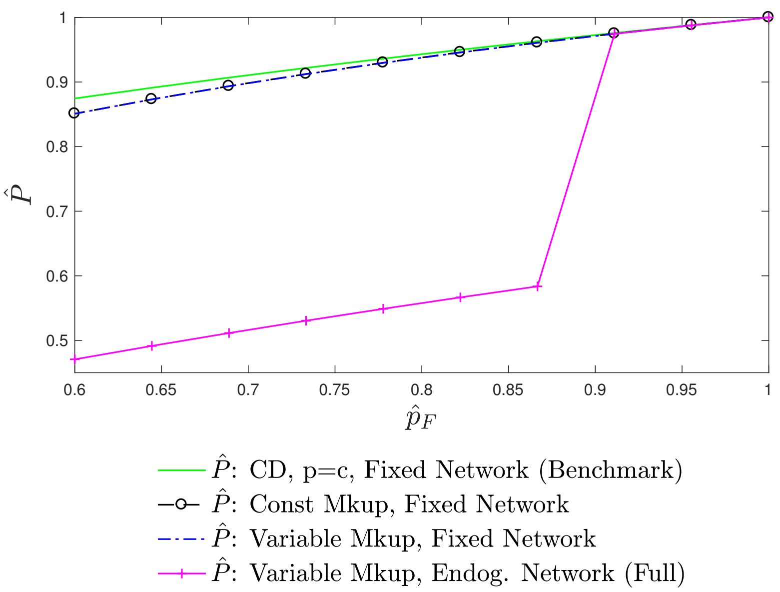
tend with the estimated model.

There are several forces that move the aggregate price index in different directions. First, as the foreign good's price falls, some firms that were initially not importers may decide to become importers. This leads to discrete reductions in unit costs of such firms, hence discrete reductions in the input costs of their customers and so on. The aggregate price index falls more as a result. Changes in domestic firm-to-firm linkages also affect the movements in the aggregate price index.

A firm will likely drop a supplier when its price becomes relatively higher. This pushes up the price index, as there are less firm-to-firm links to transmit cost reductions. On the other hand, a firm's sourcing decision may be complementary across suppliers and the firm may decide to add a new supplier, which diminishes the price index.

In Figure 9 we report the model's predictions on how aggregate price moves under four different cases. For the first three cases under fixed network - the baseline case, model with constant markups, and model with variable markups - the estimated model displays similar patterns as we have seen in Figure 6. Price index falls more under constant markups, but adding variable markups has small net effect.[39] The fourth line depicts the change in price index under the full model, where firms charge variable markups and change linkages. One can see that allowing firms to change linkages amplifies changes in price index. The kink when $\hat{p}_F$ is around 0.9 indicates the start of importing for a firm that originally was not an importer. This result is expected, as the new importer will be capitalizing on cheaper foreign goods. The discrete drop of the firm's unit cost leads to a further reduction in aggregate price.

Figure 9: $\hat{P}$ from the estimated model

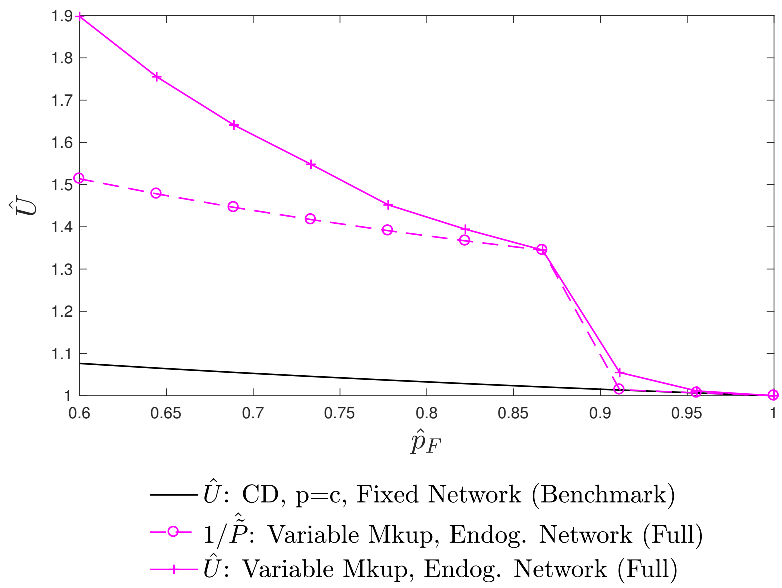


[39]The estimated model predicts a smaller change in aggregate prices, compared to the predictions using the full firm-to-firm network data. This is because of the calibration strategy that we employ. We parametrize the model so that it matches the average imported goods' share for the importing firms, and not the aggregate import share over GDP.

The movement in aggregate welfare is of natural interest. In the benchmark case, the change in aggregate welfare is simply the inverse of the change in the aggregate price index, as firms do not earn profits. But in the full model, it is also positively related to the change in aggregate net profits. In Figure 10 we compare the change in aggregate welfare implied by the benchmark case of the model with the change in aggregate welfare implied by the full model. We also plot the inverse of the change in the aggregate price index to illustrate the contributions of the change in aggregate net profits to the change in welfare in the full model.

We find that the changes in aggregate profits greatly magnify the changes in welfare, further differentiating the implications from our full model from those of the benchmark case. We also find that when a firm switches from a non-importer to an importer when $\hat{p}_F$ is around 0.9, the difference between the $\hat{U}$ and $1/\hat{\tilde{P}}$ diminishes. This is because the firm starts to pay additional fixed costs of importing, which reduces its profits net of fixed costs.

Figure 10: $\hat{U}$ in the benchmark case and full model



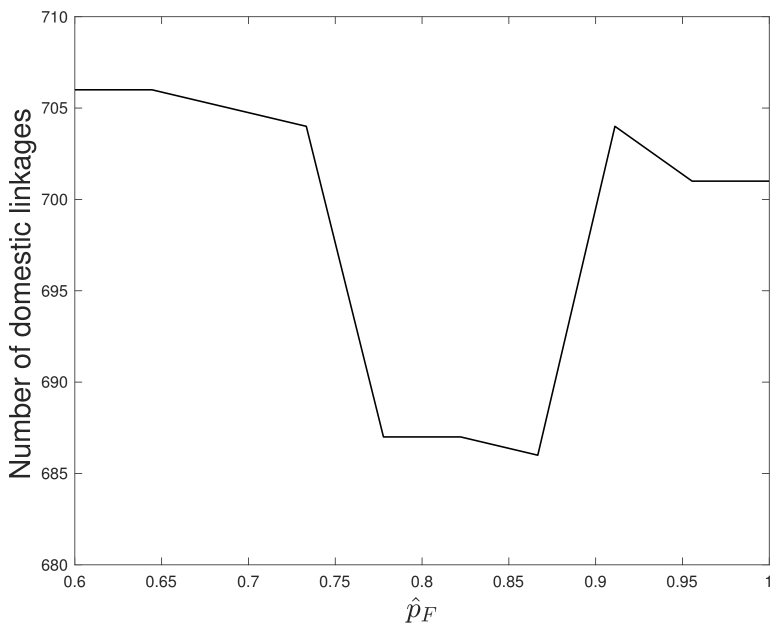
Changes in domestic firm-to-firm linkages

We also see changes in domestic firm-to-firm linkages, which we show in Figure 11. First note that as we have seen in Table 8, the firm-to-firm network is extremely sparse in the Belgian data. However, in the model, we generate a dense firm-to-firm input-output matrix. In order to reduce the number of possible sourcing sets, we assume fixed costs for domestic sourcing to be at the firm-level, and not at the pair level. Nevertheless, analyzing how the network evolves in our model provides important insights.

One can see from Figure 11 that the number of domestic linkages generally increases as the foreign price falls, except when $\hat{p}_F$ is around 0.9, which is where the non-importing firm decides to become an importer. The increase in number of linkages come from firms adding new suppliers with reduced output prices. The large drop in linkages when $\hat{p}_F$ is around 0.9 comes from the customer firms of the firm which became an importer. Facing large reduction in one of their input prices, they drop some of their other domestic suppliers.[40]

With regard to the empirical evidence that we presented in Section 3, we cannot test whether the same results hold true in this model, as we have too few firms. However, in the model we see the effects that we found in the Belgian data: as firms experience positive cost shocks, they experience larger churn in their suppliers. In the model, we see firms adding new suppliers as their existing suppliers' prices become cheaper. Also, we see firms drop existing suppliers in response to a larger input cost reduction.

Figure 11: Number of domestic firm-to-firm linkages



The interaction between variable markups and endogenous networks

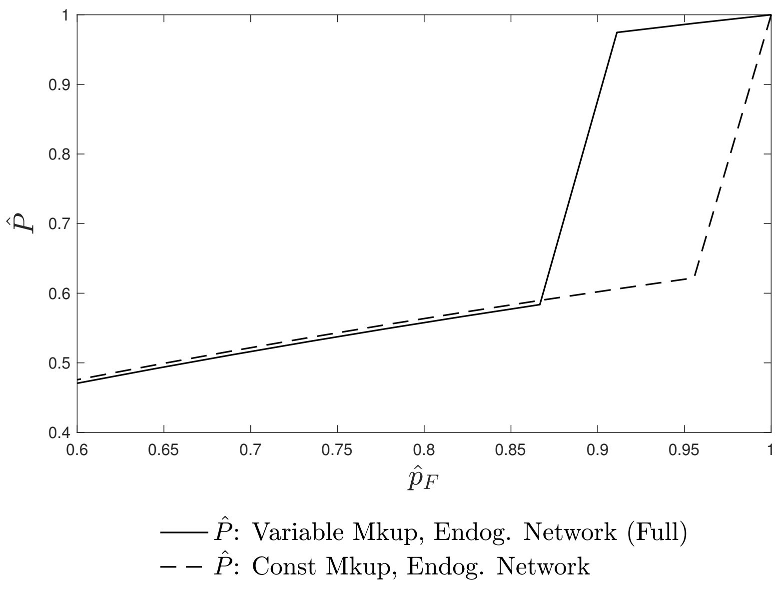
Lastly, we discuss the interaction between variable markups and firms' sourcing decisions. To investigate how much of the aggregate movements implied by our full model are coming from the

[40]The fact that firms may either drop or add suppliers in response to a reduction in one of its input prices may be confusing to readers familiar to Antras, Fort, and Tintelnot (2017), Tintelnot, Kikkawa, Mogstad, and Dhyne (2017), or Furusawa, Inui, Ito, and Tang (2017). In these papers the authors construct models where the firm's marginal benefit of adding a supplier is increasing in the set of other suppliers. If the same feature holds in our model, we would expect firms to only add new suppliers when hit by a positive input price shock. However these complementarities across sourcing sets do not necessarily hold in our model. As in Tintelnot, Kikkawa, Mogstad, and Dhyne (2017), in our model the marginal profit that a firm gains from sales to final demand or from exports is indeed increasing in the firm's sourcing set. However, the marginal profit that a firm gains from sales to other domestic firms is decreasing in the set of other suppliers. Thus whether a firm's sourcing decision is complementary across suppliers depends on the share of profits that come from firm-to-firm sales or from sales to final demand. We confirm this in the simulation results. We find that the firms which dropped other suppliers when one of its suppliers became an importer, had higher output shares to other domestic firms, than those which did not drop suppliers.

interaction between variable markups and endogenous network formation, we construct an economy where firms charge constant markups in firm-to-firm trade and form optimal sourcing sets. We contrast the model's counterfactual implications with those of our full model, where firms charge variable markups and make optimal sourcing decisions.

Figure 12 plots the changes in the aggregate price index implied by the two models.[41] Though the predictions of $\hat{P}$ from the two models are not far apart when the change in foreign price is large, there is a stark difference when a large shift in aggregate price occurs. In the constant markup case, firms charge markups of $\frac{\rho}{\rho-1}$ when selling goods to other domestic firms. This markup is the lower bound of markups implied by the variable markup case, where firms charge $\frac{\rho}{\rho-1}$ only when their input shares to the customers are infinitesimally small. This smaller degree of double marginalization lets firms in the constant markup case face cheaper input prices and generate larger variable profits given firm-to-firm networks compared to those in the variable markup case. Therefore, in the constant markup case, firms are able to add domestic suppliers and switch to importing, even under a smaller reduction in foreign price. This explains why the large drop in aggregate price change - caused by a firm switching from a non-importer to an importer - occurs upon higher $\hat{p}_F$ in the constant markup case.

Figure 12: $\hat{P}$ under endogenous networks: variable and constant markups



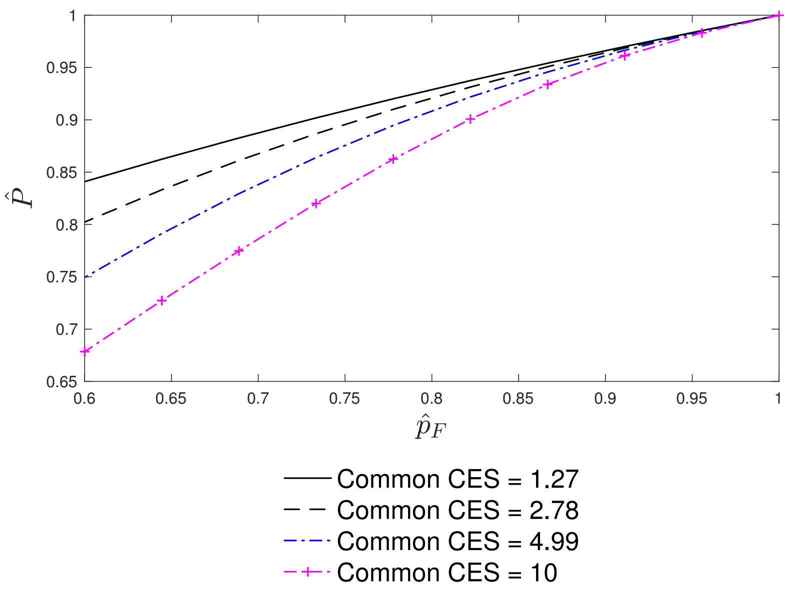
As we have seen in Section 6.1, adding variable markups in firm-to-firm trade alone contributes to a small change in aggregate variables when fixing firm-to-firm networks. We then documented that most of the changes in aggregate variables in the full model are due to firms changing their sourcing sets. But variable markups in firm-to-firm trade produce both qualitative and quantitative differences in aggregate changes, through the interaction with endogenous network formation. These results imply that the difference in the aggregate implications are driven by both margins.

[41] We provide discussions for the changes in welfare in Appendix F.7.

6.3 Network irrelevance under common CES parameter

Finally, we consider the case of the model described in Proposition 1, where change in price index and welfare can also be written by firm-level variables, but with an assumption for the value of $\tilde{\sigma}$. Figure 13 plots the movement in aggregate price, under four different values of $\tilde{\sigma}$. Higher value of $\tilde{\sigma}$ translates to higher substitutability of inputs, thus resulting in larger reduction in aggregate price. By assigning value of $\tilde{\sigma}$ that is between the estimated values of η and ρ, one can match the prediction of $\hat{U}$ from the variable markup case. However, the predictions under the value of $\tilde{\sigma}$ as high as 10 do not match the predictions under the full model. The magnitudes of aggregate price changes caused by endogenous network formation are so large that this model of common CES parameter is unable to generate such large changes under the plausible range of $\tilde{\sigma}$.

Figure 13: $\hat{P}$ under Proposition 1



7 Conclusion

In this paper we studied how oligopolistic competition in firm-to-firm trade and firms' ability to choose suppliers affect aggregate response to shocks. With a model that incorporates the two elements, we analyze how aggregate variables, such as price index and welfare, respond to an exogenous reduction in the foreign good's price. We contrast them with the predictions from the benchmark case, in which the network is irrelevant. While we focus on the transmission of a foreign trade shock, all results and intuitions offer insight into the response other types of shocks: shocks at the industry- or firm-level, or domestic shocks.

Our model proposes a novel view on competition between firms. Instead of the market share within the sector being the determinant of the firm's market power, we suggest that the relative size of the firm in the total input sourcing of its customers is the relevant metric. The novel data on firm-to-firm transactions support this view: firms charge higher markups if they have higher average input shares within their customer firms, controlling for their sectoral market shares.

We find that the model produces both qualitatively and quantitatively different aggregate predictions compared to the benchmark case. The benchmark case of the model can only capture less than a quarter of movements in price index and welfare that are implied by the full model. In particular, allowing firms to optimally decide their sourcing set significantly alters aggregate predictions. When the foreign price goes down, firms that initially did not import switch and become importers. This amplifies the movement in the aggregate price index and welfare. We also find that oligopolistic competition in firm-to-firm trade makes a quantitative difference in the aggregate responses through the interaction, with firms making optimal sourcing decisions.

Our findings contrast that of Hulten (1978), where the network structure is irrelevant in the aggregate in an efficient economy, up to the first order. Our results imply that firm-level variables do not work as sufficient statistics when evaluating aggregate outcomes, and indicate the need for information on firm-level input-output structures.

This paper also adds depth to various policy questions, as it lays a framework analyzing how aggregate variables are affected by the two market frictions in firm-to-firm trade. Our counterfactual analysis considers the effect of a particular policy episode: exogenous reduction in the foreign good's price. Using this framework, one can explore other policy experiments and analyze their aggregate effects.

References

Acemoglu, D., U. Akcigit, and W. Kerr (2015a): "Networks and the Macroeconomy : An Empirical Exploration," in *NBER Macroeconomics Annual 2015, Volume 30*, ed. by M. Eichenbaum and J. Parker, University of Chicago Press.

Acemoglu, D., V. M. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi (2012): "The Network Origins of Aggregate Fluctuations," *Econometrica*, 80, 1977–2016.

Acemoglu, D., A. Ozdaglar, and A. Tahbaz-Salehi (2015b): "Systemic Risk and Stability in Financial Networks," *American Economic Review*, 105, 564–608.

——— (2017): "Microeconomic origins of macroeconomic tail risks," *American Economic Review*, 107, 54–108.

Altinoglu, L. (2015): "The Origins of Aggregate Fluctuations in a Credit Network Economy," 1–62.

Amiti, M., O. Itskhoki, and J. Konings (2017): "International Shocks and Domestic Prices: How Large Are Strategic Complementarities?" .

Anderson, J. E. and E. van Wincoop (2004): "Trade Costs," *Journal of Economic Literature*, 42, 691–751.

Antràs, P. and A. de Gortari (2017): "On the Geography of Global Value Chains," .

Antras, P., T. C. Fort, and F. Tintelnot (2017): "The Margins of Global Sourcing: Theory and Evidence from U.S. Firms," *American Economic Review*, 107, 2514 – 64.

Atalay, E. (2017): "How Important Are Sectoral Shocks?" *American Economic Journal: Macroeconomics*.

Atkeson, A. and A. Burstein (2008): "Trade Costs, Pricing to Market, and International Relative Prices," *American Economic Review*, 98, 1998–2031.

Autor, D. H., D. Dorn, and G. H. Hanson (2013): "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 103, 2121–2168.

Bak, P., K. Chen, J. Scheinkman, and M. Woodford (1993): "Aggregate Fluc Tuations from Independent Sectorial Shocks: Self-Organized Criticality in a Model of Production and Inventory Dynamics," *Ricerche Economiche*, 47, 3–30.

Baqaee, D. R. (2014): "Cascading Failures in Production Networks," 1–60.

Baqaee, D. R. and E. Farhi (2017): "The Macroeconomic Impact of Microeconomic Shocks: Beyond Hulten's Theorem," .

BARROT, J. N. AND J. SAUVAGNAT (2016): "Input Specificity and the Propagation of Idiosyncratic Shocks in Production," *Quarterly Journal of Economics*, 131, 1543 – 1592.

BARTIK, T. (1991): *Who Benefits from State and Local Economic Development Policies?*, W.E. Upjohn Institute.

BERNARD, A. B., A. MOXNES, AND Y. U. SAITO (2016): "Production Networks, Geography and Firm Performance," .

BIGIO, S. AND J. LA'O (2017): "Financial Frictions in Production Networks," .

BLAUM, J., C. LELARGE, AND M. PETERS (2016): "The gains from input trade with heterogeneous importers," .

BOEHM, C. E., N. PANDALAI-NAYAR, AND A. FLAAEN (2016): "Input Linkages and the Transmission of Shocks: Firm-Level Evidence from the 2011 Tohoku Earthquake," .

CARVALHO, V. M. (2010): "Aggregate Fluctuations and the Network Structure of Intersectoral Trade," 1–54.

CARVALHO, V. M. AND X. GABAIX (2013): "The Great Diversification and its Undoing," *American Economic Review*, 103, 1–39.

CARVALHO, V. M., M. NIREI, Y. SAITO, AND A. TAHBAZ-SALEHI (2014): "Supply Chain Disruptions: Evidence from the Great East Japan Earthquake," .

COLLARD-WEXLER, A., G. GOWRISANKARAN, AND R. S. LEE (2016): ""Nash-in-Nash" Bargaining: A Microfoundation for Applied Work," .

DE LOECKER, J., C. FUSS, AND J. VAN BIESEBROECK (2014): "International competition and firm performance : Evidence from Belgium," *NBB Working Paper Series*.

DE LOECKER, J. AND F. WARZYNSKI (2012): "Markups and Firm-Level Export Status," *American Economic Review*, 102, 2437–2471.

DEKLE, R., J. EATON, AND S. KORTUM (2007): "Unbalanced Trade," *American Economic Review Papers & Proceedings*.

DHYNE, E., G. MAGERMAN, AND S. RUBINOVA (2015): "The Belgian production network 2002-2012," *National Bank of Belgium Working Paper Series*, 288.

DHYNE, E., A. PETRIN, V. SMEETS, AND F. WARZYNSKI (2017): "Multi-Product Firms, Import Competition, and the Evolution of Firm-product Technical Efficiencies," .

Di Giovanni, J., A. A. Levchenko, and I. Mejean (2014): "Firms, Destinations, and Aggregate Fluctuations," *Econometrica*, 82, 1303–1340.

Domar, E. D. (1961): "On the Measurement of Technological Change," *The Economic Journal*, 71, 709–729.

Durlauf, S. (1993): "Nonergodic Economic Growth," *The Review of Economic Studies*, 60, 349 366.

Edmond, C., V. Midrigan, and D. Y. Xu (2015): "Competition, markups, and the gains from international trade," *American Economic Review*, 105, 3183 – 3221.

Elliott, M., B. Golub, and M. O. Jackson (2014): "Financial Networks and Contagion," *American Economic Review*, 104, 3115 – 3153.

Feenstra, R. C., J. E. Gagnon, and M. M. Knetter (1996): "Market share and exchange rate pass-through in world automobile trade," *Journal of International Economics*, 40, 187–207.

Foerster, A. T., P.-D. G. Sarte, and M. W. Watson (2011): "Sectoral versus Aggregate Shocks: A Structural Factor Analysis of Industrial Production," *Journal of Political Economy*, 119, 1–38.

Furusawa, T., T. Inui, K. Ito, and H. Tang (2017): "Global Sourcing and Domestic Production Networks," .

Gabaix, X. (2011): "The Granular Origins of Aggregate Fluctuations," *Econometrica*, 79, 733–772.

Gopinath, G. and B. Neiman (2014): "Trade Adjustment and Productivity in Large Crises," *American Economic Review*, 104, 793–831.

Grassi, B. (2016): "IO in I-O : Competition and Volatility in Input-Output Networks," .

Halpern, L., M. Koren, and A. Szeidl (2015): "Imported inputs and productivity," *American Economic Review*, 105, 3660–3703.

Horvath, M. (1998): "Cyclicality and Sectoral Linkages: Aggregate Fluctuations from Independent Sectoral Shocks," *Review of Economic Dynamics*, 1, 781–808.

——— (2000): "Sectoral shocks and aggregate fluctuations," *Journal of Monetary Economics*, 45, 69–106.

Hulten, C. R. (1978): "Growth Accounting with Intermediate Inputs," *The Review of Economic Studies*, 45, 511–518.

Hummels, D., R. Jørgensen, J. Munch, and C. Xiang (2014): "The Wage Effects of Offshoring : Evidence from Danish Matched Worker-Firm Data," *American Economic Review*, 104, 1597–1629.

JOVANOVIC, B. (1987): "Micro Shocks and Aggregate Risk," *Quarterly Journal of Economics*, 102, 395 – 410.

KRUGMAN, P. R. (1979): "Increasing Returns, Monopolistic Competition, and International Trade," *Journal of International Economics*, 9, pp. 469–479.

LEVINSOHN, J. AND A. PETRIN (2003): "Estimating production functions using inputs to control for unobservables," *Review of Economic Studies*, 70, 317–341.

LIM, K. (2015): "Firm-to-firm Trade in Sticky Production Networks," .

LIU, E. (2016): "Industrial Policies and Economic Development," .

LONG, J. AND C. I. PLOSSER (1983): "Real Business Cycles," *Journal of Political Economy*, 91, 39–69.

MAGERMAN, G., K. DE BRUYNE, E. DHYNE, AND VAN HOVE (2016): "Heterogeneous firms and the micro origins of aggregate fluctuations," *National Bank of Belgium Working Paper Series*.

MAGYARI, I. (2016): "Firm Reorganization, Chinese Imports, and US Manufacturing Employment," .

MELITZ, M. J. AND G. I. P. OTTAVIANO (2008): "Market size, trade, and productivity," *Review of Economic Studies*, 75, 295–316.

NEIMAN, B. (2011): "A state-dependent model of intermediate goods pricing," *Journal of International Economics*, 85, 1–13.

OBERFIELD, E. (2017): "A Theory of Input-Output Architecture," *Econometrica*.

OTTAVIANO, G., T. TABUCHI, AND J.-F. THISSE (2002): "Agglomeration and trade revisited," *International Economic Review*, 43, 409–436.

PASTEN, E., R. SCHOENLE, AND M. WEBER (2017): "Price Rigidities and the Granular Origins of Aggregate Fluctuations," .

SCHEINKMAN, J. AND M. WOODFORD (1994): "Self-organized criticality and economic fluctuations," *American Economic Review: Papers & Proceedings*, 84, 417.

STELLA, A. (2015): "Firm dynamics and the origins of aggregate fluctuations," *Journal of Economic Dynamics and Control*, 55, 71–88.

TINTELNOT, F., A. K. KIKKAWA, M. MOGSTAD, AND E. DHYNE (2017): "Trade and Domestic Production Networks," .

U.S. DEPARTMENT OF JUSTICE AND FEDERAL TRADE COMMISSION (2010): "Horizontal Merger Guidelines," Tech. rep.

Yeh, C. (2016): "Are firm-level idiosyncratic shocks important for U.S. aggregate volatility?" .

Zhelobodko, E., S. Kokovin, M. Parenti, and J.-F. Thisse (2012): "Monopolistic Competition: Beyond the Constant Elasticity of Substitution," *Econometrica*, 80, 2765–2784.

A Data and other statistics

A.1 Aggregating VAT-ids into firms

Our datasets are all at the VAT-id level. Using the same procedure as in Tintelnot, Kikkawa, Mogstad, and Dhyne (2017), we aggregate the VAT-ids into firms. As mentioned in the main text, we group all VAT-ids into firms if they are linked with more than or equal to 50% of ownership, or if they share the same foreign parent firm that holds more than or equal to 50% of their shares. To determine if the two VAT-ids share the same foreign parent firm, we use a "fuzzy string matching" method and compare the all possible pairs of the foreign parent firms' names. In order to correct for misreporting, we also make the following correction. If the two separate VAT-ids were paired as one firm in the year before and the year after, we pair the two into one firm in that year.

We then identify one VAT-id as the "head VAT-id" for each group of multiple VAT-ids. This "head VAT-id" will work as the identifier of the firm. We also make corrections on which VAT-id becomes the "head VAT-id" of the firm, so that the identifiers of the firms become consistent over time. For the procedure to choose the "head VAT-id" and the corrections, see Appendix C.1 of Tintelnot, Kikkawa, Mogstad, and Dhyne (2017).

In converting the VAT-id level variables into firm level variables, we simply sum up the variables if the variables are numeric. For variables such as total sales and inputs, we correct for double counting that arises from VAT-id-to-VAT-id trade that occur within firms. For non-numeric variables, we take the values of its "head VAT-id".

A.2 Coverage and descriptive statistics

Table 7 reports the coverage of the full sample constructed in Dhyne, Magerman, and Rubinova (2015).

Table 7: Coverage of all Belgian firms

Year	GDP	Output	Imports	Exports	All Belgian firms				
					Count	V.A.	Sales	Imports	Exports
2002	275	556	210	229	714,469	210	812	204	217
2007	345	715	300	314	782,006	274	1080	294	282
2012	387	823	342	347	860,373	300	1244	320	317

Notes: All numbers except for Count are in terms of billion Euro in current prices. Data for Belgian aggregate statistics are from Eurostat. Value added is the sum of value added reported in the annual accounts. Total sales in our selected sample are larger total output in the aggregate statistics because the output values in the aggregate statistics sum up value added for trade intermediaries instead of their gross output.

Table 8 shows the aggregate statistics of the dataset. The number of firm-to-firm links in the economy is much smaller than the number of all possible links among all firms. This indicates that the production network is extremely sparse. We also note that the amount of total firm-to-firm sales sums up to an amount larger than the total value added.

Table 8: Aggregate statistics of the B2B dataset

Year	Num. links	Num. links / Possible links	Total B2B sales	Total B2B sales / V.A.
2002	4,905	0.03%	208	170%
2007	5,752	0.03%	220	140%
2012	6,097	0.03%	245	144%

Notes: Number of links are in the thousands and the total B2B sales are in terms of billions of Euro in current prices.

Table 9 shows the distribution of the pairwise input shares s^m_{ij}, defined as the share of goods from firm i, among j's input purchases. We also report the distributions for the number of suppliers and customers. Though the median firm has as many as 28 suppliers, the median value of the pairwise input share s^m_{ij} is very small. In addition, one can see that the distribution of the number of customers is much more skewed than the number of suppliers.

Table 9: Descriptive statistics of the production network

	Mean	Percentiles				
		10%	25%	50%	75%	90%
s^m_{ij} = $\text{Sales}_{ij}/\text{InputPurchases}_j$	1.62%	0.00%	0.00%	0.18%	0.82%	3.15%
Num. suppliers	45	8	15	28	49	86
Num. customers	45	0	1	7	27	86

A.3 HHI of input shares across suppliers

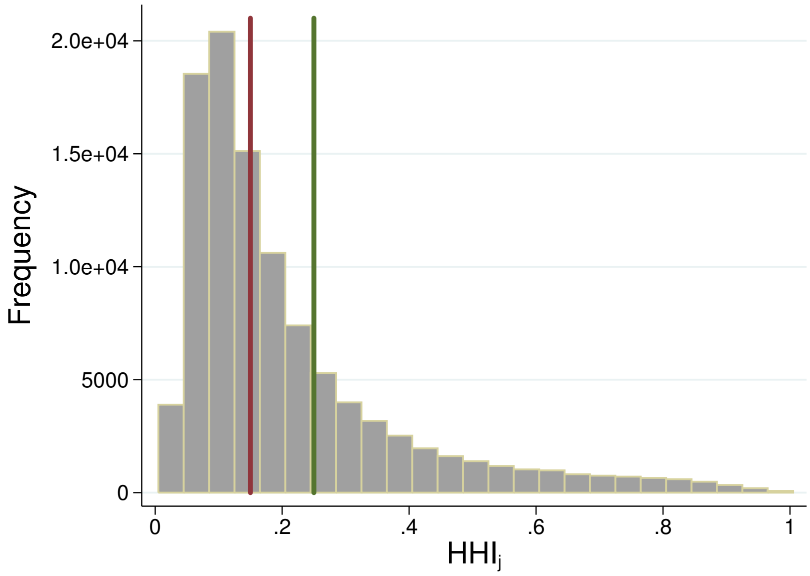
In this section we compute the HHI of s^m_{ij} for all customer firms j, across suppliers i. Figure 14 displays the histogram of these firm-level HHI. We find that 50% of firms have a HHI above 0.15. 26% of firms have a HHI above 0.25%.

While there is no perfect reference for the HHI for s^m_{ij} for each customer firm j, the US Department of Justice and FTC consider markets in which the HHI is between 0.15 and 0.25 to be moderately concentrated. Markets in which the HHI is above 0.25 are considered highly concentrated (U.S. Department of Justice and Federal Trade Commission, 2010).

A.4 Distribution of firms' output shares

Figure 15 plots a histogram for the output shares of the largest customers for all supplier firms in 2012 that have more than 10 customers. The output share of the largest customer for the median firm in this figure is 22%.

Figure 14: HHI of suppliers' input shares



Notes: s_{ij}^m is defined as firm i's goods share among firm j's input purchases from other Belgian firms and abroad. The above histogram shows the HHI of s_{ij}^m for all customer firms j in 2012 that have more than 10 suppliers. The median value is 0.15. The two vertical lines indicates HHI being 0.15 and 0.25.

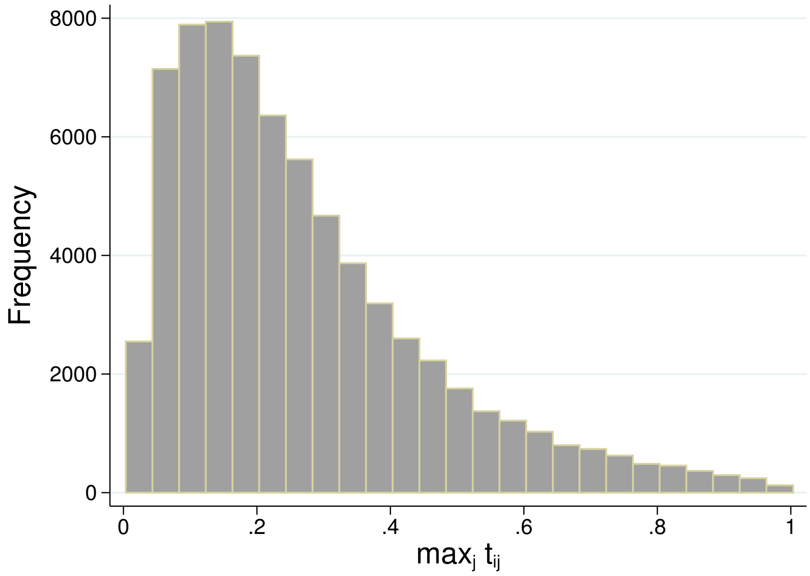
A.5 Disconnect between pairwise input shares and market shares

In this section we show that firms that have high input shares on a particular customer are not necessarily the ones that are large, even after looking at supplier-customer relationships within each sector-to-sector pair. For each firm, we compute the rank correlations of suppliers' input shares and their total sales. But unlike what was done in Section 2.3, we do so for each group of suppliers in each sector at the NACE 2-digit level. We compute the rank correlation for suppliers in a sector, if there are 5 or more suppliers in that sector supplying to the firm.

We obtain distributions of rank correlations, for each sector-to-sector pair. Figure 16 plots the histogram of the median rank correlations, for each distribution. The median value of these median rank correlations is 0.20, which is higher than the unconditional median value from Figure 3. However, we still see a large role that pairwise match components play, even within the same sector-to-sector relationships.

Instead of computing the rank correlations, we find that the results when we compute the Pearson correlations are qualitatively the same. Figure 17 shows the histogram of the correlation coefficients, not taking into account the sectoral heterogeneity. Figure 18 shows the histogram of the median correlations coefficients, for each sector-to-sector pair. Compared to the rank correlation distributions, both figures have fatter right tails. However, the median values are lower than those from the rank correlations.

Figure 15: Output shares of the largest customers



Notes: t_{ij} is defined as the share of firm i's goods that were sold to firm j, out of firm i's total sales to other domestic firms. The above histogram shows the distribution of $\max_j (t_{ij})$, which is the maximum value of t_{ij} for each supplier firm i in 2012 that have more than 10 customers. The median value is 0.22.

A.6 Changes in suppliers and customers

Table 10 shows the median values for firms' supplier and customer churning. This shows that is a significantly high rate of churn in both suppliers and customers. A median firm loses around 19% of suppliers and 26% of customers in terms of value at a yearly basis. They also add around 25% and 34% of suppliers and customers, relative to the previous years' values.

Table 10: Median values for changes in suppliers and customers

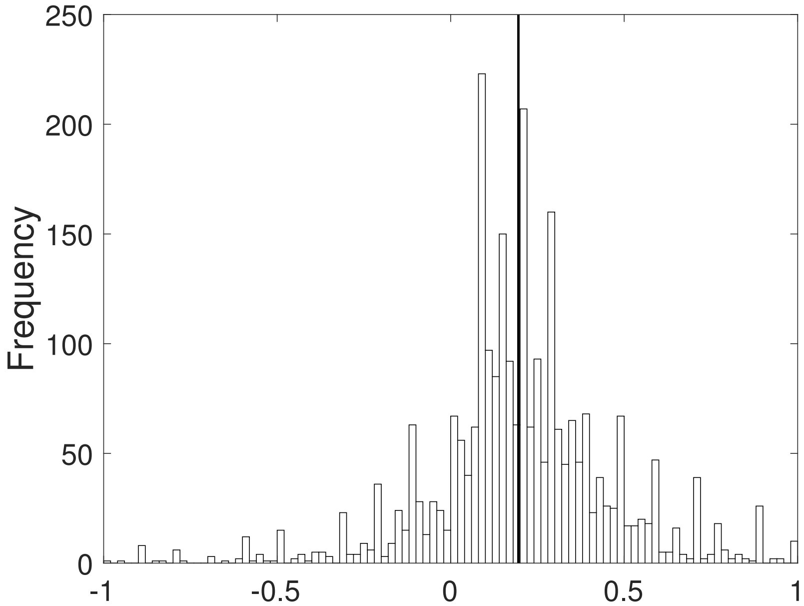
	Yearly avg. (02-12)		10-year (02-12)	
Median	Cont. Share	Added Share	Cont. Share	Added Share
Supplier (Number)	0.60	0.43	0.22	0.92
Supplier (Value)	0.81	0.25	0.32	0.92
Customer (Number)	0.51	0.55	0.13	0.86
Customer (Value)	0.74	0.34	0.19	0.88

A.7 Chinese imports

The following figures compare the change in Chinese imports with those from other countries. Figure 19 shows the evolution of Chinese imports compared with imports from the top five exporters to Belgium. Figure 20 shows the same series, now compared with imports from countries that are classified as in the same income category with China.[42] These figures indicate that the increase in

[42] See World Bank classifications by income.

Figure 16: Median rank correlations



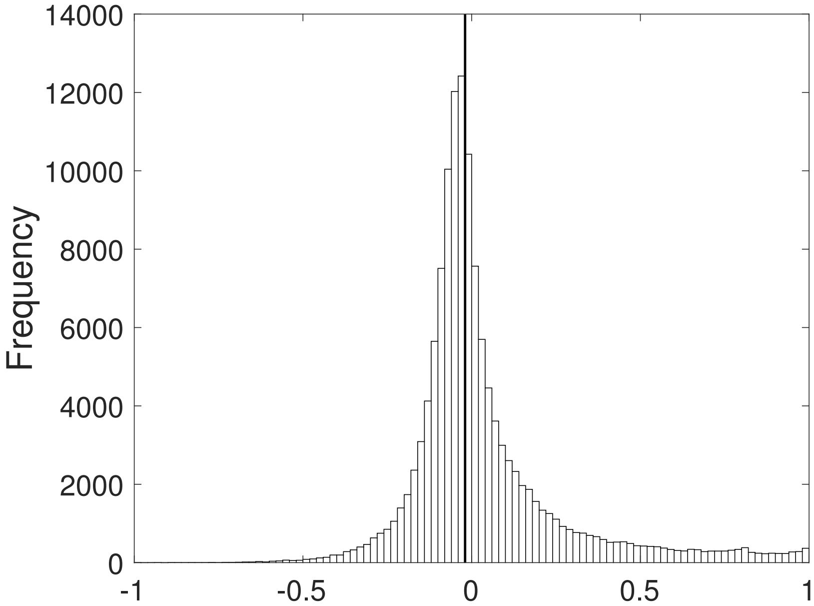
Notes: For each customer firm j, we compute the rank correlations of suppliers' input shares s_{ij}^m and their total sales, for each sector in which 5 or more of j's suppliers are in. This figure shows a histogram of the median correlation coefficients, across each sector-to-sector pairs. The vertical line depicts the median value of 0.20.

imports as rapid as that of China did not occur to other comparable countries.

A.8 Sales and number of domestic suppliers

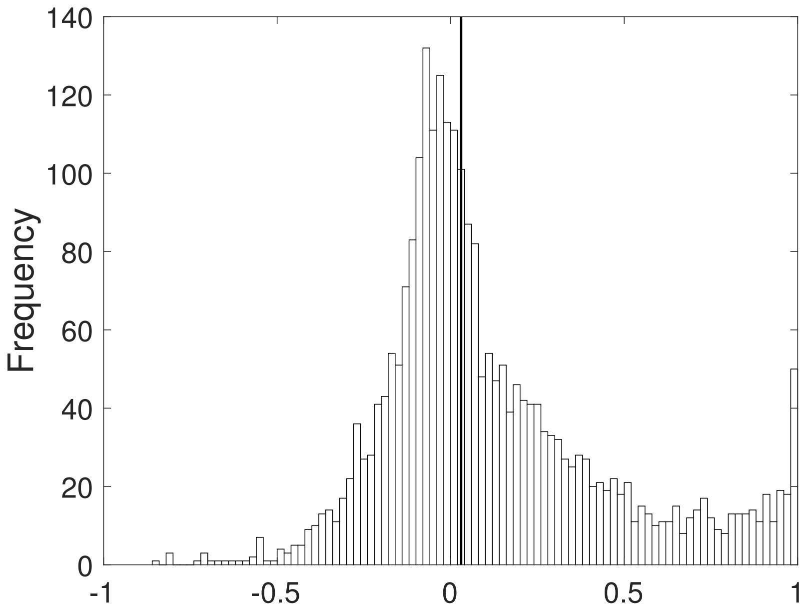
Figure 21 shows the relationship between firms' sales to domestic final demand and their number of domestic suppliers. The positive relationship remain robust when taking firms' total sales instead. It is also robust after demeaning the sales variable with sector fixed effects, or when only considering firms that are not importing from abroad. These size advantages for firms with larger number of domestic suppliers are suggestive of fixed costs associated with domestic sourcing.

Figure 17: Histogram of Pearson correlation of suppliers' input shares and total sales



Notes: This figure shows a histogram of Pearson correlation coefficients between s^m_{ij} and TotalSales_i, for suppliers of j for all j with 5 or more suppliers. The vertical line depicts the median correlation coefficient of -0.02.

Figure 18: Median Pearson correlations



Notes: For each customer firm j, we compute the Pearson correlations of suppliers' input shares s^m_{ij} and their total sales, for each sector in which 5 or more of j's suppliers are in. This figure shows a histogram of the median correlation coefficients, across each sector-to-sector pairs. The vertical line depicts the median value of 0.03.

Figure 19: Chinese imports compared with other top exporters

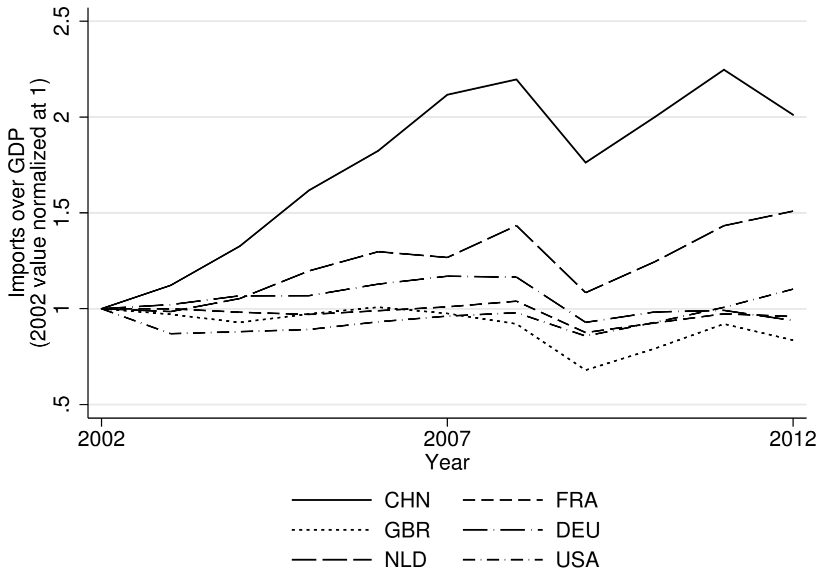


Figure 20: Chinese imports compared with other middle income countries

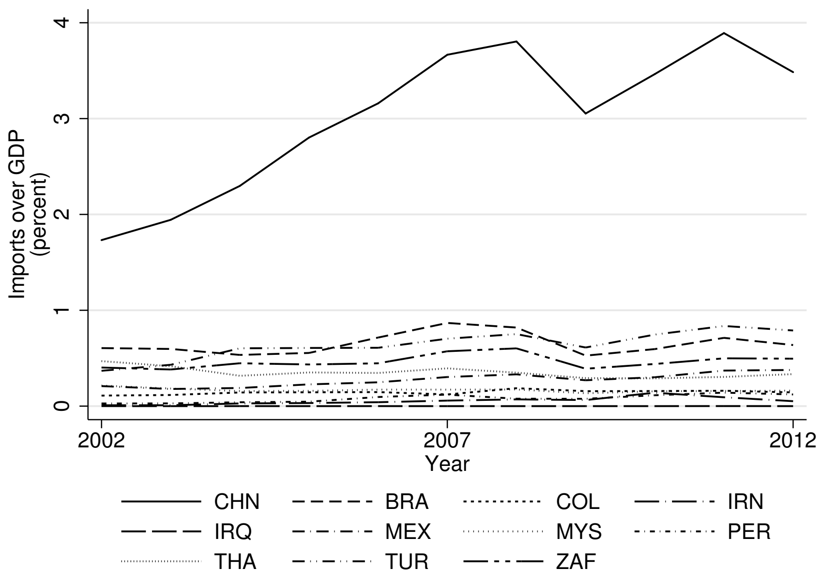
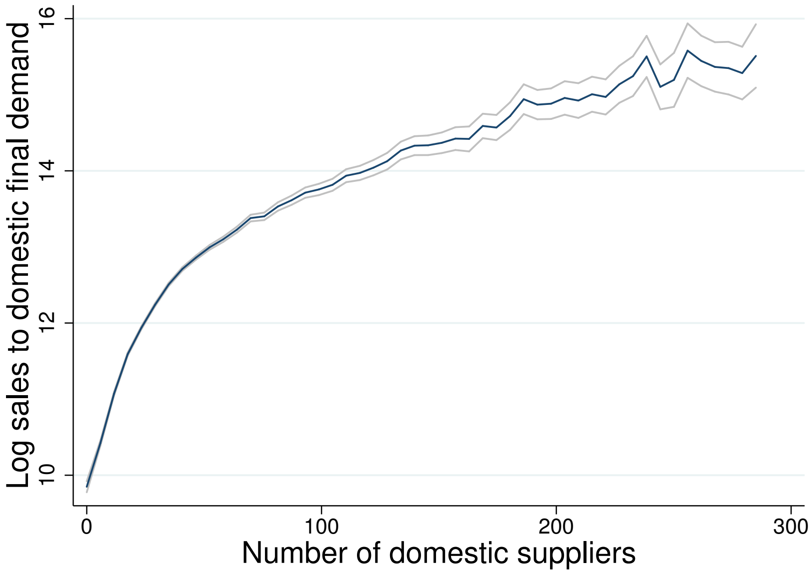


Figure 21: Sales to domestic final demand and number of domestic suppliers



Notes: This figure shows the local polynomial regression plots of firms' log sales to final demand on the number of domestic suppliers, along with the 95% confidence intervals.

B Additional empirical results

B.1 Additional results on markups and input shares

First, we show that firms' average input shares on customers have greater power in explaining the variation of firms' average markups, compared to firm-level market shares. In Table 11 we report the regression results when we add the two RHS variables one by one, for each of the three specifications in Table 2. The 4th, 8th and 12th columns are identical to the three columns in Table 2. For each specification reported in the main text, we add three additional specifications. One with neither average input shares nor firm-level market shares on the RHS, and ones with each variable without the other. In all three sets of specifications, the increase in R-squared by adding average input shares alone on the RHS is larger than the increase in R-squared by adding sectoral market shares alone.

We then show that the positive relationship between markups and firms' average input shares are robust in other specifications. Table 12 shows additional results when firm-level fixed effects are included. The second and the third columns are identical to the second and the third columns in Table 2.

Table 13 shows additional results when sector-level fixed effects are included. The second column is identical to the first column in Table 2.

In our main specification, we drop firms that have no sales to other Belgian firms. Table 14 shows the results when we include such firms in the regression, by treating their average input shares to other firms as zero.

B.2 Alternative markup estimates

In the main text, we recover firm-level average markups using the equation implied from the static model with CRS production function: $\mu_i = \frac{p_i q_i}{c_i q_i}$. To account for additional heterogeneity such as usage in capital inputs, here we recover firm-level markups following De Loecker and Warzynski (2012) and show that the positive correlation between firms' markups and their average input shares within their customers are still present even under these alternative markup estimates.

Let us first briefly describe the estimation procedure. When a firm is engaging in cost minimization under the existence of at least one flexible input X, the markup of firm i at time t can be expressed as

$$\mu_{it} = \theta_{it}^X \frac{p_{it} q_{it}}{p_{it}^X X_{it}},$$

where θ_{it}^X is firm i's output elasticity with respect to X, and $p_{it}^X X_{it}$ is the input value of X. As the input value share of the flexible input X is directly observed, it remains for us to estimate the value of θ_{it}^X to recover firm-level markups. In order to estimate the output elasticity, we assume a translog production function. We also assume that the technology parameters do not vary within sectors, thus we estimate the production function sector by sector at the NACE 2-digit level. We also allow for measurement errors in the output. Therefore, the production function to estimate becomes

$$\begin{aligned} y_{it} =& \alpha_l l_{it} + \alpha_k k_{it} + \alpha_m m_{it} + \alpha_{ll} l_{it}^2 + \alpha_{kk} k_{it}^2 + \alpha_{mm} m_{it}^2 \\ &+ \alpha_{lk} l_{it} k_{it} + \alpha_{km} k_{it} m_{it} + \alpha_{lm} l_{it} m_{it} + \omega_{it} + \varepsilon_{it}, \end{aligned}$$

where y_{it}, l_{it}, k_{it}, and m_{it} denote gross output, labor, capital, and material inputs, all in logs. The estimates from a least squares model would be biased as firm productivity ω_{it} is unobserved, and is potentially correlated with the inputs of the firm, which results in biased estimates of the technology parameters $\boldsymbol{\alpha}$. To overcome this issue, we follow Levinsohn and Petrin (2003) and use a "proxy" method. We assume that the innovation process of the firm-level productivities follow:

$$\omega_{it} = g_t\left(\omega_{it-1}\right) + \xi_{it}.$$

We identify $\boldsymbol{\alpha}$ via the following moment conditions:

$$E\left[\xi_{it}\left(\boldsymbol{\alpha}\right) \boldsymbol{z}_{it}\right] = \mathbf{0},$$

where $\boldsymbol{z}_{it}$ is a vector of lagged input variables:

$$\begin{aligned} \boldsymbol{z}_{it} = & \left[l_{it-1}, k_{it}, m_{it-1},\right. \\ & l_{it-1}^2, k_{it}^2, m_{it-1}^2, \\ & \left. l_{it-1} k_{it}, k_{it} m_{it-1}, l_{it-1} m_{it-1}\right]. \end{aligned}$$

The underlying assumption is that capital inputs are chosen a period ahead, and should be orthogonal to the future innovations of productivity. For other inputs, it is assumed that lagged variables are orthogonal to productivity innovations, as they are already chosen by the firm.

We estimate $\boldsymbol{\alpha}$ via GMM, and recover θ_{it}^X by assuming that material inputs are flexible. Once we recover firm-level markups μ_{it}, we run the regression of equation (1) in the main text. Table 15 reports the results. Also in these alternative estimates of firm-level markups, there is a positive relationship between markups and firms' average input shares within their customers even after controlling for firm size variables.

Table 11: Firm-level markups and input shares, R-squared across specifications

	Firm-level markups											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SctrMktShare$_{i,t}$ (4-digit)		0.0960***		0.0929***		0.0431***		0.0430***		0.0691***		0.0686***
		(0.00954)		(0.00928)		(0.00965)		(0.00963)		(0.0130)		(0.0129)
Average input share $\overline{s^m_{i\cdot,t}}$			0.301***	0.298***			0.182***	0.182***			0.174***	0.173***
			(0.0132)	(0.0130)			(0.00939)	(0.00938)			(0.00929)	(0.00925)
N	1099496	1099496	1099496	1099496	1089209	1089209	1089209	1089209	1070602	1070602	1070602	1070602
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE (4-digit)	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	No	No	No	No	Yes	Yes	Yes	Yes
R2	0.09200	0.09379	0.09772	0.09940	0.6177	0.6179	0.6186	0.6188	0.6232	0.6237	0.6240	0.6246

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. The coefficients are X-standardized. Standard errors are clustered at the NACE 2-digit-year level. Controls include firms' indegree, outdegree, employment, total assets, and age.

Table 12: Firm-level markups and input shares, with firm fixed effects

	Firm-level markups					
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{SctrMktShare}_{i,t}$ (4-digit)	0.0431***	0.0430***	0.0686***			
	(0.00965)	(0.00963)	(0.0129)			
$\text{SctrMktShare}_{i,t}$ (2-digit)				0.0348***	0.0347***	0.0755***
				(0.00902)	(0.00895)	(0.0110)
Average input share $\overline{s^m_{i\cdot,t}}$		0.182***	0.173***		0.182***	0.172***
		(0.00938)	(0.00925)		(0.00937)	(0.00924)
N	1089209	1089209	1070602	1089694	1089694	1071051
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	No	No	Yes
R2	0.618	0.619	0.625	0.618	0.619	0.624

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. The coefficients are X-standardized. Standard errors are clustered at the NACE 2-digit-year level. Controls include firms' indegree, outdegree, employment, total assets, and age.

Table 13: Firm-level markups and input shares, with sector fixed effects

	Firm-level markups			
	(1)	(2)	(3)	(4)
$\text{SctrMktShare}_{i,t}$ (4-digit)	0.0960***	0.0929***		
	(0.00954)	(0.00928)		
$\text{SctrMktShare}_{i,t}$ (2-digit)			0.0696***	0.0670***
			(0.00886)	(0.00848)
Average input share $\overline{s^m_{i\cdot,t}}$		0.298***		0.314***
		(0.0130)		(0.0140)
N	1099496	1099496	1099987	1099987
Year FE	Yes	Yes	Yes	Yes
Sector FE	4-digit	4-digit	2-digit	2-digit
Controls	Yes	Yes	Yes	Yes
R2	0.0938	0.0994	0.0665	0.0728

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. The coefficients are X-standardized. Standard errors are clustered at the NACE 2-digit-year level. Controls include firms' indegree, outdegree, employment, total assets, and age.

Table 14: Firm-level markups and input shares, including firms without firm-to-firm sales

	Firm-level markups		
	(1)	(2)	(3)
SctrMktShare$_{i,t}$ (4-digit)	0.101***	0.0449***	0.0746***
	(0.00998)	(0.00967)	(0.0136)
Average input share $\overline{s^m_{i\cdot,t}}$	0.248***	0.146***	0.146***
	(0.0124)	(0.00805)	(0.00801)
N	1285251	1293120	1259087
Year FE	Yes	Yes	Yes
Sector FE (4-digit)	Yes	No	No
Firm FE	No	Yes	Yes
Controls	Yes	No	Yes
R2	0.100	0.622	0.620

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. The coefficients are X-standardized. Standard errors are clustered at the NACE 2-digit-year level. Controls include firms' indegree, outdegree, employment, total assets, and age.

Table 15: Firm-level markups and input shares, using alternative markup estimates

	(1)	(2)	(3)
SctrMktShare$_{i,t}$ (4-digit)	0.00395***	-0.00179**	-0.000488
	(0.00122)	(0.000830)	(0.00103)
Average input share $\overline{s^m_{i\cdot,t}}$	0.0690***	0.0117***	0.0112***
	(0.00375)	(0.00139)	(0.00136)
N	602903	584131	584131
Year FE	Yes	Yes	Yes
Sector FE (4-digit)	Yes	No	No
Firm FE	No	Yes	Yes
Controls	Yes	No	Yes
R2	0.629	0.917	0.917

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. We use firm-level markups recovered using methods from De Loecker and Warzynski (2012) as the LHS variables. The coefficients are X-standardized. Standard errors are clustered at NACE 2-digit-year level.

B.3 Additional results for Section 3

We start by reporting the results when the LHS share variables are calculated in terms of numbers. Table 16 shows the results analogous to those of Table 3, but now shares are computed in terms of numbers. The results are qualitatively similar compared to the results in the main text where shares are calculated in terms of values: as firms experience exogenous reductions in Chinese goods' price they also experience larger churn in both suppliers and customers.

Next, we report in Table 17 the results analogous to Table 3, but taking the changes in customers on the LHS. The results are qualitatively the same as when we take the changes in suppliers on the

LHS. The coefficients on the customer changes are larger, but as reported in Appendix A.6 there are larger churn in customers than in suppliers.

Finally, we report in Table 18 the OLS results for the specification shown in Table 3. We find that the OLS coefficients are smaller in magnitude than the IV estimates, and the differences in magnitudes are broadly similar to those of Antras, Fort, and Tintelnot (2017) and Hummels, Jørgensen, Munch, and Xiang (2014).

Table 16: First and second stage results for changes in suppliers (in terms of number)

Panel A: Second stage result					Panel B: First stage result	
	(1)	(2)	(3)	(4)		(1)
	Continuing suppliers	Added suppliers	Added suppliers: Incumbent firms	Added suppliers: New firms		ΔCS
ΔCS	-0.149^{***}	0.122^{***}	0.119^{***}	0.00275^{***}	ΔIV	0.00370^{***}
	(0.0275)	(0.0236)	(0.0238)	(0.00134)		(0.000649)
N	56146	56146	56146	56146	R2	0.0255
Controls	Yes	Yes	Yes	Yes	F Stat	32.48

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. The coefficients of the second stage results are X-standardized. Controls include firm age and employment size in 2002 with sector fixed effects (NACE 2-digit) and geographic fixed effects (NUTS 3). The same controls are used in the first stage results. ΔCS is the firm's average yearly increase of Chinese imports from 2002 to 2012 scaled by its total inputs in 2002. ΔCS is instrumented by the weighted sum of the sectoral change in Chinese goods' share in developed countries' total imports from 2002 to 2012. Standard errors are clustered at the NACE 2-digit-NUTS 3 level.

Table 17: First and second stage results for changes in customers (in terms of value)

Panel A: Second stage result					Panel B: First stage result	
	(1)	(2)	(3)	(4)		(1)
	Continuing customers	Added customers	Added customers: Incumbent firms	Added customers: New firms		ΔCS
ΔCS	-0.325^{***}	0.314^{***}	0.285^{***}	0.0395^{***}	ΔIV	0.00377^{***}
	(0.0686)	(0.0890)	(0.0815)	(0.00832)		(0.000660)
N	55280	55280	55280	55280	R2	0.0256
Controls	Yes	Yes	Yes	Yes	F Stat	32.74

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. The coefficients of the second stage results are X-standardized. Controls include firm age and employment size in 2002 with sector fixed effects (NACE 2-digit) and geographic fixed effects (NUTS 3). The same controls are used in the first stage results. ΔCS is the firm's average yearly increase of Chinese imports from 2002 to 2012 scaled by its total inputs in 2002. ΔCS is instrumented by the weighted sum of the sectoral change in Chinese goods' share in developed countries' total imports from 2002 to 2012. Standard errors are clustered at the NACE 2-digit-NUTS 3 level.

Table 18: OLS results for changes in suppliers (in terms of value)

	(1) Continuing suppliers	(2) Added suppliers	(3) Added suppliers: Incumbent firms	(4) Added suppliers: New firms
ΔCS	-0.00121^{***}	0.0104^{***}	0.00919^{***}	0.00114^{***}
	(0.000390)	(0.000948)	(0.000898)	(0.000112)
N	56146	56146	56146	56146
R2	0.140	0.108	0.100	0.0753
Controls	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. The coefficients are X-standardized. Controls include firm age and employment size in 2002, with sector fixed effects (NACE 2-digit) and geographic fixed effects (NUTS 3). ΔCS is the firm's average yearly increase of Chinese imports from 2002 to 2012 scaled by its total inputs in 2002. Standard errors are clustered at the NACE 2-digit-NUTS 3 level.

C Algorithm for network formation

Given firms' productivities ϕ_i and parameters, we follow the steps below to simulate the network formation game. As mentioned in the main text, we focus on an equilibrium that results from firms sequentially making sourcing and international trade participation decisions. This sequential sourcing decisions serve as an equilibrium selection rule.

1. Initialize the economy where no firm is sourcing from any other domestic firm, and no firm is participating in international trade. Solve for all prices and aggregate expenditure E, from equations (5), (7), (9), (10), (13), (15), (16), (18), and (20).

2. Order firms in terms of productivity, from the most productive to the least productive.

3. Start with the most productive firm, $i = 1$. Taken as given all other firms' decisions $\{Z_i, I_{Fi}, I_{iF}\}_{i\neq 1}$, evaluate $4N$ possible sets of decisions and choose the set $\left\{\hat{Z}_1, \hat{I}_{F1}, \hat{I}_{1F}\right\}$ that yields the largest variable profit net of fixed costs.[43] To compute the net profits for each possible set of $\{Z_1, I_{F1}, I_{1F}\}$, solve the system of equations (5), (7), (9), (10), (13), (15), (16), (18), and (20). Update the firm's decision to its optimal set $\left\{\hat{Z}_1, \hat{I}_{F1}, \hat{I}_{1F}\right\}$.

4. Repeat the previous step for firms $i = 2, 3, \cdots N$ in sequence. After the last firm makes its decision, record the economy's network structure $\{Z_i, I_{Fi}, I_{iF}\}_{i\in\Omega}$.

5. Repeat steps 3 and 4, until the resulting network structure $\{Z_i, I_{Fi}, I_{iF}\}_{i\in\Omega}$ converges to a fixed point.

[43] There are N possible sets of Z_1: {no sourcing, source from a firm with lowest unit cost, source from two firms with lowest unit costs, $\cdots$, source from all}. Interacting with two possible choices for both importing and exporting decisions, $I_{F1} \in \{0, 1\}$ and $I_{1F} \in \{0, 1\}$, the firm has $4N$ possible sets of $\{Z_1, I_{F1}, I_{1F}\}$ to evaluate.

D Theoretical results

D.1 Derivation of equation (15)

Consider firm i selling its goods to j. Firm i chooses p_{ij} to maximize profits, taking into account the effect of p_{ij} on j's price index for its intermediate goods, p_{mj}. It takes as given j's unit cost and production, c_j, and q_j, as well as j's sourcing set, Z_j and I_{Fj}. The firm's problem is as follows:

$$\begin{aligned}
&\max_{p_{ij}} \left(p_{ij} - c_i\right) q_{ij} \\
s.t. p_{ij} q_{ij} &= \alpha_{ij}^{\rho} p_{ij}^{1-\rho} p_{mj}^{\rho} m_j \\
p_{mj} m_j &= \omega_m^{\eta} p_{mj}^{1-\eta} \phi_j^{\eta-1} c_j^{\eta} q_j.
\end{aligned}$$

Solving the above problem while taking into account that $\frac{\partial p_{mj}}{\partial p_{ij}} \neq 0$ yields

$$\begin{aligned}
p_{ij} &= \frac{\varepsilon_{ij}}{\varepsilon_{ij} - 1} c_i \\
\varepsilon_{ij} &= \rho\left(1 - s_{ij}^m\right) + \eta s_{ij}^m.
\end{aligned}$$

D.2 Alternative market structures

In our model we assume the following when firms participate in firm-to-firm trade. When selling to firm j, firm i sets price p_{ij} by internalizing the effect of p_{ij} on j's price index for its intermediate goods, p_{mj}. However, it takes as given j's unit cost and total production, c_j and q_j. This yields our pricing equation of

$$\begin{aligned}
p_{ij} &= \frac{\varepsilon_{ij}}{\varepsilon_{ij} - 1} c_i \\
\varepsilon_{ij} &= \rho\left(1 - s_{ij}^m\right) + \eta s_{ij}^m.
\end{aligned}$$

In this section we discuss alternative market structures in firm-to-firm trade. We discuss the pricing equations that result in firms internalizing their prices' effect on the customers' unit costs and total production.

D.2.1 Fixed demand shifters

First we consider a case where firm i takes as given the two demand shifters that firm j faces - one from sales to other firms $\left(D_{jB}\right)$ and another from sales to final demand $\left(D_{jH}\right)$:

$$q_j = c_j^{-\rho} D_{jB} + c_j^{-\sigma} D_{jH}.$$

When one solves this problem the pricing equation becomes

$$p_{ij} = \frac{\varepsilon_{ij}}{\varepsilon_{ij} - 1} c_i$$
$$\varepsilon_{ij} = \left(1 - s_{ij}^m\right)\rho + s_{ij}^m \left(\left(1 - s_{mj}\right)\eta + s_{mj}\left(s_{jB}^q \rho + s_{jH}^q \sigma\right)\right).$$

The term s_{jB}^q is the quantity output share of firm j's goods that were shipped to other firms, and the term s_{jH}^q is the quantity output share of firm j's goods that were shipped to final demand:

$$s_{jB}^q = \frac{c_j^{-\rho} D_{jB}}{q_j}$$
$$s_{jH}^q = \frac{c_j^{-\sigma} D_{jH}}{q_j} = 1 - s_{jB}^q.$$

This implies that the firm needs to know the quantity output shares of its customers.

D.2.2 Constant demand elasticity for customers' goods

We also consider a case where firm i does not know the output compositions of its customer j, but assumes that j is facing a common demand elasticity of ν. In this case q_j can be written as

$$q_j = c_j^{-\nu} D_j,$$

in which firm i takes as given the demand shifter, D_j. When one solves the problem of firm i under this setup, the pricing equation becomes

$$p_{ij} = \frac{\varepsilon_{ij}}{\varepsilon_{ij} - 1} c_i$$
$$\varepsilon_{ij} = \left(1 - s_{ij}^m\right)\rho + s_{ij}^m \left(\left(1 - s_{mj}\right)\eta + s_{mj}\nu\right).$$

Notice that if we additionally assume that $\nu = \eta$, the above equation collapses to equation (15).

D.3 Proof of Proposition 1

From Assumption 3, no firm generates profits. Hence, the change in welfare, $\hat{U}$, is the inverse of the change in the aggregate price index:

$$\hat{U} = \hat{P}^{-\alpha}. \tag{37}$$

From Assumptions 2, 3 and equation (6), we have

$$\hat{P}^{1-\tilde{\sigma}} = \sum_{i \in \Omega} s_{iH} \hat{c}_i^{1-\tilde{\sigma}}, \tag{38}$$

where $\tilde{\sigma}$ is the common CES parameter and s_{iH} is firm i's share in the final demand market for the heterogeneous goods sector: $\frac{p_{iH}^{1-\tilde{\sigma}}}{P^{1-\tilde{\sigma}}}$. From Assumptions 2, 3, and equation (9), we obtain the change in unit costs: $\hat{c}_i^{1-\tilde{\sigma}} = \sum_k s_{ki}\hat{c}_k^{1-\tilde{\sigma}} + s_{li} + s_{Fi}\hat{p}_F^{1-\tilde{\sigma}}$. Rearranging this into matrix form yields

$$\hat{\boldsymbol{c}}^{1-\tilde{\sigma}} = \left(I - S'\right)^{-1}\left(\boldsymbol{s}_{l\cdot} + \boldsymbol{s}_{F\cdot}\hat{p}_F^{1-\tilde{\sigma}}\right), \tag{39}$$

where the (i, j) element of matrix S is s_{ij}, and $\boldsymbol{s}_{F\cdot}$, $\boldsymbol{s}_{l\cdot}$ are vectors where their i'th elements are s_{Fi} and s_{li}.

On the output side, the revenue of firm i, $p_i q_i$, is the sum of sales to households, exports, and sales to other firms. From Assumption 1, the share of each firm among exports are equal to that among sales to households, s_{iH}. Thus from Assumptions 1 and 3, we obtain

$$p_i q_i = s_{iH}\alpha E + s_{iH}\text{Exports} + \sum_j s_{ij} p_j q_j. \tag{40}$$

Rearrange this into matrix form and obtain

$$\frac{\boldsymbol{p} \circ \boldsymbol{q}}{\alpha E + \text{Exports}} = (I - S)^{-1}\, \boldsymbol{s}_{\cdot H}, \tag{41}$$

where $\boldsymbol{s}_{\cdot H}$ is a vector where its i'th element is s_{iH}. Equation (41) implies that the firm-level measure $\frac{p_i q_i}{\alpha E + \text{Exports}}$ captures the centrality of each firm as a supplier of goods to final demand (including exports). This is analogous to the "supplier centrality" defined in Baqaee (2014).

Finally, combine equations (38), (39) and (41) to yield

$$\hat{P}^{1-\tilde{\sigma}} = \sum_{i\in\Omega} \frac{p_i q_i}{\alpha E + \text{Exports}} \left(s_{li} + s_{Fi}\hat{p}_F^{1-\tilde{\sigma}}\right).$$

Then from equation (37), we have

$$\hat{U} = \left(\sum_{i\in\Omega} \frac{p_i q_i}{\alpha E + \text{Exports}} \left(s_{li} + s_{Fi}\hat{p}_F^{1-\tilde{\sigma}}\right)\right)^{\frac{-\alpha}{1-\tilde{\sigma}}}. \quad \square$$

D.4 Case of constant markups in firm-to-firm trade

Consider a case where firms charge constant and common markups $\tilde{\mu}$ in firm-to-firm trade. Then Proposition 1 no longer holds because of the following. Equations (38) and (39) remain the same, but equation (40) no longer holds. Since there are markups in firm-to-firm trade, we instead have

$$\begin{aligned} p_i q_i &= s_{iH}\alpha E + s_{iH}\text{Exports} + \sum_j s_{ij} c_j q_j \\ &= s_{iH}\alpha E + s_{iH}\text{Exports} + \sum_j s_{ij}\tilde{\mu}^{-1} p_j q_j. \end{aligned}$$

Rearranging to matrix form, we find

$$\frac{\boldsymbol{p} \circ \boldsymbol{q}}{\alpha E + \text{Exports}} = \left(I - \tilde{S}\right)^{-1} \boldsymbol{s}_{\cdot H},$$

where the (i, j) element of matrix $\tilde{S}$ is now $s_{ij}\tilde{\mu}^{-1}$. In this case, the matrix used in capturing firms' centrality as consumers of foreign goods does not match with the one used in capturing firms' centrality as suppliers of goods to final demand.

D.5 System of price changes under fixed networks

In this section we present the system of price changes for the variable markup case and derive its first order approximations. When firms charge pairwise variable markups in firm-to-firm trade and the network is fixed, we have the following system of equations for the changes in prices, given $\hat{p}_F$ and parameters.

$$\begin{aligned} \hat{c}_i^{1-\eta} &= s_{li} + s_{mi}\hat{p}_{mi}^{1-\eta} \\ \hat{p}_{mi}^{1-\rho} &= \sum_{j\in Z_i} s_{ji}^m \hat{\mu}_{ji}^{1-\rho}\hat{c}_j^{1-\rho} + s_{Fi}^m \hat{p}_F^{1-\rho} \\ \hat{\mu}_{ji} &= \hat{\varepsilon}_{ji}\frac{\varepsilon_{ji} - 1}{\hat{\varepsilon}_{ji}\varepsilon_{ji} - 1} \\ \varepsilon_{ij} &= \rho\left(1 - s_{ij}^m\right) + \eta s_{ij}^m \\ \hat{\varepsilon}_{ji} &= \frac{1}{\varepsilon_{ji}}\left(\rho\left(1 - s_{ji}^m\hat{s}_{ji}^m\right) + \eta s_{ji}^m\hat{s}_{ji}^m\right) \\ \hat{s}_{ji}^m &= \hat{\mu}_{ji}^{1-\rho}\hat{c}_j^{1-\rho}\hat{p}_{mi}^{\rho-1}. \end{aligned} \tag{42}$$

Taking first order approximations, we obtain

$$\begin{aligned} \frac{\mathrm{d}c_i}{c_i} &= s_{mi}\frac{\mathrm{d}p_{mi}}{p_{mi}} \\ \frac{\mathrm{d}p_{mi}}{p_{mi}} &= \sum_{j\in Z_i} s_{ji}^m\left(\frac{\mathrm{d}\mu_{ji}}{\mu_{ji}} + \frac{\mathrm{d}c_j}{c_j}\right) + s_{Fi}^m\frac{\mathrm{d}p_F}{p_F} \\ \frac{\mathrm{d}\mu_{ji}}{\mu_{ji}} &= -\frac{\left(\rho - \varepsilon_{ji}\right)(\rho - 1)}{\left(\varepsilon_{ji} - 1\right)\varepsilon_{ji} + \left(\rho - \varepsilon_{ji}\right)(\rho - 1)}\left(\frac{\mathrm{d}c_j}{c_j} - \frac{\mathrm{d}p_{mi}}{p_{mi}}\right). \end{aligned}$$

Further manipulating the above equation:

$$
\begin{aligned}
\frac{\mathrm{d}c_i}{c_i} &= \sum_{j \in Z_i} s_{ji} \left(\frac{\mathrm{d}\mu_{ji}}{\mu_{ji}} + \frac{\mathrm{d}c_j}{c_j} \right) + s_{Fi} \frac{\mathrm{d}p_F}{p_F} \\
\frac{\mathrm{d}\mu_{ji}}{\mu_{ji}} &= -\Gamma_{ji} \frac{\mathrm{d}c_j}{c_j} + \Gamma_{ji} \frac{\mathrm{d}p_{\not{j}i}}{p_{\not{j}i}},
\end{aligned}
\tag{43}
$$

where Γ_{ji} equals the elasticity of markup μ_{ji} with respect to the supplier's cost c_j:

$$
\begin{aligned}
\Gamma_{ji} &= -\frac{\partial \mu_{ji}}{\partial c_j} \frac{c_j}{\mu_{ji}} \\
&= \frac{\Upsilon_{ji} \left(1 - s_{ji}^m\right)}{1 - \Upsilon_{ji} s_{ji}^m} \\
\Upsilon_{ji} &= \frac{\left(\rho - \varepsilon_{ji}\right)(\rho - 1)}{\left(\varepsilon_{ji} - 1\right)\varepsilon_{ji} + \left(\rho - \varepsilon_{ji}\right)(\rho - 1)},
\end{aligned}
$$

and $\hat{p}_{\tilde{j}i}$ represents the average price change from suppliers other than j:

$$
\frac{\mathrm{d}p_{\not{j}i}}{p_{\not{j}i}} = \frac{\sum_{k \in Z_i, k \neq j} s_{ki}^m \left(\frac{\mathrm{d}\mu_{ki}}{\mu_{ki}} + \frac{\mathrm{d}c_k}{c_k} \right) + s_{Fi}^m \frac{\mathrm{d}p_F}{p_F}}{1 - s_{ji}^m}.
$$

The first order approximation of the change in aggregate price is

$$
\frac{\mathrm{d}P}{P} = \sum_i s_{iH} \frac{\mathrm{d}c_i}{c_i}.
$$

Combining with equation (43) yields

$$
\begin{aligned}
\frac{\mathrm{d}P}{P} &= \sum_i s_{iH} \left(\sum_{j \in Z_i} s_{ji} \frac{\mathrm{d}c_j}{c_j} + s_{Fi} \frac{\mathrm{d}p_F}{p_F} \right) \\
&\quad + \sum_i s_{iH} s_{mi} \left(-\sum_{j \in Z_i} s_{ji}^m \Gamma_{ji} \frac{\mathrm{d}c_j}{c_j} + \sum_{j \in Z_i} s_{ji}^m \Gamma_{ji} \frac{\mathrm{d}p_{\not{j}i}}{p_{\not{j}i}} \right).
\end{aligned}
\tag{44}
$$

E Additional estimation results

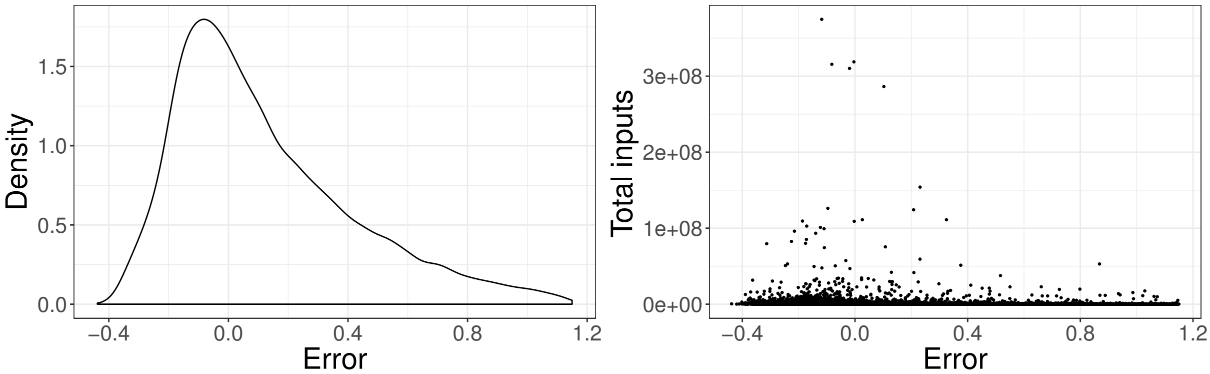
E.1 Distribution of errors

Here we provide the distribution of firm-level errors under the estimated CES parameters. We compute the size of the relative error for each firm i, where $\hat{\mu}$'s are the implied markups from estimated $\hat{\eta}, \hat{\rho}, \hat{\sigma}$:

$$\text{Error}_i = \frac{c_i q_i - \left(\sum_j \frac{V_{ij}}{\hat{\mu}_{ij}} + \frac{V_{iH}}{\hat{\mu}_{iH}} + \frac{V_{iF}}{\hat{\mu}_{iF}}\right)}{c_i q_i}.$$

We plot the distribution of these firm-level errors on the left of Figure 22, and on the right we plot these errors against firms' size of total inputs, $c_i q_i$. One can see that the distribution of errors is concentrated around zero, and firms with large errors tend to be small firms.

Figure 22: Distribution of firm level errors



Notes: The left figure displays the distribution of firm-level errors. The errors are defined as the difference between the LHS and the RHS of equation (27), relative to the size of the firm's total inputs. The right figure plots these errors against firms' total inputs.

E.2 Assuming Cournot competition in estimating CES parameters

When assuming Cournot competition in firm-to-firm trade instead, equation (15) becomes

$$p_{ij} = \frac{\varepsilon_{ij}}{\varepsilon_{ij} - 1} c_i$$
$$\varepsilon_{ij} = \left(\frac{1}{\rho}\left(1 - s_{ij}^m\right) + \frac{1}{\eta} s_{ij}^m\right)^{-1}.$$

We follow the same procedure described in Section 5.1 and obtain the estimates shown in Table 19.

Table 19: Estimated values for $\{\eta, \rho, \sigma\}$ under Cournot competition

	$\frac{1}{\eta}$	$\frac{1}{\rho}$	$\frac{\sigma}{\sigma-1}$
Estimate	0.62	0.36	1.25
s.e.	0.18	0.04	0.05
	η (Labor and goods)	ρ (Firms' goods in production)	σ (Firms' goods in consumption)
Implied value	1.63	2.79	5.00

E.3 Assuming constant markups in estimating CES parameters

When assuming that firms charge constant markup $\frac{\rho}{\rho-1}$ when selling goods to other domestic firms, equation (15) becomes

$$p_{ij} = \frac{\rho}{\rho - 1} c_i.$$

We follow the same procedure described in Section 5.1 and obtain the estimates of ρ and σ shown in Table 20.

Table 20: Estimated values for $\{\rho, \sigma\}$ under constant markups

	$\frac{\rho}{\rho-1}$	$\frac{\sigma}{\sigma-1}$
Estimate	1.57	1.25
s.e.	0.11	0.04
	ρ (Firms' goods in production)	σ (Firms' goods in consumption)
Implied value	2.74	4.99

E.4 Accounting for capital inputs in estimating CES parameters

In the model, total input $c_i q_i$ is an aggregate of labor costs and goods purchases. Here we account for capital inputs by interpreting labor as the composite input of labor and capital. As we do not directly observe capital rental costs for each firm, we take two alternate approaches.

First, we assume that firms have common labor shares, and uniformly scale up labor cost. We use the aggregate labor share of 0.6 that we compute as the total labor cost divided by the total value added. We report the estimation results in Table 21.

Table 21: Estimated values for $\{\eta, \rho, \sigma\}$ assuming common labor share

	η	ρ	$\frac{\sigma}{\sigma-1}$
Estimate	1.00	3.03	1.25
s.e.	0.66	0.47	0.05
	η	ρ	σ
	(Labor/capital and goods)	(Firms' goods in production)	(Firms' goods in consumption)
Implied value	1.00	3.03	4.96

Second, we assume that the user cost of capital consists of capital depreciation rate and the interest rate. Following Dhyne, Petrin, Smeets, and Warzynski (2017), we set the yearly depreciation rate as 8% and set the interest rate as the long-term interest rate in Belgium. We compute the capital rental costs using fixed tangible assets reported in the annual accounts. We report the estimation results in Table 22.

Table 22: Estimated values for $\{\eta, \rho, \sigma\}$ using capital from annual accounts

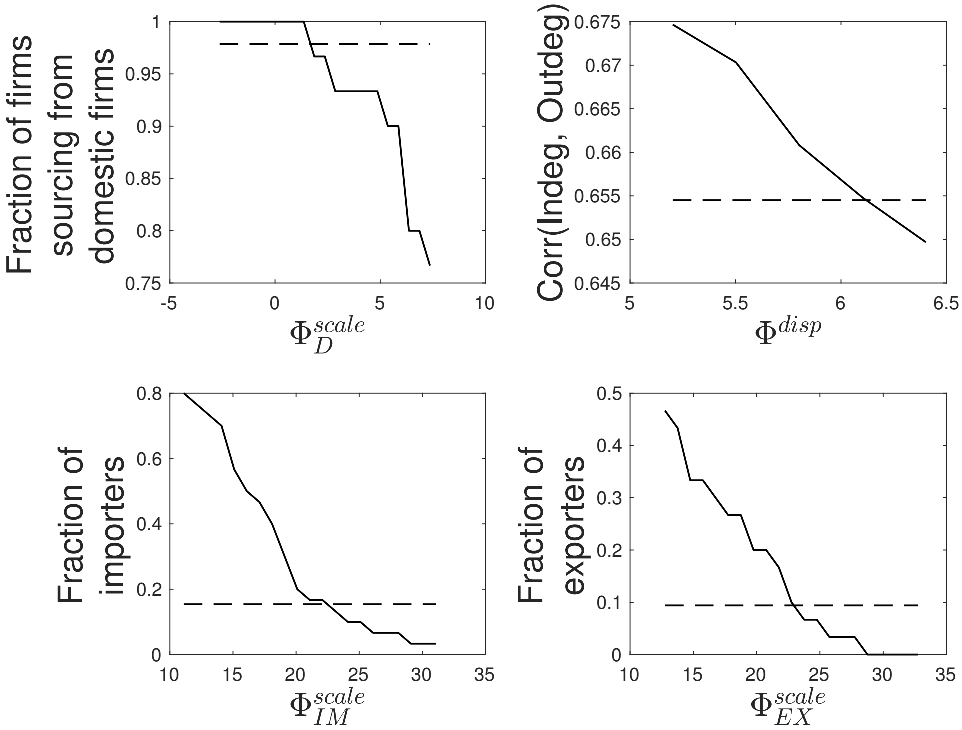
	η	ρ	$\frac{\sigma}{\sigma-1}$
Estimate	1.00	3.59	1.27
s.e.	0.93	0.65	0.04
	η	ρ	σ
	(Labor/capital and goods)	(Firms' goods in production)	(Firms' goods in consumption)
Implied value	1.00	3.59	4.77

In the two cases above, the estimates of η are both one. If a firm is a sole supplier to a customer, then its implied markup will be $\frac{\eta}{\eta-1}$, which is not well defined if $\eta = 1$. In our selected sample, there are only around 1000 firms that have single supplier, and we drop them from our estimation sample.

E.5 Local identification for the fixed cost parameters

Figure 23 shows the local identification for all parameters that we estimate via SMM.

Figure 23: Local identification of the fixed cost parameters



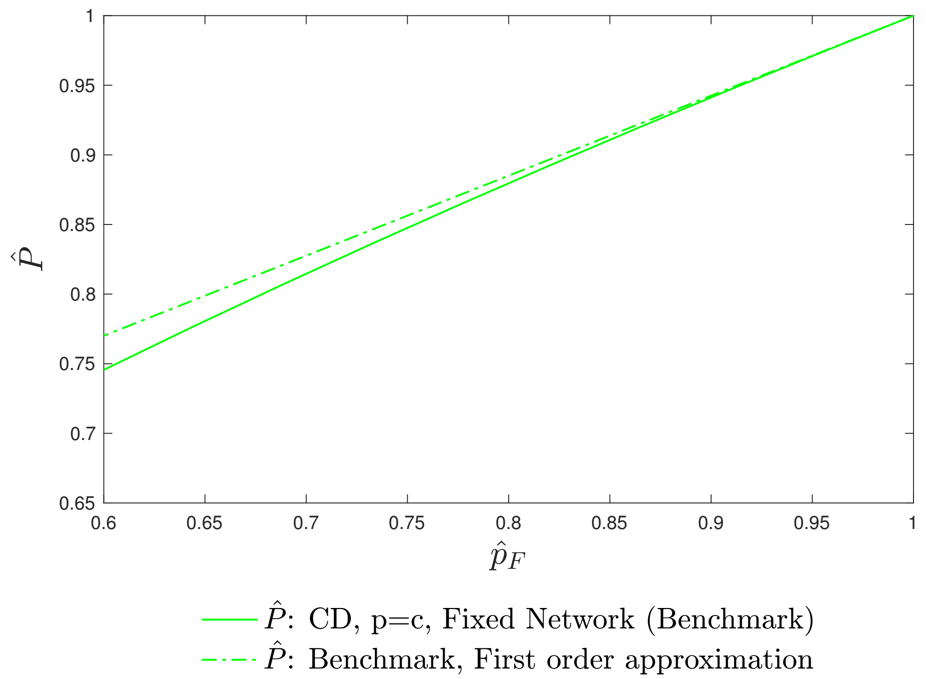
Notes: These figures illustrate local identification of the four fixed cost parameters. In each figure, on the x-axis we plot the parameter to identify, which we vary while fixing all other parameters to their estimated values. On the y-axes we plot the moments we use to identify the parameters. The horizontal lines indicate the observed value of the moment in the data.

F Additional results from the counterfactual analysis

F.1 First order approximation of the benchmark case

Here we provide the first order approximated change in the aggregate price index under the benchmark case. The solid line in Figure 24 displays the global change in price index under the benchmark case, and is identical to the first line in Figure 6 in the main text. The dotted line displays the first order approximation. The first order approximation requires smaller set of assumptions. While we assume Assumptions 1, 3, 4, and 5 for our benchmark case, we only need Assumptions 1 and 3 for the first order approximation.

Figure 24: $\hat{P}$ under the benchmark case and its first order approximation



F.2 Pairwise attenuation and pro-competitive effects

We decomposed the change in pairwise markups into attenuation and pro-competitive effects in equation (32) of the main text:

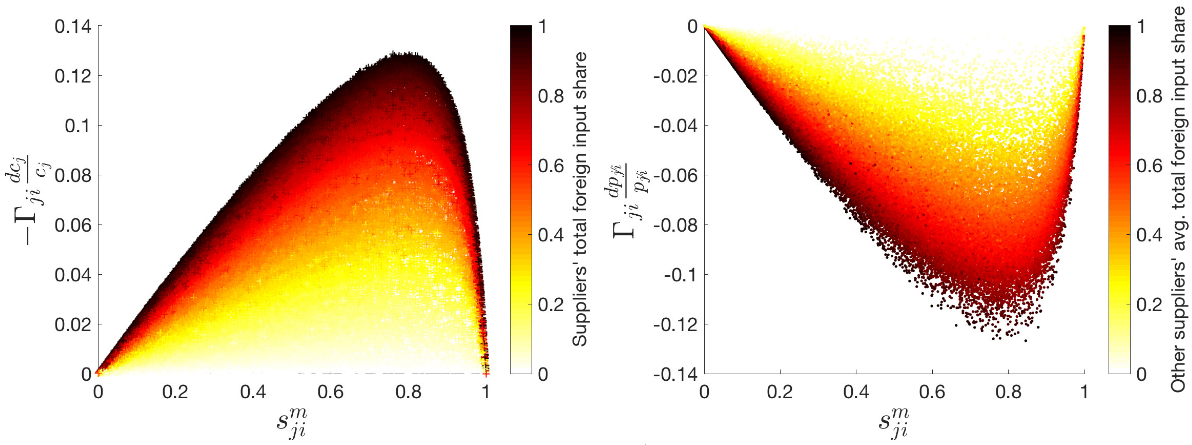
$$\frac{d\mu_{ji}}{\mu_{ji}} = \underbrace{-\Gamma_{ji}\frac{dc_j}{c_j}}_{\text{attenuation effect}} + \underbrace{\Gamma_{ji}\frac{dp_{\not{j}i}}{p_{\not{j}i}}}_{\text{pro-competitive effect}}.$$

Here we plot these two effects, along with the net effects of $\frac{d\mu_{ji}}{\mu_{ji}}$. First, in Figure 25 we plot the pairwise attenuation and pro-competitive effects against the input shares s^m_{ji}. As we have argued in the main text, the upper bounds of the both effects display a hump shape with respect to s^m_{ji}. Within the same values of s^m_{ji}, there are variations in the two effects, depending on how much shock the supplier or other suppliers received, $\frac{\mathrm{d}c_j}{c_j}$ and $\frac{\mathrm{d}p_{\not{j}i}}{p_{\not{j}i}}$. The cost changes at the firm-level can be approximated by firm-level measures of total foreign input share, s_{Fj}^{Total}:

$$s_{Fj}^{Total} = s_{Fj} + \sum_k s_{kj} s_{Fk}^{Total}.$$

From Figure 25, one can indeed see that within the same value of s_{ji}^m, pairs in which suppliers have a higher total foreign input share experience greater attenuation effect. Likewise, within the same value of s_{ji}^m, pairs in which the other suppliers have higher total foreign input share on average experience a greater pro-competitive effect.

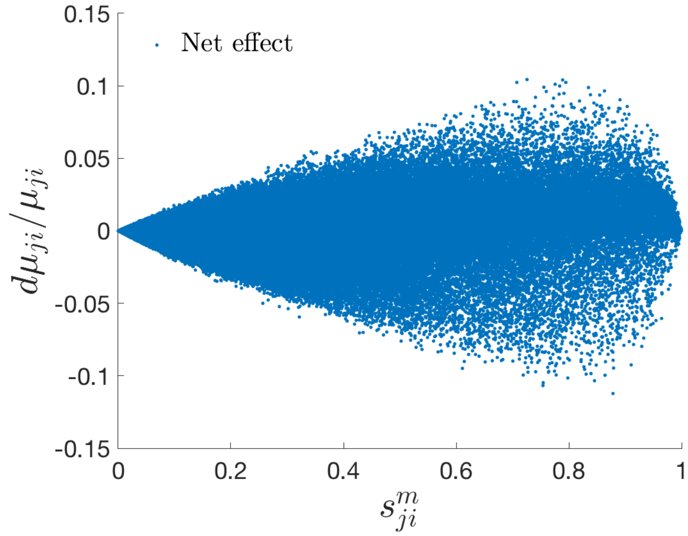
Figure 25: Attenuation and pro-competitive effects



Notes: The left figure plots the pairwise attenuation effect, $-\Gamma_{ji}\frac{\mathrm{d}c_j}{c_j}$, against the input shares, s_{ji}^m. The right figure plots the pairwise pro-competitive effect, $\Gamma_{ji}\frac{\mathrm{d}p_{\not{j}i}}{p_{\not{j}i}}$, against the input shares. In both figures, we add colors that represents suppliers' total foreign input share, s_{Fj}^{Total}. In the left figure, the darker color indicates the higher value of s_{Fj}^{Total}. In the right figure, the darker color indicates the higher value of other suppliers' total foreign input share: $\frac{\sum_{k \in Z_i, k \neq j} s_{ki}^m s_{Fk}^{Total} + s_{Fi}^m}{1 - s_{ji}^m}$.

Finally we plot the net effects of the two, $\frac{\mathrm{d}\mu_{ji}}{\mu_{ji}}$, in Figure 26.

Figure 26: Change in markups



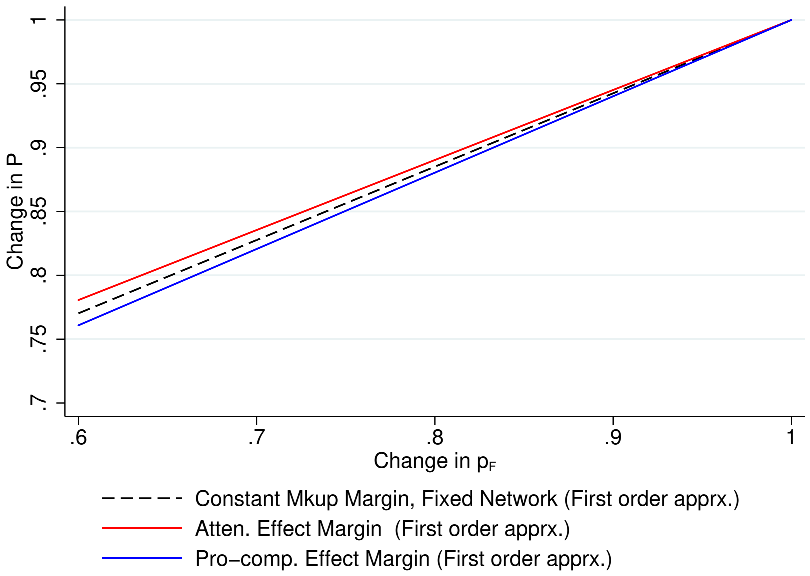
F.3 First order approximated changes in price index

Further manipulating equation (36), we can decompose the first order approximated change in price index into three components:

$$
\begin{aligned}
\frac{\mathrm{d}P}{P} = & \sum_i s_{iH}\left(\sum_{j\in Z_i} s_{ji}\frac{\mathrm{d}c_j}{c_j} + s_{Fi}\frac{\mathrm{d}p_F}{p_F}\right) \\
& - \sum_i s_{iH}s_{mi}\sum_{j\in Z_i} s^m_{ji}\Gamma_{ji}\frac{\mathrm{d}c_j}{c_j} \\
& + \sum_i s_{iH}s_{mi}\sum_{j\in Z_i} s^m_{ji}\Gamma_{ji}\frac{\mathrm{d}p_{fi}}{p_{fi}}.
\end{aligned} \tag{45}
$$

The first line of equation (45) describes the channels that are present in the constant markup case. The second line represents the aggregate attenuation effect, and the third line represents the aggregate pro-competitive effects. We plot in Figure 27 the three components of the change in aggregate price index, computed from the firm-to-firm trade data in 2012.

Figure 27: Attenuation and pro-competitive effects



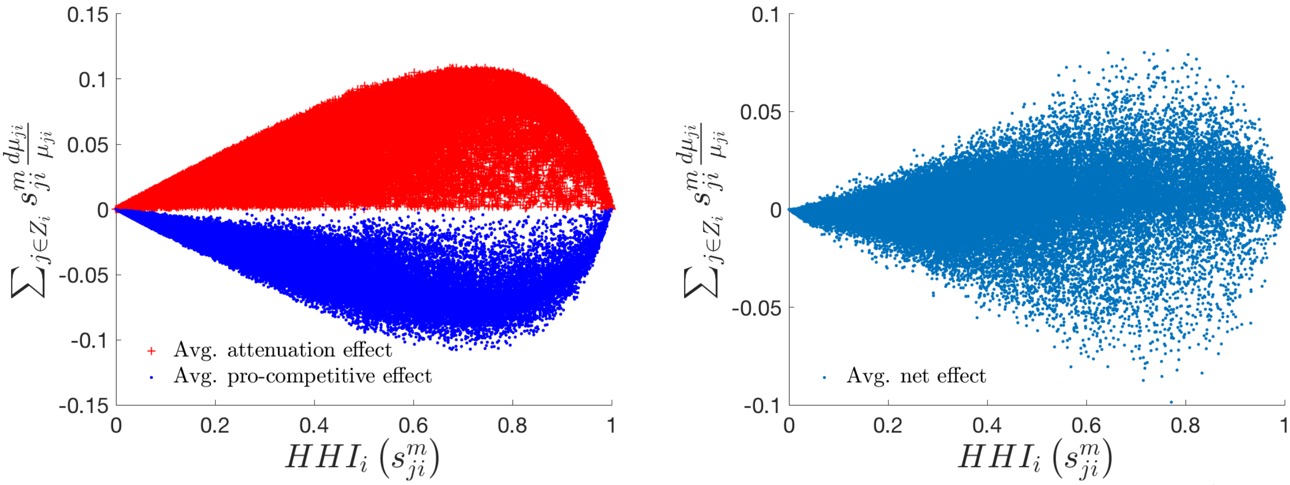
F.4 Average attenuation and pro-competitive effects

The average change in markups that firm i faces, $\sum_{j\in Z_i} s^m_{ji}\frac{\mathrm{d}\mu_{ji}}{\mu_{ji}}$, can be decomposed into to: the average attenuation effect that the firm faces, and the average pro-competitive effect that the firm faces:

$$\sum_{j\in Z_i} s^m_{ji}\frac{\mathrm{d}\mu_{ji}}{\mu_{ji}} = \underbrace{-\sum_{j\in Z_i} s^m_{ji}\Gamma_{ji}\frac{\mathrm{d}c_j}{c_j}}_{\text{avg. attenuation effect}} + \underbrace{\sum_{j\in Z_i} s^m_{ji}\Gamma_{ji}\frac{\mathrm{d}p_{fi}}{p_{fi}}}_{\text{avg. pro-competitive effect}} .$$

Here we plot these two effects at the firm-level, along with the net effects of $\sum_{j\in Z_i} s^m_{ji}\frac{\mathrm{d}\mu_{ji}}{\mu_{ji}}$. We plot these against the HHI of input shares s^m_{ji} across suppliers j. Maximum magnitudes of both average attenuation and pro-competitive effects display a hump shape with respect to the HHI of input shares. If the input shares are completely diversified (HHI close to 0), then their markups do not change as all suppliers have infinitesimal input shares. Also, if the input shares are very skewed (HHI close to 1), suppliers' markups do not change, since one supplier has an input share close to 1 and all others have shares close to 0. The variation within the same value of HHI comes from different combinations of suppliers' input shares s^m_{ji} and their exposure to the shock $\left(\frac{\mathrm{d}c_j}{c_j}, \frac{\mathrm{d}p_{fi}}{p_{fi}}\right)$.

Figure 28: Average attenuation/pro-competitive effects



Notes: In the positive region of the left figure, we plot the average attenuation effect for each firm i, $-\sum_{j\in Z_i} s_{ji}^m \Gamma_{ji} \frac{\mathrm{d}c_j}{c_j}$, against the HHI of input shares, s_{ji}^m, across supplier firm j. In the negative region of the left figure, we plot the average pro-competitive effect for each firm i, $\sum_{j\in Z_i} s_{ji}^m \Gamma_{ji} \frac{\mathrm{d}p_{ji}}{p_{ji}}$, against the HHI of input shares, s_{ji}^m, across supplier firm j. In the right figure, we plot the net effect, $\sum_{j\in Z_i} s_{ji}^m \frac{\mathrm{d}\mu_{ji}}{\mu_{ji}}$, against the HHI of input shares.

F.5 Shock to one importer

Here we consider a shock of foreign price reduction that hits a single importer, firm I. Analogous to Figure 8 in the main text, in Figure 29 we plot the firms' average change in markups, $\sum_{j\in Z_i} s_{ji}^m \left(\hat{\mu}_{ji} - 1\right)$, against the measure capturing firms' closeness to the shock. Instead of firms' indirect exposure to imports $s_{Fi}^{Indirect}$, we construct a measure s_{Ii}^{Total} that captures firms' exposure to firm I's goods:

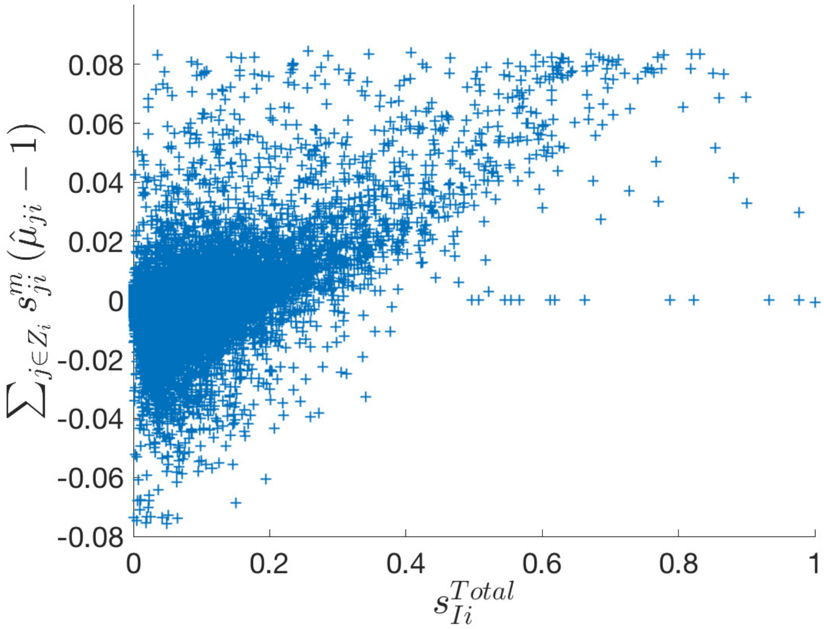
$$s_{Ii}^{Total} = \sum_{k\in Z_i} s_{ki} s_{Ik}^{Total} \quad \text{if } i \neq I$$

$$s_{Ii}^{Total} = 1 \quad \text{if } i = I.$$

One can see that the positive correlation between the two measures are stronger than in Figure 8.

In Table 23, we report the changes in aggregate price index in response to the two different shocks. The magnitude of the change is smaller when the shock hits a single importer, but the magnitude of the net effects of adding oligopolistic competition becomes larger.

Figure 29: Average change in markups and s_{Ii}^{Total}



Notes: The figure plots $\sum_{j\in Z_i} s_{ji}^m \left(\hat{\mu}_{ji} - 1\right)$ upon $\hat{p}_F = 0.6$, against s_{Ii}^{Total}.

Table 23: Changes in price index under two different shocks

	Shock to all importers	Shock to one importer
$\hat{P}_{const}$	0.707	0.976
$\hat{P}_{var}$	0.709	0.977
$\left(\hat{P}_{var}-\hat{P}_{const}\right)/\left(1-\hat{P}_{const}\right)$	0.005	0.053

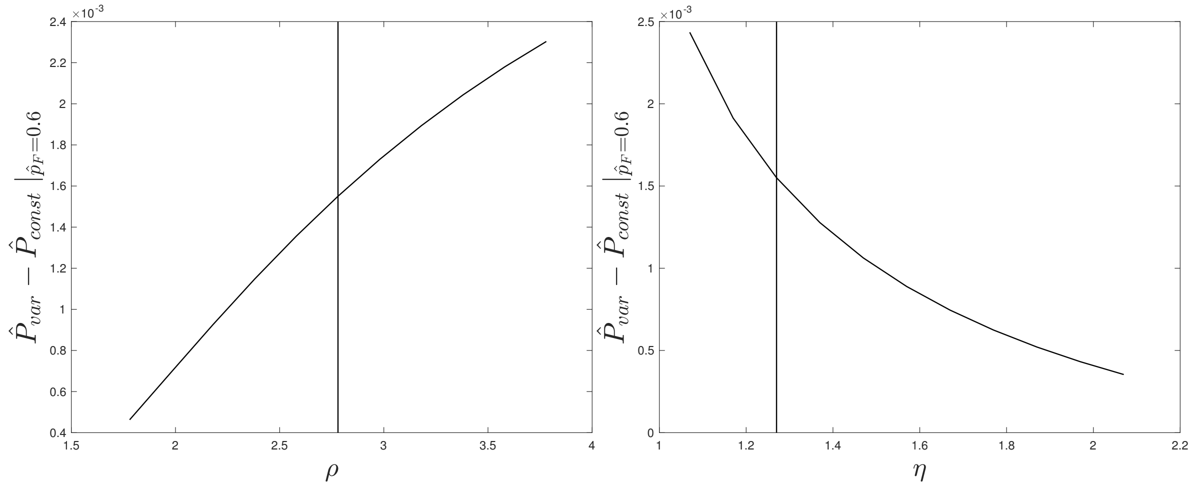
Notes: The changes in price index are evaluated when $\hat{p}_F = 0.6$.

F.6 Changes in price index under different CES parameters

Here we show that the net effect of adding variable markups on the aggregate price index depends on the values of the underlying CES parameters. Figure 30 plots the net effect of variable markups on price index, $\hat{P}_{var} - \hat{P}_{const}$, against different parameters of ρ and η. The changes in price index are evaluated at $\hat{p}_F = 0.6$. One can see that larger values of ρ and smaller values of η lead to larger net effects, where the attenuation effect dominates the pro-competitive effect.

The effects of different ρ and η on the net effects can be explained by their effects on markup elasticities Γ_{ji}. As ρ gets larger and as η gets smaller, Γ_{ji} increases for all regions of s_{ji}^m. As explained in the main text, higher Γ_{ji} means larger maximum magnitudes of the pairwise attenuation and pro-competitive effects.

Figure 30: The net effect of variable markups on $\hat{P}$ under different CES parameters

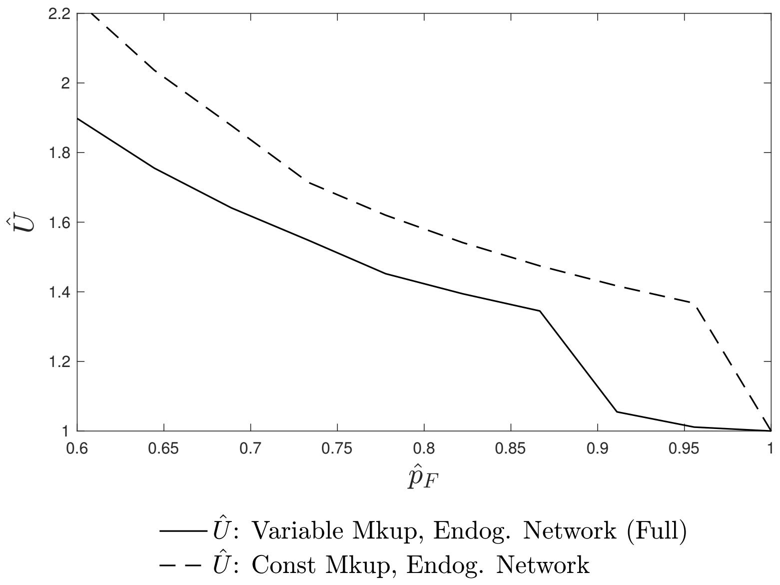


Notes: These figures plot the net effects of variable markups on price index, $\hat{P}_{var} - \hat{P}_{const}$, against different parameters of ρ and η. The changes in price index are evaluated at $\hat{p}_F = 0.6$. The vertical lines depict the estimated values of the CES parameters.

F.7 Changes in welfare under variable and constant markups

Here we explore the implications of the interaction between variable markups and endogenous networks on the changes in aggregate welfare, $\hat{U}$. Figure 31 shows the analogous result for Figure 12, but now for $\hat{U}$. In addition to the change in price index, the change in welfare also reflects the change in aggregate welfare as well as its initial level. Facing cheaper costs and smaller degree of double marginalization, both the level of initial aggregate profits and the increase in aggregate profits are much larger in the constant markup case. These contribute to larger predicted increase in aggregate welfare.

Figure 31: $\hat{U}$ under endogenous networks: variable and constant markups



G One sector model of firm-to-firm trade

In this section we outline a model of firm-to-firm trade within a single sector. We focus on firm-to-firm trade that occurs within the sector, and assume firms take demand and prices of goods outside the sector as exogenous. Estimating the parameters in this partial equilibrium model, we conduct the same counterfactual exercise as in main text, and show that it yields qualitatively the same results.

G.1 Model outline

We assume that firms take demand and prices outside the sector as exogenous. Let demand for firms' goods from domestic households be D, and those from firms outside the sector to be D_o. All firms in the sector produce goods by using labor input and outside sector goods. They all sell to households and to firms outside the sector. Their network decisions involve which firms in the same sector to source from, and whether to import/export.

Firms in the sector have the same production technologies as the heterogeneous goods sector in the main text, but treat the price of goods outside the sector, p_o, as exogenous. The implied unit cost of firm i in the sector is

$$c_i = \phi_i^{-1}\left(\omega_l^{\eta} w^{1-\eta} + \omega_m^{\eta} p_{mi}^{1-\eta}\right)^{\frac{1}{1-\eta}},$$

where p_{mi} is the firm specific price index for i's goods input. p_{mi} varies with the firm's sourcing strategy Z_i and I_{Fi}. Z_i is now a set of i's suppliers that belong to the same sector. We assume that all firms in the sector buy intermediate inputs from the outside sector.

$$p_{mi} = \left(\sum_{j\in Z_i} \alpha_{ji}^{\rho} p_{ji}^{1-\rho} + \alpha_{oi}^{\rho} p_o^{1-\rho} + I_{Fi}\alpha_{Fi}^{\rho} p_F^{1-\rho}\right)^{\frac{1}{1-\rho}}.$$

Now let us describe the market structure. As in the main text, we assume monopolistic competition when firms sell to final demand and export:

$$p_{iH} = p_{iH} = \frac{\sigma}{\sigma-1}c_i.$$

We also assume that when firms sell their output to firms outside the sector, they engage in monopolistic competition. Given our assumption that all firms in the sector sell at least part of their output to firms outside the sector, it is reasonable to assume that firms act as if they were infinitesimally small. We posit that firms in the outside sector have the same production function, which leads to the price that firm i charges when selling goods to an outside sector firm being

$$p_{iO} = \frac{\rho}{\rho-1}c_i.$$

As for the intra sector firm-to-firm trade, we maintain oligopolistic competition as in the main text. Firm i charges higher markup to j if i has larger input share in j's goods bundle:

$$p_{ij} = \frac{\varepsilon_{ij}}{\varepsilon_{ij} - 1} c_i$$
$$\varepsilon_{ij} = \rho \left(1 - s^m_{ij}\right) + \eta s^m_{ij}.$$

Firms make their linkage formation decisions by maximizing their variable profits net of fixed costs. Their decisions involve choosing the set of suppliers in the same sector, Z_i, and importing/exporting statuses, I_{Fi} and I_{iF}. The variable profit of i is:

$$\begin{aligned}
\pi_i^{var}\left(Z_i, I_{Fi}, I_{iF}\right) =& \frac{1}{\sigma} \underbrace{\beta_{iH}^{\sigma} \left(\frac{\sigma}{\sigma - 1}\right)^{1-\sigma} c_i \left(Z_i, I_{Fi}\right)^{1-\sigma} D}_{\text{Sales to HH}} + I_{iF} \frac{1}{\sigma} \underbrace{\left(\frac{\sigma}{\sigma - 1}\right)^{1-\sigma} c_i \left(Z_i, I_{Fi}\right)^{1-\sigma} D^*}_{\text{Exports}} \\
&+ \frac{1}{\rho} \underbrace{\left(\frac{\rho}{\rho - 1}\right)^{1-\rho} c_i \left(Z_i, I_{Fi}\right)^{1-\rho} D_o}_{\text{Sales to outside sector}} \\
&+ \sum_{j \in W_i} \frac{1}{\varepsilon_{ij}} \underbrace{\alpha_{ij}^{\rho} p_{ij} \left(Z_i, I_{Fi}\right)^{1-\rho} \frac{s_{mj} c_j q_j}{p_{mj}^{1-\rho}}}_{\text{Sales to } j},
\end{aligned}$$

where W_i is now the set of customers of i in the same sector. Taking as given other firms' decisions, the exogenous demand parameters D, D^* and D_o, and exogenous prices w, p_o and p_F, the firm maximizes the total net profit:

$$\pi_i \left(Z_i, I_{Fi}, I_{iF}\right) = \pi_i^{var} \left(Z_i, I_{Fi}, I_{iF}\right) - \sum_{j \in Z_i} w f_{Di} - I_{Fi} w f_{Fi} - I_{iF} w f_{iF}.$$

G.2 Estimation

We then apply this partial equilibrium model to the data. For the sector in which we focus on firm-to-firm trade, we use the NACE 2-digit sector 10, which is the "Manufacture of food products". In 2012, there were 3481 firms in that sector in our sample. Out of all the B2B inputs that firms in the sector purchased in 2012, around 25% were from firms in the same sector. Out of all the goods that firms in the sector sold, around 23% were to firms in the same sector.

Analyzing the firm-to-firm network with only 30 firms in this sector is reasonable, as the largest 30 firms accounted for around 99% of total sales in the sector. Moreover, around 99% of all the B2B sales values that occurred within that sector were sales where both the supplier and the customer firm were among the largest 30 firms.

For the three CES parameters $\{\eta, \rho, \sigma\}$ and the dispersion parameter of the productivity distribution, we use the values estimated in Section 5.1 and Section 5.2. We re-estimate the four fixed costs parameters in the same way as in Section 5.3, using the same set of moments.

For the rest of the parameters, we do the following calibration. First, we set the saliency terms $\left\{\beta_{iH}, \alpha_{ij}, \alpha_{oi}, \alpha_{Fi}\right\}$ to be equal to 1. We set the production weights on labor inputs and goods input, ω_l and ω_m to be 0.3 and 0.7 to match the average labor input share of 0.27 for the sector. We set the demand parameters D and D_o to be 5×10^{12} and 2×10^{10}, to match firms' average output shares to domestic final demand (0.58) and to firms outside the sector (0.28). We set D^* to 2×10^{12} to match exporting firms' average export share, 0.31. We normalize wage w to one, and set foreign price p_F and price of outside good p_o to be 1 and 2 so that they match importers' average import share (0.20) and firms' average input share of the outside goods (0.53), respectively.

Table 24 reports the estimated fixed costs parameters, estimated via simulated methods of moments.

Table 24: Estimated values for the fixed cost parameters

	Φ_{D}^{scale}	Φ_{IM}^{scale}	Φ_{EX}^{scale}	Φ^{disp}
Estimate	6.07	27.01	27.17	10.05

And in Table 25 we report the fit of the model for the targeted moments under the estimated parameters.

Table 25: Targeted moments

	Data	Model
Fraction of firms sourcing from domestic firms	0.90	0.90
Fraction of importers	0.19	0.20
Fraction of exporters	0.17	0.17
Corr(Indeg, Outdeg)	0.47	0.47

G.3 Counterfactual analysis

Here we conduct counterfactual analysis, analogous to Section 6.1 in the main text. We take an exogenous reduction in the foreign good's price, p_F, as the shock and focus on how the price index of the sector, P, changes. We define P as

$$P = \left(\sum_{i \in \Omega} \beta_{iH}^{\sigma} p_{iH}^{1-\sigma} \right)^{\frac{1}{1-\sigma}},$$

where Ω is the set of firms in the sector. Analogous to Figure 9 in the main text, we plot in Figure 32 the changes in P under four cases. One can see that the qualitative results still hold in our one sector partial equilibrium model: firms' endogenous network formation can significantly alter aggregate implications.

Figure 32: $\hat{P}$ in four cases