Essays on Production Networks and International Trade

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Network analysis offers a rich framework to study questions of international trade. Trade has natural network applications with firms, sectors, and countries connected to buyers and suppliers through their sales within and across borders. Its applications have also been used to study financial, social, and transport networks within the economic discipline to deliver new insights. I apply network tools of analysis to address questions on the impact of network structure on future export competitiveness following a negative trade shock; and develop an endogenous production network model to quantify the bias of abstracting from the reorganisation of trade linkages that is assumed in a standard fixed production network model.

In Chapter 1, I introduce the types of network models, both microfounded and non-microfounded, with their international trade applications. Microfounded models are useful to understand producer-level decision-making and how these decisions are then reflected in the prevailing structure of the production network. Non-microfounded models focus on explaining aggregate trade patterns, either through pre-specified functional form assumptions, or stochastic algorithms, to match the model to the data and recover stylized facts documented in the empirical literature.

In Chapter 2, I document a set of stylized facts about the global production network and ask how network structure affects countries' future comparative advantage. I study whether a more interconnected sector when facing a negative trade shock, finds its connections have an amplifying or insuring effect on its future export competitiveness. Using the 2008 Financial Crisis as the negative final demand shock, I find my results support the insurance hypothesis, whereby being well-connected reduces the decline in future export competitiveness relative to more peripheral sectors.

In Chapter 3, I develop a general equilibrium trade network model, exploiting data on the 2018 US-China trade war to study the impact of import tariffs on inter-firm links in supply chains and GDP losses. I find failing to account for the reorganisation of trade linkages leads to a 60% overestimation of GDP losses. In Chapter 1 and 2, I introduce the types of network models, and the relative effects of a trade shock, respectively, in Chapter 3, I work with a general equilibrium model to comment on the aggregate effects of a trade shock.

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Introduction

Trade can be thought of as a naturally networked activity. Producers, be it at the country, sector, or firm level are embedded in a production network together with their buyers and suppliers. The interconnectedness due to these exchanges both within and across borders has become especially prominent over the last couple of years. The US-China protectionist trade policy episode in 2018, the coronavirus pandemic in 2020, and the ongoing Russia-Ukraine conflict in 2022 have brought attention to the importance of global supply chains. It is with the disruption and the subsequent propagation of shocks across production networks, that the importance of these linkages has become prominent. The ability to reorganise trade connections - be it due to supply problems, changes in production costs due to the enactment of trade policy, or otherwise - through a model featuring input supplier choice is a valuable exercise in explaining network formation.

In Chapter 3, I build a trade network model, exploiting data on the 2018 US-China trade war to study the impact of the increase in import tariffs on inter-firm links in supply chains and GDP losses. In my methodological contribution, I quantify the size of the bias associated with abstracting from the reorganisation of trade linkages, comparing a fixed production network to an endogenous network model. I find abstracting from trade reorganisation leads to a 60% overestimation of GDP losses in the fixed production network model.

Countries, sectors, and firms rely on producers beyond those directly in their local markets. Be it due to their direct trade relationships with foreign buyers and suppliers, or trade with local suppliers who themselves rely on foreign partners in their production process. Individual producer decisions, therefore, contribute to the specialisation patterns of countries as a whole, where shocks can have knock-on consequences on trading partners. In Chapter 2, I document a set of novel stylized facts about the global production network, including the 'small world phenomenon' common in social networks. I also ask how a sector's position in the production network affects its future export competitiveness. That is, does being more central amplify or insure against a negative trade shock, in the form of the decrease in final demand associated with the 2008 Financial Crisis? I test this hypothesis by constructing a shift-share instrument to isolate the exogenous variation in the change in global final demand. I find more interconnected sectors experience relatively smaller declines in their future export competitiveness relative to their more peripheral counterparts. This evidence supports the insurance hypothesis.

More broadly, modelling assumptions influence the conclusions drawn from the framework of analysis. An awareness of the assumptions and features built into models can help guide the interpretation of results from comparative static and counterfactual analysis. This is especially important where the use of such models may be used in the advocacy of trade policy. I introduce the types of network models that have previously been employed in international trade in Chapter 1, distinguishing also between the relative merits of continuous versus discrete models. In Chapter 3, in my comparison of the fixed and endogenous production network modelling choice, I find different mechanisms contribute to the GDP losses estimated by the model. For example, in the fixed production network GDP loss is primarily due to larger price increases, but a relatively smaller decline in trade flows, compared to the endogenous production network. This is because in the fixed case, firms cannot substitute away from (weakly) more expensive inputs in their production process, as they can in the endogenous case.

Chapter 1

Network Models and their International Trade Applications

Network tools of analysis offer a complementary lens to standard economic models through which to address questions of international trade. Models with an exogenous (or fixed) production network are the workhorse for answering questions concerning shock propagation through networks and performing counterfactual analysis following a shock. However, models of endogenous network formation are increasingly important to allow for the possibility of reorganising trade connections in response to shocks. Such network models may be i) microfounded, such as costly-relationship network models featuring a cost-benefit trade-off of forming links, or ii) non-microfounded, such as extreme value class models, where a specific functional form is assumed for tractability, or stochastic network approach models, where a pre-specified algorithm governs the formation of the network. I consider each model type in turn, introducing the trade literature that has employed each strategy, distinguishing between continuous and discrete models, and their relative merits.
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1.1 Introduction

Network tools of analysis offer a rich framework through which to engage with questions in the international trade literature and offer new insights. There are a number of documented stylized facts that network models can replicate in trade, such as accounting for the sparsity of trade networks and providing the microfoundations for firms' sourcing decisions (Antràs et al., 2017; Armenter & Koren, 2014).[1]

Endogenous network formation models enrich the standard framework used to study questions of intermediate input supplier choice. Johnson & Noguera (2012) document two-thirds of global trade is in intermediate inputs, a quantitatively significant share, and therefore an important feature of the world economy. Canonical models of trade assume anonymous intermediate inputs are bundled into a final good that is sold to firms or consumers, abstracting from input-output linkages (Melitz, 2003).

Previous work has predominantly used exogenously defined networks. In this framework, papers study how shocks to interconnected producers (at the sector- or firm-level) may propagate and contribute to aggregate fluctuations (Long & Plosser, 1983; Horvath, 1998; Dupor, 1999). Acemoglu et al. (2012) find sectoral shocks may lead to aggregate fluctuations if there is a significant asymmetry in the pattern in which sectors supply to one another. Acemoglu et al. (2017) also find sector-to-sector linkages may contribute to macroeconomic tail risks. This body of work emphasises the importance of the (fixed) network structure in propagating idiosyncratic shocks.

This fixed network framework is convenient when taking the model to the data. However, it abstracts from the possibility of reorganising trade connections in response to a shock to the system. Given that optimising firms minimise costs conditional on a certain set of conditions, changes to production costs may also lead to the reorganisation of trade linkages. As global supply chains are the endogenous outcome of producer decisions, accounting for supplier choice as an additional margin of adjustment, is important for modelling trade.

In recent years, there has been a proliferation of work endogenising network formation to understand trade patterns. A variety of network models have been developed to endogenise firms' input sourcing decisions and match documented stylized facts. One challenge for such theoretical work has been to remain computationally tractable and suitable for empirical applications.

In this paper, I sort production network models into microfounded and non-microfounded categories. Within these categories I distinguish a further three sub-categories, explaining their uses and introducing international trade papers that fall under each type. Within the microfounded category are the costly-relationship network models. Here, firms must trade off the benefit of forming or maintaining a trade link against the relative cost of doing so. Only when the benefit is at least as great as the cost that must be incurred, does a link in the model persist. Acemoglu & Azar (2020) apply this idea in a general setting with the possibility of distortions. Antràs et al. (2017) explain firms' self-selection into importing

[1] There is a growing empirical literature documenting the characteristics of production networks that I do not cover in detail. For an introductory review, see Bernard & Moxnes (2018a).

also following a similar cost-benefit decision with regard to its "sourcing capability". Lim (2018) develops a model that features input-output linkage formation in a similar setting to explain business cycle fluctuations. Costly-relationship models are useful for understanding the trade-off firms make with regard to their trade connections and how such micro-level decisions are reflected in macroeconomic outcomes.

In the non-microfounded category are the extreme value class and the stochastic network approach models. Extreme value models achieve tractability by assuming a specific functional form that is classed in the extreme value class distributions. In trade models, this functional form tends to be applied to the productivity (or technology) that governs trade flows in a Ricardian model of trade. A common productivity distribution used in the trade literature is the Fréchet distribution, in the spirit of the seminal work of Eaton & Kortum (2002); Caliendo & Parro (2015); Caliendo et al. (2022). Oberfield (2018) assumes firm productivity follows a power law distribution to obtain tractability.

Within the non-microfounded category is also the stochastic network approach. In a stochastic network, the formation of the network is determined by a pre-specified algorithm. This sub-category is closest in the spirit of classical network formation models found in graph theory, that then apply these ideas to economic networks. The building blocks are the random and preferential attachment models of Erdős & Rényi (1959); Barabási & Albert (1999). The trade literature has used the principles from these seminal works to model buyer-supplier links and explain trade barriers. In non-microfounded models, greater emphasis is placed on the shape of the production network and how closely it matches empirical evidence.

A more recent discourse uses the principles of a stochastic network approach to inform the design and assumptions in structural models of trade Armenter & Koren (2014); Bernard & Zi (2022). This probabilistic model of trade, a balls-and-bins model, does a good job of replicating stylized facts of trade. Where the statistical model matches the data, trade models do not improve our understanding of the mechanisms yielding observed outcomes. However, where the statistical model differs from the data, this can offer direction as to the assumptions that should be added to trade models to match what is observed in the data. This is a benefit of using discrete models to inform modelling choices in a systematic manner and avoiding the implications for network structure that continuous models can suffer from. Given that there exist a finite number of firms, that engage in a discrete number of transactions, discrete models are also arguably a more realistic representation of categorical trade data. This is not to say there are no limitations to using a discrete model. The combinational discrete choice problems that may arise in this framework can be computationally intensive and challenging to solve. However, there is a complementary literature on the most efficient ways to solve computational problems that suffer from this curse of dimensionality (Jia, 2008; Arkolakis et al., 2021).

A holistic understanding of the set of potential model types available to the researcher and their applications in the trade literature is a useful exercise to guide informed modelling choices given the research question of interest.

In Section 1.2, I outline the microfounded class of costly-relationship network models; in Section 1.3 the non-microfounded, extreme value class and stochastic network approach models. Then, in Section 1.4 I introduce the trade-offs of using continuous versus discrete models in production network analysis; and Section 3 concludes.

1.2 Microfounded models

1.2.1 The Costly-Relationship Network

In the first class of costly-relationship network models, firms face a cost to forming or maintaining connections with other firms that supply inputs to their production process. A firm's choice to add, maintain, or sever a link according to this cost-benefit trade-off generates the prevailing extensive margin of trade.

In microfounded models, the expression for this trade-off is derived from the firm's profit maximisation (or the isomorphic cost minimisation) problem. I illustrate the firm's problem of adding suppliers in three examples. In the first example, I borrow from Acemoglu & Azar (2020), where the authors develop a tractable, general equilibrium model of endogenous network formation in a general setting. Each firm combines different inputs together with labour to produce its output, where each input carries its own input-specific productivity. The firm's chosen set of intermediate inputs, S_i, then determines its firm-level productivity. From the firm's cost minimisation problem, one can derive the expression for the unit cost function such that:

$$K_i(S_i, A_i(S_i), P_i) = \frac{1}{A_i(S_i)} \prod_{j \in S_i} P_j^{\alpha_{ij}} \tag{1.1}$$

where α_{ij} is firm i's expenditure on input j. The unit cost function illustrates the firm's trade-off when it chooses the set S_i to minimise its production costs, thereby endogenously determining the prevailing production network. Primarily the trade-off is between sets of suppliers where prices ($\prod_{j \in S_i} P_j^{\alpha_{ij}}$) may be low, but productivity is high ($A_i(S_i)$), or vice versa. Given firms operate in a perfectly competitive market, higher unit costs of production due to a negative trade shock, for example, translate to higher prices. When re-optimising, firms must weigh up whether the input-specific benefit still outweighs the new, higher costs of purchasing it from the supplier.

In the second example, Antràs et al. (2017) develop a multi-country sourcing model where firms select into importing based on their productivity and country-specific variables such as wages, trade costs, and technology. The focus of the model is firms' extensive margin decisions as to which products to offshore and the countries from which to purchase them. The authors treat foreign sourcing decisions as interdependent across markets such that a firm's choice to import from a market will affect whether it is optimal to import from another, i.e. moving away from constant marginal costs to a model where sourcing costs are dependent on firm heterogeneity. In the firm's profit maximisation problem, its marginal costs are decreasing in what Antràs et al. (2017) refer to as its "sourcing capability", where this term is a function of the set of countries a firm imports from and that countries' characteristics. A firm's share of intermediate input purchases sourced from any country, conditional on its sourcing strategy is:

$$\chi_{ij}(\varphi) = \frac{T_j\left(\tau_{ij} w_j\right)^{\theta}}{\Theta_i(\varphi)} \quad \text{if} \quad j \in \mathcal{J}_i(\varphi) \tag{1.2}$$

or $\chi_{ij}(\varphi) = 0$ otherwise, where

$$\Theta_i(\varphi) \equiv \sum_{k \in \mathcal{J}_i} T_k(\tau_{ik} w_k)^{\theta}. \tag{1.3}$$

The $\Theta_i(\varphi)$ is the "sourcing capability" of firm φ from country i. Countries in the set $\mathcal{J}_i(\varphi)$ with lower wages (w_j), more advanced technology (T_j), or lower trade costs when selling to country i (τ_i) will have higher market shares in the intermediate input purchases of firms based in country i. The term θ determines the variability of productivity draws across inputs which comes from the shape parameter of the Fréchet distribution governing the efficiency of intermediate inputs the firm uses to produce.

The marginal cost of firm φ from country i can be expressed as:

$$c_i(\varphi) = \frac{1}{\varphi}\left(\gamma \Theta_i(\varphi)\right)^{-\frac{1}{\theta}}, \tag{1.4}$$

where the addition of a new location to the sourcing set $\mathcal{J}_i(\varphi)$ increases the sourcing capability of the firm and thereby lowers its marginal cost in Equation 1.4. The intuition behind this result is that the inclusion of an additional location increases competition amongst potential suppliers reducing the minimum sourcing cost for each intermediate. Here, the firm trades off the reduction in costs associated with the inclusion of an additional country in the set $\mathcal{J}_i(\varphi)$ increasing sourcing capability against the payment of an additional fixed cost $w_i f_{ij}$.

In Antràs et al. (2017) there exists a continuous measure of final goods producers, and in Acemoglu & Azar (2020) a discrete number of producers. The discrete nature of Acemoglu & Azar (2020) precludes the need for a fixed cost of sourcing. A fixed cost is necessary for models with a continuum of firms and constant elasticity of substitution (CES) technology to prevent all firms from purchasing from all others. In Section 1.4, I discuss the use of discrete versus continuous models in more detail.

In the third example, Lim (2018) develops a structural model of trade between heterogeneous firms in which the firm-level input-output linkages are endogenously determined, and applies it to explain business cycle fluctuations in the US. Firms are heterogeneous over productivity (ϕ) and the demand (δ) for a firm's product, $\chi = (\phi, \delta)$. This exogenous firm-level heterogeneity is independent of a firm's connections.

In this model, firms use a CES production technology implying access to additional suppliers reduces the marginal cost of the firm (through love-for-variety) and increases the firm's variable profit (through constant returns to scale). To counteract the incentive of firms to form as many links as possible, relationship formation is assumed to be costly.

A firm's relationship is active as long as the static profits accruing to a firm are at least as large as the relationship cost in each period. The probability that firm χ' sells to firm χ at date t is:

$$m_t(\chi, \chi') = G_{\xi,t}[\pi_t(\chi, \chi')] \tag{1.5}$$

where $G_{\xi,t}$ is the unconditional distribution of ξ at date t implied by some predefined stochastic process. Equation 1.5 fully characterises the endogenous matching function that governs firm-to-firm trade in the economy. Firm profits at date t depend on contemporaneous firm network characteristics (the firm's marginal cost and the firm's demand shifter relative to the household's demand), and the firm's variable employment, for a given distribution of fundamental firm characteristics $G_{\chi,t}$.[2]

Depending on the application in mind, the linkages a producer may include in its set can range from other suppliers as in Acemoglu & Azar (2020) and Lim (2018), or other countries as in Antràs et al. (2017). Matching between buyers and suppliers in microfounded models is derived from the firm's profit maximisation problem, from which a (closed-form) expression can be derived that governs the trade-off of the firm. This approach has also been used in the empirical works of Tintelnot et al. (2018) who study the production network of Belgian firms and Taschereau-Dumouchel (2020) who study US firm networks. In models where firms are assumed large enough to affect aggregate outcomes, solving for model equilibria becomes

[2] A firm's network characteristics are a function of both the fundamental exogenous firm-level characteristics and the network characteristics of its suppliers.

computationally challenging. Tractability can be introduced in one of two ways. Previous work has exogenously limited the set of connections that firms can form in the model or assumed firms to be small enough such that individual firm-level decisions do not influence other firms (Lim, 2018; Acemoglu & Azar, 2020). Lim (2018) assumes the set of firms is large enough that a single firm has no impact on aggregate variables in a continuum of firms. Acemoglu & Azar (2020) assume perfect competition in the production of intermediate inputs in a discrete modelling framework.

Costly-relationship network models are useful for understanding how firms trade off the relative costs and benefits of connections, and how their supplier choices endogenously affect the overall network structure. Such models are especially useful when asking questions concerning firms' input supplier choice, at home or abroad, and for performing policy evaluations, where an interconnected firm may face a shock, such as an increase in trade costs through an import tariff.[3] There are a number of international trade papers that have sought to endogenise firms' input supplier choice through this costly relationship structure to address open trade questions.

Antràs et al. (2017) (henceforth AFT) develop a multi-country sourcing model to explain firms' extensive margin decision to offshore certain products and the countries from which they purchase. Firms select into importing where this decision is dependent on their productivity and country-specific variables including wages, trade costs, and technology. AFT treat foreign sourcing decisions as interdependent across markets such that a firm's choice to import from a market will affect whether it is optimal to import from another, i.e. moving away from constant marginal costs to a model where sourcing costs are dependent on firm heterogeneity. In the firm's profit maximisation problem, marginal costs are decreasing in the firm's "sourcing capability", where this term is a function of the set of countries a firm imports from and that countries' characteristics. The intuition behind this setting is that firms may buy intermediate inputs from any country, but the ability to import carries a market-specific cost. Relatively unproductive firms may therefore choose not to import from a country selling an attractive set of inputs due to the high fixed cost of importing from that country. The main trade-off for a firm is the reduction in costs due to the inclusion of a country in its souring set (thereby increasing the firm's sourcing capability) against the cost of paying the fixed cost needed to employ the input. One complication which arises in such a framework is that the interdependence in firms' sourcing decisions poses a combinatorial choice problem for firms' extensive margin import decisions. This problem can be made tractable using Jia (2008)'s iterative algorithm to reduce the dimensionality of the firm's

[3] I adopt this approach in Chapter 3 where I exploit the increase in import tariffs during the 2018 US-China trade war to study the impact of rising trade costs on trade connections.

sourcing problem.[4] Nevertheless, the endogenous network element, through modelling firms optimising their foreign sourcing strategy rather than the location of final good production moves the model beyond a two-country framework. The model also accommodates interdependencies in firm-level decisions. AFT characterise firm sourcing strategies with multiple inputs and countries. Therefore, optimising over firms' foreign sourcing decisions allows for a richer, tractable model that collapses to the well-known gravity equation, such as that of Eaton & Kortum (2002) (when fixed costs are zero and so there is universal importing) and Chaney (2008) (where interdependencies are shut down across markets).

Bernard & Moxnes (2018c) develop a multi-country model to provide a microfoundation for the buyer-seller relationships observed in trade data. While AFT focuses on the importer dimension, Bernard & Moxnes (2018c) incorporates both importer and exporter heterogeneity. In the model, exporters are heterogeneous in their ability to produce differentiated intermediate goods and pay a relationship-specific fixed cost (e.g. bureaucratic processes, customisation of output) to match with each buyer. Importers vary in their ability to bundle a set of intermediate inputs into a final good. The authors assume intermediates are produced by a continuum of firms, heterogeneous in productivity, with each firm producing one differentiated variety. A sorting function governs whether a given firm will find it worthwhile to sell to a particular buyer, with productivity higher than some lower bound threshold value that will still generate a profitable match for the seller. However, the lower support of seller productivity includes the case where the buyer (final goods producer) may meet every seller (intermediate goods producer). This introduces a discontinuity in the Pareto distribution of productivity at this lower bound threshold. Hence, the authors work in a limiting case, where even the most productive buyer will not find it profitable to match with the smallest seller. Given this assumption is needed in addition to the firm's cost-benefit trade-off, the framework may fall within the extreme value class as well, which I outline in Section 1.3.1. Guided by a set of empirical facts concerning the pattern of buyer-seller trade relationships, the authors build a multi-country model to explain lower variable trade costs lead to higher export growth when buyers in the destination market are more homogeneous in their productivity. With more similar buyers, an exporter will find more profitable matches than when buyers are more varied in their productivity. This work illustrates that access to suppliers is important for firm outcomes and marginal costs, and hence the interdependencies created

[4] The combinatorial discrete choice problem (CDCP) literature is especially salient for such problems given the dimension of the firm's potential choice set. Jia relaxes the independence assumption of firm market entry decisions. The resulting 'chain effect' creates a profit maximisation problem that is complicated to solve. Jia transforms the profit problem into a search for the fixed points of the necessary conditions to limit the dimension of the problem with minimum and maximum points that can be easily found. See Arkolakis et al. (2021) for more recent work in solving CDCP problems with interdependencies and agent heterogeneity.

by such trade linkages.

Arkolakis et al. (2023) microfound a model of spatial production networks to study how firms form production networks across regions and countries. The aggregate production network arises endogenously from firms' sourcing decisions, depending on productivity and location. Firms search for buyers and suppliers, featuring two-sided heterogeneity similar to Bernard & Moxnes (2018c), within and across locations. Firms maximise (anticipated) profit subject to location-pair-specific search costs. Buyer and supplier search turns into successful relationships with some probability determined by a matching technology and the number of buyers and suppliers searching in each pair of locations. The authors find that endogenous network formation amplifies the effects of a shock so long as the search costs are directly affected by the shock. The production network depends on the search and matching process of the firm, where firms post advertisements to search for buyers and suppliers in each search location. Advertisements to final good consumers result in a match with probability one, while advertisements for intermediate goods buyers feature a matching friction with the success rate governed by a matching technology. The third search type for the firm is for suppliers where each advertisement turns into a successful match with random suppliers, again governed by the matching technology. The matching rates between buyers and suppliers are determined between each pair of locations and depend on the aggregate buyer and supplier postings. The endogenous network formation component is applied to study the spatial distribution of economic activity, as shaped by spatial frictions, and introduces a geographic component to production network analysis. It highlights an additional mechanism through which the endogenous formation of production network across space influence aggregate outcomes.

To summarise, microfounded models are useful in understanding the firm's decision process in adding or dropping linkages from their production set. These linkages may be other products, suppliers, or countries depending on the nature of the research question and the unit of analysis. Existing work has begun to document the extensive margin of trade, and with the digitization of customs records and computational power, more work can investigate endogenous network formation in an open economy with multiple dimensions of firm heterogeneity in a tractable framework. There has been work at the firm-level in this direction in developing countries such as Uganda and developed countries, like Belgium (Spray, 2021; Dhyne et al., 2023).

1.3 Non-microfounded models

1.3.1 Extreme Value Class

The second class of non-microfounded models is the extreme value class. Tractability in this category is obtained by assuming a specific functional form that is classed in the extreme-value class of distributions. In (Ricardian) trade models, this functional form tends to be applied to the technologies that govern trade flows.

A commonly used extreme value class distribution is the Fréchet distribution, as in Eaton & Kortum (2002) (henceforth EK). EK develop a Ricardian trade model, where differences in technology spur trade, incorporating a role for geography in the observed patterns of trade. The EK model is a gravity trade model that features an exogenous production network with roundabout intermediate good production. It has been a useful benchmark model to study the macroeconomic impacts with exogenous production networks (Antràs & Chor, 2021).

EK assume a country i's efficiency in producing a good j is the realisation of a random variable Z_i, drawn independently, for each good, from its country-specific probability distribution $F_i(z) = Pr[Z_i \leq z]$. The probability theory of extremes provides a form for $F_i(z)$ that yields simple expressions for the variables of interest; the likelihood that country i supplies a particular good to country n, and the price distribution.

A country's efficiency distribution is assumed to be Fréchet:

$$F_i(z) = e^{-T_i z^{-\theta}} \tag{1.6}$$

where $T_i > 0$ and $\theta > 1$. The (country-specific) parameter T_i governs the location of the distribution. A bigger T_i implies a country is more likely to draw a high productivity for any good j. The term, θ, is the shape parameter that governs the amount of variation in the distribution. A bigger θ implies less variability. In a trade context, this functional form can parsimoniously summarise a country's absolute and comparative advantage across a continuum of goods. The parameter T_i reflects a country's technology (absolute advantage) across the continuum of goods and θ the heterogeneity of countries' productivity across goods (comparative advantage).

Oberfield (2018) develops a theoretical framework for the formation of the production network, where who buys inputs from who forms endogenously. The main results describe how individual-level choices lead to the emergence of star suppliers that are well documented. Oberfield (2018) assumes the distribution of productivity follows a power law to obtain tractability. Each entrepreneur uses labour and one other intermediate input to produce their product. Each input has a certain productivity and the entrepreneur's input choice depends on its productivity compared to its price, where the price is a function of the production cost of the entrepreneur producing the good.

While the extreme value class assumption delivers tractability in the model, it restricts the extensive margin of firm-to-firm linkages in Oberfield (2018). Given the extensive margin is an important component of endogenous network formation, this is a limitation. The strength of the model is its ability to deliver the stylized facts of superstar firms. That is, individual entrepreneur-level choices lead to the endogenous emergence of star suppliers, where in equilibrium there are a few entrepreneurs who sell their inputs to many other entrepreneurs. Here, the extreme value class distribution demonstrates that models of network formation, potentially microfounded or not, can replicate stylized facts of trade.

1.3.2 The Stochastic Network Approach

The third class of model is where there is an exogenous stochastic network algorithm that governs the formation of the network. This class is closest to the classical network formation models in graph theory that apply these ideas to economic networks.

The seminal work of Erdős & Rényi (1959) develops a model of random attachment and Barabási & Albert (1999) of preferential attachment where linkages are governed by a pre-defined algorithm. In a random attachment model, each node has some probability of being connected, independent of all other nodes present. However, in a preferential attachment model, the probability a node receives more links is increasing in the number of connections it already has, generating a scale-free network.[5]

Atalay et al. (2011) combines elements from both Erdős & Rényi (1959) and Barabási & Albert (1999) to model buyer-supplier relationships in the US economy. However, the scale-free feature of network models overstates the connectivity of the economy's most central firms and the number of peripheral firms. The firm network is constructed through three processes governed by a pre-specified structure, i) firm death, ii) the reorganisation of surviving firms, and iii) firm birth.

I now place more structure on these three processes. Firms uniformly and permanently exit the market with some probability q^*. With $q(2-q)N(t)m(t)$ edges (or connections) destroyed. $N(t)$ is the total number of nodes (or firms) in the network at any time t, and $m(t) \equiv \frac{\sum_k kn(k,t)}{N(t)}$ the average number of customers (or suppliers) per firm, with $n(k,t)$ the number of nodes with in-degree k at time t.

Surviving firms attempt to replace their destroyed links with the existing firms still in the

[5] A scale-free network is one whose degree distribution follows a power law. The World Wide Web, citation networks, and social networks, such as co-authorship or collaboration of actors in film, are approximately scale-free.

network. By construction, some fraction r of edges is reallocated uniformly with probability $\frac{1}{(1-q)N(t)}$ across the surviving firms, and $1-r$ edges are allocated via preferential attachment, $\frac{k}{(1-q)N(t)}$, where k in the numerator gives it its preferential characteristic.

The birth of new firms has $(g+q)N(t)$ firms enter the network, where g is the net average growth rate of the number of firms in the network and q is the average probability of firm death, each forming $m(t)$ edges, with a fraction δ extending to existing firms. A share of $1-r$ is allocated by a preferential attachment rule, whereas the other r of the $\delta(q+g)N(t)m(t)$ edges are allocated uniformly across the existing nodes. $1-\delta$ of the $(q+g)N(t)m(t)$ new edges are assumed to be distributed uniformly and independently among the other $(q+g)N(t)$ new firms that entered at the same time.

Work by Duernecker & Vega-Redondo (2018) develop a dynamic model to understand the role of social networks in the process of globalisation. Globalisation arises from the formation of connections between agents, dependent on some minimal 'geographic cohesion' through which agents build connections when starting from a sparse network. For any given level of connectivity, the underlying network structure is governed by an Erdős-Rényi type model. The formation of the network structure, both link creation and destruction, is governed by a symmetric and stochastically independent mechanism, whereby links are formed or destroyed with some probability. For a given random network, an agent is randomly presented with an opportunity to create a new link according to some conditional probability, $\phi(z; \alpha, \mu, n)$, where z is the expected degree of the network; α the geographic cohesion; μ the institutional quality; and n the size of the population. A key insight of this theoretical work is that some degree of geographic cohesion is needed to facilitate the globalisation process.

Chaney (2014) develops a theory of trade where information frictions are a barrier to trade, incorporating geography to explain observed trade patterns. Potential exporters meet foreign partners in one of two ways. A firm can search directly for foreign partners through geographically biased random search. Then, once a firm has set up foreign contacts in various locations, it can search remotely for new trading partners from these locations, reminiscent of a two-stage random, then preferential attachment network model. This feature of firms using existing contacts to find new ones gives rise to a fat-tailed distribution for the number of foreign contacts across firms. The model offers a parsimonious framework to study the extensive margin of trade but is silent on the intensive margin. Chaney likens this framework to the work of Jackson & Rogers (2007) on social networks that draw on features of a random and preferential network, where Chaney embeds this in geographic space.

Bernard & Zi (2022) propose a model for a production network based on random matching and firm heterogeneity. For given buyer and supplier heterogeneity, a simple allocation model with buyer purchases randomly assigned to sellers on the basis of buyer-seller size can generate documented sparse production networks and empirical regularities of firm-to-firm connections. The authors then characterise the family of statistics and data-generating processes the elementary model generates.

While the stochastic network approach offers a parsimonious framework for network formation, one limitation is that the firm's decision-making process remains a black box. A firm's optimising behaviour is not explicitly modelled and hence such models cannot be used to study how the production network may respond to shocks due to changes in firms' incentives. Nevertheless, stochastic network models can replicate important empirically documented features of networks and offer direction as to the modelling assumptions to make.

1.4 Continuous versus Discrete Models

Continuous models are generally used as they tend to be more tractable than discrete models and allow for somewhat greater modelling simplicity. However, in the context of modelling production networks, continuity has implications for network structures that necessitate the introduction of additional assumptions to explain certain network characteristics.[6] The assumption of a CES production technology necessitates the addition of a fixed cost to forming a trade relationship to prevent all firms from trading with one another. As additional suppliers reduce the marginal cost of production (due to love for variety) and increase the firms' variable profit (due to constant returns to scale), firms have the incentive to form as many links as possible. Hence, in practice, a discrete model with firm heterogeneity may better match the data than one that is continuous and deterministic (Bernard & Zi, 2022).

In practice, firms are linked to their customers and suppliers and do not operate independently from these connections. The nature of trade lends itself to being described as a networked activity, where buyers-sellers form the nodes of a network, and the transactions between them are the edges of an economic network. Given there are a finite number of firms engaging in discrete transactions, this combination of firm heterogeneity and sparsity of trade in the network provides structure to the prevailing production network, in a discrete model.

There have been multiple papers that use techniques employed in production network-type questions to explain the sparseness of trade data. Armenter & Koren (2014) propose a (discrete) statistical model to account for the sparsity of trade. The authors apply the balls-and-bins model to international trade, allocating the shipment of traded goods to different

[6] Herkenhoff et al. (2021) use a continuum of heterogeneous firms and add constraints to the model in order to match the sparsity of network data.

country, product, and firm-level categories.[7] Following the documentation of a number of stylized facts concerning the pattern of zero trade flows, the authors ask how useful these facts are in explaining the extensive margin of trade. The authors propose an atheoretical benchmark for sparse categorical data to help systematically choose data moments most informative about the most suitable model of the extensive margin. This model falls under the stochastic network approach described in Section 1.3.2. No systematic relationship is assumed between the categories into which the trade flows (balls) are shipped (bins). The intuition underlying the model is to predict the extensive and intensive margin of trade. Each observation is a discrete unit (ball) which is then randomly allocated to a mutually exclusive category (bin). The probability of a ball falling into a particular bin is independent and identically distributed, dependent only on the size of the bins themselves. Researchers can calibrate the parameters governing the number of balls and the distribution of bin sizes to the data.

The balls-and-bins model can replicate the zero product-level trade flows found in the data given cross-country trade flows follow a gravity-type model and the trade shares across products are skewed. Where the balls-and-bins model does not match the data well, predicting 74% of firms should export while only 18% in practice do, signals that the relationship between firms and export flows would be a useful statistic to include in structural models. This benchmark model can help distinguish which statistics are determined by the sparsity of network data, and thus providing little direction as to the determination of the extensive margin, and those that are not. In the latter case, structural trade models may help correctly specify the joint distribution of trade across categories by country, product, and firm.

The model is limited when using a dense dataset, i.e. when there are a large number of observations relative to the number of categories. With dense data, the model cannot replicate facts on the extensive margin, with all bins non-empty.

Bernard & Zi (2022) develop an elementary model for a production network formed via random matching, also using a balls-and-bins model. The elementary model improves on the Armenter & Koren (2014) model by generalising the allocation problem considered, where the extensive margin for buyers can differ, and firms can be both buyers and sellers. To link the statistical balls-and-bins model to economic theory, the authors derive the elementary model from a competitive environment, where models with an EK structure are a special case. Where the elementary model fails to match the documented empirical regularities, the authors define what they term "instructive" statistics that can help to guide the introduction of additional assumptions such that the model can match the relevant stylized facts.

[7] A balls and bins model uses probability theory to assign each ball to a bin following an assumed modelling distribution governing this allocation.

For example, production networks have been documented to feature negative assortative matching. Small firms are more likely to match with large firms. This has been used to motivate the inclusion of relationship-specific fixed costs. That is, only the most productive sellers may find it worthwhile to incur a fixed cost of connecting to a small buyer. Under the elementary, balls-and-bins model, this arises without the need of assuming a relationship-specific cost. A similar intuition holds for the elementary model fitting the hierarchical stylized fact of production networks; that more productive firms sell to a wider range of buyers. However, one statistic where the elementary model yields a different sign from the empirical relationship observed is that of the number of customers and the average market share of the seller to those customers. That is, a firm's outdegree and its average market share should be negatively correlated. This illustrates that introducing additional assumptions that allow the model to accommodate this empirical pattern may be necessary where this relationship would be considered an important feature in a researcher's research question.

Pros	**Cons**
Provides a more realistic characterisation of the data than a continuous model. There's a finite number of firms, engaging in discrete transactions.	Combinational discrete choice problems (CDCP) can be computationally intensive and challenging to solve.
Avoids implications for network structure that continuous models carry, where continuity is generally assumed for modelling simplicity and tractability.	May introduce discontinuities due to the granular nature of discrete data. As data becomes more disaggregated, it is more sparse and stochastic.

Table 1.1: The pros and cons of discrete models

One drawback of discrete models is the additional complexity introduced in solving a firm's problem when choosing among a finite set of alternatives, termed the combinatorial discrete choice problem (CDCP). For example, consider a firm choosing its set of intermediate input suppliers with which to produce its output. As the size of this set increases from 5 to 6 inputs, the number of possible production combinations increases from 31 to 63 distinct combinations. One additional input just more than doubles the number of input combinations which can significantly increase the computational time and power needed to calculate production costs as the dimensions are scaled up.

With a relatively limited number of choices, a researcher may be able to solve the problem using brute force; checking through each individual combination and choosing the lowest cost option. However, in the majority of applications, the curse of dimensionality necessitates a different approach. Jia (2008) uses a reduction method to solve a CDCP with fixed costs and a return function to the agent (a firm in this application) that is supermodular. Arkolakis et al. (2021) add to the literature on solving CDCP with both negative and positive complementarities. As negative complementarities feature in plant location and multi-stage sourcing problems, negative complementarities are a useful extension to the Jia (2008) algorithm, as is developing a methodology to aggregate combinatorial discrete choice problems in a model with heterogeneous agents.[8]

1.5 Conclusion

Network tools of analysis can complement existing trade theory given the strong applicability across the two subfields. Production network models, featuring an endogenous adjustment along the extensive margin can replicate well-documented stylized trade facts. Depending on the question of interest, this can be done through microfounded models of costly-relationship networks where firms must balance the relative costs and benefits of forming and maintaining a link with a buyer-supplier. Such models are especially useful when the firm's optimisation problem and the mechanisms that deliver the prevailing production network are of interest. The extreme value class of model is more limited in that the researcher must assume a specific functional form, usually the productivity (or technology) used in production. The stochastic network model also relies on pre-specified assumptions, but with regard to the network formation process itself. Trade applications in this third category tend to use a combination of the seminal random and preferential attachment models in graph theory. Nevertheless, as illustrated in more atheoretical work using balls-and-bins models to explain the sparsity of trade networks, statistical, probabilistic models can offer systematic guidance when developing trade network models. Where balls-and-bins model results differ from classic trade models, there is a clear dimension where assumptions need to be made in trade models to match the stylized facts documented in the empirical literature.

Beyond the international trade literature, networks have plenty of applications to other sub-fields, which in the interests of brevity I do not cover in this paper. This includes closely related work on shipping networks (Brancaccio et al., 2020; Fajgelbaum & Schaal, 2020; Heiland et al., 2022); financial networks (Elliott et al., 2014; Acemoglu et al., 2015); and social networks (Jackson & Rogers, 2007; Jackson, 2011) to list a few. There is also

[8] While models with a continuum of firms or products may side-step the combinatorial choice problem in discrete models, models with a matching function cannot be non-smooth or feature discontinuities. To prevent a function that is not continuously differentiable, authors must work within a limiting case that avoids introducing the discontinuity into the matching function (Bernard & Moxnes, 2018c).

growing empirical literature documenting common features of production networks (Bernard & Moxnes, 2018b,a; Carvalho et al., 2020; Fadinger et al., 2022).

Networks models have steadily become more common in mainstream economics, especially given their applicability to a wide range of economic sub-fields. International trade is a particularly good fit given trade can be thought of as a naturally networked activity and there is plenty to learn from the application of network tools to questions in international trade.

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Chapter 2

Networks and Trade: Applications to the 2008 Financial Crisis

I document a set of novel stylized facts to study the relationship between the structure of the production network and the competitiveness of exports. I find evidence for the small-world phenomenon - the average number of links separating any two sectors - is relatively low and holds at the level of the global trade network. Sectors in which a country has a revealed comparative advantage (RCA) tend to be more central in the production network, and sectors more connected domestically, tend to be more connected internationally. I also ask how a sector's network position may amplify or insure against potential losses in its future export competitiveness in response to negative final demand shocks. I test this hypothesis by constructing a shift-share instrument to isolate the exogenous variation in the change in sectors' global final demand, associated with the 2008 Financial Crisis. My findings suggest that more central sectors experience a relatively smaller decline in their future value-added RCA compared to their more peripheral counterparts.
Keywords: Comparative advantage, trade, economic networks.
JEL: B17, C67, L14

2.1 Introduction

The economy can be thought of as a web of specialised production units, comprising sectors, firms, or entrepreneurs depending on the unit of analysis and research question of interest. Earlier literature on production networks has established firms do not operate in a vacuum, with their performance depending on their buyers and suppliers (Bernard & Moxnes, 2018a). Nevertheless, research investigating trade in domestic and international production networks remains in its infancy.

Recent evidence emphasises the importance of the production network influencing firm-level and aggregate outcomes (Ciccone, 2002; Jones, 2011a,b; Bartelme & Gorodnichenko, 2015; Fadinger et al., 2022). Such outcomes include the level of economic development, aggregate productivity of the producer, and productivity along the supply chain. The pattern of trade in global supply chains is a natural starting point that dictates a country's specialisation and its prevailing comparative advantage. For example, Hausmann et al. (2007a) establish that the goods a country exports matter for its economic performance. That is, there exists some hierarchy in the set of possible goods that can be produced which are more conducive to growth than others. Therefore, understanding how network structures are associated with a country's export production is important for aggregate economic outcomes.

In this paper, I examine how a country's comparative advantage in a given sector varies with the sector's network position. That is, are the most interconnected sectors, the same sectors in which a country has a comparative advantage? I document a set of novel stylized facts at the intersection of the international trade and production network literature. First, I find the small-world phenomenon, a principle first applied in the social networks literature that there are only a few links separating any two individuals in a network, also holds in the context of the global production network at the sector level (Travers & Milgram, 1977). According to the small-world phenomenon, large networks can be traversed from end to end over a small number of links (small diameter), and the average number of links separating any two sectors in the network is also low (low average path length). This feature is important to consider if a sector is hit by a negative shock and the subsequent diffusion across the economy. Earlier literature has found the production structure to be important in a closed economy setting, where the network is exogenous.[1] However, to the best of my knowledge, the literature on network structures in an open economy framework has been understudied, yet is important to the patterns of specialisation (Imbs & Wacziarg, 2003; Levchenko & di Giovanni, 2009; Levine, 2012). My findings are consistent with the established fact that production networks tend to be dominated by a small number of hubs (Carvalho, 2014; Acemoglu et al., 2012). That is, some sectors play a disproportionately important role as input suppliers to other sectors, such as general purpose technologies (GPT) that are widely adopted across the supply chain. This small-world property, such that most sector pairs are indirectly linked by such hub-like sectors, suggests shocks may have sizeable effects on economic outcomes. I also find sector centrality is positively correlated with a revealed comparative advantage in the same sectors. I test the robustness of this relationship across

[1] Chaney (2014) is an exception on both fronts, modelling the dynamics of French exporting firms to characterise the evolution of an international network of exporters. See also Lim (2017) and Oberfield (2018).

a number of alternative specifications and find it remains persistent and positive. I document that locally more interconnected sectors, tend to be more connected internationally.

I also investigate how a sector's position in the supply chain affects its future export competitiveness following a negative demand shock. I exploit the 2008 financial crisis as a negative final demand shock to study whether being more connected amplifies or insures future export competitiveness. I measure connectedness using both first- and second-order network statistics, constructing local and global measures of centrality to document the relative interconnectedness of sectors domestically and internationally. By using the World Input-Output Database (WIOD) to characterise the trade network, I observe both within and cross-border sales of goods to construct local and global centrality measures. While the digitization of customs forms and firm-to-firm trade relationships are gradually becoming available to researchers, there are very few to no comprehensive datasets with which one can observe domestic and international trade flows.[2] I find more globally interconnected sectors experience a relatively smaller decline in their future export competitiveness compared to their more peripheral counterparts. To address potential endogeneity concerns, I construct a shift-share instrument, following Joya & Rougier (2019) to isolate the exogenous variation in final demand, to study the impact of the fall in final demand on future export competitiveness.

I study the potential heterogeneous effects within my sample across sectors and country income levels. To do so, I re-estimate my baseline model on different sub-samples. I find it is primarily middle-income countries, including the BRIC economies and the manufacturing sector driving the positive coefficient on the interaction term which summarises whether a sector's network position amplifies or reduces the negative effects of the final demand shock.[3]

Previous theoretical work investigates shock propagation in financial networks and in the macroeconomy that I apply in the context of the trade network (Acemoglu et al., 2012, 2015). Acemoglu et al. (2015) posit the extent of financial contagion depends on the size of the shock and the structure of the financial network. Given a sufficiently small shock, a more densely connected network improves financial stability, while, above a certain threshold, these connections propagate the shock and introduce fragility into the system. In my paper, I test this theory, applying it to the global trade network allowing the data to determine which state of the world the economy in 2008 falls under. That is, was the financial crisis sufficiently large to introduce fragility into the trade network through buyer-supplier connections thereby deteriorating export competitiveness, or did trade connections reduce the negative impacts?

[2] One exception is the Belgian firm-level dataset compiled by the National Bank of Belgium comprising the universe of domestic and international transactions. However, even with this dataset, the foreign importing firms' connections in their respective economies are not observed (Dhyne et al., 2021).

[3] Brazil, Russia, India, and China.

My findings provide evidence in favour of the latter hypothesis, whereby the density of the international trade network for more central sectors, on average, was able to reduce the negative effects of the final demand shock of future export competitiveness, relative to their more peripheral counterparts.

There is also a related literature on the propagation of shocks in a network, documenting how such trading structures may amplify shocks. Carvalho et al. (2020) study the impact of the 2011 Great East Japan Earthquake and find that input-output linkages accounted for a 1.2 percentage point fall in Japanese gross output. Di Giovanni et al. (2014) also find indirect firm linkages are three times as important as the direct effect of firm shocks in influencing aggregate fluctuations. Gabaix (2011) finds the idiosyncratic movement of the 100 largest firms in the US explains one-third of the variation in output growth.

This paper also relates to the literature on the factor content trade on gross and value-added trade flows. Gross trade measures the value of trade without netting the intermediate input values that have been traded across borders. To avoid this double counting, I work with value-added measures in my analysis and find revealed comparative advantage is overstated when using gross values, consistent with earlier work (Brakman & Van Marrewijk, 2017; Johnson, 2014).

The remainder of this paper is structured as follows. Section 3.3 describes the data set I use; Section 2.3 explains the network measures and theory underlying the analysis; Section 2.4 presents the stylized facts; Section 2.5 the theoretical framework of the production network; Section 2.6 the identification strategy; Section 2.7 the results; and Section 2.8 concludes.

2.2 Data

I use data from the World Input-Output Database (WIOD) 2016 release covering 43 countries plus a rest of the world (ROW) aggregate, with 56 sectors using the ISIC Rev 4 classification. Taken together, the 43 countries included represent more than 85% of world GDP (measured at current exchange rates) available from 2000 to 2014. The WIOD is supplemented by the WIOD Socio-Economic Accounts (SEA) containing sector-level data on employment, capital stocks, gross output, and value-added, at current and constant prices.[4]

Input-output tables (IOTs) are commonly used to characterise the network structure of the domestic economy specifying the inter-sector flow of products. The technical coefficients, $a_{ij} \geq 0$, show the importance of sector j products as an intermediate input for the production of goods by sector i. The technical coefficients form the adjacency matrix of the domestic

[4]For a full list of the sectors and countries included see Section C and D in the Appendix.

economy detailing the network structure at the sectoral level. From this A matrix one can define the Leontief inverse as $L = (I - A)^{-1}$, which accounts for the importance of sector j as a direct and indirect input supplier to sector $i \neq j$. I use the terms centrality and interconnectedness interchangeably.

One country input-output tables measure intra- and inter-sector trade. From these national input-output tables, one can calculate local centrality measures. However, world IOTs can account for inter-country, inter-sector trade too. Hence, one can observe how important country-sector output is for foreign country-sectors. This added international dimension measures the extent to which sectoral networks extend across borders exploiting cross-country variation within sectors and enabling the construction of a global centrality measure. Thus, the WIOT provides the basis for constructing a weighted directed network, one node may be connected to a second, without the second being connected to the first. The weight for each country-sector in the adjacency matrix is the "dollars" worth of inputs from sector 1 per dollar's worth of output of sector 2.

2.3 Network measures and theory

Economic analysis has tended to focus attention on the direct impacts a variable of interest has on another. Drawing on network theory measures, I quantify both the first-order degree (direct) and second-order degree (indirect) impacts of a sector's network position on its specialisation decision. I use sectors' weighted outdegree to identify the first-order impacts on revealed comparative advantage (RCA) and eigenvector centrality for quantifying second-order effects. I discuss each measure in more detail below.

2.3.1 Degree

Sector i's outdegree is the number of sectors it supplies. To calculate a sector's weighted outdegree, I sum over the weights in the production network where sector j appears as an input-supplying sector. The weights are the dollars worth of inputs sector i supplies to sector j, as is commonly defined in input-output analysis.

$$d^j_{out} = \sum_{i=1}^{n} \omega_{ij} \tag{2.1}$$

where ω_{ij} is the dollars worth of inputs sector i supplies to j.

A sector's weighted outdegree may be equal to zero if the sector does not supply inputs to any other sectors, up to n, the number of total sectors, if a single sector is the sole supplier

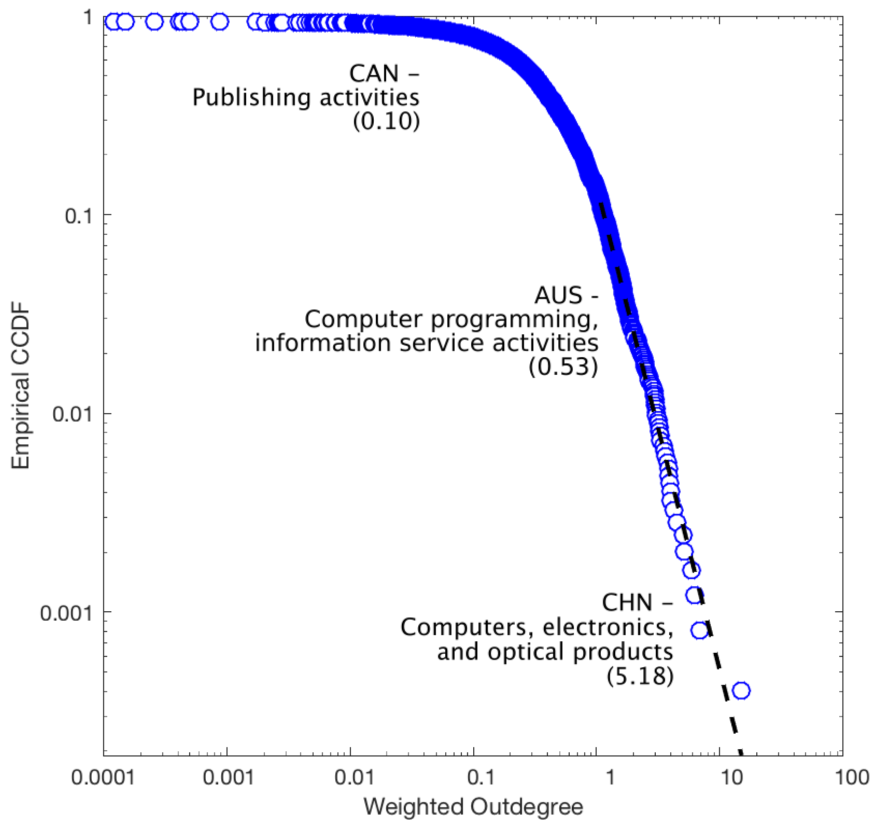


Figure 2.1: The Weighted Outdegree Distribution. Source: The World Input Output Database, 2016 Release, using data for 2014. Author's calculations. The x axis is the weighted outdegree for each country-sector in 2014. The y axis is the empirical counter-cumulative distribution function; the probability that a country-sector selected at random from the population has an outdegree larger than some value x.

to every other sector in the network. Using the most recent data available from the World Input-Output Database, in 2014, the average weighted outdegree of the production network is 0.5. This corresponds to the weighted outdegree of Australia's computer programming, consultancy, and information service activities, supplying 12 sectors.

Figure 2.1 plots the weighted outdegree distribution in 2014. Sectors in the north-west corner are highly specialised, with nearly all sectors having an outdegree greater than 0.001. General purpose technology suppliers are located in the south-east corner of the plot. Smaller and more specialized input suppliers include Canada's publishing activities sector, supplying to two sectors only. More widely connected sectors include China's manufacture of computers, electronics, and optical products, supplying 98 sectors in the production network.

The weighted outdegree distribution is skewed and spans several orders of magnitude, indicating the differential status of sectors as input suppliers. The characteristics of the weighted outdegree distribution are useful, as large input-supplying sectors do not disappear when the economy is disaggregated into more and more sectors.[5]

However, it is important to note that the weighted outdegree treats all sectors buying from sector i as identical. Therefore, another network statistic useful to characterise sector connectedness is second-order centrality statistics. A sector may have an average weighted outdegree yet be a key input supplier to many other sectors. Even if a sector has only a few downstream sectors one link away, many production processes may still be affected by a disruption or innovation to a specialised upstream sector.

2.3.2 Eigenvector centrality

Most simply, a sector is considered to be more central in the network if its neighbours are themselves well-connected. This is known as eigenvector centrality, of which there are multiple variants altered to suit the needs of the researcher.

I will use the Katz-Bonacich centrality measure. The centrality score of sector j is defined in Equation 2.2.

$$c_j = \lambda \sum_i A_{ij} c_i + \eta \tag{2.2}$$

where $\eta = \frac{1-\alpha}{n}$ is some baseline centrality assigned to each country-sector; $\lambda > 0$ is a parameter for weighting downstream sectors; α is the share of intermediate inputs in production; and A is the matrix representation of the production network.[6]

A given sector j is more central if its neighbour i has a high centrality score. Katz-Bonacich centrality corrects for the number of neighbours i has, so that as sector i has more connections, sector j has a lower centrality being connected to sector i, all else equal.

Figure 2.2 illustrates the distribution of country-sector centrality for 2014. The x-axis measures the Katz-Bonacich sector centrality, and the y-axis the probability of finding a sector with a centrality score larger than or equal to some centrality x. All the sectors have a centrality measure greater than or equal to the most peripheral node in the network, Australia's repair and installation of machinery and equipment.

[5] Where large inequalities are a key feature of the data, e.g. city or firm sizes, the right-tail of the distribution can be well-approximated by a power-law distribution.

[6] The matrix form of Equation 2.2 is:

$$\mathbf{c} = \lambda A' \mathbf{c} + \eta \mathbf{1}. \tag{2.3}$$

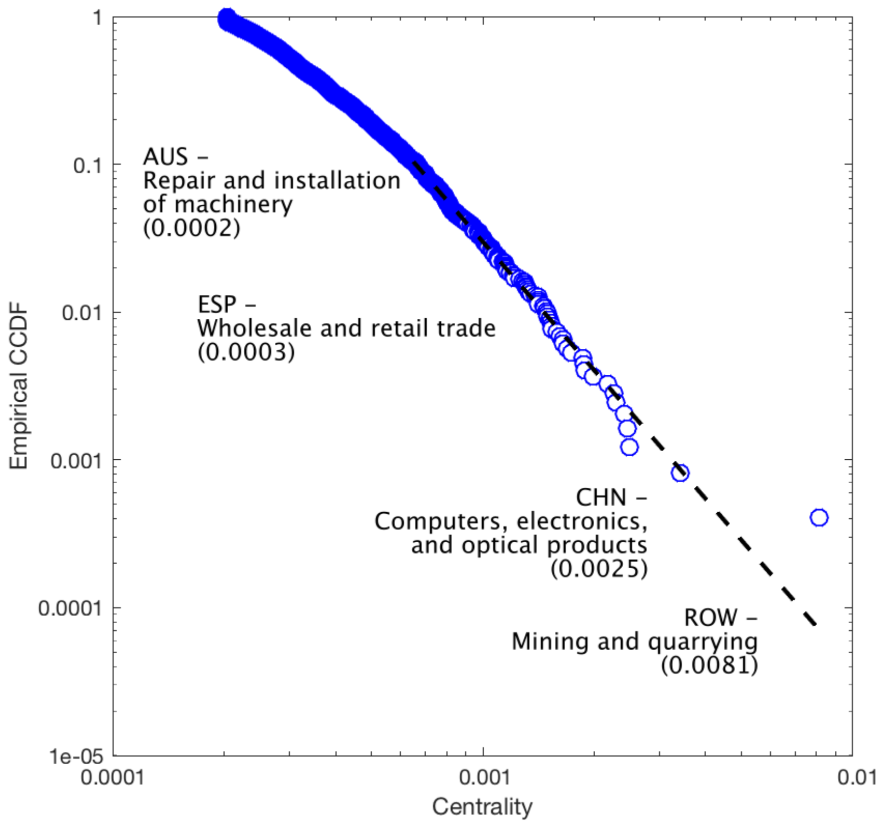


Figure 2.2: The Distribution of Sector Centralities. Source: The World Input Output Database, 2016 Release, using data for 2014. Author's calculations. The x axis is the centrality for each country-sector in 2014. The y axis is the empirical counter-cumulative distribution function; the probability that a country-sector selected at random from the population has a centrality larger than some value x.

Seminal work by Acemoglu et al. (2012) shows that a sector's Bonacich centrality is equal to its Domar weight in an efficient economy. However, the presence of distortions introduces a wedge such that Domar weights are no longer equivalent to the centrality measure. In practice, input-output data falls under the case of imperfect competition. That is, the technical coefficients a researcher observes in input-output tables contain some unobservable distortion parameter μ_i that attenuates the elements of the realised adjacency matrix towards zero, provided $\mu_i > 1, \forall \quad i$. This suggests findings using input-output data in an inefficient framework represent a lower bound, given technical coefficients characterising the edges connecting sector nodes would otherwise be greater in an efficient economy.

2.3.3 Global and local centrality

Applying the intuition underlying eigenvector centrality outlined above, I construct two additional second-order degree measures, global and local centrality. To compute a sector's global centrality; that is, its network position in the global production network, Equation 2.3 is applied to the entire adjacency matrix, A, but excludes each country's connections in their respective domestic economies, i.e. the sub-matrices along the main diagonal. Thus, global centrality measures how well-connected a particular sector is solely in the world economy.

On the other hand, local centrality determines how well-connected a country-sector node is within its domestic economy. Equation 2.3 is applied separately to each country along the main diagonal of the adjacency matrix A to compute a sector's home country centrality score. I provide further exposition in Section A of the Appendix. I now turn to the trade measures used to proxy country specialisation patterns.

2.3.4 Revealed comparative advantage

Revealed comparative advantage, also known as the Balassa index, is defined as the proportion of a country's per dollar trade in a particular sector relative to the proportion of the world's per dollar traded in that sector.

$$RCA^j_{c,t} = \frac{X^j_{c,t} / \sum_c X^j_{c,t}}{\sum_j X^j_{c,t} / \sum_c \sum_j X^j_{c,t}} \tag{2.4}$$

Where the RCA > 1, a country-sector exhibits a revealed comparative advantage relative to the rest of the world, while if RCA < 1, a country-sector has a revealed comparative disadvantage. A country c has a comparative advantage in the production of goods in sector j in time period t as its trade share in sector j is larger than the trade share of the reference group - the rest of the world.

Table 2.1: RCA distribution summary statistics, 2000-2014

	Mean	Median	Max	St. dev	RCA > 1
A) Distribution as a whole (52 sectors, 43 countries, 15 years)					
Gross exports	1.17	0.67	47.5	2.01	36.4%
Value-added	1.09	0.82	29.0	1.29	40.1%
B) Average individual country distribution per year					
Gross exports	1.17	0.65	12.8	1.69	36.4%
Value-added	1.09	0.80	8.0	1.13	40.1%
C) Individual country comparison					
Is gross export statistic larger than value-added statistic?					
No. of times	27	6	38	40	27
Percent	63	14	88	93	63

Notes: Provides summary statistics for gross export RCA and value-added RCA in three parts. Panel A) compares the two distributions, and panel B) contains the averages of the summary statistics by country. The figures in Panel B) are calculated for each country in each year; the table estimates are the averages over the 15 years of available data, except the median and the maximum (both of which are their respective values for each country over the 15-year period.) The RCA >1 column is the average share of sectors with RCA >1 as a percentage of the total sectors. Panel C) illustrates to what extent observations for the average individual country distribution hold for individual countries. More precisely, it measures whether the gross export RCA statistic calculated in Panel B) for each country is larger than the equivalent value-added RCA statistic. Excludes L68, O84, T, U sectors and the ROW.

Table 2.1 provides summary statistics for gross and value-added RCA. Panel A) compares the two distributions as a whole. Value-added RCA is more narrowly distributed as compared to gross trade; the mean and the median are much closer, with the standard deviation for value-added RCA also relatively lower. Despite this difference in distribution, the proportion of sectors in which a country has a revealed comparative advantage (i.e where RCA > 1) remains close to 40% using both measures. Panel B) contains the averages of the summary statistics by country. The average maximum and standard deviation are both much lower for value-added RCA than the associated gross RCA estimates. Panel C) highlights to what extent observations for the average individual country distribution hold for particular countries. More precisely, it measures whether the gross RCA statistic calculated in Panel B), for each country, is larger than the equivalent value-added RCA statistic. The standard deviation for value-added RCA is smaller than its gross counterpart for all but three countries - Greece, Indonesia, and Japan. In 88% of cases, countries have a lower maximum value-added. There are 27 cases where the value-added mean is higher, and six cases in which the value-added median is lower. The share of sectors with a higher gross RCA is more than its value-added counterpart in a little over half of cases (for 27 out of 43 countries, or 63%).

Table 1 suggests RCA calculated using value-added is characterised by a less extreme distribution compared as compared to gross measures. Value-added RCA provides a more cautious classification of comparative (dis)advantage while gross statistics suggest a more extreme RCA distribution where particular countries tend to be dominant traders within a particular sector. This is consistent with the findings in the value-added literature, including Brakman & Van Marrewijk (2017) and Johnson (2014).

2.3.5 Gross versus value-added trade flows

Why is there a need to distinguish between gross and value-added trade flows? Analysis based on gross versus value-added data, also known as factor-content trade, can lead to different conclusions about a country's strengths in the global market (Brakman & Van Marrewijk, 2017). Total output is composed of the sum of domestic and imported intermediate inputs and direct value-added. Gross trade measures the gross value of a good at the border, rather than netting out intermediate input values that have been traded across borders. This double-counting problem means gross estimates overestimate domestic (value-added) content. Moreover, with production networks extending across countries, bilateral trade flows are likely to include third-country contributions too.

As a result, value-added RCA sheds more light on the direct contribution of a country's trade rather than the portion of trade that is indirectly embedded by intermediate inputs. Domestic value-added captures the value paid to the factors of production of the country trading the goods produced in a particular sector. Given these differences in the underlying estimates, when calculating RCA in both gross and value-added terms, there are cases where a country may have a comparative advantage in gross terms, yet a comparative disadvantage in value-added terms, and vice versa.

For example, Germany's wholesale and retail trade sector has a comparative disadvantage in gross terms while a comparative advantage in value-added terms from 2000 to 2010. That is, German domestic value-added in this sector had a high share in overall intermediate input trade over this period. On the other hand, Germany's electricity sector had a comparative advantage in gross terms but a comparative disadvantage in value-added terms for all years except 2008. In other words, the electricity sector has a high trade share in electricity, gas, and steam, but after taking into account indirect value-added exports, the German share falls greatly relative to other countries.

Accounting for the difference in gross versus value-added trade estimates is important as it can change the conclusions drawn regarding a country's competitiveness relative to the rest of the world. Value-added provides a more accurate measure pertaining to a country's true domestic contribution within a production chain. This is important to account for when investigating questions concerning a country's location in the value chain.

Table 2.2 outlines global and local centrality distribution summary statistics for the sample. On average, sectors' local interconnectedness tends to be higher. This suggests domestic connections include higher trade values. This is consistent with the literature documenting that the main diagonal of domestic intermediate sales constitute the highest proportion of trade (Baldwin & Lopez-Gonzalez, 2015).

Table 2.2: Centrality distribution summary statistics

	Mean	Median	Max	St. dev	N
A) Distribution* for 2000-2014					
Global centrality	0.070	0.016	7.4	0.20	36,960
Local centrality	0.322	0.280	1.9	0.14	36,960
B) Average country distribution per year					
Global centrality	0.070	0.040	0.7	0.10	36,960
Local centrality	0.322	0.280	0.9	0.13	36,960
C) Distribution* for 2000-2005					
Global centrality	0.067	0.014	5.1	0.18	14,784
Local centrality	0.325	0.284	1.9	0.14	14,784
D) Distribution* for 2009-2014					
Global centrality	0.073	0.017	7.4	0.22	14,784
Local centrality	0.319	0.276	1.8	0.14	14,784

Notes: Provides summary statistics for global and local centrality. Panel A) compare the two distributions, panel B) contains the averages of the summary statistics by country. Panel C) compares the centrality distributions for the period 2000-2005, and Panel D) for the years 2009-2014. Global and local centrality has been transformed by a factor of 1000 for illustrative purposes. * 56 sectors, 43 countries + ROW

Panels C) and D), before and after the financial crisis, signal the process of globalization is still ongoing. Global centrality of sectors continued to increase, on average, from 0.067 to 0.073 with a slight increase in its standard deviation, while local centrality slightly declined from 0.325 to 0.319, its standard deviation remaining constant. The difference in the evolution of each measure's standard deviation suggests global centrality scores experience more variation over time, as would be expected of foreign trading relationships, while the domestic relations between sectors remain relatively constant during the same time period.

To test the equality of distributions for global and local centrality, I perform a two-sample Kolmogorov-Smirnov test. In line with the summary statistics presented in Table 2.2, I find the global centrality distribution contains larger values in the 2009-2014 period as compared to the 2000-2005 period. On the other hand, the local centrality distribution contained smaller values in the 2009-2014 period relative to 2000-2005. Interconnections with foreign sectors have continued their upward trend despite the interlude of the global financial crisis between the two periods. Simultaneously, the strength of domestic connections has been falling even with the advent of the financial crisis.

2.4 Stylized Facts

2.4.1 Stylized Fact 1

The small-world phenomenon holds in the context of the global production network. Despite a low density of sectoral linkages, each sector lies a few input-supply links away from other sectors. The term small-world refers to the phenomenon that large networks tend to have a small diameter and a short average path length.

The diameter of a network is the largest distance between any two nodes and provides an upper bound for path length in the network. It is a useful statistic for understanding how rapidly disruptions can diffuse through the network. To focus on the extensive margin of input trade, I discretise the adjacency matrix, constructing an unweighted directed graph where an element is equal to one if trade between two sectors exceeds one percent of the total intermediate input bill, and zero otherwise. For 2014, the diameter of the world input-output network was 33, low relative to the total number of country-sectors, 2464, where country-sectors are the base unit of analysis.

The average geodesic distance is 8. It is useful to calculate the average length of the shortest path to check whether the diameter is determined by a few outliers or if it is of the same order as the average geodesic. The order of magnitude of diameter and the average geodesic are very close so it is unlikely that outliers are driving the diameter of the network. The implications of the small-world phenomenon are important when considering a production disruption to a particular sector; the original shock can spread quickly to other sectors affecting the performance of the economy. This diffusion is further exacerbated if the sector has a high centrality within the network.

2.4.2 Stylized Fact 2

Sectors in which a country has a revealed comparative advantage tend to be more central in the production network.

In Figure 2.3, I plot centrality against RCA, and there is a visibly strong positive correlation. A higher RCA for an individual country-sector is associated with greater centrality of that country-sector. Qualitatively, the results are similar for the majority of sectors. Notably, there are some countries including the USA, Germany, China, and Taiwan for which the manufacture of chemicals sector is more central in the global production network than their RCA in this sector would imply.

Table 2.3 explore this, establishing the robustness of the relationship between countries' RCA and their respective centrality scores. First, I focus solely on global centrality. The

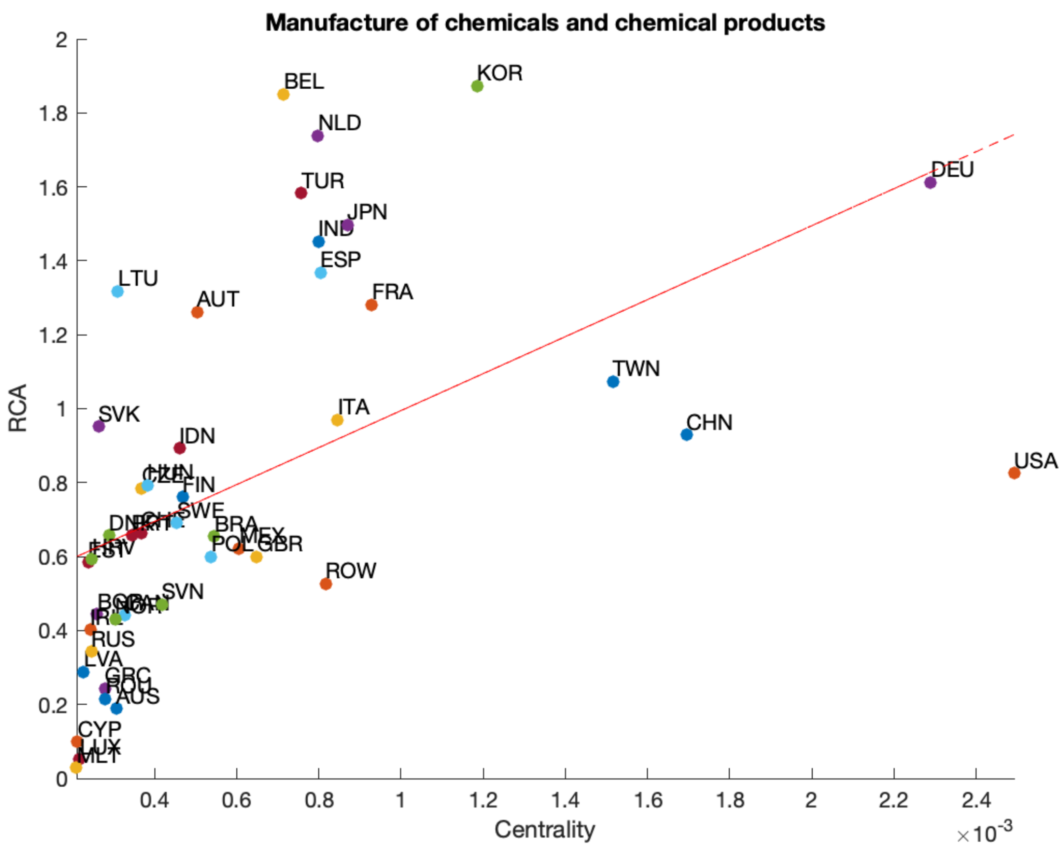


Figure 2.3: Sector RCA and centrality correlation. Source: The World Input Output Database, 2016 Release, using data for 2014. Author's calculations.

Table 2.3: VA RCA and global centrality robustness

Dep var	Value-added RCA			
	OLS	FE	FE	FD
GC	0.100***	0.079**	0.184***	
	(0.024)	(0.038)	(0.037)	
D.GC				0.160***
				(0.037)
Controls	No	No	Yes	Yes
Country-Year FE	No	No	Yes	-
Sector-Year FE	No	No	Yes	-
No. of obs	36,960	36,960	34,071	31,795
R^2	0.010	0.005	0.117	0.014

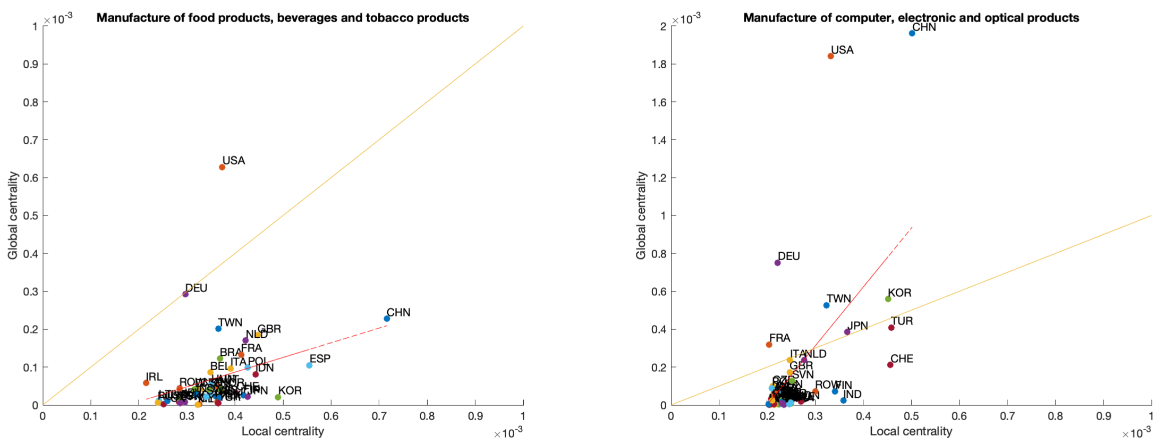
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is value-added RCA. All variables have been standardized. All regressions use robust standard errors, clustered at the country-industry level. Column (1) uses an OLS estimator, (2) and (3) are FE estimators, (4) employs first-differences.

OLS specification reveals a positive and statistically significant relationship between the two variables of interest. I use parsimonious regressions including controls for common determinants of RCA including labour, its respective productivity - measured as the ratio of real value added to persons engaged in the sector, the log of GDP per capita, the foreign share of intermediate inputs purchased by sectors, net taxation, and transport margins. I find a positive and significant coefficient on sectors' global centrality as seen in columns (1) and (2); for a one standard deviation increase in sector global centrality, there is a 0.1 standard deviation increase associated with value-added RCA.

I then use a fixed effects estimator to account for country and sector-specific unobservables such as technologies that may influence RCA. To account for the time dimension of my data, I include country-year, and sector-year fixed effects, which further increase the centrality coefficient. The results are qualitatively similar when using value-added RCA measures instead of gross-output measures. The previous results are measured in terms of levels. To check whether the change in centrality is positively associated with growth in country-sector RCA, I also construct a first differences estimator; even if independent variables are correlated with unobservables, estimates will still be consistent. Again the centrality coefficients, whether taking gross or value-added RCA, are qualitatively similar.

2.4.3 Stylized Fact 3

Sectors with higher local centrality tend to be globally more central too. Figure 2.4 provides a graphical illustration of the relationship between sectors' global and local centrality scores. The light-yellow line is a 45-degree line from the origin, and the red is the line of best fit for all observations. Taking the manufacture of food products sector and the manufacture of computers, it is clear the two centrality measures are positively correlated, but the strength of this relationship, relative to a one-to-one correlation, differs. In the left panel, most countries are more central locally than they are globally (clustered at the middle to the bottom of the chart). Germany is the only country where global and local centrality scores for food manufacturers are approximately equal. It is interesting to see the USA has many more global connections than local ones, while for China the opposite is true.



(a) (b)

Figure 2.4: Local and global centrality. Source: The World Input Output Database, 2016 Release, using data for 2014. Author's calculations.

On the other hand, for the manufacture of computers, both the USA and China have particularly high global centrality scores compared to the rest of the world. Computer manufacturing in Germany, Taiwan, and France, also has a higher global centrality than they do locally, suggesting a greater outward orientation of this sector than countries lying below the 45-degree line, such as India and Finland.

2.5 Theoretical framework of the Production Network

2.5.1 Set-up

In this section, I provide a simple theoretical framework to highlight how the properties of the production network may influence the competitiveness of a given country's exports. Through the following exposition, I formalise the connection between the topological properties of the production network and how they play a role in output and, by extension, my RCA measure.

I assume a one-world economy, with n country-sectors as the base unit of analysis. Each country-sector has a representative firm producing output for firms' intermediate input use and final demand, such that a sector i's output, x_i is given by:

$$x_i = x_{ij}^m + x_i^d$$

where $x_{ij}^m = \alpha_{ij} x_j$ is intermediate input demand; and x_i^d is final demand for sector i's output. The technical coefficient is given by α_{ij} (or the direct input coefficient) measuring the share of intermediate goods from sector i used in the production of goods by sector j.

Using $x_i^d = C_i + I_i + G_i + E_i = DD_i + E_i$, such that final demand is the sum of domestic demand (DD) and foreign demand, exports of sector i can be represented as:

$$\begin{aligned} E_i = & \quad x_i - \alpha_{ij} x_j - DD_i, \\ E = & \quad \tfrac{1}{(I-A)^{-1}} x - DD, \\ E = & \quad Mx - DD. \end{aligned}$$

Exports of sector i consist of the total output it produces, minus its intermediate input sales, and sales to domestic demand. The remaining value of its output, if any, is exported abroad. Exports depend on the production structure, summarised by an $(n \times n)$ matrix M containing the technical coefficients, sectoral output, and domestic demand ($DD = C + I + G$). The Leontief inverse matrix, $(I - A)^{-1}$, or the total requirements matrix, captures all the direct and indirect transactions in the economy. Direct transactions are flows used to produce goods for final demand, and indirect flows are those intermediate inputs used in the production process of other sectors. Thus, whether a country possesses a comparative advantage in a given sector will depend on the production structure of the economy.

With a negative demand shock, there are three possible sources from which the exports of sector i may change, given the technical coefficients, α_{ij} are assumed to be fixed in the short run.

$$\begin{aligned} \Delta E_i = & \quad \Delta x_i - \alpha_{ij}\Delta x_j - \Delta DD_i, \\ \Delta E = & \quad \tfrac{1}{(I-A)^{-1}}\Delta x - \Delta DD. \end{aligned}$$

First, is the changes in total output of sector i; the demand sector i faces as an intermediate input supplier to some sector j, and the change in final demand due to the shock. Thus, a sector will maintain its revealed comparative advantage in some sector i, if:

$$\frac{\Delta E_i}{\sum_c \Delta E_i} > \frac{\sum_k \Delta E_i}{\sum_c \sum_k \Delta E_i}$$

That is, for any underlying demand changes due to the negative demand shock, if country c continues to export more than its 'fair share' of the goods produced by sector i, compared to the rest of the world, it will maintain or improve its RCA.

2.5.2 Discussion of matrix M intuition

The M matrix summarises the structure of the production network through the intermediate input sales between sectors trading both in their domestic markets and abroad. I use a series of network statistics, such as sector degrees and centrality scores, to measure sectors' network positions to comment on how the extent of a sector's interconnectedness affects its future export competitiveness following a negative shock. A priori, the expected sign on the M matrix is ambiguous. Earlier literature has sought to address the relationship between the network structure and the extent of contagion in the context of a financial network (Acemoglu et al., 2015). One group of thought advances that a more interconnected system improves its resilience in the event of a negative shock to any one agent. For example, in the trade context, a negative shock to a well-connected sector from a given buyer may have a less detrimental effect on its RCA as the shocked sector has a large number of alternative buyers to which it can continue selling its output. On the other hand, a shock to a sufficiently well-connected sector may act to worsen other sectors' performance.

Given the ambiguity as to which direction a negative shock would tip the balance as to whether it is more advantageous for future export competitiveness to remain in the periphery or to seek a central position in the production network, I use an empirical strategy to allow the data speak as to what sign the M matrix takes in the context of the decline in global final demand between the 2007 and 2009 period.

Ranking highly in sector centrality scores suggests a sector has a large number of buyers and suppliers who are themselves well-connected in the production network. The breadth of connections may also leave sectors more vulnerable if a large enough, global negative shock hits the economy. By the same token, remaining on the periphery by serving a limited number of buyers and, in turn, buying from a limited set of input suppliers may suggest peripheral sectors are relatively unaffected by a negative shock, given their neighbours are also sufficiently insulated. However, if the shock does impact this limited set of sectors, a peripheral sector may be relatively worse off than its more central counterparts.

In light of this discussion, the size and the severity of the shock may tip the balance of interconnectedness in either direction. A global shock that hits many agents simultaneously makes it difficult to insure against the shock, and a less interconnected network would have fared better. On the other hand, smaller, more dispersed shocks can be well insured by a more interdependent production economy, where although some buyers may reduce their demand as a consequence of being hit directly, their suppliers' diversified set of buyers provide some level of insurance in maintaining intermediate input demand, and as a consequence, their export competitiveness. Work by Acemoglu et al. (2015) advances the benefits or drawbacks of network connectivity on outcomes of interest will depend on the size of the shock in question. In this application, the financial crisis can be considered to be a global phenomenon. Nevertheless, the severity of the crisis was heterogeneous across countries with Western Europe and the United States being some of the worst hit in its early stages.

2.6 Identification

2.6.1 Identification assumptions

To identify the causal impact of a sector's network characteristics on its future export competitiveness (as measured by RCA in terms of value-added), I regress sector i in country c's RCA in year $t+x$ on the interaction of the shock intensity with network characteristics for sector i in country c, and other controls as in Equation 2.5 below:

$$RCA_{ic,t+x} = \beta_1 D_{ic} + \beta_2 M_{ic} + \beta_3 D_{ic} M_{ic} + \beta' X_{ic} + \gamma_c + \upsilon_i + \epsilon_{ic} \tag{2.5}$$

where $RCA_{ic,t+x}$ is the value-added RCA of sector i in country c at time $t+x$ with x some number of years into the future after the financial crisis of 2008; D_{ic} is the Bartik indicator of the final demand shock for sector i in country c between 2007 and 2009; with $M_{ic,t=2007}$ a measure of the network characteristics of sector i in country c in the base year, 2007; $X_{ict=2007} = [X_{ic,t=2007}, ..., X_{kn,t=2007}]$ is a vector of controls at the sector-level in the base year, 2007; γ_c and υ_i are the country and sector fixed effects; and ϵ_{ic} is the error term.

I use a panel fixed effects estimator to estimate Equation 2.5. I include country and sector fixed effects to control for unobservable country- and sector-specific factors which may explain RCA, such as technological differences, pre-existing supply chain linkages, and geography. There is no time dimension as the dependent variable and D_{ic} account for variations over the 2007 and 2009 period. Additional controls include the classical determinants of trade including log GDP per capita, total employment, the nominal capital stock, labour productivity, capital productivity, plus other sectoral-level information pertaining to foreign trade including net taxes, and the foreign and local share of intermediate goods.

The direct impact of the demand shock on sector i in country c on its future RCA is given by the β_1 coefficient in Equation 2.5. I am interested in identifying the indirect impact of how the negative final demand shock interacts with a sector i's network characteristics, given by the β_3 coefficient. Thus, $\beta_1 + \beta_3$ measures the average impact of the negative final demand shock on sector i future export competitiveness, given its network characteristics. This interaction term summarises whether a sector's network position works to reduce or magnify the negative effects of the negative final demand shock.

Identifying the causal impact of the final demand shock on sector export competitiveness raises potential endogeneity concerns. First, a sector's network characteristics may be endogenous to its RCA. Do sectors with good connectivity become competitive exporters, or did competitive sectors become well-connected as a virtue of their earlier export success?

A second concern is that the final demand shock may be endogenous to a sector's RCA. The production sharing (or vertical specialisation) hypothesis posits trade is more sensitive to changes in the costs of international trade (Yi, 2003). Intuitively, the greater the number of times a good must cross a border before being sold as a final good, the higher the border costs its production incurs. Grossman & Meissner (2010) posit the trade collapse was due to a combination of uncertainty and trade cost changes in supply chains (as advanced in Yi (2003)) that led to the severity of the downturn and enhanced shock transmission. Chor & Manova (2010) document the financial crisis as one of the reasons for the lack of trade credit that contributed to the fall in trade. Thus, the vertical specialisation hypothesis suggests the structure of a sector's production network may influence its RCA. Sectors more dependent on a vertically specialised supply chain may be more vulnerable to the shock as goods cross borders more frequently.

With these concerns in mind, I define the final demand shock variable, following Joya & Rougier (2019), as:

$$D_{ict} = \frac{x^d_{ic,t=0}}{x^d_{i,t=0}} \left(\frac{X^d_{i,t=t+1} - 1}{X^d_{i,t=0}} \right) = w^d_{ic,t=2007} \Delta D_i \tag{2.6}$$

where $w^d_{ic,t=0}$ is the share of sector i in country c in the global final good production in the base year (t=2007), and ΔD_i is the change in global final demand for each sector i in country c between 2007 and 2009. The idea of the shift-share instrument is to isolate the exogenous variation in the change in final demand such that D_{ict} is exogenous to the dependent variable. Intuitively, if the final demand for some sector i adjusts at the global level, the most affected countries will be those in which the sector has a higher share of global sectoral output. This satisfies the criteria that the shock should have heterogeneous effects across sectors and be exogenous to the dependent variable.

In Figure 2.5, I plot the evolution of global final demand through the sample period. Prior to the financial crisis, average global demand was steadily rising up until 2008, then experiencing its only decline over this period between 2008 and 2009. Post-2009, average final demand steadily rose monotonically until the end of the sample period.

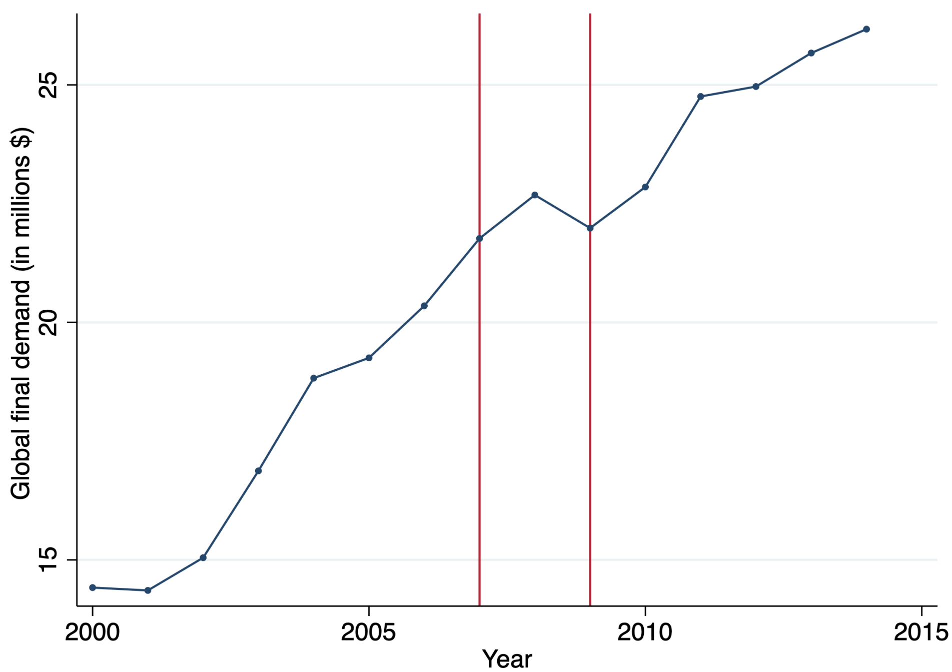


Figure 2.5: Final demand from 2000 to 2014. Source: The World Input-Output Database, 2016 Release. The two vertical red lines denote the year 2007 and 2009, respectively.

In Figure 2.6, I disaggregate final demand by country, plotting the top 10 countries impacted by the financial crisis based on the decline in final demand. Plotting average global final demand obscures the severity of the negative demand shock to certain countries in 2007. The scale and severity of the financial crisis make clear the decline in final demand at both the world and country levels. I define the negative demand shock between 2007 and 2009, as Figure 2.6 illustrates countries experienced a decline in demand in 2007. Final demand decreases over this period with a relatively muted recovery for better-performing economies, and stagnant for the less resilient economies.

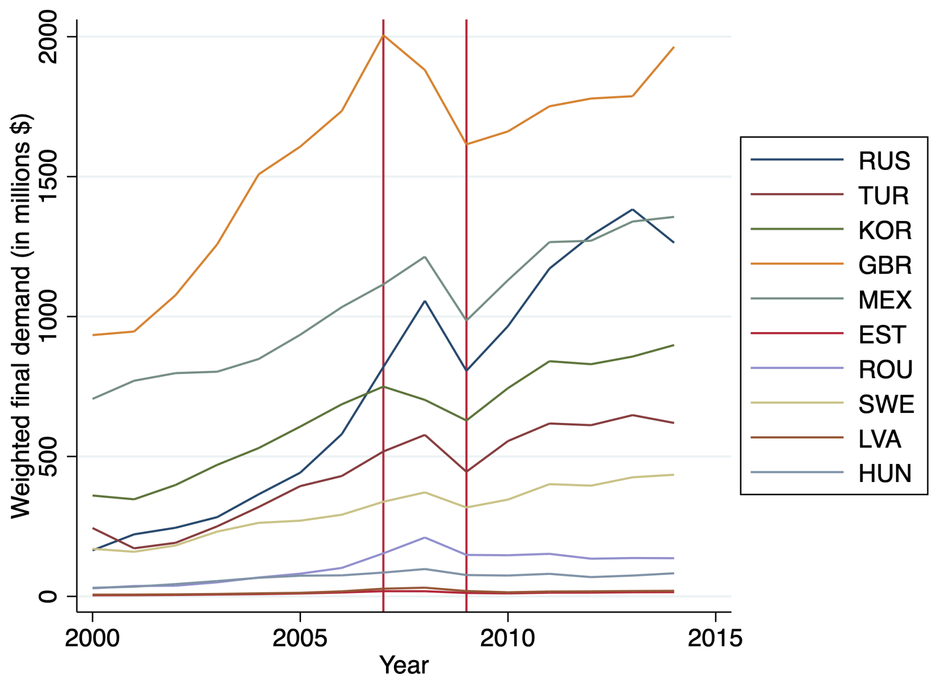


Figure 2.6: Final demand from 2000 to 2014 for top 10 affected countries. Source: The World Input-Output Database, 2016 Release. The two vertical red lines denote the years 2007 and 2009, respectively. Final demand is weighted by each sector's value-added in the respective countries, in the respective years. The top 10 countries include Russia, Turkey, South Korea, the UK, Mexico, Estonia, Romania, Sweden, Latvia, and Hungary.

In my analysis, I use sectors' exposure to the final demand shock over the 2007 to 2009 period to identify the change in its future export competitiveness. Sectors produce output to satisfy intermediate input demand, purchasing the intermediate inputs required in its production function, whereby these purchasing decisions shape the network structure and prevailing network properties, which in turn, determine the sector's RCA.

I do not explicitly model the supply side of the economy, nor the formation of the equilibrium production network. I address endogenous network formation in Chapter 3, where I explicitly model the formation of linkages between sectors using an extensive margin condition governing the intermediate input hiring and shedding process. In this chapter, I focus exclusively on how the negative final demand shock affects a sector's future export competitiveness, conditional on its network characteristics in the baseline year.

2.7 Estimation results

2.7.1 Baseline estimation results

In this section, I discuss my baseline and placebo estimation results. Table 2.4 presents the baseline regression of value-added revealed comparative advantage (RCA) in 2010 regressed on the negative demand shock and the production network in 2007, the baseline year.

Each column of Table 2.4 uses a different network connectivity statistic to measure how a sector's position in the production network affects its future export competitiveness. For example, a more globally central sector, that is well-connected abroad may find itself in one of two scenarios. First, having more buyers and input suppliers abroad may enable it to better recover from a negative shock through a more diversified set of connections. On the other hand, a highly interconnected sector may be more exposed to shocks transmitted by its connections. This trade-off is especially relevant given the current economic climate, where the coronavirus pandemic and the Ukraine-Russia conflict, have disrupted the normal operation of supply chains. Such disruptions highlight the potential risks and instability associated with the international fragmentation of production (OECD, 2021) and raise questions as to whether the gains from international specialisation without sufficient diversification, outweigh its costs.

Table 2.4: VA RCA regressions network, 2010

	(1) GC	(2) LC	(3) Outdegree	(4) Indegree
Shock	-0.044**	-0.054**	-0.037**	-0.076***
	(0.017)	(0.022)	(0.018)	(0.016)
Network	0.381***	0.304***	0.299***	-0.288***
	(0.040)	(0.042)	(0.038)	(0.047)
Shock*Network	0.027**	0.008	0.026*	0.000
	(0.013)	(0.024)	(0.014)	(0.026)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
No. of obs	2,150	2,150	2,150	2,150
R^2	0.455	0.435	0.437	0.426

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. except log GDP per capita are standardized. Standard errors are clustered at the country-industry level.

The shock variable takes the expected negative sign across specifications. That is, the decline in final demand between 2007 and 2009, worsens the average sector's future export competitiveness as final consumers reduce their expenditure. This negative effect is most acute when measuring connectivity using indegree, the shock statistically significant at the 1% level, and significant at the 5% level across the alternative measures.

In the first two columns of Table 2.4, I use centrality to measure a sector's network position. I find both local and global centrality are positively associated with future export competitiveness. A one standard deviation increase in the average sector's global centrality increases its RCA in 2010 by 0.381 units. This is the equivalent of initially being as connected as China's manufacture of rubber and plastics products (0.85) to that of the US manufacture of coke and refined petroleum products (1.17). Comparing the relative effect size of global and local centrality, on average, being connected internationally, rather than domestically, seems to have a larger absolute effect on a sector's future export competitiveness. Having sectoral connections which themselves are well-connected abroad may serve to cushion the negative effects of a shock to the production economy.

In columns 3 and 4 of Table 2.4, I use sector degrees to measure the average sector's network position. A sector's outdegree is the number of buyers it sells to, while the indegree measures the number of input suppliers from which it purchases intermediate inputs. Having a larger buyer base is associated with an improvement in RCA in 2010 suggesting that more buyers may be associated with a more diversified demand base, to the benefit of a sector's future export competitiveness when hit by a negative shock. On the other hand, purchasing from a larger set of intermediate input suppliers worsens the sectors' future RCA. Why may this be the case? For the average sector, the gains associated with greater interconnectedness may stem from the set of buyers who decide to purchase its output, rather than the set of input suppliers dictated by the sector's production function. This result is consistent with the idea that vertical specialisation in the supply chain, during such a crisis, worsens the performance of exposed sectors given the increase in trading costs.

A sector's future RCA is significantly impacted by its network position in the past. A sector's connections in the baseline year of 2007 continue to have a positive impact on its export competitiveness up to at least three years into the future. In Appendix B, I provide further evidence in support of this finding such that a sector's network position influences its future RCA up until 2014, or up to even seven years into the future from the start of the negative final demand shock. This suggests a high degree of persistence in a sector's position in the production network.

The coefficient of interest, the interaction between the shock and network terms, takes a positive sign with a similar magnitude when measuring connectivity using global centrality and outdegree. The negative impact of the final demand shock on a sector's future export competitiveness is more muted when a sector is more interconnected. The decline in a sector's future export competitiveness, given its network position, is -0.017 units. Being globally interconnected more than halves the negative impact of the shock. Using outdegree as an alternative measure produces a qualitatively similar result, -0.011. In contrast, there is less evidence that suggests being domestically more connected or purchasing from more input suppliers grants a similarly positive effect to curb the decline in future export competitiveness.

2.7.2 Heterogeneous effects within sample

There may be heterogeneous effects within the sample across sectors and country income levels. One source of heterogeneity may be related to country income levels and its export basket (Hausmann & Klinger, 2006; Hausmann et al., 2007b). Another source of variation may relate to the differences in sector connectivity within and across countries, where some sectors' output is more widely used compared to specialised sectors purchased by only a few buyers. The impact of demand shocks on manufacturing goods, which are more commonly used throughout the economy, may mitigate the negative effects on RCA as their use is so pervasive. Service sectors tend to be located in denser parts of the production network, and used with other inputs, which can be thought of as essential in facilitating output production and trade. Thus, services may be a conduit for reducing the negative effects on export competitiveness and driving the full-sample results.

Table 2.5 shows the coefficients of the interaction term when the baseline model, Equation 2.5, is re-estimated on different sub-samples, where the first row contains the coefficients from the full sample regression for comparison. In the second row, the coefficient estimates of the interaction term are for the high-income country sub-sample which is consistent in sign for global and local centrality, although estimates are not statistically significant, suggesting the full sample results are not driven by high-income countries.

Using the middle-income sub-sample, the global centrality and outdegree network measures both have a positive sign and larger magnitude, more suggestive of middle-income countries contributing to the results, including the BRIC economies.[7] While the BRIC countries did not avoid the negative effects of the financial crisis, they nevertheless managed to continue growing at a decent pace, with the downturn less persistent in emerging markets compared to the deep recession in industrial economies (Belke et al., 2019). This is suggestive evidence that middle-income countries' connections to emerging markets, paired with the poor performance in higher-income, industrialised economies, was a driver of the positive coefficient of the interaction term for the middle-income sub-sample. The positive and

[7]Middle-income countries include: Brazil, Bulgaria, China, India, Indonesia, Latvia, Lithuania, Mexico, Romania, Russia, and Turkey.

Table 2.5: Interaction between shock and network characteristics, by subsample, 2010

Dep var: RCA 2010	(1) GC	(2) LC	(3) Outdegree	(4) Indegree	N
Full sample	0.0267**	0.0083	0.0259**	0.0002	2150
	(0.034)	(0.730)	(0.073)	(0.993)	
High income subsample	0.0190	0.0085	0.0173	-0.0000	1639
	(0.388)	(0.770)	(0.440)	(0.999)	
Middle income subsample	0.0569**	0.0090	0.0607**	-0.0776	511
	(0.008)	(0.892)	(0.021)	(0.522)	
Agriculture and Mining subsample	-0.1324	-0.5824**	-0.4581	0.1412	168
	(0.607)	(0.039)	(0.167)	(0.695)	
Manufacturing subsample	0.0490**	-0.0499	0.0260	0.0520	1506
	(0.003)	(0.252)	(0.170)	(0.194)	
Services subsample	0.0218	0.0799	0.0628	-0.0806	476
	(0.757)	(0.143)	(0.470)	(0.191)	
Manufacturing and middle income	0.0676**	0.0247	0.0647**	0.0897	365
	(0.004)	(0.742)	(0.019)	(0.765)	
Services and middle income	0.0386	-0.0785	0.0022	0.0469	1141
	(0.148)	(0.139)	(0.938)	(0.244)	
Full sample, banking and finance excluded	0.0377**	0.0161	0.0319**	0.0046	2031
	(0.004)	(0.526)	(0.027)	(0.854)	
Full sample, services excluded	0.0488**	-0.0382	0.0251	0.0354	1674
	(0.003)	(0.352)	(0.175)	(0.337)	
Services, banking and finance excluded	0.1595**	0.1549**	0.1993	-0.1117	357
	(0.068)	(0.076)	(0.112)	(0.162)	

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All variables are standardized. Standard errors are clustered at the country-industry level.

statistically significant coefficient on sector outdegree lends some support to this hypothesis.

Turning to the sectoral sub-samples, it is primarily manufacturing which is driving the positive coefficient on the interaction term. This is consistent with the evidence that middle income countries, such as China and India, specialise more in manufactured goods relative to services. By comparison, the services sub-sample is not statistically significant and has a positive sign yet of a smaller magnitude than in the full sample. The agriculture and mining coefficient, however, has a negative sign under the first three specifications. It suggests that having primary sectors well-connected in the domestic economy worsens the sector's future export competitiveness by a large margin. If local sectors suffer due to the negative consequences of the financial crisis, through the final demand shock and also other channels that feed through the economy, agriculture and mining activities are especially vulnerable given their position in the production network is relatively more inward-oriented, compared to manufacturing and services. This result should be interpreted with caution given the small sample size when restricting the sub-sample to the agriculture and mining sectors.

The combination of sectors and country income sub-samples reinforces my findings above, where it is predominantly middle-income countries and the manufacturing sector that drive the results in the full sample. Given manufacturing seems to be most important, excluding services and then separately excluding banking and financial services, provides coefficients consistent with these findings. Excluding services gives a positive interaction coefficient, with a magnitude similar to that of the middle-income sub-sample. Upon excluding banking and finance from the service sector classification, there is a particularly strong, positive coefficient on the interaction term using both global and local centrality measures of interconnectedness. This suggests that services sectors, whether domestically or internationally connected, may help ameliorate the negative impacts of the final demand shock of future competitiveness. Nevertheless, this result should be interpreted with caution given the small sample size.

2.7.3 Placebo estimation results

I perform a series of placebo regressions using Equation 2.5 to corroborate that the negative final demand shock captured between 2007 and 2009 is primarily associated with the global financial crisis and not a function of some downturn in an earlier period. I use a rolling three-year window prior to the financial crisis of 2008 to construct my shock variable.

In Table 2.6, I present the shock coefficient for each three-year rolling window in my sample. The coefficients over the early 2000s have a smaller magnitude compared to the shock coefficient for 2007 to 2009. One exception is the shock coefficient from 2000 to 2002 is particularly large and negative. This significant negative decline in final demand is likely due to the early 2000 recession, primarily affecting Western Europe, the European Union, and the United States.

The remaining rolling window shock coefficients carry a particularly small coefficient despite their statistical significance in some specifications. I interpret the small magnitude of these placebo shocks as having little to no effect on sectors' future export competitiveness when compared to the much more sizeable negative final demand shock over the period of the financial crisis. The shock coefficient proxying the financial crisis, as seen in Table 2.4 is more than double that of the placebo regressions. Thus, while there is some suggestive evidence that changes in final demand in earlier periods had a small negative impact on the average sector's RCA prior to the financial crisis, it is relatively muted compared to the fall in final demand during the period of the financial crisis.

RCA 2010	(1) GC	(2) LC	(3) Outdegree	(4) Indegree	(5) GC	(6) LC	(7) Outdegree	(8) Indegree	(9) GC	(10) LC	(11) Outdegree	(12) Indegree	(13) GC	(14) LC	(15) Outdegree	(16) Indegree	(17) GC	(18) LC	(19) Outdegree	(20) Indegree
Shock 00-02	-0.053***	-0.077***	-0.043***	-0.087***																
	(0.019)	(0.021)	(0.016)	(0.022)																
Shock 01-03					-0.017*	-0.023***	-0.013	-0.041***												
					(0.009)	(0.008)	(0.010)	(0.009)												
Shock 02-04									-0.013**	-0.015***	-0.010	-0.027***								
									(0.006)	(0.006)	(0.006)	(0.007)								
Shock 03-05													-0.018**	-0.020***	-0.014*	-0.034***				
													(0.007)	(0.008)	(0.008)	(0.009)				
Shock 04-06																	-0.022**	-0.023**	-0.017	-0.040***
																	(0.010)	(0.010)	(0.010)	(0.012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs	2,151	2,151	2,151	2,151	2,152	2,152	2,152	2,152	2,152	2,152	2,152	2,152	2,152	2,152	2,152	2,152	2,152	2,152	2,152	2,152
R^2	0.382	0.370	0.375	0.361	0.390	0.370	0.378	0.366	0.406	0.379	0.389	0.376	0.417	0.390	0.401	0.388	0.419	0.395	0.403	0.394

Table 2.6: Placebo Bartik regression, 2000-2006. Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All variables except log GDP per capita are standardized. Standard errors are clustered at the country-industry level.

2.8 Conclusion

In this paper, I have documented a set of novel stylized facts at the intersection of the network and trade literature. I find the small-world phenomenon holds in the context of the global production network; sectors in which a country has a revealed comparative advantage tend to be more central in the production network; and sectors with higher local centrality tend to be globally more central as well.

A priori, it is unclear whether a country has a comparative advantage in a particular sector because it has established connections, or because a set of initial conditions made it worthwhile to devote resources to particular sectors, enabling it to supply a host of other sectors thereby increasing its centrality in the production network. Exploiting the 2008 financial crisis, by constructing a shift-share instrument to isolate the exogenous variation in the final demand shock, I find more central sectors, as measured by global centrality and outdegree, experience a relatively smaller decline in their future value-added RCA compared to their more peripheral counterparts.

The main driving force behind these results is the middle-income countries in my sample, which include the BRIC economies, Brazil, Russia, India, and China. In the lead-up to the financial crisis and during, these economies traded with other emerging economies which, while affected by the financial crisis most pervasive in the US and Western Europe, were relatively more shielded from its aftermath compared to more industrialised nations. Exploring the heterogeneous effects at the sector level, it is primarily the manufacturing sector driving the positive coefficient on the interaction term. It is sectors specialising in manufactured goods and trading with foreign countries that were key to reducing the negative impact of the financial crisis on future export competitiveness.

2.9 Appendix

A Centrality

The adjacency matrix A provides the technical coefficients; the direct importance of sector j as an intermediate input supplier for the production of goods by sector i. The A matrix can be transformed so that all IO columns sum to one, following Acemoglu et al. (2012). I denote W as the transformed A matrix. This transformation implies sectoral production functions exhibit constant returns to scale and assumes the input shares of all sectors add up to 1; $\sum_{j=1}^{n} w_{ij} = 1$

To compute the centrality score, taking the whole matrix, I calculate each country-sector's Katz-Bonacich centrality where the network comprises of each country-sector recorded in the WIOD (2464×2464 matrix when including the ROW; otherwise 2408×2408 as each entity has 56 sectors).

The baseline centrality measure of η = (1 - 0.5)/2464 and a parameter for weighting the downstream sectors of $\lambda = 0.5$, where $\lambda = \alpha$, α is the share of intermediate inputs in production. Intermediate goods' share in gross output is documented to be approximately 0.5 (Jones, 2011a).

$$c_j = \lambda \sum_i W_{ij} c_i + \eta$$

Total centrality includes a country-sector's local and global centrality. To calculate the local centrality for each country-sector, i.e. how well-connected the sector is within its domestic borders, I sum across a subset of the matrix used when calculating total centrality, i.e. only the technical coefficient belonging to other sectors located in the same country. It can also be thought of as summing each sub-matrix located along the main diagonal of the total centrality matrix. The corresponding global centrality score for each country-sector is the sum of its technical coefficients off the main diagonal.

I plot the kernel density (using the Epanechnikov kernel function) of log global centrality and find it is left-skewed while for log local centrality, it is right-skewed. That is, global centrality contains a large mass of general-purpose technology sectors that are highly connected with foreign sectors. On the other hand, local centrality is characterised by relatively more specialised sectors, the mass of the distribution concentrated around lower local centrality scores. Lower centrality scores for sectors remains fairly constant over time with negligible changes in its density for year to year. On the other hand, perhaps expectedly, there is greater variation in the density of global centrality scores. I observe particularly large movement to the left of the distribution in 2010, 2011, and 2012 before returning to the pattern

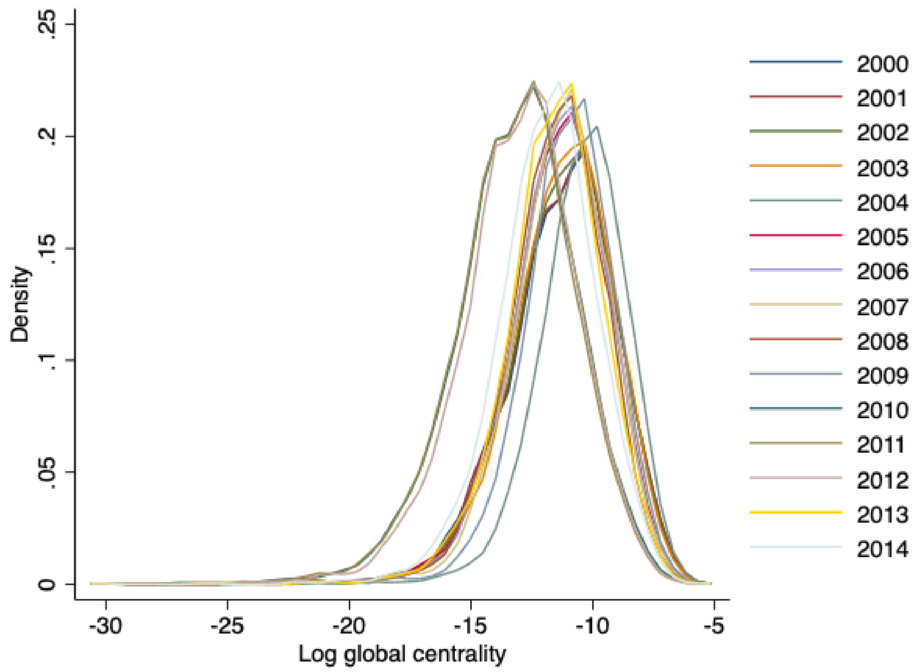


Figure 2.7: Distribution of global centrality, 2000-2014. Source: The World Input Output Database, 2016 Release. Author's calculations using the Epanechnikov kernel function.

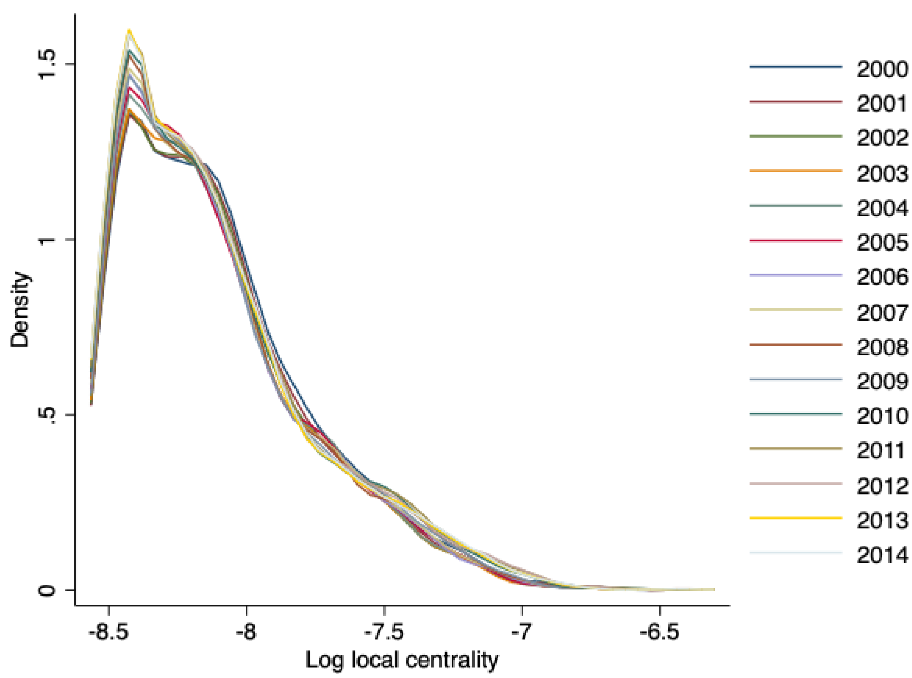


Figure 2.8: Distribution of local centrality, 2000-2014. Source: The World Input Output Database, 2016 Release. Author's calculations using the Epanechnikov kernel function.

observed prior to the 2008 financial crisis.

B Baseline estimation results

In this section, I include the baseline estimation results using measures of sectors' revealed comparative advantage further into the future. The negative final demand shock, or 'shock' variable, is consistently negative across specifications. The impact of the shock affected sectors' export competitiveness up to four years into the future. By 2014, the decline in final demand associated with the financial crisis no longer worsens the average sector's RCA.

Network measures of connectedness are statistically significant throughout the specifications, suggesting initial sectoral placement is a significant determinant of future export competitiveness. Each network measure is taken in the baseline year of 2007, and while the magnitude of the coefficients lessens over time, it remains statistically significant at the one per cent level.

Table 2.7: VA RCA network regressions, 2011

	(1) GC	(2) LC	(3) Outdegree	(4) Indegree
Shock	-0.043**	-0.055**	-0.036**	-0.075***
	(0.017)	(0.022)	(0.018)	(0.016)
Network	0.388***	0.309***	0.305***	-0.298***
	(0.041)	(0.041)	(0.038)	(0.047)
Shock*Network	0.027**	0.006	0.025*	0.000
	(0.013)	(0.025)	(0.015)	(0.025)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
No. of obs	2,150	2,150	2,150	2,150
R^2	0.453	0.433	0.434	0.423

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All variables except log GDP per capita are standardized. Standard errors are clustered at the country-industry level.

Using the average effects of the shock on future RCA, there is limited evidence to suggest the change in the average sector's future RCA in response to the negative global final demand shock is lessened or worsened by its network connectivity the more distant the estimates are from the period of the financial crisis. This set of tables perhaps underpins the need to estimate using different sub-samples, as in Table 2.5.

Table 2.8: VA RCA network regressions, 2012

	(1) GC	(2) LC	(3) Outdegree	(4) Indegree
Shock	-0.046***	-0.059***	-0.041**	-0.079***
	(0.017)	(0.022)	(0.018)	(0.016)
Network	0.379***	0.306***	0.303***	-0.294***
	(0.040)	(0.041)	(0.038)	(0.048)
Shock*Network	0.022*	-0.001	0.019	-0.009
	(0.013)	(0.026)	(0.015)	(0.025)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
No. of obs	2,150	2,150	2,150	2,150
R^2	0.447	0.428	0.430	0.419

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All variables except log GDP per capita are standardized. Standard errors are clustered at the country-industry level.

Table 2.9: VA RCA network regressions, 2013

	(1) GC	(2) LC	(3) Outdegree	(4) Indegree
Shock	-0.052***	-0.063***	-0.047***	-0.081***
	(0.017)	(0.023)	(0.018)	(0.016)
Network	0.358***	0.290***	0.280***	-0.298***
	(0.040)	(0.041)	(0.038)	(0.048)
Shock*Network	0.017	-0.003	0.016	-0.010
	(0.013)	(0.027)	(0.015)	(0.026)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
No. of obs	2,150	2,150	2,150	2,150
R^2	0.438	0.421	0.422	0.415

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All variables except log GDP per capita are standardized. Standard errors are clustered at the country-industry level.

Table 2.10: VA RCA network regressions, 2014

	(1) GC	(2) LC	(3) Outdegree	(4) Indegree
Shock	-0.056***	-0.069***	-0.051***	-0.085***
	(0.017)	(0.022)	(0.018)	(0.017)
Network	0.348***	0.287***	0.278***	-0.288***
	(0.041)	(0.041)	(0.038)	(0.047)
Shock*Network	0.014	-0.009	0.013	-0.013
	(0.013)	(0.027)	(0.015)	(0.026)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
No. of obs	2,150	2,150	2,150	2,150
R^2	0.433	0.418	0.418	0.411

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All variables except log GDP per capita are standardized. Standard errors are clustered at the country-industry level.

C WIOT sector list

Table 2.11: Sector code and description

Code	Sector Description
A01	Crop and animal production, hunting and related service activities
A02	Forestry and logging
A03	Fishing and aquaculture
B	Mining and quarrying
C10-C12	Manufacture of food products, beverages and tobacco products
C13-C15	Manufacture of textiles, wearing apparel and leather products
C16	Manufacture of wood and of products of wood and cork, except furniture
C17	Manufacture of paper and paper products
C18	Printing and reproduction of recorded media
C19	Manufacture of coke and refined petroleum products
C20	Manufacture of chemicals and chemical products
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22	Manufacture of rubber and plastic products
C23	Manufacture of other non-metallic mineral products
C24	Manufacture of basic metals

Table 2.11 – continued from previous page

Code	Sector Description
C25	Manufacture of fabricated metal products, except machinery and equipment
C26	Manufacture of computer, electronic and optical products
C27	Manufacture of electrical equipment
C28	Manufacture of machinery and equipment n.e.c.
C29	Manufacture of motor vehicles, trailers and semi-trailers
C30	Manufacture of other transport equipment
C31_C32	Manufacture of furniture; other manufacturing
C33	Repair and installation of machinery and equipment
D35	Electricity, gas, steam and air conditioning supply
E36	Water collection, treatment and supply
E37-E39	Sewerage; waste collection, treatment and disposal activities
F	Construction
G45	Wholesale and retail trade and repair of motor vehicles and motorcycles
G46	Wholesale trade, except of motor vehicles and motorcycles
G47	Retail trade, except of motor vehicles and motorcycles
H49	Land transport and transport via pipelines
H50	Water transport
H51	Air transport
H52	Warehousing and support activities for transportation
H53	Postal and courier activities
I	Accommodation and food service activities
J58	Publishing activities
J59_J60	Motion picture, video and television programme production
J61	Telecommunications
J62_J63	Computer programming, consultancy and related activities
K64	Financial service activities, except insurance and pension funding
K65	Insurance, reinsurance and pension funding, except compulsory social security
K66	Activities auxiliary to financial services and insurance activities
L68	Real estate activities
M69_M70	Legal and accounting activities; activities of head offices
M71	Architectural and engineering activities; technical testing and analysis
M72	Scientific research and development
M73	Advertising and market research
M74_M75	Other professional, scientific and technical activities; veterinary activities

Table 2.11 – continued from previous page

Code	Sector Description
N	Administrative and support service activities
O84	Public administration and defence; compulsory social security
P85	Education
Q	Human health and social work activities
R_S	Other service activities
T	Activities of households as employers
U	Activities of extraterritorial organizations and bodies

D Country codes

Table 2.12: Country codes

Code	Country	Code	Country	Code	Country
AUS	Australia	FRA	France	MLT	Malta
AUT	Austria	GBR	UK	NLD	Netherlands
BEL	Belgium	GRC	Greece	NOR	Norway
BGR	Bulgaria	HRV	Croatia	POL	Poland
BRA	Brazil	HUN	Hungary	PRT	Portugal
CAN	Canada	IDN	Indonesia	ROU	Romania
CHE	Switzerland	IND	India	RUS	Russia
CHN	China	IRL	Ireland	SVK	Slovakia
CYP	Cyprus	ITA	Italy	SVN	Slovenia
CZE	Czechia	JPN	Japan	SWE	Sweden
DEU	Germany	KOR	Korea	TUR	Turkey
DNK	Denmark	LTU	Lithuania	TWN	Taiwan
ESP	Spain	LUX	Luxembourg	USA	US
EST	Estonia	LVA	Latvia		
FIN	Finland	MEX	Mexico		

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Chapter 3

Endogenous versus Fixed Production Networks: the US-China Trade War

Bilateral trade linkages in domestic and international production networks play an important role in firm-level and aggregate economic outcomes. However, much of the earlier literature has abstracted from this channel treating production networks as exogenous, for reasons of computational tractability and the theoretical complexity of modelling endogenous link formation. The more standard approach in the economics literature has assumed an exogenous production network when modelling input-output linkages. I relax this assumption by developing a production network model where each firm's input supplier choices and quantities purchased determine the prevailing equilibrium network structure. I apply my framework to the 2018 US-China trade war, leveraging the increase in import tariffs to quantify the impact of rising production costs on trade connections. I perform a counterfactual analysis to find that, when treating the production network as endogenous, the trade war leads to smaller GDP losses at 1%, compared to the standard case where losses are 1.6%. I find the standard approach overestimates GDP losses by 0.6 percentage points, a non-negligible difference in aggregate economic outcomes.
Keywords: Input-output linkages, production networks, trade.
JEL: F13, C67, L14

3.1 Introduction

A growing body of research studies how firm-to-firm connections in the production network influence aggregate outcomes. With two-thirds of global trade in intermediate inputs, such flows are a prime example of the interdependencies in domestic and international production networks (Johnson & Noguera, 2012). Therefore, in a globalized trade system, changes in production costs have far-reaching implications, not only for the firms directly affected but also for their input suppliers and customers along the supply chain. Recent work studies the importance of the input-output network at the level of the production unit (sector- or firm-level) in shaping aggregate outcomes (Fadinger et al. (2022), Bigio & La'O (2020), Bartelme & Gorodnichenko (2015), Jones (2011a), Jones (2011b), Ciccone (2002)).

Nevertheless, the process governing the formation of production networks and the implications of this abstraction are understudied. Modelling the formation and breakage of trade relationships is valuable in understanding the potential unintended consequences of trade policy where linkages can and, in practice, do change in response to interventions. One step towards modelling the economy's underlying production structure has been to introduce input-output linkages and treat this network as exogenous. However, input-output matrices are not random, nor exogenously given, but rather the endogenous outcome of firms' sourcing decisions.

In this paper, I develop a general equilibrium (GE) trade network model that endogenizes firms' input sourcing decisions featuring cross-country, cross-sector input-output linkages. I modify the standard framework to include firms' input supplier choices which determine the trade links formed, and the subsequent structure of the domestic and international production network. Using this framework, I quantify the significance of abstracting from the reorganisation of connections between firms. Under the endogenous production network (EPN), firms have two margins of adjustment. Following a trade shock, firms can adjust the set of intermediate inputs employed (extensive margin) and the quantities purchased (intensive margin) to minimise production costs. In the standard fixed production network (FPN), firms can only pursue intensive margin adjustments.[1] Firms face variable trade costs, via an import tariff levied at the sector-to-sector level, when sourcing from the foreign market, and face frictionless domestic trade. Firms choose to purchase inputs from either the domestic market, the foreign market, or produce the input in-house when inputs in either market are insufficiently productive. For my purposes, I use a two-country setting, however, the model can be generalised to an n country environment.[2]

I apply my framework to the recent US-China trade war, leveraging the increase in import tariffs to calibrate my model, to compare economic outcomes when firms can endogenously adjust their set of intermediate input suppliers versus when they cannot. This protectionist

[1]Under the EPN, a priori one would expect losses to be smaller as firms have an additional margin of adjustment. In this paper, I quantify by how much standard models overstate losses when abstracting from firms' input supplier choices.

[2]My results can be thought of as a lower bound of the overestimation of GDP losses following the increase in import tariffs. If countries were to source from a third country, inputs continued to be imported from the third country must be productive enough to justify their purchase, and GDP losses in the EPN would be relatively smaller than under the two-country case.

policy episode is well-suited to calibrate my model as i) trade can be thought of as a naturally networked activity; ii) the import tariff hikes were heterogeneous across products and; iii) the tariffs primarily targeted intermediate input trade which I explicitly model in my framework. I then quantify the impact of the rise in import tariffs on domestic and international trade connections, and subsequent GDP losses, when modelling the economy with different margins of adjustment.

My contributions are threefold. First, I make a methodological contribution, quantifying the bias in standard input-output linkage models that abstract from the channel of endogenous input supplier choice. To do so, I extend the Acemoglu & Azar (2020) framework of (discrete) endogenous link formation, introducing sector-to-sector import tariffs to enrich the model. Earlier input-output analysis has focused on performing counterfactual exercises using a given network structure (Bigio & La'O (2020), Fadinger et al. (2022)). However, this abstracts from any reorganisation of the economy's production structure in response to shocks, which I illustrate is a non-negligible dimension. In the economic networks literature, theoretical work has focused on endogenising this network structure of production, i.e. who buys inputs from whom (Acemoglu & Azar (2020), Oberfield (2018), Lim (2017)). Lim (2017) develops a continuous model of firm-to-firm input-output linkages and in his empirical application focuses on the role of production networks in macroeconomic business cycles. However, the model lacks a geographical dimension such that it is not well-suited to studying questions concerning international trade. Caliendo et al. (2022) identify frictions in a model of input-output relationships featuring endogenous input expenditure to study how internal frictions change the structure of the world economy. I model trading frictions as inflating firms' prices, endogenising each firm's input supplier choice instead of input expenditure shares. I use ad-valorem import tariffs as one component of firms' variable trade costs that have been identified as an important trading friction. Empirical work by Dhyne et al. (2021) emphasise the role of domestic production networks in Belgian firms' reliance on foreign input purchases and sales. A robust finding in this emerging literature is that who firms buy from will determine marginal costs and productivity along the supply chain (Bernard & Moxnes (2018a)). Therefore, any trading frictions may lead to sub-optimal supplier choices. My quantitative results are complementary to this body of work, quantifying the bias when abstracting from network formation.

Second, my theoretical framework models the full trade network where each firm is simultaneously an intermediate input supplier and buyer, as observed in practice. In a full network, I observe not only the direct links of each firm but also the linkages between buyer's buyers and seller's sellers, ad infinitum. A link exists if one firm sells (or buys) intermediate inputs from another, either within the domestic market or cross-border. Canonical models of production feature anonymous intermediate inputs that are transformed into final goods and sold to final consumers (Melitz (2003)). I model the dimension one step before this bundling process takes place to focus on intermediate input trade. There are two benefits to modelling the full network. First, I can characterise a (discrete) heterogeneous extensive margin for each supplier. In other words, each firm will choose a different set of input suppliers in an effort to minimise its production costs. This discrete feature provides a more realistic characterisation of sparse network data than continuous, deterministic models (Bernard & Zi (2022)). Firms engage in a finite, discrete set of transactions, with continuity, generally assumed for modelling simplicity, having implications for network structures necessitating the introduction of additional mechanisms to explain network features. Second, tariffs have a two-fold effect, consistent with the work of Bernard & Moxnes (2018c). The direct effect of increased prices from existing foreign suppliers, and the indirect loss of suppliers in cases where the input sourcing cost exceeds the input-specific productivity benefit. This paper also relates to the literature on firms' global sourcing decisions that have tended to investigate either exporter or importer heterogeneity, and not consider both simultaneously. Multi-country models incorporate one-sided heterogeneity to investigate cross-border buyer-supplier connections (Carballo et al. (2018)). Antràs et al. (2017) develop a multi-country framework of firm-level sourcing where foreign sourcing decisions are interdependent across markets. An exception is the work on two-sided heterogeneity by Bernard & Moxnes (2018c). However, the model abstracts from domestic trade connections to focus on importer and exporter matches. In my framework, I model both within and cross-country trade to capture multiple dimensions of producer heterogeneity that influence the prevailing production structure of the economy.

Third, I contribute to the literature on the US-China trade war, using this protectionist policy episode as one possible application of my model. There has been a proliferation of empirical work studying different dimensions of the trade war including the pass-through of tariffs to import prices (Fajgelbaum et al. (2021), Fajgelbaum et al. (2020), Cavallo et al. (2021), Flaaen et al. (2020)), welfare effects (Amiti et al. (2019)) for the US and China, and recent work shifting the focus to how countries not directly targeted by the import tariffs, reallocated trade (Fajgelbaum et al., 2021). I introduce a modelling framework that is not observed in empirical work on the trade war to measure the endogenous input supplier choice channel and illustrate its importance in this policy context. I use my quantitative model as a laboratory where I can isolate the impact of the import tariffs and side-step simultaneously enacted policies, such as the Tax Cuts and Jobs Act (TCJA), contaminating my results.

I estimate a structural model to characterise firms' extensive and intensive margins of adjustment in response to a trade shock, in a general equilibrium setting. In the EPN, each firm makes a sourcing decision, choosing the set of intermediate inputs to purchase, either domestically or from the foreign market. For a given input set (extensive margin), the firm then decides how much of each input is purchased alongside the essential input (intensive margin). The intuition underlying a firm's choice to hire or drop an input is, most simply, a cost-benefit trade-off. A firm will choose to hire an intermediate input in its production set if it is cost-reducing.[3] Each input has an associated input-specific productivity parameter when used in a firm's production process. Under perfect competition, the input-specific productivity gains must be greater than the cost of hiring the input. The cost of each input is its purchase price plus any additional import tariff levied if foreign-sourced. Consistent with empirical work studying this policy episode, increases in import tariffs fully pass through to prices incurred by customers (Fajgelbaum et al., 2020). Under the standard FPN model, producers cannot optimise over the set of intermediate inputs, only choosing the quantities purchased from an exogenously given input set, governed by the input-output data.

To simulate the input-specific productivities, I calibrate a model parameter such that the GDP estimated in the model matches the total real, value-added GDP of the US and China observed in the data. The model parameter enters into an algorithm that ensures each input's assigned productivity term is consistent with whether or not a trade connection is present in the data. Following Acemoglu & Azar (2020), I assume an input is more productive if a trade link is present between two firms than if it is not. From this exercise, I obtain the equilibrium price vector of each firm, the simulated input-specific productivity matrix, and use the two objects to perform my counterfactual analysis. My baseline is calibrated to the US-China patterns under the trade war tariff rates, while my counterfactual characterises the production network had most-favoured nation tariffs remained.

I find a 1% GDP loss under the endogenous production network compared to a 1.6% loss under the fixed production network model. Thus, the GDP losses in a standard input-output model that abstracts from endogenous input supplier choice are overestimated by 0.6 percentage points. Two dimensions contribute to the GDP loss differential. First, price increases are more muted under the endogenous production network. Firms can choose who to buy from as well as how much to buy, substituting away from more (weakly) expensive firms whose inputs are no longer sufficiently productive to include in the production set. In the fixed production network, firms continue purchasing from the same set of, now more expensive, suppliers with only the intensive margin of adjustment available. Second, the decrease in domestic and international trade flows is larger in the endogenous than in the fixed production network model. When a firm decides to drop an input from its production set, its purchases of that input fall from a positive amount to zero. This causes discontinuous

[3] I assume sourcing specific inputs does not impart market power.

effects in GDP, contributing to much larger, negative quantitative changes in trade flows in the endogenous production network. Dropped intermediate inputs may be either the least productive in a firm's production set, where even a small increase in tariffs makes it infeasible to employ any longer, or those relatively productive inputs that experience particularly large increases in import tariffs. Nevertheless, firms with higher total productivity prior to the trade war possess a productivity buffer that reduces the likelihood of being dropped as a supplier in spite of large tariff increases. I illustrate the mechanisms governing this feature of the endogenous production network model using the US manufacture of computers as a case study.

In Section 3.2 I outline the endogenous network formation model; Section 3.3 describes the data and policy background; Section 3.4 the quantitative counterfactual exercise; Section 3.5 presents a case study of the US manufacture of computers sector; Section 3.6 compares the fixed and endogenous production network outcomes; Section 3.7 focuses on the endogenous production network in more detail, and Section 3 concludes.

3.2 Model

3.2.1 Endogenous network formation

I develop an endogenous link formation model with endogenous input choice following Acemoglu & Azar (2020) and extend it to include sector-to-sector distortions.

Consider a static economy with a set of $\mathcal{N} = \{1, 2, ..., n\}$ competitive sectors, each producing a distinct output, Y_i. I assume each sector is contestable; a large number of firms, with access to the same production technology, can enter with no barriers to entry. Firm entry into a sector ensures zero profits are made in equilibrium.

Each sector's output can be consumed by the representative household or used as an intermediate input in the production of other sectors in the economy.

Sector i's production technology is:

$$Y_i = F_i(S_i, A_i(S_i), K_i, X_i)$$

where K_i is the quantity of capital used, $X_i = X_{ij\,j\in S_i}$ denotes the vector of intermediate input quantities used, S_i is the endogenously determined set of intermediate input suppliers, and $A_i(S_i)$ is the resulting productivity of the inputs belonging to the set S_i. I assume F_i does not depend on inputs X_i for which $X_{ij}, j \notin S_i$.

3.2.1.1 Production technology assumptions

1. For each $i = 1, 2, ..., n$, $F_i(S_i, A_i(S_i), K_i, X_i)$ is strictly quasi-concave, exhibits constant returns to scale in (K_i, X_i) and is increasing and continuous in $A_i(S_i), K_i$ and X_i, and strictly increasing in $A_i(S_i)$ when $K_i > 0$ and $X_i > 0$. Strict quasi-concavity ensures input demand is uniquely determined.
2. Capital is an essential input, $F_i(., ., 0, .) = 0$ for each $i = 1, 2, ..., n$. Treating capital as an essential input prevents it from becoming an obsolete factor in the firm's production function and ensures output remains finite.[4]
3. For each $i = 1, 2, ..., n$, $A_i(\emptyset) > 0$; each sector can produce some positive level of output using only capital.

3.2.1.2 Consumer-side assumptions

On the consumer side, the representative household's preferences, assuming logarithmic preferences over n goods, are given by:

$$u(C_1, C_2, ..., C_n) = \sum_{i=1}^{n} log(c_i)$$

where c_i is the quantity of good i consumed.

Utility is continuous, differentiable, increasing, and strictly quasi-concave, and all goods are normal. The representative household has an endowment of one unit of capital, supplied inelastically, and receives any positive profits from all sectors. The rental rate of capital is the numeraire with:

$$R = 1.$$

Distortions are introduced as a bilateral link-specific ad-valorem tax at a rate μ_{ij}. A sector i purchasing an input from sector j faces an ad-valorem tax when $\mu_{ij} \geq 0$, and input j is sourced from a different country from where firm i is located. Some fraction, λ_i, of the revenues generated by the distortion may be rebated to the representative household. When $\lambda_i = 0$, distortions are a deadweight loss, while $\lambda_i = 1$ has all distortions rebated as tax revenue.

[4] The model requires one essential input that need not be capital. Using labour as the alternative factor has no implications for the results. However, given the mobile nature of the essential input both within and across countries, I choose capital as, although neither adjustment is in practice costless, capital can be thought of as relatively more mobile than labour.

The household's budget constraint is:

$$\sum_{i=1}^{n} P_i C_i \leq 1 + \sum_{i=1}^{n} \Lambda_i \tag{3.1}$$

where $\Lambda_i = \lambda_i \frac{\sum_{j \in S_i} \alpha_{ij}\mu_{ij}}{\sum_{j \in S_i} \alpha_{ij}(1+\mu_{ij})} P_i Y_i$ and α_{ij} is the expenditure share of firm i on input j. The left-hand side of the budget constraint is total expenditure in the economy, which cannot exceed total income. The right-hand side of Equation 3.1 is composed of the income from renting capital and the share of revenue that is rebated from the taxes levied.

3.2.2 Firm i's cost minimisation problem

A firm i's cost minimisation problem is to choose the optimal quantity of intermediate inputs, capital, and the set of suppliers from which to source its intermediate inputs subject to its production function, Y_i.[5]

Step 1: A firm minimises its unit cost function

$$UC_i(S_i, A_i(S_i), P, \mu_{ij}) = \min_{X_i, K_i} K_i + \sum_{j \in S_i} (1 + \mu_{ij}) P_j X_{ij} \tag{3.2}$$

$$\text{subject to } Y_i = F_i(S_i, A_i(S_i), K_i, X_i) = \zeta_i A_i(S_i) K_i^{1-\sum_{j \in S_i} \alpha_{ij}} \prod_{j \in S_i} X_{ij}^{\alpha_{ij}} = 1.$$

where $\zeta_i = \frac{1}{\left(1-\sum_{j \in S_i} \alpha_{ij}\right)^{1-\sum_{j \in S_i} \alpha_{ij}} \prod_{j \in S_i} \alpha_{ij}^{\alpha_{ij}}}$ is a normalising constant that has no bearings on the results. K_i is the quantity of capital employed by each sector i, X_{ij} is the quantity of good j used in the production of good i, and μ_{ij} is the sector-to-sector import tariff levied on foreign inputs, where $\mu_{ij} = 0$ if input j purchased by firm i is located in the same country. The exponents represent the expenditure share of sector i on the intermediate inputs used, with the remaining expenditure share used to employ capital. The production function features a Hicks-neutral productivity scalar for each sector i; it is a function of the set of endogenously chosen inputs used in production.

The exponents $\alpha_{ij} \geq 0$ model firms' use of other sectors' outputs as an intermediate input in their own production process. The larger the exponent, the more important sector j's output is for sector i's production. In general, $\alpha_{ij} \neq \alpha_{ji}$, sector i's use of sector j's output in its production is not necessarily mirrored by sector j's use of sector i's output. Further, the

[5] See the Appendix, Section A for firm i's isomorphic profit maximisation problem with the derivation of the log unit cost function.

assumption that technologies exhibit constant returns to scale implies that $\sum_{j=1}^{n} \alpha_{ij} = 1$ for all i. For simplicity, I assume a Cobb-Douglas production technology with constant returns to scale.[6]

Step 2: Chooses set of input suppliers that minimise Equation 3.2:

$$S_i^* \in \arg\min_{S_i} \quad UC_i(S_i, A_i(S_i), P, \mu_{ij}) \tag{3.3}$$

where $S_i \subset \{1, 2, ..., n\}$ is the set of endogenously determined intermediate input suppliers. The firm's chosen production function will depend only on the endogenously determined set of intermediate inputs contained in the set S_i.

The equilibrium price of industry i is given by $P_i^* = UC_i(S_i^*, A_i(S_i^*), P^*, \mu_{ij})$ and the share rebated to the representative household is:

$$\Lambda_i^* = \lambda_i \frac{\sum_{j \in S_i} \alpha_{ij} \mu_{ij}}{\sum_{j \in S_i} \alpha_{ij}(1 + \mu ij)} P_i^* Y_i^* \tag{3.4}$$

where Y_i^* denotes output.

3.2.3 Equilibrium

The competitive equilibrium consists of a vector of equilibrium prices, and a matrix of quantities such that i) the representative household is maximising her utility; ii) the representative firm in each sector maximises its profits while taking the rental rate of capital and prices as given; and iii) all markets clear.

3.2.3.1 Definition

1. Contestability: For each $i = 1, 2, ..., n$,

$$P_i^* = UC_i(S_i^*, A_i(S_i^*), P^*, \mu_{ij})$$

[6] A Cobb-Douglas production technology lends itself to studying input-output linkages, whereby the exponent α_{ij}, is the expenditure share of sector i on the intermediate inputs used and corresponds to the entries of the input-output matrix used as the basis of the production network. This production technology is also tractable, allowing for a closed-form solution of prices. A constant elasticity of substitution (CES) production function should yield qualitatively similar results, the size and direction of the effects depending on whether inputs are complements or substitutes in production. Intermediate inputs tend to be complementary in the production suggesting effects in the same direction and similar magnitude. Final goods tend to be substitutes.

2. Consumer Maximisation: Consumption vector C^* maximises $u(C_1, ..., C_n)$ subject to $\sum_{i=1}^{n} P_i C_i \leq 1 + \sum_{i=1}^{n} \lambda_i \frac{\sum_{j \in S_i} \alpha_{ij} \mu_{ij}}{\sum_{j \in S_i} \alpha_{ij}(1+\mu ij)} P_i Y_i$

3. Cost Minimisation: For each $i = 1, 2, ..., n$, factor demands K_i^* and X_i^* are solutions to Equation 3.2 given the price vector P^* and S_i^* is the solution to Equation 3.3.

4. Market Clearing: For each $i = 1, 2, ..., n$,

$$C_i^* + \sum_{j=1}^{n} X_{ji}^* = \left(1 - (1 - \lambda_i) \frac{\sum_{j \in S_i} \alpha_{ij} \mu_{ij}}{\sum_{j \in S_i} \alpha_{ij}(1 + \mu_{ij})}\right) Y_i^*,$$
$$Y_i^* = F_i(S_i^*, A_i(S_i^*), K_i^*, X_i^*),$$
$$\sum_{j=1}^{n} K_j^* = 1$$

The contestability condition implies price is equal to the marginal cost of production, inclusive of any distortions. Prices are endogenously determined, where the equilibrium price for each industry, P_i^*, clears the market such that there is no excess demand or supply. By the market clearing condition, the first line indicates the sum of total consumption by the representative household and intermediate input purchases by the firm is equal to the total optimal output produced by firm i, net of the output lost due to any frictions. The second line defining market clearing via a vector of output, Y_i^*, represents n simultaneous equations, with each firm producing for the representative household consumption demand, and intermediate input supply to each purchasing firm.

3.3 Data

3.3.1 World Input-Output Database (WIOD) and Socio-Economic Accounts (SEA)

To construct the production network, I use the World Input-Output Database (WIOD) 2016 release. The WIOD covers 43 countries plus a rest of the world aggregate, with 56 sectors using the ISIC Rev 4 classification. Taken together, the 43 countries included represent more than 85% of world GDP (measured at current exchange rates) available from 2000 to 2014. Importantly, the WIOD is consistent with the framework of the international System of National Accounts (SNA), obeying its underlying concepts and accounting identities (Timmer et al., 2015). The SNA is the internationally agreed set of recommendations on how to compile measures of economic activity.

Input-output tables (IOTs) are commonly used to characterise the production structure of the domestic economy, outlining inter-industry transaction flows. The technical coefficients, $\alpha_{ij} \geq 0$, show the importance of sector j's products as an intermediate input for the production of goods by sector i. The technical coefficients form the adjacency matrix of the economy detailing the network structure at the sector level.

One country input-output tables measure intra-industry trade along the main diagonal and inter-industry trade off the main diagonal. World IOTs go one step further and account for inter-country, inter-industry trade too. Hence, one can observe how important country-sector output is for foreign country-sector production. This added international dimension measures the extent to which sectoral networks extend across borders.

Using the WIOD, I construct a weighted directed network, where one sector may be connected to a second, without the second being connected to the first. The weight for each country-sector in the adjacency matrix is the cost share of input j in the production of good i. For my purposes, I use the US and China's national input-output tables that are connected by bilateral trade flows. All transaction values are in basic prices to reflect the costs borne by the producer. The columns of the WIOD contain information on the production process, i.e. the production technology, of each sector. I express the elements as ratios to gross output which gives the shares of the inputs in total costs. Imports are broken down according to the country and sector of origin. International trade flows are expressed in "free on board" (f.o.b) prices. The WIOD is supplemented by the accompanying Socio-Economic Accounts (SEA). The SEA contains sector-level data on the use of factors of production, value-added, and consumption amongst other variables.

3.3.2 Policy Background

The Trump administration oversaw a rise in import tariffs in a policy environment, spearheaded by the WTO and multilateral negotiations, that has progressively sought to reduce trade barriers between trade partners. In 2018, under the justification that imports posed a threat to US national security, the US administration raised tariffs on a variety of imported product lines. In response to the policy decision, the US' trading partners imposed retaliatory tariffs on US exports. I list some of the notable product groups targeted by the tariff increases with the documented retaliation by China.

3.3.2.1 Aluminium and steel

Several product groups, identified to be a national security threat under Section 232 of the Trade Expansion Act of 1962, were hit by higher import tariffs. One product group was steel and aluminium imports, with tariffs coming into effect from 23rd March 2018.[7] The manufacture of steel and aluminium falls under the WIOD manufacture of basic metals sector classification. As seen in Table 3.1, there was a 12% point increase in import tariffs on these basic metals, whereby post trade war, the protectionist measures on basic metals manufacturing in the US doubled. The importance of the manufacture of basic metals as an intermediate input supplier to other sectors underlies the importance of using an endogenous link formation framework. This framework is well-suited to studying the wider network effect of an increase in trade costs, especially widely used intermediate inputs and the indirect effects of rising production costs on customers.

On the 2nd April 2018, China's retaliatory tariffs came into effect on products featuring in, but not limited to, the WIOD crops and manufacture of food products sector categories, including fruits and nuts, and pork products. This tranche represented $2.4 billion of US products, in 2017 import values.[8]

3.3.2.2 Technology and Intellectual Property Concerns

Another set of products targeted by the US tariffs was justified under unfair trade practices in technology and intellectual property (IP), Section 301 of the Trade Act of 1974. The Chinese products hit by the rise in import tariffs were primarily in the machinery, mechanical appliance, and electrical equipment sectors. Approximately 85% of the targeted imports were intermediate inputs and capital goods, inflating costs of production for US producers relying on these inputs. By the WIOD sector classification, these sectors were hit by a 10% point increase in the ad-valorem tariff rate. US tariffs on Chinese products were estimated to be worth $46.2 billion in 2017.[9]

In response, China introduced tariff proposals on $49.8 billion of China's imports from the US, primarily affecting US transportation (vehicles, aircraft, and vessels) and vegetable products (largely soybeans).[10,11]

[7] https://www.piie.com/sites/default/files/documents/trump-trade-war-timeline.pdf

[8] https://www.piie.com/research/piie-charts/how-china-retaliating-us-national-security-tariffs-steel-and-aluminum

[9] https://www.piie.com/blogs/trade-investment-policy-watch/more-soybeans-trumps-section-301-tariffs-and-chinas-response

[10] https://www.piie.com/blogs/trade-investment-policy-watch/more-soybeans-trumps-section-301-tariffs-and-chinas-response

[11] A comprehensive timeline of the protectionist measures imposed by the US on its trading partners, beyond the import tariff rates I focus on are available via the Peterson Institute for International Economics (PIIE) at: https://www.piie.com/blogs/trade-investment-policy-watch/trump-trade-war-china-date-guide

3.3.3 Tariff data

To measure the import tariff schedules levied before and after the US-China protectionist policy episode, I use the dataset compiled by Fajgelbaum et al. (2020). The import tariff data is compiled at the monthly variety-level on US imports from January 2017 to April 2019. For my purposes, I focus on the import tariffs levied in 2018. The authors scrape this data from the US tariff schedule, publicly available through the US International Trade Commission (USITC) official documents. The USITC publishes the baseline tariff schedule every January and the revisions to this baseline schedule to reflect any changes made in tariff policy. These revision files document the ad-valorem tariff increases.

The retaliatory tariffs pursued by China is also compiled at the monthly variety-level. China's baseline tariff rates on US exports is the ad-valorem equivalent of the most favoured nation (MFN) rates from the most recent vintage of the WTO Tariff Database. The authors collect the official documentation released by China's Ministry of Finance, detailing the retaliatory tariffs to be implemented over the course of the trade war in this period. The retaliatory tariff is defined as the MFN tariff plus the ad-valorem retaliatory tariff increase. The dataset also compiles a monthly, variety-level panel of trade at the HS-10 level, taken from the US-Census Trade Data, over the same period.[12] I will only be concerned with the US-China trade observations for my purposes. The US Census Trade Data covers the universe of countries at the HS-10 code level, including agricultural and manufacturing sectors.

To estimate the sector-level tariffs levied in this protectionist episode, I map the HS-10 product codes to the most suitable World Input-Output Database (WIOD) sector classification. I create a concordance from the HS-10 (2017 vintage) product codes to the ISIC Revision 4 sector categories at which the WIOD is constructed. To the best of my knowledge, there is no direct concordance table linking the HS-10 product vintage to the ISIC Revision 4 sector classification. The harmonised system (HS) was constructed to serve as a standardized method of identifying traded products. The ISIC, on the other hand, was created to provide a standardized classification of economic activities. In principle, the HS product classifications combine one category of goods and services that are produced by one industry under the international standard industrial classification (ISIC) of all economic activities.

The World Integrated Trade Solution (WITS), developed by the World Bank together with the United Nations Conference on Trade and Development (UNCTAD) and other bodies, provides a crosswalk from the HS-10 2007 vintage to the ISIC revision 3 classification.[13]

I use the United Nations Trade Statistics correspondence tables to move between different

[12]Typically, the US implements tariff increases at the HS-8 code level.
[13]See https://wits.worldbank.org/product_concordance.html

HS vintages, specifically from the 2017 to its 2007 vintage for which the crosswalk to the ISIC revision 3 categories exists.[14] The UN Statistics Division also provides the correspondence tables between different vintages of the ISIC classification. Therefore, I move from ISIC Rev 3 to ISIC Rev 3.1 to ISIC Rev 4.

I aggregate the monthly HS-10 product level data compiled by Fajgelbaum et al. (2020) to arrive at the yearly ad-valorem tariff rate for each HS-10 product. I take an average of all positive ad-valorem tariff rates by HS-10 product. Then, I aggregate tariffs to the ISIC Rev 4 classification, used by the WIOD, weighting each by its traded value as a share of the total value of trade in the ISIC Rev 4 categories. Where one HS-10 product line must be split into multiple ISIC Rev 4 industry categories $(1 : n)$, I divide the total traded value by the number of ISIC categories the product line is split into.

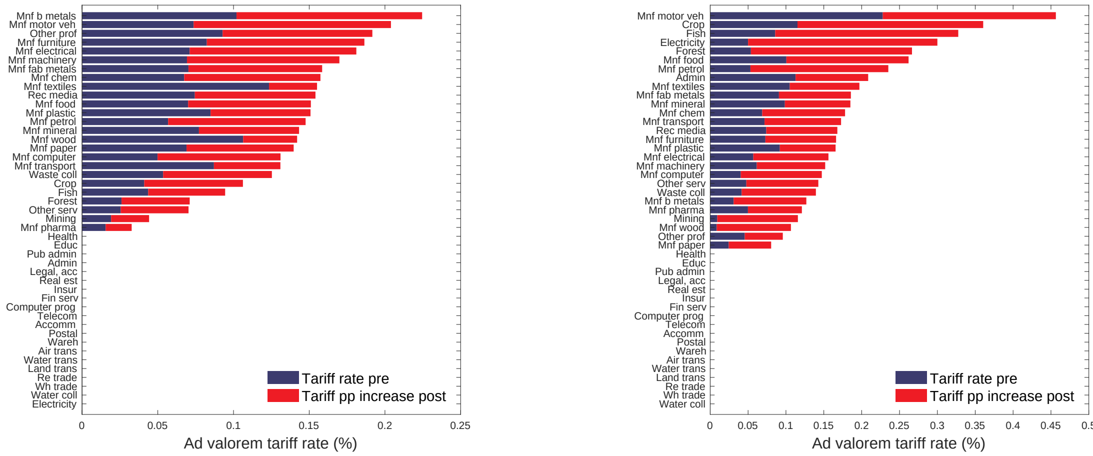
3.3.4 US-China import tariffs

To check the veracity of the tariff rates I estimate at the sector level, I compare the relative protection across sectors to which the targeted products belong. Figure 3.1 provides the sector-level ad-valorem tariff rates levied before and after the protectionist policy episode. The blue bars represent the ad-valorem tariff rates levied before the policy and in red the percentage point increase in the tariff rate following the introduction of the higher tariff rates.

Reassuringly, the relative level of protectionism at the sector level is in line with products targeted by the policy. In Figure 3.1a, US aluminium and steel products, classified under the manufacture of basic metals sector, receives the highest level of protection following the enaction of the import tariff increases. Sectors such as the manufacture of machinery and electricals, which include products the US harboured technology and intellectual property rights concerns over, are amongst the most protected sectors in the US following the tariff increase. The US manufacture of motor vehicles, electrical equipment, and basic metals sectors received the highest levels of protection after the trade war with some of the largest increases in protection. This ordering is in line with Fajgelbaum et al. (2020)'s findings.

In Figure 3.1b, sector-level protection is also consistent with the retaliatory tariffs pursued by China at the product level. China concentrated its retaliatory tariff increases in crop, fishing, manufacture of motor vehicles, and petrol; vehicles, aircraft, vessels, and vegetable products were the primary targets. These products fall under the manufacture of motor vehicles and crop sector classifications, which rank as the most protected sectors in China, following the import tariffs in place after the trade war.

[14] https://unstats.un.org/unsd/trade/classifications/correspondence-tables.asp



(a) US import tariffs

(b) China retaliatory tariffs

Figure 3.1: Tariff increases: The blue bars represent the ad-valorem tariff rates levied before the protectionist trade policy. The red bars detail the percentage point increase in the tariff rates following the trade war.

To supplement the rankings above, in Table 3.1, I provide a summary of the sector-level import tariffs levied by both countries before and after the protectionist trade policy episode in 2018. Columns (4) and (9) detail the new, higher import tariffs levied by the US and China, respectively, used in my baseline scenario. The pre-trade war tariffs are detailed in columns (3) and (8) for the US and China, respectively. Under the counterfactual scenario, these most favoured nation tariffs persist. Columns (5) and (10) list the percentage point increase in import tariffs during the trade war. Columns (6) and (11) list the number of HS2017 products belonging to each WIOD sector classification. Columns (7) and (12) detail the standard deviation of the product specific tariff increase at the HS2017 product level, prior to being weighted by the traded value share of each product code in its respective WIOD sector classification. The variation in tariff changes within a sector classification is low. Nevertheless, to estimate the level of protection at the sector level, products with a higher traded share within a WIOD sector category are assigned a larger weight when computing the weighted average sector-level tariff rate.

Using the WIOD sector classification, the US and China economies are split into 45 sectors. For the US, 26 out of 45 sectors experience some import tariff increase. For China, 27 out of 45 are affected by its retaliatory tariff increases, the additional sector facing higher import tariffs in China is the electricity, gas, steam, and air conditioning supply sector.

Average import tariffs in the US increased from 5.7% to 12%, while in China tariffs increased from 6.4% to 18.5%, where this average only includes the sectors that experienced an ad-valorem tariff rate increase during the trade war period in 2018. Tariffs in the US

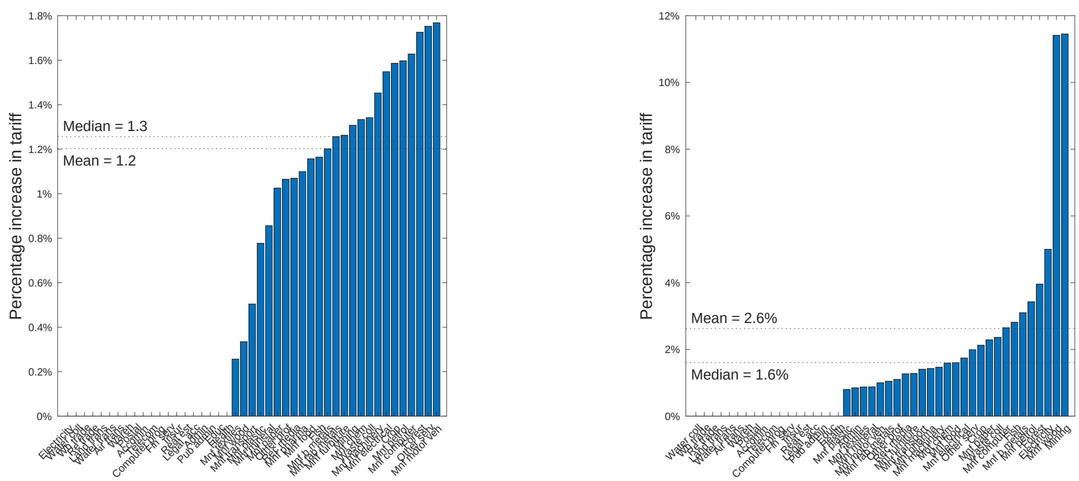
Table 3.1: Average ad-valorem tariff rates imposed by, 2018

		US					China				
WIOD	Code	Pre TW	Post TW	$\%p\Delta$	N	SD	Pre TW	Post TW	$\%p\Delta$	N	SD
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Crop	A01	0.040	0.11	0.070	187	0.050	0.12	0.36	0.25	127	0.13
Forest	A02	0.030	0.070	0.050	111	0.050	0.050	0.27	0.21	84	0.14
Fish	A03	0.040	0.090	0.050	42	0.050	0.090	0.33	0.24	33	0.090
Mining	B	0.020	0.040	0.030	69	0.050	0.010	0.12	0.11	66	0.050
Mnf food	C10-C12	0.070	0.15	0.080	500	0.050	0.10	0.26	0.16	453	0.11
Mnf textiles	C13-C15	0.12	0.16	0.030	919	0.050	0.11	0.20	0.090	633	0.020
Mnf wood	C16	0.11	0.14	0.040	186	0.050	0.010	0.11	0.10	151	0.030
Mnf paper	C17	0.070	0.14	0.070	243	0.050	0.020	0.080	0.060	221	0.030
Rec media	C18	0.070	0.15	0.080	35	0.040	0.070	0.17	0.090	30	0.020
Mnf petrol	C19	0.060	0.15	0.090	452	0.040	0.050	0.24	0.18	405	0.060
Mnf chem	C20	0.070	0.16	0.090	822	0.060	0.070	0.18	0.11	723	0.040
Mnf pharma	C21	0.020	0.030	0.020	96	0.040	0.050	0.12	0.070	55	0.020
Mnf plastic	C22	0.080	0.15	0.070	285	0.080	0.090	0.17	0.070	253	0.020
Mnf mineral	C23	0.080	0.14	0.070	156	0.040	0.10	0.19	0.090	140	0.030
Mnf b metals	C24	0.10	0.22	0.12	321	0.10	0.030	0.13	0.10	315	0.050
Mnf fab metals	C25	0.070	0.16	0.090	337	0.070	0.090	0.19	0.10	299	0.030
Mnf computer	C26	0.050	0.13	0.080	576	0.10	0.040	0.15	0.11	496	0.040
Mnf electrical	C27	0.070	0.18	0.11	433	0.10	0.060	0.16	0.10	398	0.030
Mnf machinery	C28	0.070	0.17	0.10	1163	0.10	0.060	0.15	0.090	1025	0.030
Mnf motor veh	C29	0.070	0.20	0.13	116	0.080	0.23	0.46	0.23	101	0.080
Mnf furniture	C30	0.080	0.19	0.10	214	0.10	0.070	0.17	0.090	166	0.050
Mnf transport	C31-C32	0.090	0.13	0.040	1103	0.090	0.070	0.17	0.10	906	0.030
RI machinery	C33	0.060	0.16	0.090	1569	0.10	0.050	0.15	0.10	1366	0.030
Electricity	D35	.	.	.	.	.	0.050	0.30	0.25	1	.
Waste coll	E37-E39	0.050	0.13	0.070	27	0.030	0.040	0.14	0.10	23	0.020
Publishing	J58	0	0	0	17	0	0.040	0.12	0.080	17	0.020
Cinema	J59-J60	0	0	0	4	0.050	0	0.10	0.10	4	0.030
Archit	M71	0	0	0	1	.	0	0.10	0.10	1	.
Other prof	M74-M75	0.090	0.19	0.10	3	0.060	0.050	0.10	0.050	2	0.040
Admin	N	0	0	0	7	0	0.11	0.21	0.10	7	0.030
Other serv	R-S	0.030	0.070	0.040	77	0.070	0.050	0.14	0.10	67	0.020

Source: Weighted average ad-valorem tariff rates, by sector, pre and post trade war for the US and China. A tariff change of 0.25 indicates a 25 percentage point increase. N denotes the number of products in each sector classification. The standard deviations are computed from the percentage point increase in product-specific tariffs prior to weighting by the traded value share of each product in its WIOD sector classification.

doubled in the trade war period, while the retaliatory tariffs were more severe, with Chinese import tariffs increasing almost three-fold.

There was little overlap in the sectors targeted by the import tariff increases. The sector-level tariff increases had a correlation of 0.16. China's tariff increases on US agriculture, forestry, and fishing more than twice as large as the US' own tariff increases in these sectors. After China's retaliatory tariff increase, the manufacture of motor vehicles sector received the highest level of protection. While, in the US, the manufacture of basic metals was the most protected sector. Figure 3.2 orders sectors by the percentage increase in tariffs following the protectionist trade policy episode. The retaliation by China is much larger, with the final levels of protection for Chinese sectors larger than their US counterparts.



(a) US import tariffs

(b) China retaliatory tariffs

Figure 3.2: Tariff percentage increase

3.4 Quantitative Exercise

3.4.1 Parameterize the economy

In the FPN, I assume a given input-output structure, whereby each sector can only make intensive margin decisions. In the EPN, a sector can make input choices both on the intensive and the extensive margins. I calibrate the baseline equilibrium to real GDP, estimated in the model to match US-China GDP at \$25.081 trillion, to four decimal places, under the trade war tariff rates.[15] In my counterfactual analysis, I assume most-favoured nation tariff

[15]For the analytical expression of real GDP and its derivation, please see the Appendix, Section E. US-China GDP is the total value-added of all US and Chinese sectors present in the analysis.

schedules persist.

The sectoral production functions have the following parameterisation:

$$Y_i = A_i(S_i) K_i^{1-\sum_{j \in S_i} \alpha_{ij}} \prod_{j \in S_i} X_{ij}^{\alpha_{ij}}$$

with the unit cost function and its log equivalent, represented by lowercase notation, for sector i given by:

$$UC_i = \frac{\prod_{j \in S_i} P_j^{\alpha_{ij}} \prod_{j \in S_i} (1+\mu_{ij})^{\alpha_{ij}}}{A_i(S_i)}$$

$$uc_i = \sum_{j \in S_i} (\alpha_{ij} p_j + \alpha_{ij} \log(1+\mu_{ij})) - a_i(S_i)$$

Sector i's Hicks-neutral productivity depends on the set of inputs used by the representative firm, $A_i(S_i)$ and a sector's productivity is parameterised as:

$$A_i(S_i) = B_{i0} \prod_{j \in S_i} B_{ij}$$

where log productivity of sector i, with logs denoted by lowercase letters, is given by:

$$a_i(S_i) = b_{i0} + \textstyle\sum_{j \in S_i} b_{ij}.$$

Each input has its own input-specific productivity term, b_{ij}, and the sector its underlying productivity, b_{i0}.

Taking the log unit cost function, the log productivity of each sector, and substituting for log productivity yields the condition governing whether or not the representative firm in sector i decides to adopt sector j's input in its production process.

$$uc_i = \sum_{j \in S_i} (\alpha_{ij} p_j + \alpha_{ij} \log(1+\mu_{ij}) - b_{ij}) - b_{i0}$$

where input j is employed if $b_{ij} \geq \alpha_{ij} p_j + \alpha_{ij} \log(1+\mu_{ij})$.[16] Intuitively, the representative firm in each sector i decides to adopt an input j, if the productivity gain from employing the input outweighs its purchase costs, or when indifferent. That is, input j is cost-reducing if the connection-specific productivity parameter (b_{ij}) is greater than the unit cost of hiring

[16] In my framework, firms do not incur a separate fixed cost of forming or maintaining a link. This fixed cost is implicit in the input-specific productivity parameter. A bilateral trade connection that may have required high costs would have a relatively higher input-specific productivity parameter in the model. Fixed costs tend to be assumed in models with a continuum of firms to prevent all firms from trading with all others.

said input. The unit cost of input j includes the price charged by firm j, and any positive import tariff levied, weighted by firm i's expenditure share on the input.

I calibrate the model economy to the US-China world input-output table in 2014, using the WIOD, comprising 45 sectors. I exclude nine sectors that have zero capital share and/or where there are no sector-to-sector flows recorded.[17] GDP is the value added of the remaining sectors of the economy.

Following Acemoglu & Azar (2020), I choose the following parameters for the model. For any edge (i, j) observed in the input-output matrix (IOM), the corresponding α_{ij} parameter is set equal to the observed (i, j)th entry in the input-output matrix. For any edge (i, j) not observed in the IOM, the corresponding α_{ij} parameter is set equal to $\alpha_{ij} = 0.95.(1 - \sum_{j'_i} \alpha_{ij'}) \frac{\sum_{i':j \in S_{i'}} \alpha_{i'j}}{\sum_{i',j':j' \in S_{i'}} \alpha_{i'j'}}$. This parameterisation ensures that all observed edges have cost shares equal to the cost shares in the data; all edges that are absent from the 2014 world input-output matrix have cost shares proportional to the observed outdegree of the supplier; and the row sum of the world input-output matrix (including the absent edges in 2014) sum to less than one, to ensure that capital remains an essential input.

I simulate the pairwise productivity parameters using the log unit cost function parameterisation outlined above. The input-specific productivity parameters are simulated such that it is consistent with whether or not there was an active link between each country-sector pair in the input-output table. Zero entries in the input-output table are assumed to have lower productivity, compared to active links. For further details on simulating productivity parameters, please see Section D of the Appendix.

In the post-trade war equilibrium, 55% out of all possible connections with a minimum \$0.0001 transaction value are active in the endogenous production network with trade war tariffs levied. Prior to the trade war, 65% of trade links were present. There is a 10 percentage point fall in the number of trade connections due to the import tariff increases.

To illustrate the mechanisms underlying the model, I will use the US manufacture of computers sector as a case study to walk through the effects of the trade war on the change in the production structure, prices, and the possible sources of log price changes in the model. For a simple two-firm, two-input worked illustration, see Section H of the Appendix.

[17] Excluded sectors: C33: Repair and installation of machinery and equipment; F: Construction; G45: Wholesale and retail trade and repair of motor vehicles and motorcycles; J58: Publishing activities; J59_60: Motion picture, video and television programme production, sound recording and music publishing activities; programming and broadcasting activities; K66: Activities auxiliary to financial services and insurance activities; M71: Architectural and engineering activities; technical testing and analysis; M72: Scientific research and development; M73: Advertising and market research; T: Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use; U: Activities of extraterritorial organizations and bodies.

3.5 Case study: US Manufacture of computers

I consider the US manufacture of computers and walk through the impact of the trade war on this sector, as explained by the model. Table 3.2 lists the changes in the extensive margin for the US manufacture of computers sector. Under pre-trade war tariffs, the US manufacture of computers sector sourced inputs from 67 suppliers and had 66 customers. 26 of its input suppliers were located in China and the remaining were in the US. After the trade war, US manufacture of computers dropped 18 input suppliers in China as well as losing 10 customers abroad.

	Pre	Post	Change
Input suppliers			
US input suppliers	41	41	0
CHN input suppliers	26	8	-18
Total input suppliers	67	49	-18
Customers			
US customers	44	44	0
CHN customers	22	12	-10
Total customers	66	56	-10

Table 3.2: US Manufacture of computers, set of input suppliers and customers

In Figure 3.3, I illustrate the input suppliers and customer base of the US manufacture of computers sector located one step away in the production network. Each node in the figure is a sector, and each edge represents a transaction between the manufacture of computers, its input suppliers, and its customers. The width of each edge corresponds to the cost share of the supplied input in the US manufacture of computers' production process. The nodes located at the top of the chart are input-supplying sectors only, the arrows representing the direction of the flow of goods. Along the bottom of the graph are sectors that both sell to and buy from the manufacture of computers sector. Red nodes are sectors located in China and the blue nodes are US sectors.

How do changes in input prices affect firms' sourcing decisions? How do firms' sourcing decisions affect their customer base? With an increase in production costs, catalysed by the change in trade policy, firms reconsider their intermediate input supplier choices, where inputs that no longer reduce the unit cost of production are dropped from their choice set. This extensive margin choice re-configures the shape of the resulting production network.

In the following two figures, 3.4 and 3.5, I highlight the input suppliers the US manufacture of computers dropped in response to the rise in tariffs, and the fall in the US manufacture of computers' customer base.

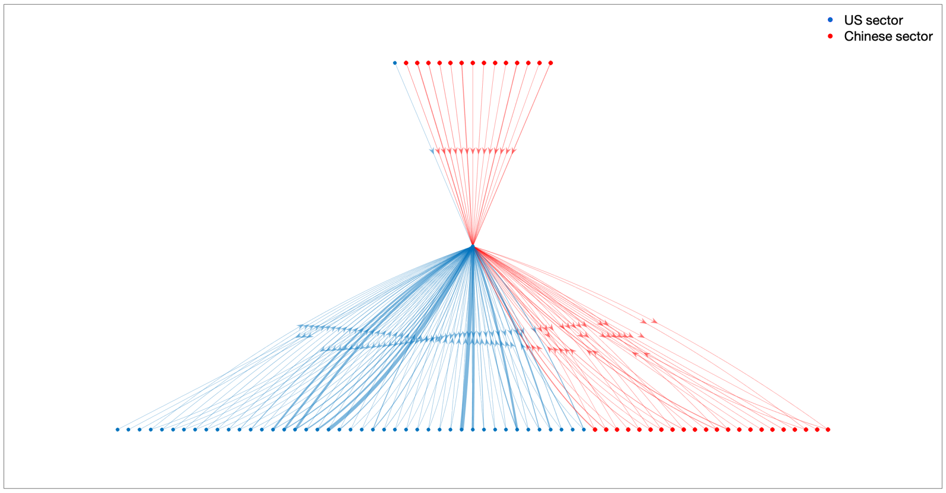


Figure 3.3: US Manufacture of computers, direct supply chain, pre-trade war: This plot shows the direct supply chain for the US manufacture of computers before the trade war. Blue nodes and edges represent a transaction between US sectors; red nodes and edges represent input sales or purchases from a firm in China. The width of the edge corresponds to the cost share of the supplied input in the US manufacture of computers' production process.

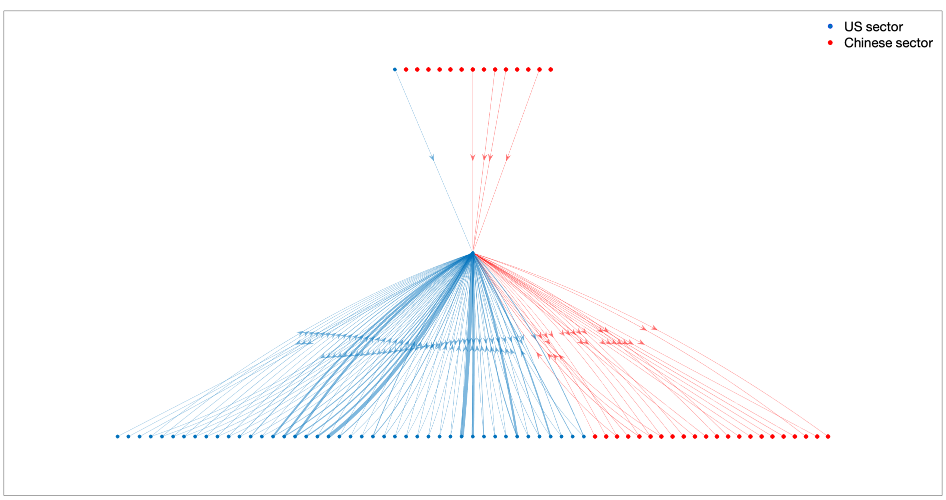


Figure 3.4: Manufacture of computers, input suppliers dropped, post-trade war: This plot illustrates the input suppliers the manufacture of computers sector dropped following the increase in trade tariffs.

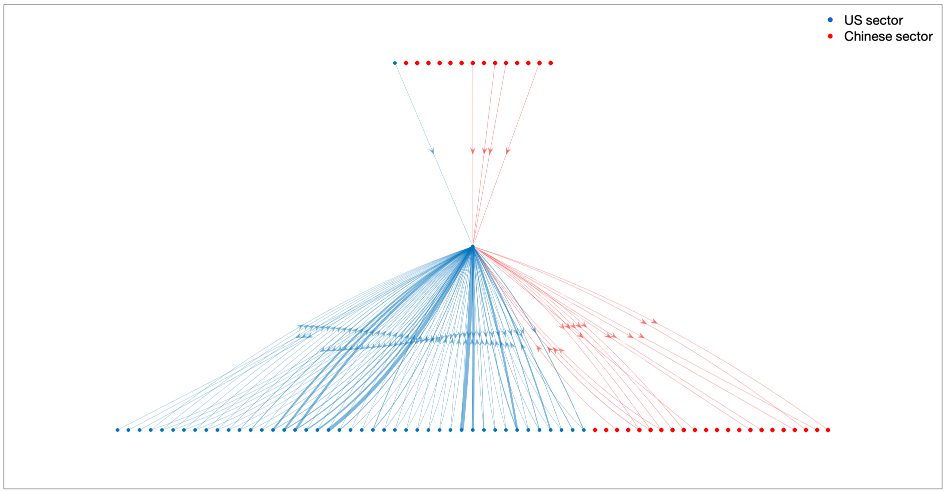


Figure 3.5: Manufacture of computers, customers lost, post trade war: This plot illustrates the input suppliers dropped and the customers lost by the manufacture of computers sector following the rise in tariffs. The direct supply chain becomes increasingly sparse as firms pursue extensive margin adjustments.

3.5.1 Tariff and price quadrants for US computer input suppliers

Figure 3.6 plots all the input suppliers to the US manufacture of computers sector facing a positive tariff rate. The x-axis is the tariff level prior to the trade war and the y-axis the percentage increase in the tariff after the trade war. Nodes in pink indicate the manufacture of computer sector dropped the input supplier after the increase in tariffs. One would expect input suppliers in the top-right and top-left quadrants, i.e. either those suppliers that already had a high tariff rate levied prior to the trade war and a large tariff increase, or with a low tariff levied prior but experiencing a large tariff increase, to be the most likely candidates to be dropped by the purchasing sector. This is, indeed, the relationship exhibited. However, one can also see there are several input suppliers kept in the firm's input set, despite being located in the top-right quadrant, suppliers with a high tariff rate before the protectionist episode and a large percentage increase in the tariff post. This includes China's manufacture of electrical, machinery, chemicals, fabricated metals, and computers. To explain why these suppliers are, nevertheless, kept, I turn to Figure 3.7.

Input suppliers that experienced large tariff increases yet remained in the US manufacture of computers' input set were able to do so for two reasons. First, these input suppliers had a low log price before the trade war; and second, experienced only a small percentage increase in price.

Figure 3.7 depicts a similar taxonomy chart, with log price along the x-axis, and the percentage increase in firm price along the y-axis. Again, one would expect that it is the firms in the top-left or top-right quadrants that are most likely to be dropped. The five sectors kept in the US manufacture of computers' input set, despite the tariffs levied on them, were relatively cheap before the trade war and experienced small price increases following the protectionist policy episode.

Nevertheless, there are also input-supplying sectors located in the bottom left quadrant that the US manufacture of computers drops from its input set post-trade war. Despite having low log prices prior to the trade war, and only experiencing small price increases, the large baseline tariffs, and subsequent tariff increases were sufficiently large, making these inputs too costly to keep in production.

Therefore, it is the combination of an input's price and tariff levels before the trade war, paired with the respective increases in each that determine whether a firm keeps an input in its production set after the import tariff increases.

3.5.2 Model Mechanisms

There are several sources of variation that influence input price changes in the model. In the equations below, I present the log price of input i as a function of the sector's input suppliers' log prices, p_j, the direct ad-valorem tariff rate, $(1+\mu_{ij})$, the cost share of each input in the firm's production set, α_{ij}, and the input-specific and firm-specific productivity parameters, b_{ij}, b_{i0}, respectively.

Equation 3.5 summarises the log price for firm i. Higher input supplier log prices and increases in the ad-valorem tariff rate on imported goods pushes up the log price of firm i. The extent to which the log price of firm i responds to an increase in input supplier prices and tariffs depends on the cost share of each input supplier in firm i's production process. Intermediate goods with higher input-specific productivity, in addition to a higher baseline firm productivity both work to reduce the log price.

$$p_i = \sum_{j \in S_i} (\alpha_{ij} p_j + \alpha_{ij} \log(1+\mu_{ij}) - b_{ij}) - b_{i0} \tag{3.5}$$

Taking the partial derivative of log price with respect to the log of the ad-valorem tariff rate gives the direct effect of a change in log tariffs on the log price of sector i: $\frac{\partial p_i}{\partial \mu_{lij}} = \frac{\partial p_i}{\partial p_j} = \alpha_{ij}$, where $\log(1+\mu_{ij}) = \mu_{lij}$. The increase in the price of sector i due to tariff rate increases depends on the input's cost share in sector i's production process. The higher sector i's

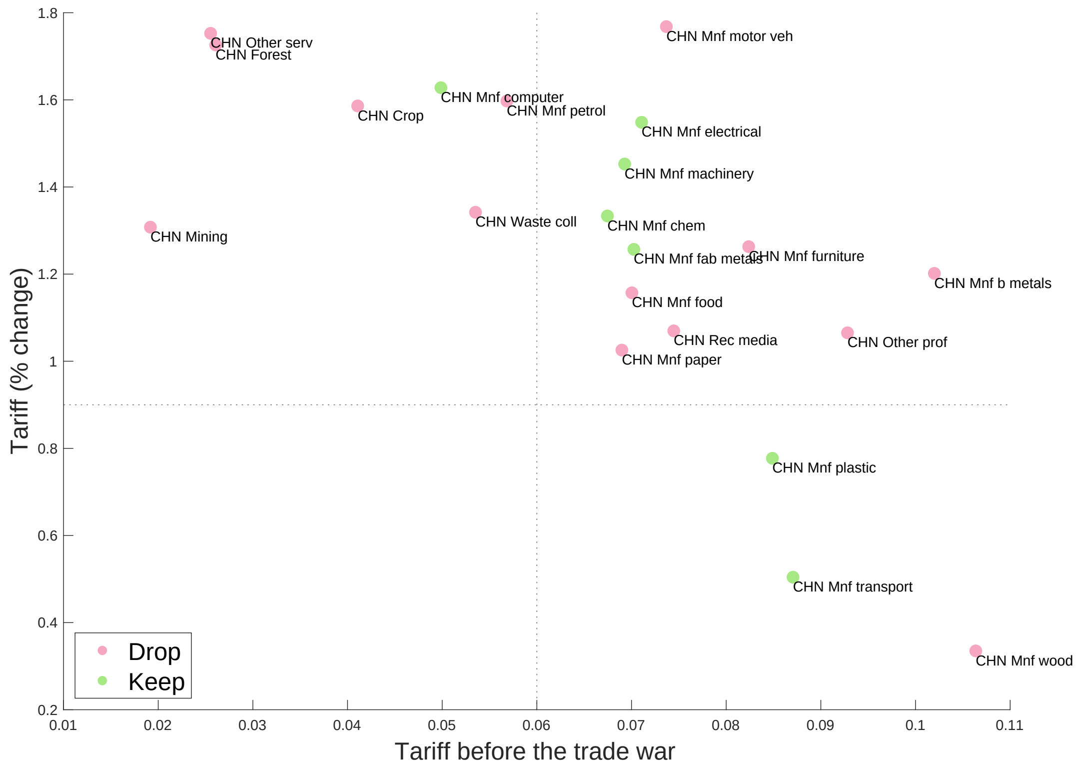


Figure 3.6: Input supplier tariff changes: This figure plots the China input suppliers of the US manufacture of computers input suppliers and the associated tariff level prior to the trade war and the percentage increase in the tariff post. Nodes in pink indicate the input supplier was dropped after the increase in tariffs. The quadrants provide a taxonomy of whether the input supplier to US manufacture of computers had a low vs high tariff level prior to the trade war, and a low vs high percentage increase in the tariff rate. It is primarily sectors that experienced large increases in tariffs there were dropped, and were found in the upper-left and upper-right quadrants.

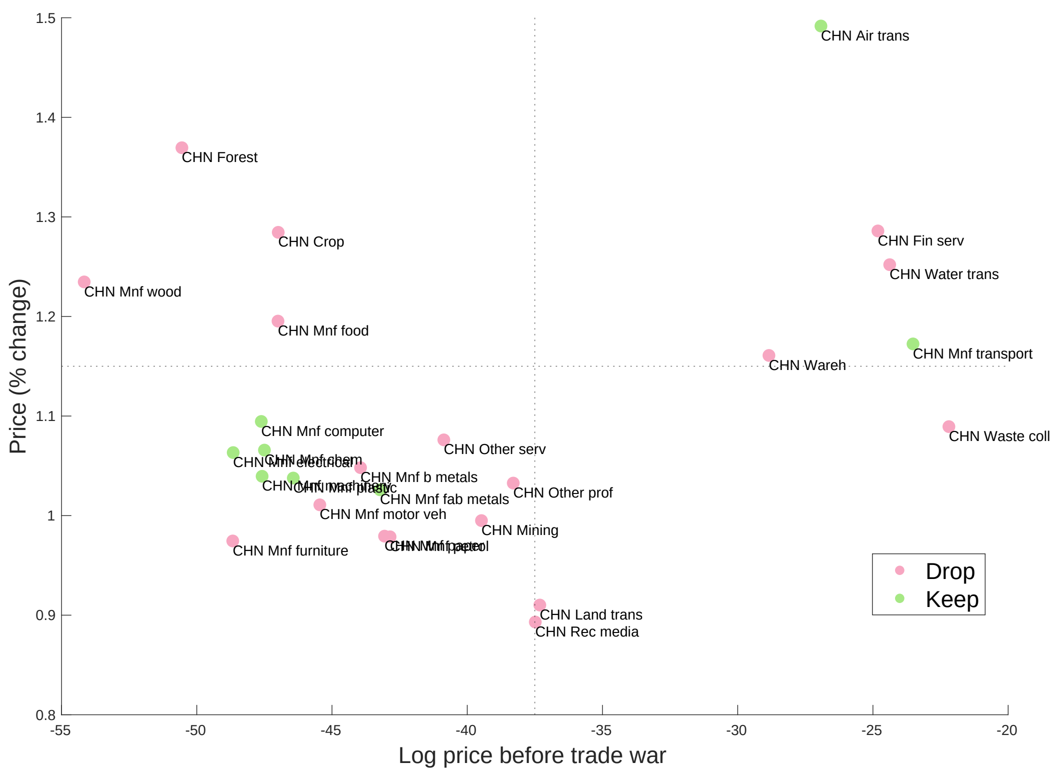


Figure 3.7: Input supplier price changes: This figure plots the China input suppliers to the US manufacture of computers input suppliers and their associated log price prior to the trade war and the percentage increase in price post-trade war. Nodes in pink indicate the input supplier was dropped after the increase in tariffs. The quadrants provide a taxonomy of whether the input supplier to US manufacture of computers had a low vs high log price prior to the trade war, and a low vs high percentage increase in the price post.

expenditure share on each taxed input, the larger sector i's associated price increase will be if the suppliers remain in the production set.

Rewriting Equation 3.5 for firm j and substituting for p_j yields Equation 3.6. Prior to the trade war, most-favoured nation tariffs were maintained for traded inputs between China and the US. However, once the US raised import tariffs and China followed with its retaliatory rates, the cost to import increased. This increase in cost has a two-fold effect. There is a direct cost increase for firm i. When considering whether to continue employing some imported input j in its set S_i, it must ensure the higher import tax does not outweigh the productivity benefit of employing input j, the b_{ij} term. Second, there is an indirect cost increase. Firm i's unit costs depend on its suppliers' prices, which themselves are dependent on the import tariff firm j may incur on its own imported inputs. Under the new higher rates, the input-specific productivity must continue to exceed input hiring costs. If this condition no longer holds under the higher import tariff equilibrium, a firm will sever its ties with supplier j in order to reduce its costs of production.

$$p_i = \sum_{j \in S_i} \left(\alpha_{ij} \left(\sum_{i \in S_j} \alpha_{ji} p_i + \sum_{i \in S_j} \alpha_{ji} \log(1 + \mu_{ji}) - a_j(S_j) \right) + \alpha_{ij} \log(1 + \mu_{ij}) - b_{ij} \right) - b_{i0} \tag{3.6}$$

The first inputs to be dropped will be those with the lowest input-specific productivity coefficient, where even a small increase in costs deems them unemployable, or inputs that experience particularly high tariff hikes for their given input-specific productivity parameter.

I provide a simple two-firm, two-input application to illustrate the workings of the model in Section H of the Appendix. Firm 1, the US manufacturer of computers, directly depends only on firm 2, the Chinese manufacturer of basic metals, to produce its output, and vice versa. In a more complex example that one would expect to observe in practice, the Chinese manufacture of basic metals may rely on its own set of input suppliers, where these input suppliers' pricing decisions will then indirectly enter into the final price charged by the US manufacture of computers. Again, the indirect effects will include the price charged by China's manufacture of basic metals suppliers, dictated by their suppliers' suppliers, ad infinitum.

Therefore, sectors that may not face immediate tariff increases, or face only small direct increases, may nevertheless experience non-negligible price increases. Such firms indirectly incur additional tariff costs, paying much higher prices for intermediate inputs, as their set of input suppliers may be facing tariff increases. While these indirect effects are tempered by the cost share of each input in the firm's production process, the degree to which the effect of the tariff increase is diluted will depend on the cost shares throughout the production network.

Taking the extensive margin condition for each sector i, let the difference between the input-specific productivity and the cost associated with hiring some input j as G.

$$G_i = b_{ij} - \alpha_{ij} p_j - \alpha_{ij} \log(1 + \mu_{ij})$$

If $G_i \geq 0$, it is worthwhile for firm i to hire input j, otherwise the sector drops the input from its choice set.

$$dG = -\sum_{j \in S_i} \alpha_{ij} dp_j - \sum_{j \in S_i} \alpha_{ij} d\mu_{lij}$$

Whether some input j will continue to be hired by sector i after the trade war depends on the initial gap between the input-specific productivity parameter and the associated input cost to the sector, the change in the log price of sector j's input, and the change in the log ad-valorem tariff rate. The larger the initial difference between an input's productivity parameter and cost, the less likely it will be dropped due to the increase in tariffs.

The upper panel of Figure 3.8 details the price increase of input suppliers to the US manufacture of computers. In the lower panel, I include the import tariff percentage increase levied by the US on imports from the respective Chinese sector. In red I highlight the sectors dropped by the US manufacture of computers following the increase in import tariffs.

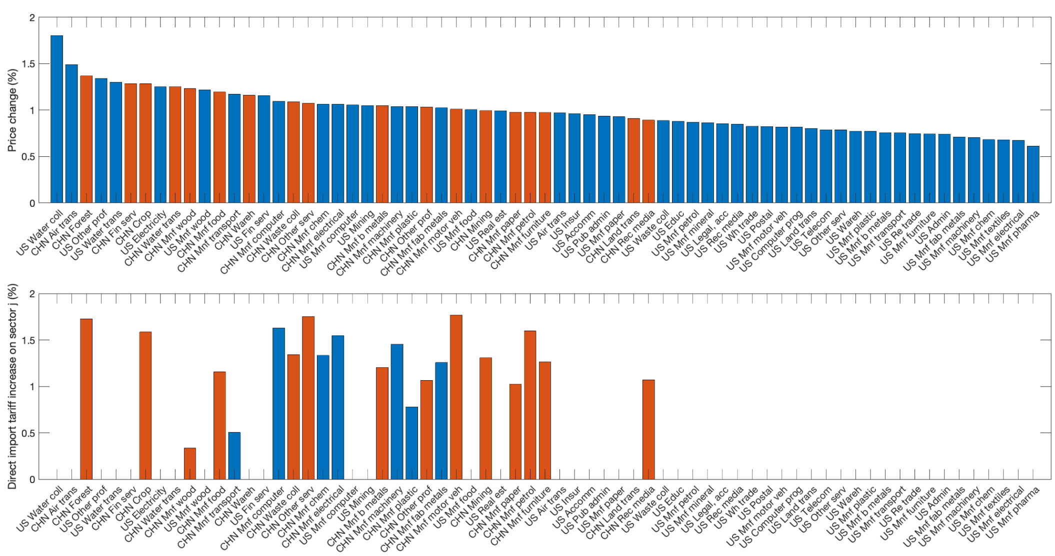


Figure 3.8: This plot illustrates the log price change for each input used by the US manufacture of computers and the associated direct tariff increase. Sectors in red were dropped by the US manufacture of computers following higher import tariffs.

As illustrated, it is not only sectors that experience large direct import tariff increases that are dropped by the US manufacture of computers. For example, China's manufacture of wood sector experiences a tariff increase of just under 0.5%, yet it is nevertheless dropped when considering its price increase after the trade policy. In this case, the price increase is partially due to the rise in the import tariff, but more sizeable is the indirect effect of input suppliers selling to the Chinese manufacture of wood sector that pushes up the price by 1.4%.

Despite dropping 18 input supplying sectors, the US manufacture of computers sector experiences a 1.06% increase in its price. The cost savings of dropping some input suppliers is, nevertheless, outweighed by the cost increases driven by the rise in import tariffs. Although the US manufacture of computers sector avoids the direct tariffs of each dropped input supplier, it faces indirect tariff effects through the input suppliers remaining in its production set.

Why is the price increase larger in the fixed as compared to the endogenous production network? Firms in the endogenous model are able to substitute away from input suppliers that are no longer cost-reducing under the higher tariff rates, while in the former case firms, by construction, cannot.

In the EPN, firms will check whether an input supplier remains cost-reducing under the new, higher import tariffs. If the input-specific productivity parameter associated with some input j exceeds the unit cost of hiring said input, the firm will continue to employ the input in its production process. Otherwise, it will cut this connection in an effort to reduce its production costs. However, under the FPN, firms must continue to purchase from a given input set. While a firm can make intensive margin adjustments, reducing how much it purchases of this set of inputs, it cannot reshuffle its intermediate input set.

3.6 Fixed versus Endogenous Production Network

In this section, I discuss the differences between the fixed and endogenous production network model estimates. In the FPN, sectors can only make intensive margin adjustments to their production decisions. Under the EPN, sectors have an additional margin of adjustment via the extensive margin. Input suppliers that are no longer feasible for use under the new set of higher prices, given the import tariff rises, can be dropped.

The first point to note in panel a) of Table 3.3 is the protectionist policy episode had a larger impact on price increases in the fixed as compared to the endogenous production network. Under the FPN, average prices in the US increase by 1.6%, and by just over 2% in China. Prices follow a similar pattern in the EPN, but with more muted increases in both

Table 3.3: Fixed vs endogenous production network comparison

	Fixed			Endogenous		
Variable	US	China	Total	US	China	Total
a) Price (%Δ)						
Mean	1.58	2.05	1.74	1.01	1.28	1.08
Median	1.40	1.79	1.68	0.86	1.08	1.02
Min	1.08	1.53	1.08	0.61	0.89	0.61
Max	2.70	3.26	3.26	1.80	2.17	2.17
SD	0.36	0.34	0.40	0.26	0.23	0.27
Skew	1.42	1.96	1.05	1.57	2.36	1.37
b) Input sales (%Δ)						
Mean	-3.80	-5.88	-4.50	-8.31	-35.10	-15.04
Median	-3.72	-5.96	-4.79	-8.41	-37.32	-15.97
Min	-5.63	-7.45	-7.45	-18.67	-61.90	-61.90
Max	-3.05	-3.86	-3.05	-2.79	-13.26	-2.79
SD	0.56	0.75	1.26	3.14	9.06	16.05
Skew	-1.39	0.45	-0.22	-0.53	0.02	-0.38
d) Input purchases (%Δ)						
Mean	-4.53	-7.15	-5.41	-10.93	-42.06	-18.75
Median	-3.74	-5.86	-4.61	-8.23	-36.58	-17.20
Min	-10.91	-11.27	-11.27	-31.65	-92.06	-92.06
Max	-0.06	-0.29	-0.06	-0.06	-1.65	-0.06
SD	2.46	2.65	2.73	7.53	19.51	20.43
Skew	-0.89	-0.04	-0.41	-1.09	-0.44	-1.02

Notes: Percentage change by sector is aggregated by taking the weighted average across all sectors. Weights are given by sector share in value-added after the trade war. The 'Total' columns weight variables by sectors' value-added share as a ratio of world value-added, while the 'US' and 'China' columns weight by sectors' value-added share as a ratio of the country's value-added totals.

countries. Given China's higher retaliatory tariffs, its higher price increases are unsurprising.

Second, there are larger adjustments in trade flows between sectors under the EPN. Under the endogenous model, US input purchases fall by 11% under higher import tariffs, while in the fixed network fall by 4.5%. The decline in US sector input sales follows a similar pattern across the two models, dropping from 8% to just under 4% in the fixed network framework. There is a larger decline in transaction flows in the endogenous production network as firms can drop suppliers according to the extensive margin condition. Where an input is deemed to be cost increasing rather than cost reducing, under the higher tariff regime, a firm's demand of the input falls from some positive amount to zero.[18] Under the FPN, firms cannot cut connections from their existing set of suppliers even though it may be cost reducing to do so. Thus, firms continue to purchase costly intermediate inputs, where the decrease in demand is more muted. Input purchases for a US sector fall by 4.5% on average, and by 7% for the average Chinese sector.

Thirdly, input purchases fall by more than input sales. The intermediate input purchases made by the average sector declines by more than the sales it makes to its customer sectors following the tariff increases. Input purchases by US sectors fall by 10% while its input sales fall by slightly less at 8%. For its Chinese counterparts, input purchases fall by 42% while its sales fall by 35%. Moreover, relatively modest price increases have large reallocation effects in sectors' purchase choices and subsequent sales. Trade flows have a much higher variation as compared to price increases.

3.7 The Endogenous Production Network

3.7.1 Overall network effects

I now focus on the EPN and consider the changes in the production structure following the trade war. Under the EPN scenario, sectors can make extensive margin decisions, with the possibility of severing connections that are no longer on net beneficial due to the rising tariffs increasing suppliers' prices.

Table 3.4 details the counterfactual changes in the network. Before the protectionist trade policy pursued by the US and China, 65% of trade connections were active out of the total potential links. Following the policy, 819 fewer trade linkages were present, representing a 10% point fall in connectivity. Assuming no tariff revenue is rebated, total GDP falls by 1.6% under the FPN and by 1.0% under the EPN. The former framework overestimates

[18] For further discussion of discontinuous effects and efficiency, please refer to Section C and B in the Appendix.

Table 3.4: Counterfactual changes in the production network

	Pre	Post		
		FPN	EPN	Diff
Active Links	5303	5303	4484	-819
Share of active links (%)	65	65	55	-10
GDP loss (%)	.	-1.6	-1.0	-0.6

Notes: The table shows the active links in each of the production network models and the change following the trade war. There are a total of 8100 potential trade links.

GDP loss by a factor of 1.6.

3.7.2 Network summary statistics

Table 3.5 presents the counterfactual changes in the aggregate network summary statistics. The indegree is a measure of how many suppliers a sector purchases inputs from for its production process. The statistic is weighted by each inputs' expenditure share in a sector's production technology. After the trade war, sectors were buying from fewer input suppliers. Similarly, a sector's outdegree, the number of customers a sector sells its output to, also fell.

Table 3.5: Counterfactual changes in network summary statistics

	Pre	Post	%Δ	p-value
Indegree	0.5841	0.5149	-12	0.0000
Outdegree	0.6219	0.5604	-10	0.0000
Centrality	0.01106	0.01090	-1	1.0000
Diameter	2	3	50	.
Distance	1.3451	1.4569	8	.
Density	0.6547	0.5536	-15	.

Notes: The table shows network summary statistics before and after the trade war. Sector-level indegree, outdegree, and centrality statistics are aggregated by taking a weighted average using sector value added in the corresponding period.

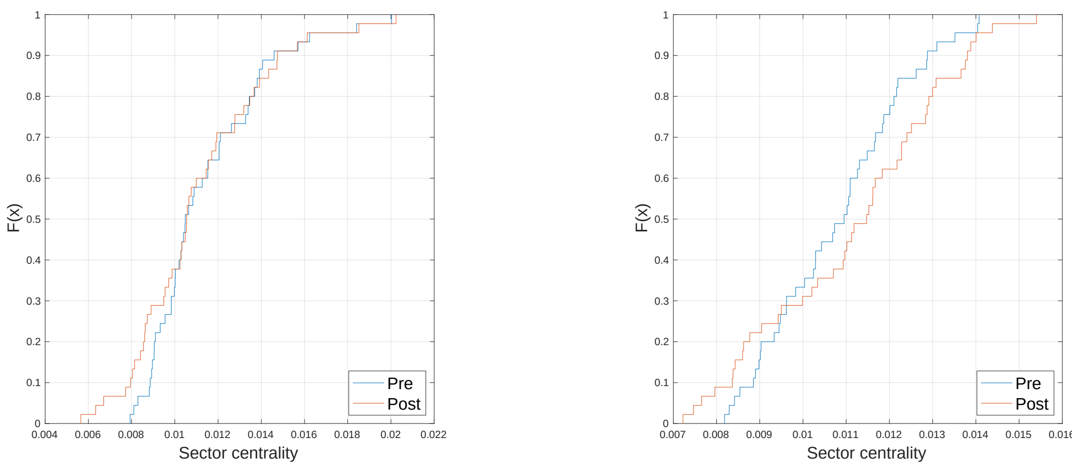
The fall in both degree metrics is consistent with a lower density network. Fewer connections between trading sector pairs increases the diameter of the network. The diameter is the longest geodesic in the network, where geodesic refers to the shortest path between two sectors. The shortest distance between two sectors increases from two to three steps after the trade war.

The network distance, or average path length, also increases after the trade war. It is calculated by finding the shortest path between all sector pairs, summing them together, and dividing by the total number of pairs in the network. Prior to the trade war it took 1.3 steps to reach another sector, while after the trade war it took 1.5 steps.

The table above highlights three important points. First, sectors purchased from a smaller set of input suppliers. Second, sectors also sold output to a more limited set of customers. Thirdly, this combination led to a sparser network where destroyed links increased the distance between sector pairs.

3.7.2.1 Sector centrality

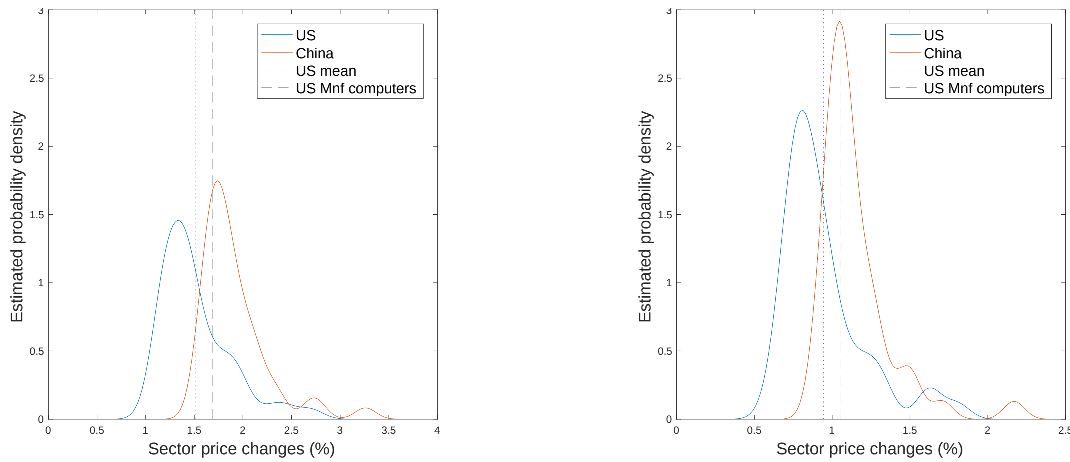
Sector centrality also experiences a small decline. Sector centrality is measured using eigenvector centrality, where a sector is described to be more central in the production network if its neighbouring sectors themselves are well-connected. I use the Katz-Bonacich measure that assigns each sector a centrality score that is the summation of some baseline centrality (equal across all sectors) and the centrality score of each of its downstream sectors. Downstream sectors located further away in the network, are given smaller weights.



(a) US (b) China

Figure 3.9: Empirical cumulative distribution function of sector centrality: The left-hand panel highlights the changes in US sector centrality before and after the trade war, with the right-hand panel for China.

Following the protectionist trade policy episode, sector centrality falls by 1%. While the mean decline in centrality is small, there is a concentrated decline in sector centrality at the bottom of the distribution in both countries. The probability of being a low centrality sector increases after the trade war. This shift is more pronounced along China's empirical CDF, where a sector is more likely to be peripheral, and less likey to be as central when compared to its centrality score before the trade war.



(a) Fixed production network

(b) Endogenous production network

Figure 3.10: Price distribution: The two panels illustrate the estimated probability density function of the sector-level price changes due to the trade war in the US (in blue) and China (in red). The left figure considers the fixed production network where sectors can only make intensive margin decisions. The right panel plots the price change distribution where sectors can make both intensive and extensive margin decisions regarding their production process. Higher price increases are more likely under the fixed production network where firms have one less margin of adjustment when facing higher import tariffs as compared to the endogenous production network.

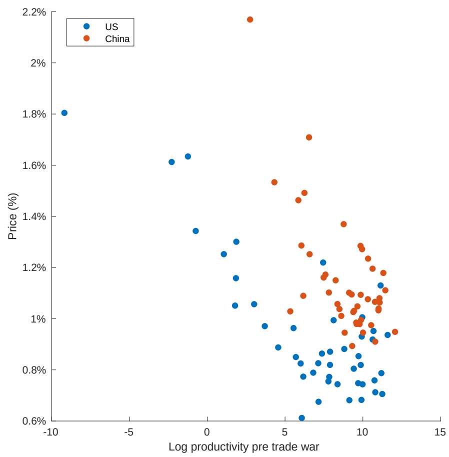
3.7.2.2 Price change distribution

The rise in import tariffs increases the equilibrium vector of prices after the trade war. Sector prices depend directly on tariffs levied on inputs imported from abroad, and indirectly via sectors' input suppliers who themselves may import goods in their production process.

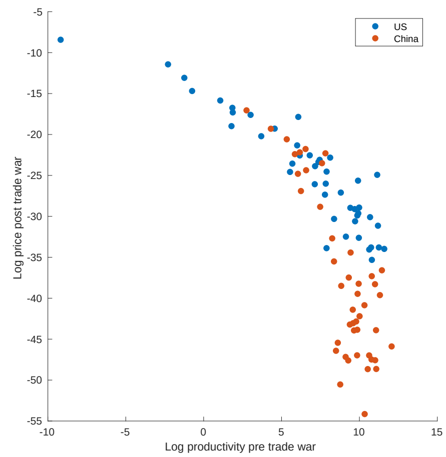
Plotting the kernel density function of the percentage change in the price vector for both countries highlights the price increase is borne out in both countries. China experiences a greater increase in prices compared to the US, with China's probability density function located further right. Both distributions are positively skewed, with the median price increase for a sector in the US and China being 1.6% and 2.0%, respectively.

The price rise in the EPN is more muted. The mass of the distribution is concentrated at lower expected price increases, with the majority of sector prices in the US increasing by 0.7%, and for China not more than 1.1%. Failing to account for the extensive margin of adjustment in the FPN leads to a sizeable overestimation of the expected price increase associated with the rise in tariffs.

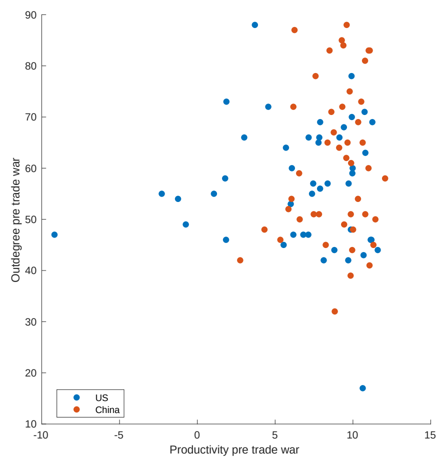
Why are there higher price increases in China as compared to the US? China, on average, levied higher tariffs in retaliation to the US' protectionist trade policy. As a consequence,



(a) Price changes



(b) Log prices after trade war



(c) Customers pre trade war

Figure 3.11: Sector-level price changes: Each blue dot represents a US sector, and each red dot a sector in China.

Chinese producers face larger rises in their production costs when sourcing intermediate inputs from abroad as a result. Hence, the overall inflationary effects of tariffs are more pronounced in China, where the tariff hikes were relatively more severe.

In Figure 3.11, I highlight lower productivity sectors experienced larger price increases, and had a higher log price following the rise in import tariffs, compared to their more productive counterparts. In Figure 3.11a, low productivity sectors before the trade war experienced larger price increases. There is a strong negative correlation between log productivity and the percentage change in sector prices of -0.53. Each blue dot represents a US sector, and each red dot a sector in China. Taking the correlation for the US and China separately, both have a much stronger negative correlation, of -0.8 and -0.68, respectively. Prices charged by Chinese sectors also increase more than their US counterparts for a given log productivity.

From Figure 3.11b, lower productivity sectors prior to the trade war had the highest prices after the trade war. Again, there is a strong negative correlation of -0.76. For the same decrease in productivity, price increases are larger in China as compared to the US, as seen in the steeper slope of the set of Chinese sectors. These effects are partially explained by the higher import tariffs in place prior to the trade war, and also that the retaliatory tariffs were of a larger magnitude than those enacted by the US.

Sectors with higher productivity prior to the trade war had more customers after the trade war, as illustrated in Figure 3.11c. Higher sector productivity has two benefits. First, higher sector productivity for a given set of inputs helps keep sector prices lower. Second, it gives sectors a larger productivity buffer when facing higher import tariffs. Although import tariffs push up prices, the relative price inflation will be lower for these sectors compared to sectors that were less efficient prior to the tariff hikes. High productivity sectors prior to the trade war passed on smaller price increases to their customers, relative to their low productivity counterparts.

3.8 Conclusion

The 2018 US-China trade war is an important recent, protectionist policy episode. Its sudden introduction in the US and China's retaliatory tariffs, makes it a well-defined, exogenous policy change. I develop a tractable endogenous link formation model to quantify how rising production costs affect trade connections, prices, and output. In this framework, I quantify the bias associated with abstracting away from the reorganisation of trade connections between firms. In my model, firms produce output using an essential input and a set of intermediate inputs. The model environment accommodates connection-specific distortions with import tariffs levied at the sector-to-sector level on US-China bilateral trade.

In the EPN, firms have two margins of adjustment. Firms choose the set of intermediate inputs used in production alongside capital, and how much of each to buy. An intermediate input is kept in a firm's production set only if it is cost-reducing. Each intermediate input has an associated input-specific productivity to the firm, which must be greater than the cost of purchasing said input, to be kept in production. The rise in import tariffs, as a consequence of the trade war, increases the costs of keeping the input in employment.

In the FPN, I shut down this extensive margin of adjustment. Each firm has a given set of intermediate input suppliers from which to purchase. This limits firms' ability to substitute away from more costly intermediate inputs. In this framework, I estimate the model parameters and then perform a counterfactual analysis. I compare how prices and GDP behave across the two models, where optimising firms have different margins of adjustment.

I find a 1% GDP loss in the EPN, where sectors make adjustments on both margins, as compared to a 1.6% loss in the FPN. Analysis failing to account for network endogeneity overestimates the losses associated with distortionary import tariff increases by 60 percent. It also highlights protectionist policy measures that discourage intermediate input trade can be more economically damaging where trading sectors do not have the opportunity to sever ties. Severing trade ties under higher import tariffs has real economic consequences: increasing prices, reducing the volume of intermediate input trade, and reducing a sector's set of input suppliers and buyers leaving a sparser trading network. While the fall in trade flows is larger in the EPN, the additional margin of adjustment tempers the rise in intermediate input prices.

Accounting for endogenous link formation in international sourcing decisions is important when quantifying the real impact of distortions. Protectionist trade policies have both direct and indirect impacts on an individual sector. Recognising a sector's wider role as an input supplier and buyer in the production structure highlights how increases in production costs may be magnified. The consequences of protectionist trade policy are felt not only in the local economy but in connected foreign ones as well.

3.9 Appendix

A Profit maximisation

Following Acemoglu & Azar (2020), the representative firm in sector i has the following profit function:

$$\Pi_i(S_i, A_i(S_i), P, K_i, X_i) = P_i \zeta_i A_i(S_i) K_i^{1-\sum_{j\in S_i}\alpha_{ij}} \prod_{j\in S_i} X_{ij}^{\alpha_{ij}} - \left(\sum_{j=1}^{n}(1+\mu_{ij})P_j X_{ij}\right) - K_i$$

where ζ_i is included as a normalisation to simplify the first-order conditions for the firm's profit maximisation problem. The representative firm earns revenue from its output sales while facing an edgewise distortion, μ_{ij}, proxied by an ad-valorem tariff on imports of intermediate goods, plus the costs of capital. For my purposes, I assume this distortion is zero for domestic intermediate input purchases and may be positive when purchasing imported intermediate inputs.

To determine equilibrium prices and quantities, I start with the firm's profit maximisation problem. Each representative firm (sector) i chooses the quantity of capital and intermediate inputs it demands from other sectors j in the economy to maximise its profits, Π_i, taking all prices $(p_1, p_2, ..., p_n)$ and the rental rate of capital, R, as given. I set the rental rate of capital to be the numeraire, so $R = 1$. Note that the productivity term is a function of the set of inputs used by the sector, S_i. In the FPN, the set of inputs used by each sector i is exogenous; each sector starts with a given set of inputs and can only make an intensive margin decision as to what quantity of capital and intermediate inputs it demands to maximise profits (minimise costs). That is, the set, S_i, is not a choice variable for the representative firm. In the EPN, the set of inputs is chosen by the firm and has this additional dimension along which to optimise, making input adjustments along both the intensive and extensive margin.

The firm's first-order conditions (FOC) are:

$$\frac{\delta \Pi_i}{\delta X_i} = 0 \Rightarrow \quad P_j X_{ij}^* = P_i (1+\mu_{ij})^{-1}\alpha_{ij}, \tag{3.7}$$

$$\frac{\delta \Pi_i}{\delta K_i} = 0 \Rightarrow \quad K_i^* = P_i\left(1 - \sum_{j\in S_i}\alpha_{ij}\right). \tag{3.8}$$

Note $UC_i(S_i, A_i(S_i), P) = P_i = \frac{K_i^*}{(1-\sum_{j\in S_i}\alpha_{ij})} = \frac{\prod_{j\in S_i} P_j^{\alpha_{ij}} \prod_{j\in S_i}(1+\mu_{ij})^{\alpha_{ij}}}{A_i(S_i)}$, where the price of good i is equal to the firm's marginal cost inclusive of the distortion. Dividing the first partial derivative w.r.t X_i, by the partial derivative w.r.t K_i gives the following expression in terms of prices, the alpha exponents, and the productivity scalar for a given set of inputs:

$$X_{ij}^* = \frac{\alpha_{ij}}{\left(1 - \sum_{j \in S_i} \alpha_{ij}\right)} \frac{1}{(1+\mu_{ij})} \frac{K_i^*}{P_j^*} \tag{3.9}$$

Why would a firm choose to employ an input with a relatively low input-specific productivity prior to the increase in import tariffs, while not after the trade war? Why does each firm not employ the single most productive input? Employing the single most productive input is not a guarantee that firm profits will be maximised. The firm may be able to achieve a larger reduction in its production costs if it employed a set of inputs over and above employing one. Recall, that the log unit cost function is a summation of all the intermediate inputs included in the production technology. Therefore, while employing a single very productive input j will lead to a large fall in the unit cost of production, the firm may be able to do better by employing another input k. While input k is still productive, but less productive than input j, as long as the input-specific productivity of input k exceeds its associated costs (the price of input k and the associated import tariff levied if imported from abroad), then the firm will be able to further increase its profits by including input k in its production technology. Although overall productivity may fall when employing input k, the firm is acting to maximise its profit function (or minimise its cost function), not to maximise its productivity term. Hence, lower overall firm productivity and lower unit costs of production are not mutually exclusive in this environment. Lower general equilibrium prices allow less efficient inputs to be employed as long as its price and firm i's expenditure on input k do not exceed input k's input-specific productivity.

While the following condition holds a firm will employ input k:

$$A_i(S_{i+k}) - A_i(S_i) < \left(\prod_{j \in Si+k} p_j^{\alpha_{ij}} \prod_{j \in S_{i+k}} (1+\mu_{ij})^{\alpha_{ij}} \right) - \left(\prod_{j \in Si} p_j^{\alpha_{ij}} \prod_{j \in S_i} (1+\mu_{ij})^{\alpha_{ij}} \right)$$

As long as the overall productivity decrease is smaller than the associated cost increase of employing input k, it will be in the best interests of firm i to add it to its production technology. It is when using an additional input k tips the balance such that the fall in overall productivity is greater than the cost increase, does a firm omit input k from its production function.

A.1 Deriving equilibrium prices

Plugging in the expression for X_{ij}^* into the firm's production function to produce one unit of output:

$$1 = \frac{1}{\left(1-\sum_{j\in S_i}\alpha_{ij}\right)^{1-\sum_{j\in S_i}\alpha_{ij}}\prod_{j\in S_i}\alpha_{ij}^{\alpha_{ij}}} A_i(S_i) K_i^{1-\sum_{j\in S_i}\alpha_{ij}} \prod_{j\in S_i}\left(\frac{\alpha_{ij}K_i^*}{\left(1-\sum_{j\in S_i}\alpha_{ij}\right)P_j^*(1+\mu_{ij})}\right)^{\alpha_{ij}},$$

$$1 = \frac{1}{\left(1-\sum_{j\in S_i}\alpha_{ij}\right)^{1-\sum_{j\in S_i}\alpha_{ij}}\prod_{j\in S_i}\alpha_{ij}^{\alpha_{ij}}} K_i^* A_i(S_i)\left(1-\prod_{j\in S_i}\alpha_{ij}\right)^{-\sum_{j\in S_i}\alpha_{ij}} \frac{\prod_{j\in S_i}\alpha_{ij}}{\prod_{j\in S_i}P_j^{*\alpha_{ij}}\prod_{j\in S_i}(1+\mu_{ij})},$$

$$1 = \frac{K_i^* A_i(S_i)}{\left(1-\sum_{j\in S_i}\alpha_{ij}\right)\prod_{j\in S_i}P_j^{*\alpha_{ij}}\prod_{j\in S_i}(1+\mu_{ij})}$$

This yields:

$$K_i^* = \frac{\left(1-\sum_{j\in S_i}\alpha_{ij}\right)\prod_{j\in S_i}P_j^{*\alpha_{ij}}\prod_{j\in S_i}(1+\mu_{ij})^{\alpha_{ij}}}{A_i(S_i)} \tag{3.10}$$

Equating K_i^* to the firm's FOC expression in 3.8 of K_i^* I get:

$$P_i^* = \frac{\prod_{j\in S_i}P_j^{*\alpha_{ij}}\prod_{j\in S_i}(1+\mu_{ij})^{\alpha_{ij}}}{A_i(S_i^*)} \quad \forall i \tag{3.11}$$

Higher intermediate input prices and tariffs will push up sector i's prices, while higher sector productivity, as dictated by the sector's chosen input set, will reduce prices.

Taking logs on both sides:

$$p_i = \sum_{j\in S_i}\alpha_{ij}p_j + \sum_{j\in S_i}\alpha_{ij}\log(1+\mu_{ij}) - a_i(S_i), \forall i$$

where lowercase symbols denote variables in logs.

Equilibrium log prices are given by a system of linear equations:

$$p = -\left(I-\alpha(S)\right)^{-1}\left(a(S) - (\alpha(S)\odot\eta)\mathbf{1}\right)$$

where $\eta = \log(1+\mu)$ is the effective ad-valorem tariff for a given sector-to-sector link, the $\alpha(S)$ matrix contains the exponents on a firm's production function, where $a_{ij} > 0$ indicates sector i uses sector j's output as an intermediate input, $a(S)$ is the sector's productivity for the given input set used, and $\mathbf{1}$ is a column vector of ones. This assumes the matrix $(I-\alpha(S))^{-1}$ is invertible.

Household demand depends on capital earnings and rebated tax revenues:

$$\sum_{i=1}^{n} P_i C_i \leq 1 + \sum_{i=1}^{n}\lambda_i \frac{\sum_{j\in S_i}\alpha_{ij}\mu_{ij}}{\sum_{j\in S_i}\alpha_{ij}(1+\mu_{ij})} P_i Y_i$$

B Inefficiency

The competitive equilibrium in the EPN, with no distortions, is Pareto efficient. Under the protectionist trade policy episode, where heterogeneous tariffs are levied across sectors, the equilibrium is no longer Pareto efficient. Heterogeneous tariffs distort the relative consumption choices of the representative household, and the tariffs generate waste as revenues are not fully rebated to the household when $\lambda_i < 1$. For further details formally characterising efficiency, see section 3.3 of Acemoglu & Azar (2020).

C Discontinuity

Under the endogenous production network, firms' discrete input supplier choices influence the prevailing production network and introduce discontinuities in GDP and the production network. In this framework, small changes in parameters, here the ad-valorem tariff rate levied on imported intermediate inputs, can lead to discontinuous effects. When the production network is exogenous, there are no discontinuous effects on GDP, irrespective of whether or not distortions are present. For worked examples illustrating the discontinuous GDP and production network effects and the accompanying proofs, see section 4.3 of Acemoglu & Azar (2020).

D Simulating productivity parameters

I assume the b_{ij}'s are drawn from truncated Normal distributions, where the truncation procedure ensures that the assigned productivity is consistent with whether or not this edge is present in the data.

Each b_{i0} is drawn independently from a Normal prior distribution with mean m and standard deviation of 1. The parameter m will be chosen such that equilibrium GDP in the model is equal to the real GDP for the US-China economy in 2014 (this is computed as \$25.081 trillion (real 2010 dollars), excluding nine sectors with zero capital shares and/or no sector-to-sector flows recorded). The calibration is precise up to four decimal places for both the fixed and endogenous production framework.

I implement the truncation process for the b_{ij}'s as follows. Each b_{ij} is drawn independently from a Normal prior distribution with mean $\frac{m}{n}$ and standard deviation $\frac{1}{n}$ (where $n = 90$ is the number of sectors in the world economy between the US and China).

1. Draw b_{i0} from a Normal prior distribution, $N \sim (m, 1)$, and the edgewise productivity coefficients, $b_{i1}, ..., b_{in}$, from the Normal distribution, $N \sim (\frac{m}{n}, \frac{1}{n})$.

2. Set $a_i(S_i) = b_{i0} + \sum_{j \in S_i} b_{ij}$.

3. Compute $p = -(I - \alpha(S))^{-1} (a(S) - (\alpha(S) \odot \eta)\mathbf{1})$.

4. Repeat the following steps until $b_{ij} \geq \alpha_{ij} p_j + \alpha_{ij} \log(1 + \mu_{ij})$ for all $i \in 1, ..., n$ and all $j \in S_i$ and $b_{ij} < \alpha_{ij} p_j + \alpha_{ij} \log(1 + \mu_{ij})$ for all $i \in 1, ..., n$ and all $j \notin S_i$:

   (a) If $j \in S_i$ and $b_{ij} < \alpha_{ij} p_j + \alpha_{ij} \log(1+\mu_{ij})$, then redraw b_{ij} from a truncated Normal distribution (with the same parameters as described above) with the support over the interval $[\alpha_{ij} p_j + \alpha_{ij} \log(1 + \mu_{ij}), \infty)$.

   (b) If $j \notin S_i$ and $b_{ij} > \alpha_{ij} p_j + \alpha_{ij} \log(1+\mu_{ij})$, then redraw b_{ij} from a truncated Normal distribution (with the same parameters as described above) with the support over the interval $(-\infty, \alpha_{ij} p_j + \alpha_{ij} \log(1 + \mu_{ij})]$.

   (c) If $j \in S_i$ and $b_{ij} \geq \alpha_{ij} p_j + \alpha_{ij} \log(1+\mu_{ij})$, or $j \notin Si$ and $b_{ij} \leq \alpha_{ij} p_j + \alpha_{ij} \log(1+\mu_{ij})$, then keep b_{ij}.

   (d) Recompute $a_i(S_i) = b_{i0} + \sum_{j \in S_i} b_{ij}$ and $p = -(I - \alpha(S))^{-1} (a(S) - (\alpha(S) \odot \eta)\mathbf{1})$.

This procedure yields two posterior distributions, one conditional on $j \in S_i$ and the other on $j \notin S_i$. The posterior distribution for sector productivities is qualitatively the same for

Table 3.6: Sector-level percentage changes, total

WIOD	Code	US Tariff	China Tariff	Fixed P%Δ	Fixed X%Δ	Endogenous P%Δ	Endogenous X%Δ
Crop	A01	1.59	2.13	1.83	-5.40	1.18	-15.52
Forest	A02	1.73	3.96	2.35	-8.25	1.61	-59.94
Fish	A03	1.16	2.82	2.06	-7.74	1.46	-59.42
Mining	B	1.31	11.45	1.83	-6.60	1.04	-47.28
Mnf food	C10-C12	1.16	1.60	1.76	-4.22	1.11	-12.65
Mnf textiles	C13-C15	0.26	0.88	1.28	-4.51	0.76	-20.98
Mnf wood	C16	0.34	11.41	1.84	-5.41	1.22	-22.03
Mnf paper	C17	1.03	2.29	1.51	-5.75	0.95	-30.25
Rec media	C18	1.07	1.27	1.44	-5.54	0.86	-30.34
Mnf petrol	C19	1.60	3.43	1.56	-5.53	0.90	-22.28
Mnf chem	C20	1.33	1.59	1.26	-4.65	0.72	-17.76
Mnf pharma	C21	1.10	1.43	1.33	-4.96	0.71	-28.07
Mnf plastic	C22	0.78	0.80	1.37	-4.91	0.83	-21.07
Mnf mineral	C23	0.86	0.88	1.41	-5.01	0.87	-27.57
Mnf b metals	C24	1.20	3.10	1.27	-5.82	0.78	-34.41
Mnf fab metals	C25	1.26	1.05	1.31	-5.36	0.77	-26.03
Mnf computer	C26	1.63	2.65	1.69	-6.03	1.06	-42.12
Mnf electrical	C27	1.55	1.74	1.24	-5.17	0.71	-27.31
Mnf machinery	C28	1.45	1.47	1.26	-5.02	0.77	-20.21
Mnf motor veh	C29	1.77	1.00	1.41	-4.86	0.88	-16.57
Mnf furniture	C30	1.26	1.28	1.48	-6.22	0.84	-31.48
Mnf transport	C31-C32	0.50	1.41	1.62	-6.69	0.96	-35.58
Electricity	D35	0.00	5.00	1.86	-5.91	1.23	-42.98
Water coll	E36	0.00	0.00	2.42	-7.16	1.65	-86.94
Waste coll	E37-E39	1.34	2.36	1.68	-6.31	0.94	-38.58
Wh trade	G46	0.00	0.00	1.62	-4.30	0.92	-16.50
Re trade	G47	0.00	0.00	1.58	-4.96	0.86	-20.79
Land trans	H49	0.00	0.00	1.51	-4.74	0.84	-21.98
Water trans	H50	0.00	0.00	2.19	-6.77	1.28	-46.07
Air trans	H51	0.00	0.00	1.99	-5.65	1.19	-34.39
Wareh	H52	0.00	0.00	1.67	-5.03	0.89	-25.26
Postal	H53	0.00	0.00	1.98	-5.84	1.10	-35.39
Accomm	I	0.00	0.00	1.55	-3.64	0.98	-7.92
Telecom	J61	0.00	0.00	1.91	-5.35	1.09	-30.00
Computer prog	J62-J63	0.00	0.00	1.49	-4.13	0.87	-15.38
Fin serv	K64	0.00	0.00	1.98	-5.60	1.19	-35.79
Insur	K65	0.00	0.00	1.70	-4.28	0.98	-17.72
Real est	L68	0.00	0.00	1.99	-4.92	1.32	-26.84
Legal, acc	M69-M70	0.00	0.00	1.47	-4.16	0.89	-14.99
Other prof	M74-M75	1.07	1.10	1.95	-6.32	1.31	-52.07
Admin	N	0.00	0.85	1.46	-4.58	0.88	-18.01
Pub admin	O84	0.00	0.00	1.52	-3.26	0.95	-3.57
Educ	P85	0.00	0.00	1.54	-3.44	0.97	-4.06
Health	Q	0.00	0.00	1.50	-3.12	0.94	-2.23
Other serv	R-S	1.75	1.99	1.39	-3.64	0.85	-8.37

Note: This table provides the sector-level breakdown for percentage change in prices and transaction flows under the fixed and endogenous production network models. Transaction flow changes are weighted by the expenditure shares of inputs used in the production set. The aggregation weight for the world total is given by each country-sector's value added post trade war.

Table 3.7: Sector-level percentage changes, US

				Fixed		Endogenous	
WIOD	Code	US Tariff	China Tariff	P%Δ	X%Δ	P%Δ	X%Δ
Crop	A01	1.59	2.13	1.72	-5.60	1.13	-11.01
Forest	A02	1.73	3.96	2.45	-8.49	1.63	-59.03
Fish	A03	1.16	2.82	2.30	-8.97	1.61	-67.57
Mining	B	1.31	11.45	1.89	-6.38	1.05	-45.30
Mnf food	C10-C12	1.16	1.60	1.54	-3.60	1.01	-4.96
Mnf textiles	C13-C15	0.26	0.88	1.15	-4.47	0.68	-20.65
Mnf wood	C16	0.34	11.41	1.83	-4.68	1.22	-13.89
Mnf paper	C17	1.03	2.29	1.37	-4.24	0.93	-15.61
Rec media	C18	1.07	1.27	1.37	-4.47	0.85	-21.99
Mnf petrol	C19	1.60	3.43	1.52	-4.64	0.87	-12.82
Mnf chem	C20	1.33	1.59	1.15	-4.17	0.68	-14.14
Mnf pharma	C21	1.10	1.43	1.18	-5.04	0.61	-27.98
Mnf plastic	C22	0.78	0.80	1.25	-4.03	0.77	-14.04
Mnf mineral	C23	0.86	0.88	1.40	-4.87	0.86	-26.69
Mnf b metals	C24	1.20	3.10	1.21	-5.47	0.76	-32.47
Mnf fab metals	C25	1.26	1.05	1.15	-4.52	0.71	-19.85
Mnf computer	C26	1.63	2.65	1.68	-5.93	1.06	-42.26
Mnf electrical	C27	1.55	1.74	1.15	-4.81	0.68	-25.50
Mnf machinery	C28	1.45	1.47	1.08	-4.16	0.71	-13.44
Mnf motor veh	C29	1.77	1.00	1.25	-3.97	0.82	-9.21
Mnf furniture	C30	1.26	1.28	1.24	-4.17	0.74	-15.98
Mnf transport	C31-C32	0.50	1.41	1.22	-3.69	0.75	-10.27
Electricity	D35	0.00	5.00	1.89	-5.94	1.25	-43.37
Water coll	E36	0.00	0.00	2.70	-7.29	1.80	-97.28
Waste coll	E37-E39	1.34	2.36	1.42	-5.18	0.89	-32.47
Wh trade	G46	0.00	0.00	1.40	-3.61	0.83	-10.20
Re trade	G47	0.00	0.00	1.29	-3.15	0.75	-4.47
Land trans	H49	0.00	0.00	1.42	-3.90	0.80	-12.50
Water trans	H50	0.00	0.00	1.98	-5.72	1.30	-41.83
Air trans	H51	0.00	0.00	1.73	-4.74	0.97	-29.73
Wareh	H52	0.00	0.00	1.39	-3.94	0.77	-15.95
Postal	H53	0.00	0.00	1.49	-4.37	0.82	-22.40
Accomm	I	0.00	0.00	1.49	-3.38	0.95	-4.69
Telecom	J61	0.00	0.00	1.28	-3.73	0.79	-15.55
Computer prog	J62-J63	0.00	0.00	1.39	-3.63	0.82	-10.36
Fin serv	K64	0.00	0.00	1.89	-5.07	1.16	-33.09
Insur	K65	0.00	0.00	1.64	-3.78	0.96	-13.31
Real est	L68	0.00	0.00	1.57	-3.95	0.99	-13.10
Legal, acc	M69-M70	0.00	0.00	1.36	-3.48	0.85	-6.55
Other prof	M74-M75	1.07	1.10	2.03	-5.92	1.34	-51.60
Admin	N	0.00	0.85	1.22	-3.76	0.74	-10.53
Pub admin	O84	0.00	0.00	1.48	-3.15	0.94	-2.48
Educ	P85	0.00	0.00	1.37	-3.26	0.88	-3.01
Health	Q	0.00	0.00	1.45	-3.05	0.92	-1.93
Other serv	R-S	1.75	1.99	1.24	-3.14	0.79	-3.30

Note: This table provides the US sector-level breakdown for percentage change in prices and transaction flows under the fixed and endogenous production network models. Transaction flow changes are weighted by the expenditure shares of inputs used in the production set.

Table 3.8: Sector-level percentage changes, China

				Fixed		Endogenous	
WIOD	Code	US Tariff	China Tariff	P%Δ	X%Δ	P%Δ	X%Δ
Crop	A01	1.59	2.13	2.03	-5.06	1.28	-25.27
Forest	A02	1.73	3.96	2.07	-7.53	1.37	-70.14
Fish	A03	1.16	2.82	1.53	-5.09	0.95	-31.17
Mining	B	1.31	11.45	1.68	-7.06	0.99	-57.81
Mnf food	C10-C12	1.16	1.60	1.91	-4.63	1.20	-18.42
Mnf textiles	C13-C15	0.26	0.88	1.80	-4.65	1.10	-22.48
Mnf wood	C16	0.34	11.41	1.87	-6.95	1.23	-61.93
Mnf paper	C17	1.03	2.29	1.63	-7.11	0.98	-54.02
Rec media	C18	1.07	1.27	1.55	-7.03	0.89	-52.99
Mnf petrol	C19	1.60	3.43	1.62	-7.03	0.98	-51.61
Mnf chem	C20	1.33	1.59	1.78	-6.87	1.07	-47.67
Mnf pharma	C21	1.10	1.43	1.77	-4.71	1.06	-28.40
Mnf plastic	C22	0.78	0.80	1.65	-6.85	1.04	-49.03
Mnf mineral	C23	0.86	0.88	1.58	-6.78	0.95	-47.86
Mnf b metals	C24	1.20	3.10	1.75	-8.61	1.05	-58.58
Mnf fab metals	C25	1.26	1.05	1.74	-7.60	1.03	-52.71
Mnf computer	C26	1.63	2.65	1.76	-6.84	1.09	-39.91
Mnf electrical	C27	1.55	1.74	1.74	-7.20	1.06	-44.46
Mnf machinery	C28	1.45	1.47	1.73	-7.25	1.04	-49.15
Mnf motor veh	C29	1.77	1.00	1.68	-6.31	1.01	-33.45
Mnf furniture	C30	1.26	1.28	1.65	-7.67	0.97	-54.34
Mnf transport	C31-C32	0.50	1.41	1.90	-8.81	1.17	-60.89
Electricity	D35	0.00	5.00	1.64	-5.68	0.95	-38.10
Water coll	E36	0.00	0.00	1.98	-6.96	1.10	-50.08
Waste coll	E37-E39	1.34	2.36	2.11	-8.20	1.09	-56.80
Wh trade	G46	0.00	0.00	1.94	-5.33	1.11	-28.74
Re trade	G47	0.00	0.00	1.90	-6.99	1.03	-45.01
Land trans	H49	0.00	0.00	1.60	-5.69	0.91	-38.91
Water trans	H50	0.00	0.00	2.36	-7.55	1.25	-51.20
Air trans	H51	0.00	0.00	2.23	-6.49	1.49	-40.61
Wareh	H52	0.00	0.00	2.12	-6.76	1.16	-46.89
Postal	H53	0.00	0.00	2.69	-8.02	1.71	-64.10
Accomm	I	0.00	0.00	1.76	-4.59	1.09	-23.88
Telecom	J61	0.00	0.00	2.77	-7.54	1.53	-51.78
Computer prog	J62-J63	0.00	0.00	1.87	-5.93	1.15	-43.68
Fin serv	K64	0.00	0.00	2.16	-6.58	1.29	-44.06
Insur	K65	0.00	0.00	1.88	-5.71	1.03	-38.31
Real est	L68	0.00	0.00	3.26	-7.90	2.17	-62.68
Legal, acc	M69-M70	0.00	0.00	1.66	-5.32	0.98	-34.81
Other prof	M74-M75	1.07	1.10	1.71	-7.63	1.03	-55.99
Admin	N	0.00	0.85	2.35	-7.57	1.46	-49.79
Pub admin	O84	0.00	0.00	2.08	-5.19	1.27	-26.14
Educ	P85	0.00	0.00	1.94	-3.89	1.18	-6.60
Health	Q	0.00	0.00	1.79	-3.52	1.08	-3.90
Other serv	R-S	1.75	1.99	1.77	-4.94	1.08	-25.41

Note: This table provides the China sector-level breakdown for percentage change in prices and transaction flows under the fixed and endogenous production network models. Transaction flow changes are weighted by the expenditure shares of inputs used in the production set.

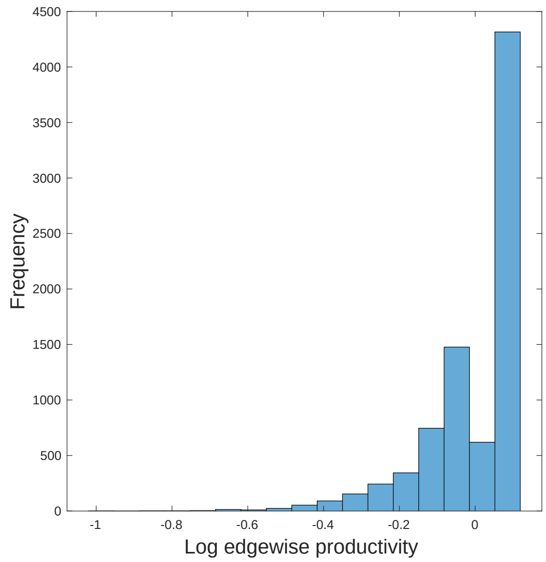


Figure 3.12: Posterior normal distribution: This chart plots the histogram of the edgewise productivity parameters simulated in the model.

both the fixed and endogenous production network framework, so I include the figure using the endogenous production network calibration.

Once the productivity parameters $(a_i(S_i))$ are sampled, I compute log prices as:

$$p = -(I - \alpha(S))^{-1}(a(S) - (\alpha(S) \odot \eta)\mathbf{1}).$$

where $\eta = \log(1 + \mu)$ is a N-by-N matrix and $\mathbf{1}$ is a column vector of ones.

E Nominal (and real) GDP

To compute nominal GDP, I assume no tax revenues are rebated to the representative household, with $\lambda_i = 0$ for each sector i. That is, all tax revenue generated from levying tariffs is treated as a dead weight loss. In practice, import duties as a share of GDP only account for 0.3% in GDP according to the OECD and can be considered to be a negligible income source. With Cobb-Douglas utility and production functions, the following holds:

$$P_i C_i = \beta_i \left(1 + \sum_{i=1}^{n} \lambda_i \frac{\sum_{j \in S_i} \alpha_{ij} \mu_{ij}}{\sum_{j \in S_i} \alpha_{ij}(1 + \mu_{ij})} P_i Y_i \right) \tag{3.12}$$

Let GDP^N denote nominal GDP and $d_i = \frac{P_i Y_i}{GDP^N}$ the Domar weight for sector i, the above can be written as:

$$P_i C_i = \beta_i \left(1 + \sum_{i=1}^{n} \lambda_i \frac{\sum_{j \in S_i} \alpha_{ij}\mu_{ij}}{\sum_{j \in S_i} \alpha_{ij}(1+\mu_{ij})} d_i GDP_i^N\right)$$

Summing over all sectors, obtain nominal GDP in terms of their Domar weights:

$$GDP^N = \frac{1}{1 - \sum_{i=1}^{N} \lambda_i \frac{\sum_{j \in S_i} \alpha_{ij}\mu_{ij}}{\sum_{j \in S_i} \alpha_{ij}(1+\mu_{ij})}} \tag{3.13}$$

I can express the Domar weights in terms of input-output entries. Let $\hat{\alpha}_{ji} = \frac{P_j X_{ji}}{P_i Y_i}$ denote the amount (in dollars) of good j necessary to produce one dollar's worth of good i. α_{ji} is the cost share of input i in the production of good j (the fraction of the cost of good j that goes into input i).

$$\hat{\alpha}_{ji} = \frac{\alpha_{ji}}{1+\mu_{ji}}.$$

Rearranging the market clearing condition for sector i:

$$P_i Y_i = P_i C_i + \sum_{j \in S_i} P_j X_{ji},$$

and substituting for $P_j X_{ji}$

$$P_i Y_i = P_i C_i + \sum_{j \in S_i} \hat{\alpha}_{ij} P_i Y_i. \tag{3.14}$$

Dividing both sides of the equation above by nominal GDP, get:

$$d_i = \beta_i + \sum_{j \in S_i} \hat{\alpha}_{ij} d_i,$$

$$d = (I - \alpha)^{-1}\beta.$$

Given the Domar weights and nominal GDP, I compute real GDP as:

$$Y = \frac{Y^N}{\prod_{i=1}^{n} (P_i)^{\beta_i}} \tag{3.15}$$

Taking logarithms of real GDP:

$$\log(Y) = \beta'(I-\alpha)^{-1}\left(a - (\alpha \odot \eta)\mathbf{1}\right) - \log\left(1 - \sum_{i=1}^{n} \lambda_i \frac{\sum_{j \in S_i} \alpha_{ij}\mu_{ij}}{\sum_{j \in S_i} \alpha_{ij}(1+\mu_{ij})} d_i\right)$$

Variable	Definition	Sources
Calibrated externally		
α_{ij}	Input exp share	WIOD
μ_{ij}	Ad-valorem tariff	USITC, WTO TB
β_i	Consumption share	WIOD
Calibrated internally		
Y	GDP (value added)	WIOD
$A_i(S_i)$	Sector productivity	Simulated

where $\eta = \log(1+\mu)$ is a N-by-N matrix and $\mathbf{1}$ is a column vector of ones.

F Alternative calibration exercise

Arkolakis et al. (2012), henceforth ACR, show that for a given class of models, a country's domestic trade share and the elasticity of imports with respect to trade costs are sufficient statistics to characterise the welfare implications of trade. This implies if models satisfying ACR's set of assumptions are calibrated using the same domestic trade share and trade elasticity, they yield the same welfare implications, irrespective of the underlying microeconomic structure of the trade model.

Melitz & Redding (2015), hereon MR, find that the model micro-structure, via an additional margin of adjustment, implies smaller welfare losses from increases in trade costs. The authors compare the heterogeneous firm case, where aggregate productivity responds to changes in trade costs via firms' entry-exit decisions in domestic and foreign markets, to the homogeneous case, where aggregate productivity is exogenous, with a degenerate productivity distribution.

MR posit ACR's welfare formula is a sufficient statistic using a Pareto productivity distribution. MR's 'micro' approach compares models that differ in their productivity distribution while keeping all other structural parameters the same. In my work, the EPN is analogous to the heterogeneous firm model, where sector productivity changes as sectors adjust their input choices. The FPN corresponds to the homogeneous firm model, where the set of input suppliers remains fixed.

In the first quantitative exercise presented in the main body of my paper, I calibrated the productivity parameters to minimise the difference between the GDP estimated by the model and the GDP observed in the data. An alternative method is to calibrate the reduction in trade flows across models. In this second quantitative exercise, I keep both the GDP level and the trade flow margins constant. According to Melitz & Redding (2015), firms' optimisation over the intensive and extensive margins should lead to smaller welfare losses from increases in trade costs, as compared to a case where firms only have one margin of adjustment.Holding both margins constant across the EPN and FPN models shows that the endogeneity of the production network provides an additional margin of adjustment through which the economy responds to the trade policy change, reducing GDP losses. My results are consistent with MR's findings, both when using real GDP as an approximation of the economy's welfare losses and when using ACR's welfare formula.

Table 3.9: Calibrate trade flow loss (TFL) across models

Strategy	VA weight	EPN tariff	EPN matched TFL	EPN/FPN GDP loss	FPN TFL	FPN US TFL	FPN CHN TFL
Match EPN to FPN							
0	After TW	t pre + 0.03005	-11.10	-6.2915	-11.11	-8.80	-13.43
1	Change in VA	t pre + 0.03200	-6.60	-6.7221	-7.36	-4.00	-10.72
2	Before TW	t pre + 0.03126	-11.18	-6.5586	-11.18	-8.84	-13.52

In Table 3.9, I calibrate the trade flow loss in the EPN to match the loss in the FPN using alternative weighting strategies. I estimate the trade flow loss in the FPN to be between -7% and -11%, with the breakdown by country listed in the last two columns of Table 3.9. I use alternative weighting strategies listed in the first column, using each sector's value-added either after the trade war, the change in the value-added of each sector as a result of the trade war, or the sector's value-added prior to the trade war. For example, the first weighting strategy uses the value-added of each sector after the trade war to estimate the trade flow declines. The trade flows, at the sector-to-sector level, are weighted by each input's expenditure share leaving a column vector by sector. I then weight this column vector by each sector's value-added after the trade war to estimate a scalar of the total trade flow decline. The second strategy follows the same intuition, except using the change in the value-added of each sector before and after the trade war; and the final weighting strategy uses the value-added of each sector before the trade war to do the same.

In order to match the trade flow loss in the EPN to the FPN, I apply a homogeneous tariff increase to all sectors in the counterfactual scenario. Taking the first row of Table 3.9, each sector faces the MFN tariff rates plus an additional, homogeneous 3.0% tax rate to match the 11% trade flow loss observed in the FPN. The EPN predicts a 6.3% loss in GDP upon matching across the two margins: the trade flows losses observed in the FPN, and world GDP. The 1% GDP loss in the EPN model, under the first calibration, serves as a lower bound for GDP losses, under my model assumptions. Using alternative weighting strategies in rows two and three yield GDP losses of a similar magnitude ranging between 6.5 - 6.7%.

G Welfare loss from protectionist trade policy

To estimate the welfare changes associated with the trade war, I use ACR's formula capturing the gains from trade as:

$$\hat{W} = \hat{\lambda}^{\frac{1}{\epsilon}}$$

For a class of models satisfying ACR's set of primitive and macro assumptions, the formula computes the change in welfare in terms of real income, in response to a foreign shock. $\hat{W} = \frac{W'}{W}$ is the change in welfare; $\hat{\lambda} = \frac{\lambda'}{\lambda}$ the change in the share of expenditure on the domestic good, where λ and λ' denote the aggregate share of spending on domestic goods before and after the rise in trade costs, and ε is the trade elasticity.[19]

The share of expenditure on domestic goods, λ, is equal to one minus the import penetration ratio. In my model, I estimate the import penetration ratio using total cross-border trade in goods divided by total domestic demand.

I define the trade elasticity as follows:

$$\begin{aligned}
\varepsilon &= -\frac{dtradeflow}{d\mu}\frac{\mu}{tradeflow}, \\
\varepsilon &= -\frac{tradeflow^{\mu+\epsilon} - tradeflow^{\mu}}{\epsilon}\frac{\mu^{SS}}{tradeflow^{SS}}
\end{aligned}$$

where ϵ is an infinitesimal change in trade costs around the steady state equilibrium; μ^{SS} is the weighted average tariff rate in the steady state of my counterfactual scenario. The pairwise tariffs are weighted by each input's expenditure share, leaving a column vector by sector, which I then weight by each sector's value-added, in the steady state of the counterfactual economy. I apply the same weighting procedure when collapsing the trade flow matrix to a scalar, $tradeflow^{SS}$. The resulting trade elasticity, ε, measures how a small percentage increase in the ad-valorem tariff rate changes the trade flows observed in the counterfactual, pre-trade war, scenario. I numerically estimate the trade elasticity at the steady state of my counterfactual. I perturb the steady state tariffs by some small ϵ, such that $\mu_{pre} + \epsilon$.

A priori, from my findings in the quantitative exercise and those of MR, I expect the welfare losses to be larger in the FPN, as compared to the EPN, for an increase in trade

[19] ACR list four primitive assumptions: a) Dixit-Stiglitz preferences; b) one factor of production; c) linear cost functions; and d) perfect or monopolistic competition; and three macro-level restrictions: a) trade is balanced; b) aggregate profits are a constant share of aggregate revenues; and c) the import demand system is CES. See Arkolakis et al. (2012) for further details.

costs. In the context of MR, there are smaller welfare losses from increases in trade costs in the heterogeneous- (EPN) than in the homogeneous- (FPN) firm model. Applying the ACR formula such that: $WL = \frac{1}{\varepsilon} \log \frac{\lambda_{\mu^{pre}}}{\lambda'_{\mu^{pre+\epsilon}}}$, I measure the welfare loss associated with moving from a state of low to relatively higher tariffs, where WL×100 gives the percentage loss in welfare, in real income terms. As in the second quantitative exercise, I keep the GDP level and the share of expenditure on domestic goods constant across the FPN and EPN for comparability, using the share of expenditure on domestic goods as estimated in the EPN model.

Table 3.10: Welfare loss using ACR formula

	ε	λ'	λ	$\hat{\lambda}$	WL×100
One-sided: $\mu + \epsilon = 0.001$					
FPN	-0.6721	0.8753	0.8292	0.9473	-8.05
EPN	-3.8642	0.8753	0.8292	0.9473	-1.40
One-sided: $\mu + \epsilon = -0.001$					
FPN	-0.6817	0.8753	0.8292	0.9473	-7.94
EPN	-1.0405	0.8753	0.8292	0.9473	-5.20

I aggregate sector import penetration ratios with a weighted average, using sector value-added as the weight. As would be expected, the share of expenditure on domestic production increases after the trade war, by just under five percentage points. The trade elasticity is also more elastic in the EPN, where firms are able to sever connections with input suppliers that are no longer sufficiently beneficial to keep in production. Given firms' more limited ability to adjust input choices in the FPN, ε is relatively inelastic. The key parameter contributing to the difference in welfare loss across the two models is this trade elasticity.

The magnitude of the ACR welfare loss estimates is in line with those in my second quantitative exercise, where I keep both the GDP level and trade flow margins constant across the EPN and FPN (see Section F). For a given share of expenditure on domestic goods, the welfare loss in the EPN is smaller than in the FPN, given the additional margin of adjustment. This is consistent with MR's findings where, for an increase in trade costs, the welfare loss is smaller in the heterogeneous firm model. In the EPN, the welfare loss ranges between -1.40% and -5.20% of real GDP. This is reasonably close to the GDP loss estimates in my second quantitative exercise. Moreover, the welfare loss in the FPN is approximately 8% of GDP. The estimated welfare loss in the FPN is approximately 1.6 times higher than in the EPN, using the negative perturbation to the counterfactual equilibrium, and 6 times higher in the positive tariff adjustment.

Welfare in my model, approximated by the difference in real GDP in the counterfactual and baseline scenarios, is calculated following Acemoglu & Azar (2020) as $Y = \frac{Y^N}{\prod_{i=1}^{N} P_i^{\beta_i}}$ where real GDP, Y, is given by the nominal GDP of the world economy, divided by prices, weighted by sector consumption share.[20] Thus, the change in real GDP, serving as an approximation of welfare loss, is given by $\Delta = \frac{Y' - Y}{Y}$, where Y and Y' is the real GDP of the economy before and after the increase in tariffs. Under the assumptions of the first quantitative exercise performed, I find the welfare losses are 1.6% and 1% in the FPN and EPN models, respectively.

H Two firm, two input illustration

Consider a simple example of two firms to illustrate the extensive margin mechanism. Firm 1 is located in the US manufacturing computer, electronic, and optical products sector. Firm 2 is located in China, specializing in the manufacture of basic metals. The two firms rely on their own output and each others' to produce output.

Take firm 1, it manufactures microprocessors, resistors, and capacitors, needed in the production of desktop and laptop computers. To produce the microprocessors, firm 1 also requires lead, copper, and other metals supplied by firm 2. Firm 2 in turn requires, say, the infrared products also produced by firm 1, in its manufacturing process for plating and anodizing metals that is then sold onto firm 1 as an intermediate input.

Hence, the starting expenditure share matrix, or input-output matrix, is given by:

$$\alpha = \begin{array}{cc} US & CHN \\ \left[\begin{array}{cc} 0.6 & 0.35 \\ 0.1 & 0.6 \end{array}\right] & \end{array} \begin{array}{ll} US & \text{manufacture of computers purchases} \\ CHN & \text{manufacture of basic metals purchases} \end{array}$$

The first row represents the expenditure shares of the US manufacture of computers firm, 0.6 of its expenditure spend is on its own output of microprocessors, and 0.35 is spent on imported Chinese basic metals such as lead. The second row represents the expenditure share of the basic metals manufacturing firm. It spends 0.6 on its own output, and 0.1 on the US computer manufactures. Its remaining expenditure share is allocated to purchasing capital.

With the pre and post-trade war ad-valorem tariff rates given by:

[20] Prices in the economy can be determined solely on the production side without reference to consumer preferences due to the contestability assumption in equilibrium definition. Moreover, the Cobb-Douglas production function facilitates a closed-form solution of the equilibrium vector of sector prices. Again, the expression for log prices illustrates that equilibrium prices are determined without reference to consumer preferences.

	Pre	Post	a_i
p_1	-0.13 (0.88)	-0.05 (0.95)	0.08 (1.08)
p_2	-0.02 (0.98)	0.05 (1.06)	0.02 (1.02)

The table shows log prices pre and post trade war for firm 1 and 2. The last column lists the log productivity of each firm. Figures in brackets are the exponents of the log terms.

$$\mu_{pre} = \begin{bmatrix} 0 & 0.1 \\ 0.3 & 0 \end{bmatrix}, \quad \mu_{post} = \begin{bmatrix} 0 & 0.12 \\ 0.6 & 0 \end{bmatrix}$$

Consider the μ_{pre} matrix. The element $\mu_{12} = 0.1$ denotes the 10% import tariff the US firm in the manufacture of computers must pay when importing a unit of the basic metals input from the firm in China. I assume no distortions on inputs sourced domestically.

The log productivity is denoted by the a_i equations below, where b_{i0} is some baseline productivity specific to the firm, and the b_{ij} is the input-specific productivity parameter. Lowercase letters denote log variables.

$$a_1 = b_{10} + b_{12} = 0.01 + 0.07 = 0.08$$
$$a_2 = b_{20} + b_{21} = -0.02 + 0.04 = 0.02$$

Given the expenditure shares, import tariffs, and productivity parameters above, one can compute the equilibrium vector of log prices with the matrix equation below:

$$p = -(I - \alpha)^{-1} \left(a - (\alpha \odot \eta)\mathbf{1}\right)$$

where $\eta = \log(1 + \mu)$ is a N-by-N matrix and $\mathbf{1}$ is a column vector of ones.

Substituting the expressions of log productivity into the log unit cost function $p_i = uc_i = \sum_{j \in S_i} \alpha_{ij} p_j + \sum_{j \in S_i} \alpha_{ij} \log(1 + \mu_{ij}) - a_i(S_i)$, the firm pursues the following extensive margin adjustments.

Firm 1 checks whether the input-specific productivity of input 2 exceeds the associated costs of hiring it, where costs include the price of the input and the import tariff levied. If the input-specific productivity is greater than the cost, i.e. the input reduces the unit cost of production, then the input is added to the firm's input set.

$$
\begin{aligned}
b_{12} &> \alpha_{12}\left(p_2 + \log(1+\mu_{12}^{pre})\right) \\
0.07 &> 0.012 \quad \text{(keep input)} \\
b_{21} &> \alpha_{21}\left(p_1 + \log(1+\mu_{21}^{pre})\right) \\
0.04 &> 0.013 \quad \text{(keep input)}
\end{aligned}
$$

Purchasing the foreign input reduces the unit costs of production prior to the rise in import tariffs for both the US and China firms. This is illustrated in panel a) below.

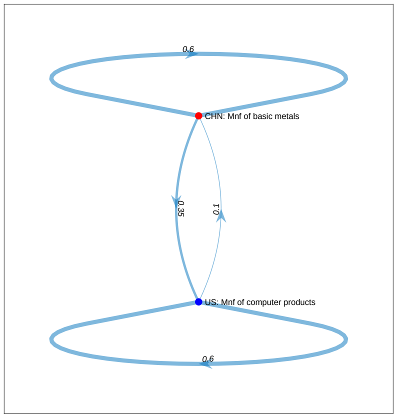
However, with a rise in the import tariff, prices and costs change; firms reappraise their existing input suppliers to check whether it is still cost reducing to employ them in production.

$$
\begin{aligned}
b_{12} &> \alpha_{12}\left(p_2' + log(1+\mu_{12}^{post})\right) \\
0.07 &> 0.025 \quad \text{(keep input)} \\
b_{21} &> \alpha_{21}\left(p_1' + log(1+\mu_{21}^{post})\right) \\
0.04 &< 0.047 \quad \text{(drop input)}
\end{aligned}
$$

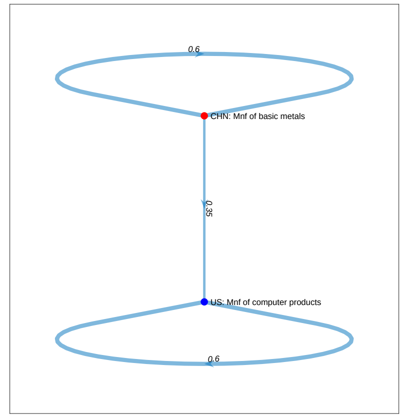
With the increase in import costs, the input-specific productivity parameter for the basic metals firm in China no longer exceeds the costs associated with importing computer products from the US, and thus drops the US firm as an input supplier, see panel b).

H.1 Log unit cost function illustration

The relationship between the tariff rate and the firm's log unit cost function of employing input j can be illustrated by varying the tariff rate, as in Figure 3.14. Take firm 1, the US manufacture of computers, electronic, and optical products firm. In Figure 3.14a I plot firm 1's log unit cost function associated with employing input 2. Under the parameters given provided in the two firm, two input example, I plot this log unit cost function, varying the ad-valorem tariff rate levied on input 2, imported from the China manufacture of basic metals firm. The horizontal, grey dashed line represents the input-specific productivity parameter, $b_{12} = 0.07$, that firm 1 uses as the threshold value up to which it is willing to hire input 2 in its production process. The point at which the blue log unit cost function intersects with the dashed line identifies the maximum tariff rate firm 1 is willing to tolerate when importing input 2. Beyond this μ_{ij}^*, importing input 2 in the production process will only serve to increase the log unit costs of production of input 1 if firm 1 were to employ input 2.



(a) Pre trade war tariffs

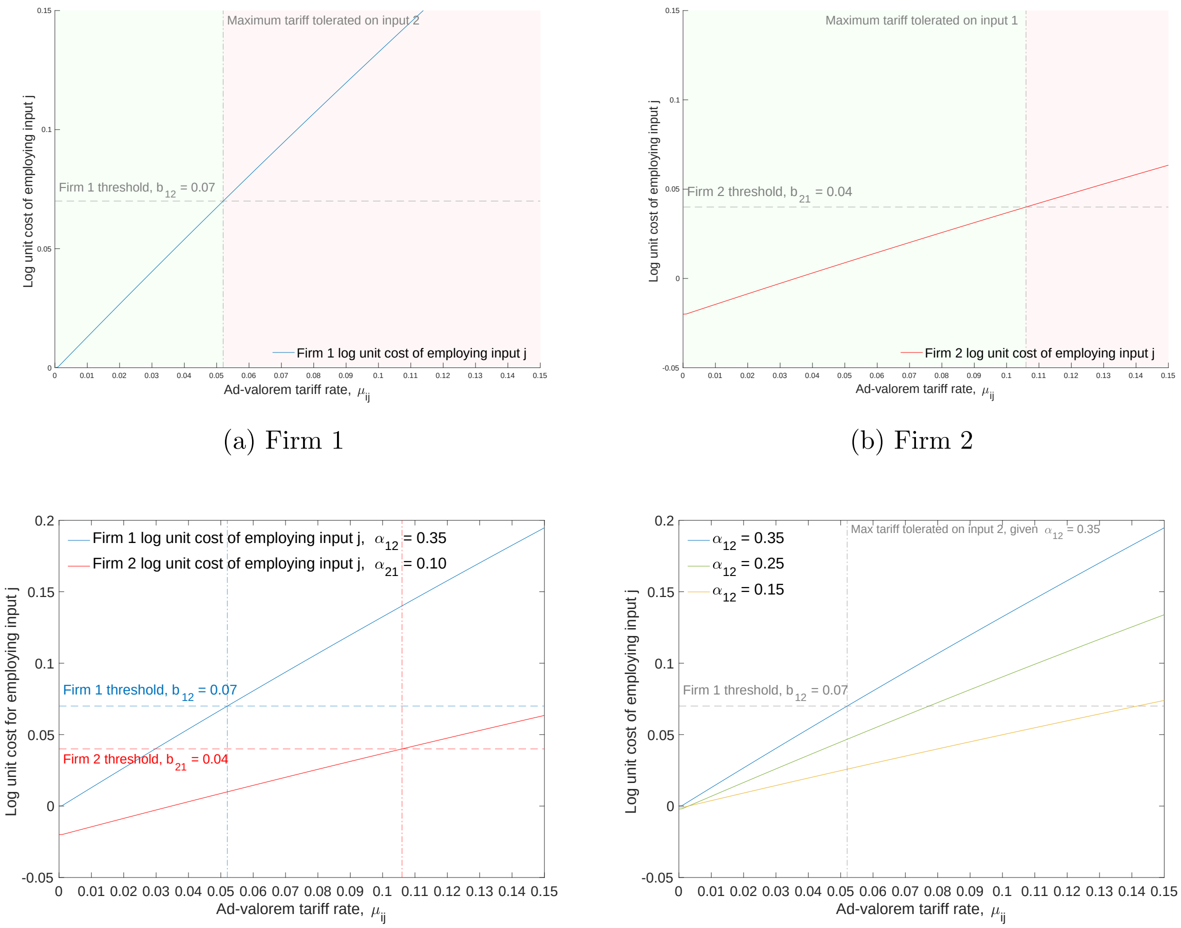


(b) Post trade war tariffs

Figure 3.13: Simple two firm example: Figure 3.13a illustrates the trade connections under the pre trade war tariff rates, μ_{ij}^{pre}. The blue node is the US manufacture of computers firm, and the red node, China's manufacture of basic metals firm. Each firm buys the intermediate input supplied by the other, as well as their own output, indicated by the self loop. Figure 3.13b illustrates the resulting production network when ad-valorem tariffs are raised to their μ_{ij}^{post} levels. China's manufacture of basic metals firm stops purchasing from the US manufacture of computers firm under the new, higher tariffs.

Figure 3.14b depicts the same functions for firm 2. The input-specific log productivity determines the cut-off threshold the firm observes. The lower the input-specific log productivity, i.e. the lower this threshold, the firm is more likely to drop an input from its production set for a given increase in the tariff rate.

Superimposing the log unit cost functions for both firms in Figure 3.14c, there are several points of note in this comparative static. First, the input-specific productivity of each input in the firms' production process differs. Input 2 is more productive in firm 1's production process than input 1 is in firm 2's production. Hence, the blue dashed line lies above the red dashed line. Second, the cost shares of each input in a firm's production process affect the slope of the log unit cost function of employing some input j. Where firms have a higher cost share for more expensive inputs, the slope of the log unit cost function is steeper. As such, the maximum tolerated ad-valorem tariff rate, for a given input, is lower. As seen in 3.14a, firm 1 is willing to pay about 8.6% when importing unit 2. On the other hand, firm 2 is willing to incur a tariff rate of just under 13% to import input 1. The maximum tolerated tariff will depend on both the cost shares of each firm, the input-specific productivity associated with the imported input that governs the threshold of its employment, and the equilibrium price vector that is a function of firm-level productivity, the tariff rates levied, and prices of



(a) Firm 1

(b) Firm 2

(c) Firm 1 and 2

(d) Vary α_{ij} for firm 1

Figure 3.14: Log unit cost function and tariff rates: This panel illustrates how the log unit cost function varies with changes in the ad-valorem tariff rate, for a given set of parameters for firm 1 and 2, with a given input set. Figure 3.14a plots the log unit cost function for firm 1 of employing input 2, with the input-specific productivity governing whether input 2 should be imported from the supplier in China, as well as the maximum tariff the firm is willing to tolerate for this input. Figure 3.14b plots the same as above for firm 2. Figure 3.14c superimposes the two panels above. Figure 3.14d illustrates how the slope of the log unit cost function changes with the inputs' cost shares in the production technology.

purchased inputs.

In Figure 3.14d, I illustrate how the slope of the log unit cost function changes when I vary the cost share of input 2, α_{12} for firm 1. That is, how does the log unit cost function of firm 1 employing input 2 change as I vary its importance in firm 1's production process. As the expenditure share on input 2 increases, the slope of the log unit cost function becomes steeper. Hence, a firm is willing to tolerate a higher tariff rate increase on inputs that are relatively less important in the production of its output, as it is a small fraction of its overall expenditure on intermediate inputs. On the other hand, for more important inputs that account for a higher expenditure share, the firm's maximum tolerated tariff, will be lower.

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Conclusion

In this thesis, I apply network tools of analysis to questions of international trade, in both empirical and structural analysis. While networks have been applied to a number of subfields within the economic discipline, including financial and social networks, trade is a natural, yet understudied, extension. Over the past decade, the financial crisis and series of protectionist policy episodes, such as Brexit and the US-China trade war, have highlighted the interdependencies in the global economy. Given firms, sectors, and countries do not exist in a vacuum, it is important to understand how network structure, and a producer's position within it, affects producer-level and aggregate outcomes. In Chapter 2, I study whether being relatively more interconnected acts as an amplifying or insurance mechanism on a sector's future export competitiveness, following a negative final demand shock. I find evidence in favour of the insurance mechanism, where being more interconnected dampens the negative effects of the decline in future export competitiveness relative to more peripheral sectors. To explore the nature of bilateral linkages further, in Chapter 3, I develop an endogenous link formation model to study the impact of the rise in import tariffs during the US-China trade war on inter-firm links in supply chains and GDP losses. Failing to account for the reorganization of trade connections overestimates GDP losses by 60%.

A related and important area of research that I have omitted from this thesis, but remains a future direction of research, is the spatial network literature. Container shipping is an important vehicle through which goods are traded internationally, with container ships serving ports worldwide. This unit of analysis is an alternative networked environment through which to study the impact of a trade shock on the costs of shipping and trade flows. More specifically, it lends itself to characterising the optimal transport network through the social planner problem and comparing how far the actual shipping network is from this configuration. The inefficiencies contributing to this difference, as well as the impact of logistical bottlenecks in times of disruption, are both promising avenues of research in the application of economic networks.

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