Trade Intermediation and Market Structure in Global Production Networks

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Declaration

I, Oscar Ignacio Perelló Perez confirm that the work presented in my thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Date: March 17, 2025

Signature:

Abstract

This thesis studies how firms use intermediation services to respond to frictions and how imperfect competition shapes firm performance in global production networks. Chapter 1 explores the role of intermediaries in mitigating disruptions in input markets. Combining customs and tax records from Chile, I show that intermediation increases with supply chain risk, as intermediaries offer a more resilient sourcing technology. I develop a model of global sourcing with matching costs and insecure supply relationships, where more productive firms diversify suppliers and less productive firms contract with intermediaries. Despite double marginalization, intermediaries relax the efficiency–risk trade-off for producers that lack the scale to diversify directly. Chapter 2 examines the role of intermediaries from the seller's perspective. Exporters of all sizes use intermediaries, mix trade modes across buyers, and charge lower prices to intermediaries. We explain these facts in a model with sellers of heterogeneous productivity and matchability, buyers of heterogeneous productivity, and intermediaries that reduce matching costs. A key result is that sellers' attributes are negatively correlated, so intermediation enables high-productivity sellers with low matchability to reach smaller buyers. Chapter 3 studies how production networks shape the impact of trade policy under imperfect competition. We propose a model of network formation with two-sided firm heterogeneity, matching frictions, and imperfectly competitive input markets, where more productive buyers match with more suppliers, inducing tougher competition and lowering input costs. Package reforms that reduce matching costs or promote competition amplify the welfare gains from shallow trade agreements. In summary, this thesis shows that intermediation services complement in-house firm operations and that the market structure mediates the impact of policy shocks in global markets.

Impact Statement

This thesis documents how firms interact and respond to frictions in global markets and how these frictions shape both their performance and the gains from economic integration. I consider the role of supply chain risk, imperfect competition, and matching frictions, with a particular focus on intermediation services as an alternative to in-house strategies. Understanding firms' optimal responses is essential for effective policy design, especially in the presence of rising concerns about resilience, market concentration, and protectionist shifts.

My work makes both empirical and theoretical contributions to the academic literature. Chapter 1 provides the first empirical evidence on the supply networks of intermediaries and their resilience advantage. This chapter also expands previous models of global sourcing by incorporating supply chain risk and trade intermediation in a tractable manner. Chapter 2 presents new evidence on how exporters of all sizes use intermediaries and mix trade modes. These patterns are explained by incorporating intermediation services and differences in sellers' matching abilities into a model of production networks. Finally, Chapter 3 integrates oligopolistic competition among suppliers into a model of global sourcing, offering both theoretical insights and empirical results on how upstream market entry enhances downstream firm performance.

All chapters contribute to the debate on globalization by providing counterfactual analyses of trade or industrial policies. The findings demonstrate that a robust intermediation sector plays a substantial role in mitigating supply chain disruptions for smaller producers and helps high-productivity sellers reach smaller buyers. Moreover, package reforms that reduce matching costs or promote competition amplify the welfare gains from shallow trade agreements. These results point to the scope for welfare gains from modern trade agreements that pursue deep integration, which combine tariff reductions with trade promotion, competition policy, and trade in services.

Contents

Introduction

Global value chains (GVCs) have transformed economic activity as firms transact with upstream suppliers, downstream producers, and final consumers worldwide. This has provided access to a greater variety of inputs and a larger customer base, thereby promoting both firm and aggregate productivity. More recently, the growth of GVCs has been accompanied by rising concerns about supply chain resilience, especially after the Great Recession and the COVID-19 pandemic. At the same time, despite dramatic declines in transportation and communication costs, these buyer-supplier networks remain sparse and are dominated by a few highly connected firms. This suggests that significant barriers to network formation persist, limiting the potential gains from globalization and raising additional concerns about market concentration.

Underlying these trends are several frictions that firms face when interacting in global markets, including supply chain risk, high search and matching costs, and imperfect competition. The following chapters explore how firms respond to these frictions, how optimal strategies differ across the firm productivity distribution, and what are the implications for their performance. I place special focus on the role of intermediation services, which are provided by firms that specialize in buying, reselling, and distributing goods, and offer producers an alternative to in-house trading strategies. Ultimately, my analysis informs the design of policies such as modern trade agreements that pursue deep integration, which combine tariff reductions with trade in services, trade promotion, and competition policy.

Chapter 1 studies how input sourcing through intermediaries helps firms mitigate disruptions in risky markets. Combining customs and tax records from Chile, I document that the share of intermediated imports rises with supply chain risk, as intermediaries maintain more diversified and robust supply networks. These findings motivate a model of global sourcing with costly supplier matching and insecure supply relationships, where heterogeneous producers balance input prices and disruption probabilities across source locations. More productive firms match with multiple suppliers per location, while less productive firms contract with intermediaries, paying higher markups for a more resilient network than they could build directly. Despite double marginalization, intermediaries can relax the efficiency-risk trade-off due to greater supply network operability. Model quantification reveals sizable profit losses from disruptions, which intermediaries halve for producers that lack the scale to diversify. Policies that make these services more accessible can thus enhance supply chain resilience.

Chapter 2, joint work with Kalina Manova and Andreas Moxnes, explores the role of intermediaries from the seller's perspective to unpack the firm attributes and matching costs that govern firm-to-firm networks. Exploiting rich customs data for Chile, we show that exporters of all sizes use intermediaries, mix trade modes across buyers, and set lower prices on intermediated flows. We rationalize these patterns in a model of network formation with suppliers of heterogeneous productivity and matchability, buyers of heterogeneous productivity, and intermediaries that reduce matching costs for a brokerage fee. Empirical evidence informs how geographic distance, logistics and customs efficiency, formal institutions, and cultural-linguistic similarity shape network costs. Model estimation reveals that sellers' attributes are negatively correlated, such that intermediaries enable highly productive sellers with low matchability to reach smaller buyers. This amplifies the welfare gains from intermediation due to wider and deeper network connectivity.

Chapter 3, joint work with Hanwei Huang, Kalina Manova, and Frank Pisch, examines the role of imperfect competition in input markets for the performance of downstream producers. Using French, Chilean, and Chinese customs data, we show that import prices are lower for products with more Chinese suppliers, that suppliers price discriminate across buyers, and that diversified buyers pay lower prices. These patterns motivate a model of network formation with matching frictions and oligopolistic competition upstream, where more productive buyers match with more suppliers, inducing tougher competition and lower input costs. Empirical evidence confirms that French and Chilean firms pay lower prices as more Chinese suppliers enter the market. Model quantification reveals that entry upstream primarily benefits high-productivity buyers, while lower trade or matching costs favor mid-productivity buyers. Moreover, package reforms that reduce matching costs or promote competition amplify the welfare gains from shallow trade agreements.

Chapter 1

Trade Intermediation and Resilience in Global Sourcing

1.1. Introduction

Global markets provide access to a variety of inputs for production that enhance firm and aggregate productivity, but they also expose producers to disruptions overseas. Although these concerns intensified after the Great Recession and the COVID-19 pandemic, contributing to the backlash against globalization, firms report frequent disturbances in their supply chains even outside crisis episodes. Examples range from strikes and industrial accidents to supplier bankruptcies, transportation failures, regulatory changes, and natural disasters (Baldwin and Freeman 2022; Elliott and Golub 2022). Producers can in principle protect themselves by diversifying their supplier base (Blaum et al. 2023; Castro-Vincenzi et al. 2024). However, evidence on firm networks suggests that maintaining multiple suppliers is often prohibitive for all but the largest producers (Bernard and Moxnes 2018a; Bernard et al. 2018a). Alternative approaches to supply chain resilience have thus become focal to debates on sustainable growth, reshoring, and deep economic integration.

This chapter examines for the first time the role that trade intermediaries play in managing supply chain risk. Intermediaries offer firms an indirect mode of input sourcing by specializing in buying, reselling and distributing goods. They mediate a large share of international trade (Blum et al. 2009; Bernard et al. 2010; Ahn et al. 2011), and are believed to reduce sourcing costs by exploiting economies of scale (Grant and Startz 2022; Ganapati 2024). At the same time, they are blamed for charging steep markups that may hinder local producers, particularly in less developed contexts (Antràs and Costinot 2011). Yet, little is known about intermediaries' supply networks and their role for resilience downstream. Anecdotal evidence, however, suggests that intermediaries advertise their expertise in managing supply chain risk, with producers favoring indirect sourcing from riskier locations.[1]

Can producers effectively protect from supply chain disruptions by using intermediation services? I use data on the supply networks of Chilean importers to show that intermediation increases with measures of supply chain risk, and that intermediaries maintain a larger and more robust supplier portfolio. I then develop a model where producers select global sourcing strategies in the expectation of supply link disruptions. More productive firms optimally incur higher matching costs to diversify suppliers in risky markets, while less productive firms rely on intermediaries. When producers face an efficiency-risk trade-off in sourcing, intermediaries can relax it by offering a more resilient network than firms could build on their own, despite double marginalization. Leveraging the rich microdata to estimate the model, I find a substantial mitigation role of intermediaries, especially for mid-size producers that offshore inputs but lack the scale to diversify. Counterfactual analysis underscores the scope for resilience gains through policies that lower brokerage fees in the intermediation sector.

My first contribution is to establish four facts on input sourcing under risk. I use Chilean customs data on the universe of import transactions from 2005 to 2019, matched with tax records that report firms' business activities. This enables me to distinguish between Chilean producers and intermediaries, and to identify their foreign suppliers for each HS 6-digit product and origin country. Specifically, I focus on wholesalers that mediate firm-to-firm transactions as opposed to firm-to-consumer retailers. Wholesalers are prominent in global sourcing, representing only 7% of firms but around 40% of imports and operating across a wide range of sectors.

Fact 1 documents that the share of intermediated imports by origin country and product increases with supply chain risk. This holds for three indices capturing different risk dimensions: *Geopolitical Risk* (Caldara and Iacoviello 2022), *Economic Policy Uncertainty* (Baker et al. 2016), and *Trade Volatility*, which I construct by residualizing trade flows to capture fluctuations within origin-product over time. Analysis of five-year long differences shows that exogenous changes to risk factors abroad shape the sourcing mode of Chilean firms: a one standard deviation increase in any index raises the intermediation share by nearly one percentage point.

Fact 2 unpacks differences in the supply networks of producers and intermediaries that inform this pattern: intermediaries maintain more suppliers and less concentrated input purchases within origin-products. Fact 3 reveals that the supply links of intermediaries are also more stable than those of producers. Finally, Fact 4 shows that, under direct sourcing, both the average

[1] A leading chemicals intermediary, Univar, claims that *"safety and compliance are the foundation of our supply chain network"*, while Li & Fung in apparel *"focus on managing complexity and risk to maximize profitability"*. Interviews with clothing supply chain actors suggest that firms use intermediaries in riskier markets (Vedel and Ellegaard 2013). As stated by one respondent, *"life goes on in these countries despite repeated riots and crises...but we don't establish ourselves"*. See Appendix A.1 for details.

number of suppliers and separation rates with suppliers are higher in riskier markets. Taken together, these findings suggest that producers actively seek protection from disruptions, and intermediaries offer a more resilient sourcing technology in the face of risk.

My second contribution is to develop a model of global sourcing with supply chain risk and trade intermediation. Heterogeneous final-good producers face fixed matching costs per input supplier, but also idiosyncratic risk that a supply link might turn out inoperable.[2] Input costs and disruption probabilities both vary across source locations. At each location, producers can either source directly from one or multiple suppliers, or use intermediaries for a brokerage fee on input prices, gaining access to a diversified network with lower disruption probability. I consider scenarios with either identical or imperfectly substitutable suppliers.

Producers make global sourcing decisions in the expectation of disruptions by choosing source locations, the sourcing mode at each location, and the number of suppliers where they source directly. Sourcing indirectly raises *ex-post* input costs at any given location. However, *ex-ante* expected input costs can be lower due to greater network operability, depending on the resilience advantage of intermediaries over a producer's direct alternative. Producers weigh input costs and disruption probabilities across locations, and optimally protect against disruptions in risky markets. More productive firms engage in *diversification*, incurring higher matching costs to establish direct links with multiple suppliers, while less productive firms opt for *intermediation*. Thus, despite double marginalization, intermediaries can improve the efficiency-risk trade-off for smaller producers.

I provide empirical evidence supporting the model's prediction on how a rise in supply chain risk impacts producers' sourcing strategies. The model implies that smaller, less productive direct buyers would switch to indirect sourcing, while the smallest, least productive indirect buyers would altogether stop sourcing from the now riskier location.[3] The net effect on the total use of intermediation is thus ambiguous. Producers that continue sourcing directly would have greater incentives to diversify suppliers, particularly when substitution is easier within than across locations. Empirically, I confirm heterogeneity in the use of direct diversification and intermediation services in response to risk: fewer firms source directly as risk increases, but the largest firms expand their supplier base.

My third contribution is to quantify the role of trade intermediation in mitigating supply

[2] I focus on the role of intermediaries in mitigating idiosyncratic disruptions, which are reported to be most frequent (McKinsey 2020). This aligns with the low correlation across link breakages observed in the data, even for the same buyer, product, and origin country ($\rho \approx 0.09$). Section 1.3.8 discusses how the model can accommodate correlated shocks.

[3] Risk shocks in one location affect decisions elsewhere, as they jointly determine producers' marginal costs. Under sourcing complementarities, these interdependencies amplify the responses observed in a single-location setting, driving more buyers to switch modes or stop sourcing altogether. The extent of these responses also depends on the substitutability across input locations and among suppliers within locations.

chain disruptions. The producer's problem can be stated as a two-step maximization: the *ex-ante* sourcing strategy is a combinatorial discrete-choice problem, given *ex-post* production decisions conditional on an operational network. I solve this problem numerically, using recent computational methods to tackle the dimensionality of the choice set (Antràs et al. 2017; Arkolakis et al. 2023a; Huang et al. 2024), and Monte Carlo simulations to approximate complex expectations at each choice. I then operationalize this setting for Chile and five source regions: Latin America, China, the US, Europe, and Rest of the World.

The estimation strategy leverages the rich microdata for Chilean firms and their foreign suppliers. Based on model-driven equations, I exploit input price variation across locations within firms and differences in direct links across firms within locations to back out elasticities of substitution. I use the panel structure of the data to isolate location-specific costs from input prices, parameterize supplier separations based on risk measures to estimate disruption probabilities, and infer brokerage fees from additional export price data for producers and intermediaries. Finally, I apply the simulated method of moments to estimate aggregate demand and matching costs. I find elasticities consistent with the trade literature (Atkeson and Burstein 2008a; Edmond et al. 2015a; Huang et al. 2024), indicating greater substitution within locations than across them. Regions with lower input costs experience more disruptions, reflecting an efficiency-risk tradeoff, and matching costs are convex in the number of direct suppliers, suggesting high diversification costs. Brokerage fees are lower than estimates for domestic trade in developed countries (Ganapati 2024; Alexander et al. 2024).

My results show that trade intermediaries substantially reduce the impact of disruptions for mid-size producers that lack the scale to diversify directly. Profit losses are around 20% for this group, but would rise to nearly 40% in a counterfactual scenario without intermediation.[4] Large firms face smaller losses from disruptions (16%) and are almost unaffected by the absence of intermediaries, while small firms source mainly domestically. I also evaluate the role of brokerage fees, which entail a 20% markup on input prices in the baseline model. I consider alternatives of 10% and 30% markups, which are documented respectively for Chilean exporters and domestic transactions in developed countries. These bounds translate into 3 to 5 percentage point changes in the profit losses from disruptions for mid-size producers. Overall, these findings shed light on firms' responses to supply chain risk through trade intermediaries, and point to the scope for resilience gains through a more competitive intermediation sector.

Related Literature. This chapter bridges and advances three strands of literature. First, I contribute to emerging work on supply chain resilience, exploring the effects of disruptions on

[4]The term *mid-size producers* refers to firms large enough to import but relatively small among importers. I define these firms as being below the 90th percentile of importers. Alternative thresholds would affect the magnitude of results but not the overall patterns and conclusions.

aggregate production (Carvalho et al. 2021a; Elliott et al. 2022; Kopytov et al. 2022; Alessandria et al. 2023; Acemoglu and Tahbaz-Salehi 2024; Korovkin et al. 2024), optimal policy responses (Grossman et al. 2023a, 2024), and market responses through various mechanisms (Castro-Vincenzi 2022; Khanna et al. 2022; Balboni et al. 2023; Blaum et al. 2023; Castro-Vincenzi et al. 2024). Also relevant are works on export and FDI decisions under risk (Ramondo et al. 2013; Fillat and Garetto 2015; Esposito 2022). My paper is most closely related to Blaum et al. (2023) and Castro-Vincenzi et al. (2024), which respectively study how firms diversify suppliers in response to shipping and climate risks. Relative to these studies, I characterize heterogeneous sourcing responses where not all firms can afford diversification, considering matching costs alongside differences in firm productivity. Diversification is therefore restricted to the largest producers, leaving smaller firms unprotected in the absence of additional mechanisms.

A second line of research explores the role of intermediaries for trade and development. Intermediaries are responsible for a significant share of trade across and within countries (Bernard et al. 2010; Abel-Koch 2013; Crozet et al. 2013; Utar 2017). They are believed to reduce transaction costs (Antràs and Costinot 2011; Bernard et al. 2015), but their operations generate price wedges that can harm local producers (Bergquist and Dinerstein 2020; Dhingra and Tenreyro 2020; Alexander et al. 2024). While canonical models focused on intermediaries' role in facilitating exporting (Blum et al. 2009; Antràs and Costinot 2011; Ahn et al. 2011; Akerman 2018), recent work highlights how they exploit economies of scale for input sourcing (Grant and Startz 2022; Ganapati 2024). My paper provides the first evidence on the resilience advantage of intermediaries, unpacking the characteristics of their supply networks and offering a microfoundation for economies of scale to arise. Intermediaries can thus relax efficiency-risk trade-offs in input sourcing despite imposing additional markups.

Bringing these literatures together, I unpack a novel adaptation mechanism to supply chain risk: sourcing from intermediaries with a bigger and more resilient portfolio of suppliers. Evidence on firm-to-firm networks shows that only the largest firms transact with multiple suppliers (Bernard and Moxnes 2018a; Bernard et al. 2018a, 2022a), suggesting high diversification costs. I show that intermediaries play a critical role for firms unable to diversify directly, underscoring the importance of firm heterogeneity in risk management strategies.

This chapter also contributes to the literatures on global value chains and endogenous production networks. These works have shown that access to foreign inputs enhances firm productivity through various mechanisms (Amiti and Konings 2007a; Goldberg et al. 2010a; Gopinath and Neiman 2014; Bøler et al. 2015a; Halpern et al. 2015a; Blaum et al. 2018a; Boehm and Oberfield 2020). Global sourcing amplifies the cost advantage of more productive firms, as they access more input locations (Antràs et al. 2017), and lower upstream markups disproportionately benefit larger buyers (Huang et al. 2024). In this setting, supply chain risk and intermediaries jointly shape sourcing patterns, respectively reducing and increasing access to foreign inputs. Moreover, changes in intermediation markups have a greater impact on mid-size producers, broadening the gains from global sourcing across the firm size distribution.

Recent studies have focused on the formation of firm networks under search and matching frictions (Chaney 2014a; Carballo et al. 2018; Bernard et al. 2018c, 2019a; Eaton et al. 2022a). Intermediation influences the structure of these networks by enabling more matches, thereby increasing overall connectivity (Blum et al. 2024; Manova et al. 2024). By incorporating supply chain risk, I demonstrate how intermediaries generate additional gains from network stability, influencing resilience outcomes through producers' endogenous supply network decisions.

The rest of the chapter is organized as follows. Section 2. describes the data and presents stylized facts on input sourcing under risk. Section 3 develops a global sourcing model with supply chain risk and trade intermediation. Section 4 provides empirical evidence supporting model predictions on sourcing responses. Section 5 estimates the model and quantifies the role of intermediaries in supply chain resilience. The final section concludes.

1.2. Stylized Facts

1.2.1. Data

Firm-to-Firm Trade and Intermediaries. I exploit data for Chile that includes the universe of firm-to-firm international transactions and detailed information on the business activity of domestic firms. First, the Chilean Customs Service provides the value, quantity, and unit value for all trade flows from 2005 to 2019, reporting origin country, HS 6-digit product, and buyer-seller identities for each transaction. Second, the Chilean Tax Authority provides data on the primary industry, sub-industry, and activity of Chilean firms over the same period, along with additional firm-level characteristics such as sales and number of employees. I match these datasets using a unique firm tax identifier (RUT).

I classify Chilean firms into three types based on their main industry: producers, wholesalers, and retailers. At this level, the Chilean Tax Authority closely follows the International Standard Industrial Classification (ISIC, rev. 4). Wholesalers specialize in the *"resale without transformation of new and used goods to retailers, to industrial, commercial, institutional or professional users, or to other wholesalers"*, and their operations may include trade-related services such as sorting, packaging, or storage. Retailers, on the other hand, specialize in the resale of goods to the general public for personal or household consumption. Thus, wholesalers focus on firm-to-firm transactions, while retailers carry out firm-to-consumer trade.

Table 1.1 presents summary statistics for trade activity by firm type. Producers are the largest group in number (80%) and contribute nearly half of all imports (45%) and the majority of exports (85%). Wholesalers represent only 7% of firms and 14% of exports, but they are prominent in global sourcing, accounting for a disproportional share of imports (44%).[5] Notably, 89% of imported products pass through wholesalers, indicating a significant overlap with producers in the types of goods sourced. Moreover, they engage with 45% of all foreign suppliers selling to Chile and conduct 41% of import transactions at the buyer-product-supplier level. Retailers, on the other hand, make up 13% of firms but are less relevant for international trade, accounting for 11% of imports and under 1% of exports.

TABLE 1.1. Trade Activity by Firm Type

	Producers	Wholesalers	Retailers
# firms	528,617	43,084	86,627
% firms	0.803	0.065	0.132
% importers	0.439	0.302	0.259
% imported value	0.454	0.439	0.107
% imported products (HS6)	0.909	0.889	0.747
% foreign suppliers	0.448	0.446	0.242
% import transactions	0.331	0.405	0.264
% exporters	0.527	0.372	0.101
% exported value	0.852	0.141	0.008
% exported products (HS6)	0.874	0.722	0.382
% foreign customers	0.682	0.352	0.058
% export transactions	0.566	0.382	0.052

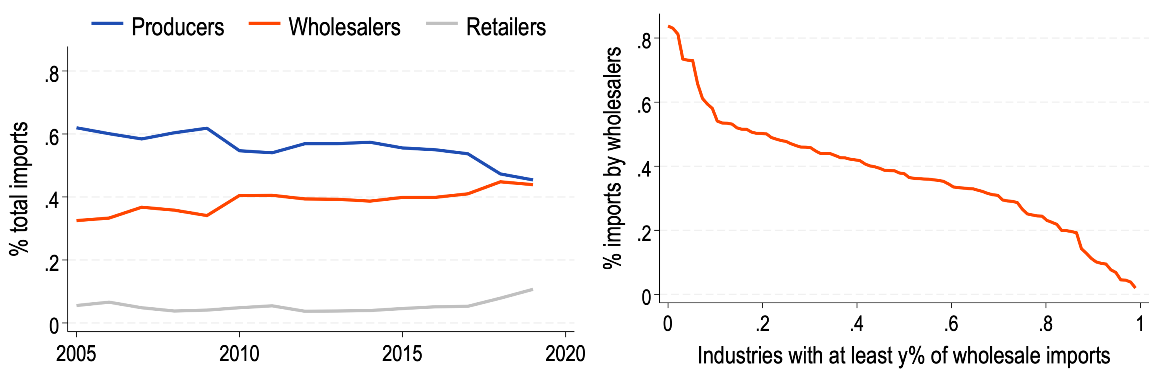
Notes: Summary statistics are reported for the universe of Chilean firms with positive sales in 2019. Firms are classified by their main business activity according to the Tax Authority of Chile (SII), closely following ISIC, rev. 4. International transactions are defined at the buyer-product (HS6)-supplier level.

Figure 1.1 shows firms' import shares over time in Panel A and the share of wholesale imports across broadly-defined sectors in Panel B. The role of wholesalers in global sourcing has increased over the past decades, particularly since the Great Recession, with their share rising from 33% in 2005 to 44% in 2019. Conversely, the import share of producers has steadily declined over the same period. Wholesalers account for at least 20% of imports in 85% of all HS 2-digit sectors active in Chile, and for at least 40% in nearly half of these sectors, indicating that their sourcing activities are widely spread across the economy. Since I study the use of intermediaries to mitigate disruptions, I restrict the analysis to producers and wholesalers,

[5] The relative importance of wholesalers in input sourcing aligns with recent evidence from developed countries. Utar (2017) documents that wholesalers' import shares exceed 50% in Denmark. Ganapati (2024) reports that wholesalers' domestic share in manufacturing trade increased from 43% to 54% in the US, driven by their global sourcing activities and technological advancements.

excluding retailers. Therefore, I use the terms 'wholesaler' and 'intermediary' interchangeably hereinafter.

Figure 1.1. Import Shares Over Time and Across Sectors



(A) Import shares over time

(B) Wholesale imports across HS2-sectors

Notes: Panel A displays import shares for producers, wholesalers and retailers from 2005 to 2019. Panel B considers data across HS 2-digit sectors for 2019, showing the share of sectors where wholesalers comprise at least y% of imports on the x-axis and the corresponding share of imports on the y-axis.

Supply Chain Risk. My analysis relies on three risk measures that proxy for the probability of disruptions in origin markets. First, the *Geopolitical Risk* (GPR) index developed by Caldara and Iacoviello (2022) provides a news-based measure of adverse events and threats associated with political tensions. This indicator has been linked to lower investment across firms and industries, although its relevance for sourcing decisions remains unexplored. The second variable is the *Economic Policy Uncertainty* (EPU) index developed by Baker et al. (2016), which follows a similar methodology to assess overall economic uncertainty and specific issues related to legislation and regulations. Both indexes capture variation across origin countries and over time. In terms of coverage, the GPR spans 44 economies, representing 92% of Chilean imports in 2019, while the EPU includes 29 countries, accounting for 78% of imports.

I also build a measure of *Trade Volatility* using a residualization procedure to isolate variation within origin-products over time, which covers the universe of Chilean imports. Specifically, I use trade flows from the *CEPII* database (Gaulier and Zignago 2010), considering exports X_{opdt} of HS 6-digit product p from origin country o to destination d in year t, excluding Chile. I residualize using product-destination-year and origin-destination-year fixed effects to account for shocks affecting buyer demand within a destination-product and bilateral trade costs, thus capturing supply-side volatility. I then compute the (log) standard deviation of residualized flows within origin-products over 5-year windows, as indicated below.

$$X_{opdt} = \delta_{pdt} + \delta_{odt} + \varepsilon_{opdt}\,, \qquad Risk_{opt} = \log\left(SD_{[t-4,t]}\left(\hat{\varepsilon}\right)\right) \tag{1.1}$$

The three measures are positively correlated but far from being collinear. As reported in Table A1, the correlation between economic policy uncertainty and the other indexes is around 0.4 in 2019, while the correlation between geopolitical risk and trade volatility is 0.35. Figures A3, A4, and A5 display heat maps for each risk measure across origin countries for 2019.[6]

1.2.2. Facts on Input Sourcing under Risk

I establish novel facts on input sourcing under supply chain risk. First, the share of intermediated imports for a given product and origin country rises with measures of risk. Second, intermediaries are more diversified than producers, maintaining a larger number of suppliers and less concentrated input purchases within origin-products. Third, intermediaries have more stable supply links than producers, experiencing lower separation rates. Fourth, the average number of suppliers and supplier separation rates are higher for producers sourcing directly from riskier locations. These facts suggest that producers actively seek protection from disruptions, and that intermediaries offer producers a more resilient sourcing technology in the face of risk.

Stylized Fact 1: *The aggregate share of intermediated imports increases with supply chain risk within an origin country and product.*

I use specification (1.2) to explore how the use of intermediaries varies with supply chain risk. Y_{opt} indicates the share of intermediated imports for a given origin country o and HS 6-digit product p in year t, while $Risk_{opt}$ is a time-varying measure of supply chain risk. I estimate this equation in long differences, considering the 5-year period from 2014 to 2019. Identification then comes from risk changes within origin country-product pairs, which are presumably orthogonal to economic conditions in a small economy like Chile. This approach also rules out the effect of time-constant origin country and product characteristics that may confound the relationship between risk and intermediation, since riskier locations can differ systematically from safer ones. Moreover, Z_{opt} controls for time-varying covariates that may affect firms' sourcing strategies.

$$\Delta_{t,t+5}\, Y_{op} = \alpha\left(\Delta_{t,t+5}\, Risk_{op}\right) + \Delta_{t,t+5}\, Z'_{op}\,\gamma + \epsilon_{op} \tag{1.2}$$

[6]For comparison, the trade volatility index built for origin-product pairs is aggregated at the origin-country level in this analysis.

Table 1.2 shows that the share of intermediated imports increases with all risk measures described in Section 1.2.1: the *Geopolitical Risk* (GPR) and *Economic Policy Uncertainty* (EPU) indexes defined across input origins, and the *Trade Volatility* index at the origin-product level. The coefficients are normalized to reflect the effect of one standard deviation in each measure. Column (1) reports that an increase in *Geopolitical Risk* expands the intermediation share by one percentage point. Column (2) confirms this result when controlling for changes in origin-country productivity and trade costs, as well as changes in total imports by product to account for industry conditions.[7] Columns (3) to (6) display similar results for changes in *Economic Policy Uncertainty* and *Trade Volatility*, with effects ranging from 0.5 to 1.3 percentage points.

Overall, these results suggest that risk factors abroad shape firms' sourcing strategies, with intermediaries playing a greater role for input sourcing when risk increases. The next fact unpacks differences in the supply networks of producers and intermediaries that inform this pattern.

TABLE 1.2. Trade Intermediation and Supply Chain Risk

	Δ % Intermediated imports					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Geopolitical risk	0.010***	0.011***				
	(0.003)	(0.003)				
Δ Economic policy uncertainty			0.010	0.013**		
			(0.006)	(0.005)		
Δ Trade volatility					0.007***	0.005**
					(0.002)	(0.002)
Δ Origin-country productivity	No	Yes	No	Yes	No	Yes
Δ Origin-country trade costs	No	Yes	No	Yes	No	Yes
Δ Product total imports	No	Yes	No	Yes	No	Yes
Observations	33,074	32,768	23,791	23,791	35,155	34,393

Notes: This table considers changes in the share of intermediated imports at the origin country-product (HS6) level over a 5-year period. Supply chain risk is measured by Geopolitical Risk and Economic Policy Uncertainty at the origin-country level, and by Trade Volatility at the origin country-product level. The coefficients are normalized to reflect the effect of one standard deviation. Controls include changes in origin country's total factor productivity and trade procedures, and changes in total imports by product. The sample includes all Chilean import transactions for 2014 and 2019. Standard errors are clustered at the level of the risk measure.

[7] I control for changes in total factor productivity (*Penn World Table 9.1*) and the number of trade procedures (*World Development Indicators*) as a proxy for trade costs. Note that there are virtually no changes in Chilean import tariffs during the period of analysis. On the other hand, time-constant trade barriers, such as distance or cultural differences, are subsumed under the long-differences approach.

Stylized Fact 2: *Intermediaries transact with more suppliers and have less concentrated input purchases across suppliers within origin-products compared to producers.*

I compare the structure of supply networks between producers and intermediaries. Table 1.3 considers the (log) number of suppliers that firms have per origin-product (HS 6-digit), and a Herfindahl-Hirschman index (HHI) for the concentration of input purchases across suppliers. I regress these variables on a dummy indicating whether the firm is an intermediary. Columns (1) to (3) show that intermediaries systematically source from more suppliers than producers, while columns (4) to (6) indicate less concentrated input purchases. On average, intermediaries have 5% more suppliers and a 2 percentage points lower HHI within origin-products.[8] Since wholesalers may operate at a larger scale, I control for buyer size by including 10 bins based on total sales. Similarly, I control for imports per buyer-origin-product, ensuring that supplier differences are not driven by wholesalers purchasing larger amounts. Product and country fixed effects account for the possibility of intermediaries specializing in different input markets.

Table 1.3. Number of Suppliers and Concentration of Input Purchases

	(log) # suppliers			HHI suppliers		
	(1)	(2)	(3)	(4)	(5)	(6)
Intermediary dummy	0.061***	0.046***	0.049***	-0.024***	-0.018***	-0.019***
	(0.006)	(0.005)	(0.006)	(0.002)	(0.002)	(0.002)
Firm size (sales)	Yes	Yes	Yes	Yes	Yes	Yes
Imported value	Yes	Yes	Yes	Yes	Yes	Yes
Product FE (HS6)	No	Yes	No	No	Yes	No
Country FE	No	Yes	No	No	Yes	No
Product - country FE	No	No	Yes	No	No	Yes
Observations	371,200	370,834	346,949	371,200	370,834	346,949

Notes: This table compares the supply networks of producers and intermediaries. All regressions are at the firm-HS6 product-origin country level. The dependent variable in columns (1) - (3) is the (log) number of suppliers, and in columns (4) - (6) is a Herfindahl-Hirschman index (HHI) across suppliers. The independent variable is a dummy indicating whether the firm is a wholesaler. Controls include firm sales (10 bins) and imports per buyer-origin-product. The sample includes all import transactions by Chilean producers and wholesalers in 2019. Standard errors are clustered at the firm level.

In principle, intermediaries might be sourcing different input varieties from different suppliers: while HS 6-digit codes are narrowly defined for some goods, they allow for substantial

[8] Figure A6 displays the average number of suppliers per origin-product for producers and intermediaries of different sizes, along with their Herfindahl-Hirschman index, with observations weighted by import value. While the median firm sources from a single supplier, larger firms tend to multi-source, and the differences between producers and intermediaries persist across the distribution. These patterns are further explored in Section 1.4 and then used for model estimation.

heterogeneity within others. However, further exploration suggests that intermediaries maintain multiple suppliers even for the same variety. Table A2 restricts the sample to homogeneous goods according to the Rauch classification (i.e., goods traded in organized exchanges or with reference prices), reducing the scope for differentiation within product codes. This analysis confirms that intermediaries source from more suppliers than producers.[9]

Fact 2 indicates that producers can access a more diversified supply network by contracting with intermediaries. The next fact shows that, conditional on the number of suppliers, there are also systematic differences in the stability of supply links between producers and intermediaries.

Stylized Fact 3: *Intermediaries have more stable supply links within origin-products compared to producers.*

Table 1.4 compares the stability of links established by producers and intermediaries with foreign suppliers. The dependent variable is a dummy indicating whether supply links in period t will break in $t+1$, while the independent variable indicates whether the firm is an intermediary.[10] Columns (1) to (3) perform the analysis at the firm-origin-product (HS6) level, controlling for the initial number of suppliers, such that the coefficients reflect differences in the probability of a separation. Columns (4) to (6) repeat the analysis at the firm-origin-product-supplier level, where the dependent variable is defined for individual relationships. As before, I control for firm size and imported value, and include fixed effects to compare supply links within origin-products.

My results indicate significant differences between producers and intermediaries, with intermediated links being around 10 percentage points less likely to break. These patterns are consistent with intermediaries having more robust supply networks. However, separations can also be demand-driven due to changes in downstream conditions that induce firms to stop sourcing from their suppliers. This would affect my results if such shocks differ systematically between producers and intermediaries, as it would be the case, for example, if intermediaries hold more diversified customer portfolios. To address this possibility, I control for changes in firm-level outcomes that respond to downstream conditions, such as firms' total imports and number of suppliers. Table A3 shows that the differences between producers and intermediaries

[9] See Grant (2021) for a discussion on how heterogeneous goods are grouped in standard classifications, and how this process may ultimately reflect policy motives. The Rauch classification was originally proposed in Rauch (1999) and then updated in 2007, which is the version used in this study.

[10] Link separations are defined on a yearly basis for this analysis. Similar patterns emerge when considering breaks over longer intervals (t to $t+k$ with $k>1$), although the number of observations decreases significantly. A potential concern is that some products, such as capital goods, are not sourced every year and may appear as separations in the data. However, this should not affect my results as long as the comparison between producers and intermediaries is made within the same product.

TABLE 1.4. Probability of Supply Link Separations: $\mathbb{D}(\text{separation} = 1)$

	Firm-product-country			Firm-product-country-supplier		
	(1)	(2)	(3)	(4)	(5)	(6)
Intermediary dummy	-0.115***	-0.114***	-0.113***	-0.094***	-0.095***	-0.092***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Firm size (sales)	Yes	Yes	Yes	Yes	Yes	Yes
Imported value	Yes	Yes	Yes	Yes	Yes	Yes
Number of suppliers	Yes	Yes	Yes	No	No	No
Product FE (HS6)	No	Yes	No	No	Yes	No
Country FE	No	Yes	No	No	Yes	No
Product - country FE	No	No	Yes	No	No	Yes
Observations	312,724	312,346	289,355	427,739	427,390	406,481

Notes: This table compares the probability of a separation with foreign suppliers for producers and intermediaries. The dependent variable is a dummy indicating whether supply links break from period t to $t+1$, and the independent variable is a dummy indicating whether the firm is an intermediary. Columns (1) - (3) perform the analysis at the firm-HS6 product-origin country level, controlling for the log-number of suppliers. Columns (4) - (6) are at the firm-HS6 product-origin country-supplier level. The sample considers all import transactions in 2018 for firms active in 2018 and 2019. Standard errors are clustered at the firm level.

are smaller but remain significant in this case.[11]

The fact that intermediaries face lower disruption probabilities can be microfounded in several ways that, while not explicitly modeled, are supported by the data. One possibility is that intermediaries match with safer suppliers due to better *screening* capabilities, which is explored by introducing supplier fixed effects. Another option is that intermediaries are more important customers, and can *monitor* suppliers more closely or be placed *first-in-line* during disruptions. This is assessed by controlling for the share of buyers in suppliers' total sales. Furthermore, intermediaries may source multiple products from the same supplier, maintaining relationships during *product-specific shocks*, which is tested by defining links at the supplier-product level. Table A4 shows that each channel individually reduces the gap in separation rates by nearly 3 percentage points. When all three are considered simultaneously, separation rates are only 2 percentage points lower for intermediaries, explaining a significant part of the differences.

Stylized Fact 4: *The average number of direct suppliers and separation rate with suppliers are higher in riskier origin-products.*

I now document how the outcomes of direct sourcing vary with supply chain risk. Table 1.5 examines the number of suppliers per producer buyer and the separation rate between buyers and

[11] These demand controls are also included when estimating disruption probabilities across input locations for model quantification (Section 1.5). Moreover, the analysis shows that the probability of disruptions increases with all three risk measures: *Geopolitical Risk*, *Economic Policy Uncertainty*, and *Trade Volatility*.

suppliers by origin country and product. Columns (1) to (3) show that, on average, producers transact with more suppliers in riskier origin-products, according to any of the risk indexes described in Section 1.2.1. This pattern aligns with recent evidence on supplier diversification in countries such as India and the US, particularly in response to climate and shipping risks (Blaum et al. 2023; Castro-Vincenzi et al. 2024).[12] Columns (4) to (6), on the other hand, show that supply link separations occur more frequently in riskier origin-products. All columns include product fixed effects to account for industry-level covariates and also control for origin-country productivity and trade costs.

TABLE 1.5. Average Number of suppliers and Separation Rate under Direct Sourcing

	(log) # Suppliers			Separation rate		
	(1)	(2)	(3)	(4)	(5)	(6)
Geopolitical Risk	0.105***			0.055*		
	(0.018)			(0.029)		
Economic Policy Uncertainty		0.049**			0.067***	
		(0.023)			(0.019)	
Trade Volatility			0.039***			0.010***
			(0.001)			(0.002)
Product FE (HS6)	Yes	Yes	Yes	Yes	Yes	Yes
Origin-country productivity	Yes	Yes	Yes	Yes	Yes	Yes
Origin-country trade costs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63,025	44,880	66,434	52,799	38,801	54,186

Notes: This table considers how the outcomes of direct sourcing vary with supply chain risk at the origin country-product (HS6) level. Columns (1) - (3) consider the average number of suppliers per producer buyer. Columns (4) - (6) consider the average separation rate with suppliers across producer buyers. Supply chain risk is measured by Geopolitical Risk and Economic Policy Uncertainty at the origin-country level, and by Trade Volatility at the origin country-product level. All columns include product fixed effects and control for origin country's total factor productivity and trade procedures. The sample includes all Chilean import transactions for 2019. Standard errors are clustered at the level of the risk measure.

In sum, Fact 4 indicates that producers sourcing directly tend to diversify suppliers in riskier locations, where their supply links are more likely to break. Facts 2 and 3 in turn establish that intermediaries provide a means of indirect supplier diversification and of reducing the frequency of link separations. Finally, Fact 1 documents that the use of intermediation services increases systematically in locations that become riskier.

[12] I confirm this positive correlation at the firm level for both producers (Table A5) and intermediaries (Table A6) in the Chilean data. Furthermore, the difference in the number of suppliers between producers and intermediaries documented in Fact 2 is even larger in riskier locations (Table A7).

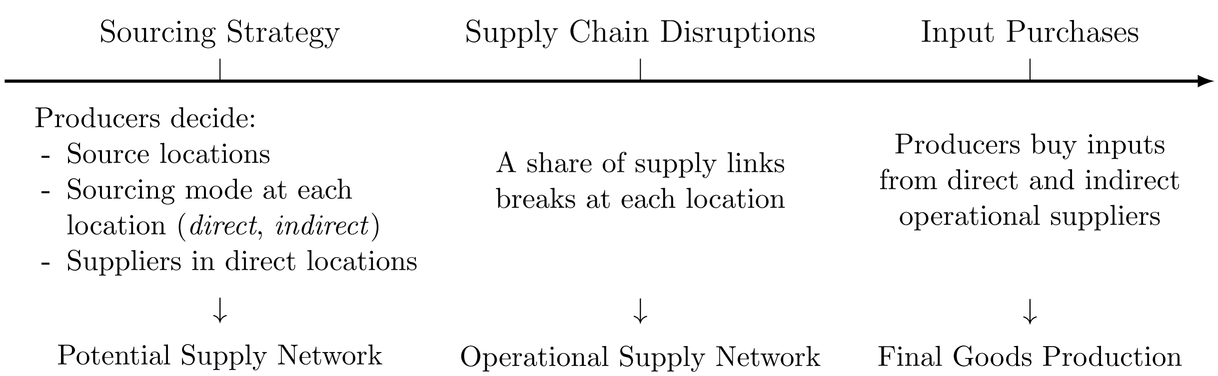
1.3. Theoretical Framework

Motivated by stylized facts 1-4 above, I next develop a general-equilibrium model of global sourcing that incorporates supply chain risk and trade intermediation. Specifically, I model the problem of heterogeneous final-good producers that source inputs from discrete sets of locations and suppliers, and face idiosyncratic risk of supplier link failure. Producers trade off input costs against disruption probabilities when selecting source locations, and have two mechanisms to mitigate disruptions within locations: matching directly with multiple suppliers (*diversification*) or sourcing inputs indirectly (*intermediation*), where intermediaries provide access to a more diversified network with lower disruption probability. The model characterizes producers' optimal sourcing strategies and their use of intermediation services under risk.

1.3.1. Setup

Timing. The model is static but producers make decisions in sequential stages. In the first stage, producers define their sourcing strategies to maximize expected profits. This includes the set of source locations, the sourcing mode at each location (i.e., directly or indirectly through an intermediary), and the set of suppliers when sourcing directly.[13] These choices involve sunk investments and define a *potential network* of direct and indirect suppliers. Supply chain disruptions are then realized, such that a share of supply links break at each location. Finally, producers make optimal input purchases and production decisions conditional on their *operational network*. Figure 1.2 summarizes the timeline of events.

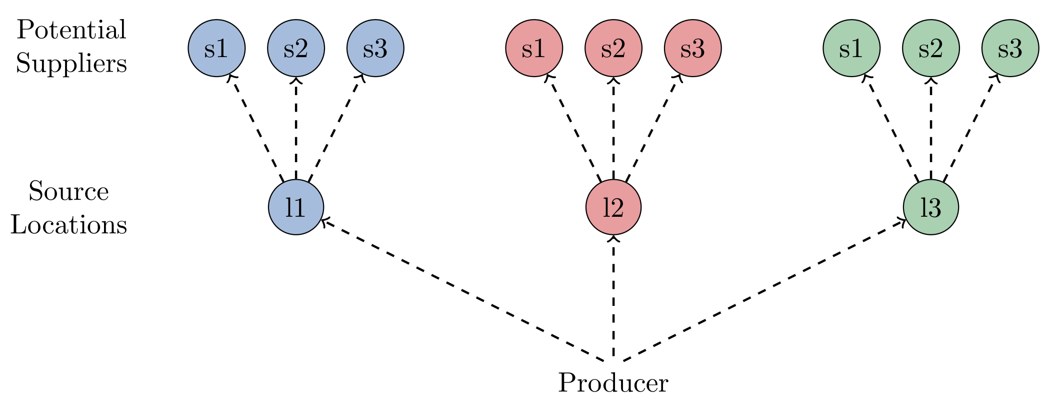
FIGURE 1.2. Timeline of Events



[13]The concept of *location* can accommodate different geographic and industry partitions. In this context, they can be thought of as markets defined by the origin country and HS-sector of the intermediate goods.

Input Markets. Consider producers in country i with access to a discrete set of source locations $\mathcal{L}$, each populated by a discrete set of suppliers $\mathcal{S}_l$. Locations differ in unit production costs (α_l), iceberg-type trade costs (τ_{il}), the probability of disruptions (ζ_l), and fixed sourcing costs (f_l). I assume that each location offers a differentiated input x_l that can be produced by all local suppliers. I first consider suppliers with homogeneous productivity, normalized to one, such that input prices are simply $p^x_{il} = \tau_{il}\alpha_l$.[14] In this case, suppliers are perfect substitutes within locations and precautionary motives are the only reason to establish multiple links. I later relax this assumption in Section 1.3.6 to consider variety-specific efficiencies that generate imperfect substitution across suppliers. As long as input prices are not perfectly correlated with supply chain risk across locations, producers face a risk-efficiency trade-off in sourcing decisions. Figure 1.3 illustrates the structure of input markets.

FIGURE 1.3. Input Markets with Discrete Locations and Suppliers



Supply Chain Risk. I model supply chain disruptions as shocks that break the links established with suppliers in the first stage. This captures any failures in production and distribution that prevent suppliers from serving their customers. Thus, if a link is disrupted in location l, the firm cannot purchase l-inputs unless it has another operational link in l.[15] Formally, I consider a discrete shock Z^M_l that disrupts supply links with an exogenous probability ζ^M_l and leaves them operational otherwise, allowing for differences across locations l and sourcing modes M. The assumption of independent disruptions is consistent with the low correlation of link separations observed in the data, so I focus on the role of intermediaries in mitigating idiosyncratic

[14] I abstract from a detailed microfoundation of input markets. However, α_l can be rationalized as the unit cost of production in a setting with perfect or monopolistic competition (e.g., $\alpha_l = \frac{w_l}{\phi_l}$ for wages w_l and labor productivity ϕ_l when inputs use only labor under constant returns to scale).

[15] This *on-and-off* approach is analogous to *percolation analysis* in graph theory (i.e., disabling edges at random). While my model considers supply networks that are bi-partite in nature, Elliott et al. (2022) implement this approach in the context of complex networks with multiple layers.

failures.[16] Although this structure adds tractability, the model can also accommodate correlated shocks under more general conditions, which are discussed as an extension.

Sourcing Modes. Producers have two modes to access any given location l. Under direct sourcing, producers select a set of suppliers S_l^D, face disruption probability ζ_l^D, and incur matching costs $f_l^D(S_l^D)$ that increase with the number of supply links. Under indirect sourcing, intermediaries charge a brokerage fee κ on input prices and offer a sourcing technology $\left\{S_l^I \geq S_l^D, \zeta_l^I \leq \zeta_l^D\right\}$, consistent with the empirical evidence in Section 1.2. The fixed cost of contracting with intermediaries is assumed to be lower than that of matching with suppliers directly, $f_l^I \leq f_l^D(\cdot)$.[17] Thus, producers have two risk mitigation strategies at each location: they can engage in *diversification* by establishing direct links with multiple suppliers, which involves higher matching costs, or they can opt for *intermediation*, accessing a resilient network at higher input prices. Figure 1.4 illustrates both sourcing modes before and after the realization of disruptions.

1.3.2. Final Demand

Consumers in country i have Cobb-Douglas preferences over homogeneous and differentiated final goods. The homogeneous good q_{i0} is freely traded and produced using labor under constant returns to scale, such that one unit of labor generates w_i units of output. Using the homogeneous good as *numeraire* sets wages to w_i. Consumers exhibit CES preferences for varieties $\omega \in \Omega_i$ of the non-tradable differentiated final good:

$$U_i = q_{i0}^{1-\beta}\left(\int_{\Omega_i} q_i(\omega)^{\frac{\sigma-1}{\sigma}} d\omega\right)^{\beta\sigma/(\sigma-1)},$$

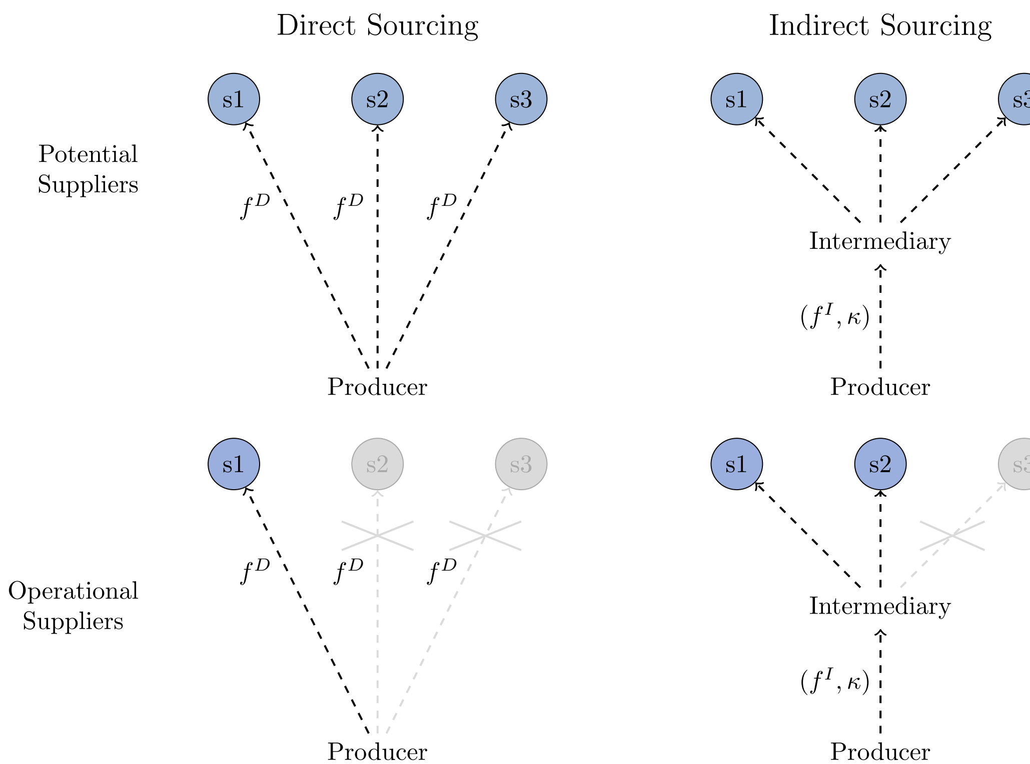
where β is the expenditure share on differentiated goods, and $\sigma > 1$ is the elasticity of substitution across varieties. Given aggregate expenditure E_i and the price index P_i for differentiated goods, demand for variety ω with price $p_i(\omega)$ is:

$$q_i(\omega) = p_i(\omega)^{-\sigma} P_i^{\sigma-1} E_i\,. \tag{1.3}$$

[16]The correlation across supply link breakages within the same buyer, product, and origin country is around 0.09 (Table A8). This aligns with business reports indicating that idiosyncratic disruptions are the most frequent (McKinsey 2020) and suggests that a substantial part can be treated as independent.

[17]The idea of intermediaries reducing fixed trade costs in exchange for a markup is well-established in the trade literature (Ahn et al. 2011; Bernard et al. 2015) and underlies recent works on intermediated production networks (Blum et al. 2024; Manova et al. 2024). My setting follows this insight but emphasizes the role that the attributes of the intermediation technology play under supply chain risk.

Figure 1.4. Sourcing Modes and Disruptions within Locations



1.3.3. Producers

Country i contains a continuum of heterogeneous final goods producers. They own a blueprint for a single variety ω under monopolistic competition, and draw productivity $\varphi \in [\underline{\varphi}_l, \overline{\varphi}_l]$ from some distribution $G(\varphi)$. The production technology transforms intermediate inputs into final goods under constant returns to scale:

$$q_i(\omega) = \varphi(\omega) X_i(\omega) \qquad X_i(\omega) = \left(\sum_{l \in \mathcal{L}(\omega)} x_{il}(\omega)^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}, \tag{1.4}$$

where $X(\omega)$ is a composite intermediate combining inputs with an elasticity of substitution $\eta > 1$, and $x_{il}(\omega)$ is the quantity purchased from each location to which the producer has access, as indicated by $\mathcal{L}(\omega)$.[18] The marginal cost of producers thus depends on their own productivity and their input cost $C(\omega)$, which aggregates the prices $p_{il}^{x,M}(\omega)$ paid for inputs across locations

[18] I assume that inputs are the only factor of production for differentiated final goods. Although incorporating labor in a technology of the form $q(\omega) = \varphi(\omega) L(\omega)^{\beta} X(\omega)^{1-\beta}$ is straightforward, it adds complexity to the derivations without providing additional insights into sourcing responses.

given a sourcing mode M:

$$c_i(\omega) = \frac{C_i(\omega)}{\varphi(\omega)} \qquad C_i(\omega) = \left(\sum_{l \in L(\omega)} p_{il}^{x,M}(\omega)^{1-\eta} \right)^{\frac{1}{1-\eta}} . \tag{1.5}$$

Producers pay the price set by suppliers under direct sourcing, and a constant markup above it under indirect sourcing, which the intermediary charges as a brokerage fee:

$$p_{il}^{x,I} = \kappa \, p_{il}^{x,D} , \tag{1.6}$$

For now, input prices are not affected by the number of suppliers as they are perfect substitutes within locations: the only reason for having multiple links per location is to ensure input access. On the other hand, the CES structure generates variety gains from sourcing in multiple origins, since locations offer differentiated inputs that are imperfect substitutes in production.[19]

Note that heterogeneous producers will optimally make different decisions regarding the set of source locations and the sourcing mode and suppliers within them. Moreover, even if their decisions were identical, the realization of disruptions may lead to different outcomes.

1.3.4. Optimal Sourcing with One Location

I first characterize the producer's problem when only one input location is available, and then extend the analysis to multiple locations in Section 1.3.5. Given the timing of events, producers make decisions in two steps. First, they select their optimal sourcing strategy internalizing the probability of disruptions. After disruptions materialize, they make optimal input purchases and production decisions. I work in reverse order, starting with the *ex-post* problem followed by the *ex-ante* problem given the *ex-post* solution.

Ex-Post Problem. Producers have already selected a sourcing mode $M_l(\omega) \in \{D, I\}$ and a set of suppliers $S_l^D(\omega) \in \mathcal{S}_l$ if sourcing directly, and supply chain disruptions Z_l have materialized. Conditional on these choices and realizations, producers make input purchases and production decisions to maximize their *ex-post* operating profits:

$$\max_{p_i(\omega), q_i(\omega), x_{il}(\omega)} \pi_i^{\text{ex-post}}\left(\omega \,\middle|\, M_l, S_l^D, Z_l\right) = \left[p_i(\omega) - c_i\left(\omega \,\middle|\, M_l, S_l^D, Z_l\right) \right] q_i(\omega)$$

[19] Under perfect substitutability, $\eta \to \infty$ and the production function is $q_i(\omega) = \varphi(\omega) \left(\sum_{l \in \mathcal{L}(\omega)} x_{il}(\omega) \right)$, such that the only incentive for having multiple locations is to ensure that at least one remains active. However, the literature on global value chains suggests that firms benefit from sourcing in multiple origins for reasons beyond variety gains, such as inducing tougher competition among suppliers (Antràs et al. 2017; Huang et al. 2024).

Given final demand (2.1) and monopolistic competition, producers optimally set a constant markup over their marginal cost such that $p_i(\omega) = \frac{\sigma}{\sigma-1} c_i(\omega \,|\, M_l, S_l^D, Z_l)$, which determines downstream quantities and therefore input purchases according to the production technology (1.4). The marginal production cost depends on the *ex-ante* sourcing strategy and disruption realizations. Conditional on direct sourcing, producer ω has access to inputs at a price p_{il}^{xD} if at least one direct link remains operational. Similarly, under indirect sourcing, inputs can be bought at p_{il}^{xI} if the intermediary has at least one operational supplier. *Ex-post* profits can be expressed as follows, where $p_{il}^{x} \to \infty$ when the supply network is not operational.[20]

$$\pi_i^{\text{ex-post}}\left(\omega \,\middle|\, M_l, S_l^D, Z_l\right) = \begin{cases} \varphi(\omega)^{\sigma-1}\left(p_{il}^{x,M}\right)^{1-\sigma} \frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} P_i^{\sigma-1} E_i & \text{if operational} \\ 0 & \text{otherwise} \end{cases} \tag{1.7}$$

Indirect sourcing reduces *ex-post* profits conditional on network operability. The brokerage fee increases input costs as stated in (1.6), which raises producers' marginal costs and is passed on to consumers in the form of higher final-good prices. This, in turn, reduces producers' competitiveness and market shares downstream. On the other hand, inspection of (1.7) reveals *negative* complementarity between firm productivity and input costs. The impact of intermediation markups is thus amplified for more productive firms.

Proposition 1. (ex-post profits) *Conditional on network operability, producers' ex-post profits are lower under indirect sourcing, especially for more productive firms.*

Proof. *See Appendix A.3.*

Ex-Ante Problem. Before disruptions are realized, producers determine their optimal sourcing strategy at location l to maximize expected profits, which includes the sourcing mode $M_l(\omega) \in \{D, I\}$ and the set of suppliers $S_l^D(\omega) \in \mathcal{S}_l$ when sourcing directly. Given ex-post profits (1.7), the producer's *ex-ante* problem is:

$$\begin{aligned} \max_{M_l(\omega)\in\{D,I\},\; S_l^D(\omega)\in\mathcal{S}_l} \pi_i^{\text{ex-ante}}\left(\omega, M_l, S_l^D, Z_l\right) &= \mathbb{E}_{Z_l}\left[\pi_i^{\text{ex-post}}\left(\omega, M_l, S_l^D, Z_l\right)\right] \\ &\quad - \mathbb{1}_{\{M_l(\omega)=D\}} f_l^D\left(S_l^D(\omega)\right) - \mathbb{1}_{\{M_l(\omega)=I\}} f_l^I \end{aligned}$$

[20] While losing access to l-inputs leads to zero operational profits in this simplified setting, the impact of disruptions is smoother in the general case with multiple locations. This is particularly true when a *safer* location is available (e.g., inputs sourced domestically may be less prone to disruptions). In that case, disruptions increase marginal production costs without forcing firms out of the market.

where $\mathbb{I}_{\{M_l\}}$ are indicator variables for the selected sourcing mode, f_l^D is the cost of matching directly with suppliers, and f_l^I is the cost of contracting with an intermediary. Since these payments are irreversible, the expectation operates over *ex-post* profits, specifically over the input cost that determines producers' marginal cost in (2.4).

The probability of network operability and input prices jointly determine producers' expected input cost. Under idiosyncratic disruptions, the number of operational links $S_l^O(\omega)$, conditional on a sourcing mode $M_l(\omega)$ and set of suppliers $S_l^M(\omega)$ for producer ω, follows a Binomial distribution:

$$\Pr\left(S_l^O(\omega) = S \,\middle|\, M_l(\omega), S_l^M(\omega)\right) = \binom{S_l^M(\omega)}{S}\left(1 - \zeta_l^M\right)^S \left(\zeta_l^M\right)^{S_l^M(\omega)-S},$$

Sourcing from location l requires that at least one link remains operational, such that the probability of network operability is given by:[21]

$$\Pr\left(S_l^O(\omega) \geq 1 \,\middle|\, M_l(\omega), S_l^M(\omega)\right) = 1 - \left(\zeta_l^M\right)^{S_l^M(\omega)}. \tag{1.8}$$

Enhancing operability is costly for producers. Under direct sourcing, establishing links with multiple suppliers ($S_l^D > 1$) entails greater matching costs $f^D(S_l^D)$. Indirect sourcing, by contrast, influences network operability through two channels: the number of potential links $S_l^I \geq S_l^D$ and the probability of facing disruptions $\zeta_l^I \leq \zeta_l^D$, but increases *ex-post* input prices due to the brokerage fee. Expected input costs under direct and indirect sourcing are then:

$$\mathbb{E}_{Z_l}\left[p_{il}^x(\omega)^{1-\sigma} \,\middle|\, M_l(\omega) = D, S_l^M(\omega)\right] = \left(1 - \left(\zeta_l^D\right)^{S_l^D(\omega)}\right)\left(p_{il}^x\right)^{1-\sigma} \tag{1.9}$$

$$\mathbb{E}_{Z_l}\left[p_{il}^x(\omega)^{1-\sigma} \,\middle|\, M_l(\omega) = I\right] = \frac{\left(1 - \left(\zeta_l^I\right)^{S_l^I}\right)}{\kappa^{\sigma-1}}\left(p_{il}^x\right)^{1-\sigma} \tag{1.10}$$

Producers' sourcing decisions weigh expected input costs and the fixed costs of transacting with suppliers or intermediaries. While there is no closed-form solution to this discrete-choice problem, I characterize its properties below. To facilitate comparison among sourcing modes, I define a mapping that converts the intermediation technology into an *equivalent* number of

[21] Recall that suppliers are assumed to be perfect substitutes within locations. When this assumption is relaxed in Section 1.3.6, the number of suppliers itself affects input costs, and the full distribution of operational suppliers must be considered. Also note that there is a slight abuse of notation, as $S_l^O(\omega)$ and $S_l^M(\omega)$ are sets of suppliers, while network operability considers the cardinality of these sets.

direct suppliers in terms of expected input costs, $\tilde{S}^I_l(S^I_l, \zeta^I_l, \kappa)$. Intuitively, this number increases with a greater resilience advantage of intermediaries or lower brokerage fees.

$$\tilde{S}^I_l\left(S^I_l, \zeta^I_l, \kappa\right) \equiv \left\{S^D_l : \mathbb{E}_{Z_l}\left[\left(p^x_{il}(\omega)\right)^{1-\sigma} \middle| M_l(\omega) = D, S^D_l\right] = \mathbb{E}_{Z_l}\left[\left(p^x_{il}(\omega)\right)^{1-\sigma} \middle| M_l(\omega) = I\right]\right\}$$

$$= \frac{\left|\ln\left(1 - \frac{1-(\zeta^I)^{S^I}}{\kappa^{\sigma-1}}\right)\right|}{\left|\ln(\zeta^D)\right|} \tag{1.11}$$

Sourcing Strategies. I first characterize producers' optimal strategies under direct sourcing and then consider their optimal sourcing mode. Part (a) of Proposition 2 states that direct supplier diversification increases network operability and lowers expected input costs compared to sourcing from a single supplier, which follows directly from (1.9). Part (b) shows that more productive firms are more likely to diversify suppliers when sourcing directly. Higher productivity amplifies the gains from network operability due to complementarities in the *ex-ante* profit function, while matching costs constrain diversification for less productive firms. This rationalizes precautionary diversification among risk-neutral producers and suggests that these responses vary across the firm size distribution.

Proposition 2. (direct sourcing) *Producers' direct sourcing strategy is such that:*

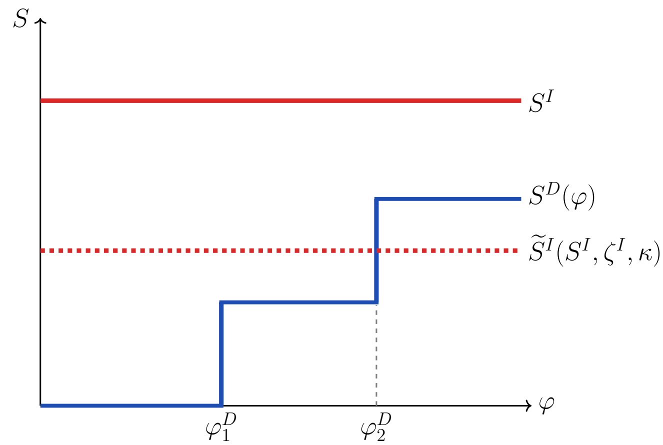
a. *Direct supplier diversification increases network operability and reduces expected input costs for producers.*
b. *The optimal number of direct suppliers (weakly) increases with firm productivity:* $S^D_l(\varphi^H) \geq S^D_l(\varphi^L)$ *for* $\varphi^H \geq \varphi^L$.

Proof. *See Appendix A.3.*

Proposition 3 incorporates indirect sourcing into the analysis. Part (a) states that intermediaries enhance network operability and reduce expected input costs, but only for producers that could match directly with fewer than a certain number of suppliers. Although indirect sourcing implies higher *ex-post* input prices, from an *ex-ante* perspective, expected input costs can be lower if intermediaries' resilience advantage offsets the brokerage fee in (1.10). This relative advantage depends on the characteristics of the intermediation technology, as well as on the alternative network that producers could optimally build directly.

Proposition 3. (indirect sourcing) *Producers' use of intermediaries is such that:*

FIGURE 1.5. Direct and Indirect Suppliers



Notes: The blue line shows the optimal number of suppliers under direct sourcing, $S^D(\varphi)$. The solid red line shows the intermediation technology, which provides access to S^I indirect suppliers. The dashed red line indicates the *equivalent* number of indirect suppliers $\tilde{S}^I(S^I, \zeta^I, \kappa)$, after accounting for indirect disruption probabilities and the brokerage fee. Producers are sorted by productivity on the x-axis.

a. *Intermediation increases network operability and reduces expected input costs for producers that can match fewer than* $\tilde{S}_l^I(S_l^I, \zeta_l^I, \kappa)$ *suppliers directly.*

b. *There is a productivity threshold* φ^* *above which producers switch from indirect to direct sourcing:*

$$\varphi_l^* = \min_{S_l^D} \left[\frac{f_l^D(S_l^D) - f_l^I}{\left(1 - (\zeta_l^D)^{S_l^D} - \frac{1-(\zeta_l^I)^{S^I}}{\kappa^{\sigma-1}}\right)\left(P_{il}^x\right)^{1-\sigma} B} \right]^{\frac{1}{\sigma-1}} \quad \textit{for } S_l^D \in |\mathbb{S}_l|$$

Proof. *See Appendix A.3.*

Figure 1.5 illustrates this result. The blue line depicts the optimal choice of direct suppliers $S^D(\varphi)$, which follows a step function based on firm productivity, as described in Proposition 2. The solid red line S^I represents the number of indirect suppliers offered by intermediaries. The dashed red line indicates the *equivalent* number of direct suppliers $\tilde{S}_l^I(S_l^I, \zeta_l^I, \kappa)$ defined in (1.11), which adjusts the number of indirect suppliers for disruption probabilities and brokerage fees. In this example, producers with productivity $\varphi_1^D < \varphi < \varphi_2^D$ source from one supplier directly, while those with $\varphi > \varphi_2^D$ source from two. Intermediaries reduce expected input costs for the former, while the latter can further lower costs by diversifying directly.

Part (b) of Proposition 3 characterizes producers' optimal sourcing mode and shows that more productive firms are less likely to source indirectly.[22] Producers compare *ex-ante* profits

[22]High-productivity firms may use intermediaries in locations where low-productivity firms refrain from

under indirect sourcing with those under direct sourcing, evaluated at the firm-specific optimal choice of direct suppliers. More productive firms can protect themselves by diversifying directly and are also more sensitive to brokerage fees. This implies a productivity cutoff φ_l^* at which firms switch from indirect to direct sourcing, determined by the minimum number of direct suppliers needed to equalize *ex-ante* profits under both sourcing modes. This threshold rises with a more resilient intermediation technology, lower brokerage fees, and higher matching costs with suppliers.[23]

Figure 1.6 plots several *ex-ante* profit lines to illustrate producers' indirect sourcing, direct sourcing from 1 supplier, and direct sourcing from 2 suppliers. Several patterns consistent with Propositions 2 and 3 stand out. First, *ex-ante* profits increase with firm productivity along each line. Second, more direct matches entail higher fixed costs but lower *expected* input costs, such that the $D(S=2)$ line crosses the $D(S=1)$ line once from below. And third, more productive firms are more likely to engage in direct sourcing: firms in the productivity range $[\varphi^I, \varphi^*]$ use intermediaries, while those with productivity $\varphi > \varphi^*$ source directly.[24] In turn, contracting with intermediaries is cheaper than matching suppliers directly, $f^I < f_l^D(S_l^D)$, so indirect sourcing reduces both expected input costs and fixed costs for firms below φ_2^D. In contrast, intermediation imposes a trade-off for more productive firms, reflecting the effect of incurring higher matching costs or paying brokerage fees to enhance operability.[25]

Supply Chain Risk. I next analyze how producers adapt to changes in supply chain risk. Consider a proportional increase in direct and indirect disruption probabilities.[26] This reduces the profitability of inputs from l, increasing the minimum productivity required to source either directly or indirectly. As a result, some mid-productivity firms previously sourcing directly would now switch to indirect sourcing, while the least productive firms that previously source indirectly would stop sourcing from l altogether.[27] Intuitively, the attributes of the intermediation

sourcing. This is consistent with Proposition 3, which establishes monotonicity in sourcing modes, ruling out the case where low-productivity firms source directly and high-productivity firms indirectly in the same location.

[23] I assume a technological condition is satisfied for intermediation to take place, as shown in Appendix A.3. Intuitively, for some firms to use intermediaries, the greater resilience and lower contracting costs of using intermediaries must to some extent compensate for the brokerage fee.

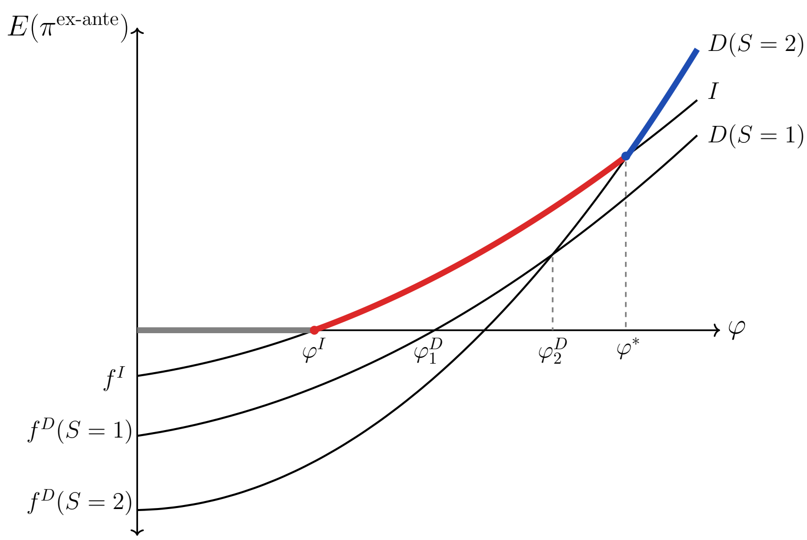
[24] While this strict sorting pattern is unlikely to hold in the data, deviations can be rationalized with heterogeneous matching costs across producers that are not perfectly correlated with their productivity (Bernard et al. 2022a; Manova et al. 2024). I allow for this possibility in the numerical solution.

[25] Note that firms between φ_2^D and φ^* could further reduce expected input costs through direct diversification, but source indirectly to save on matching costs. This is consistent with a broader role of intermediaries in facilitating transactions even without supply chain risk.

[26] One can think of intermediaries as being able to lower the probability of disruptions by some factor $\mu < 1$, such that $\zeta^I = \mu\zeta^D$. Therefore, changes in ζ^D generate proportional changes in ζ^I.

[27] Higher disruption probabilities make direct sourcing even less profitable for these firms. Therefore, in this single-location setting, producers in the productivity range $[\varphi_l^I(\zeta_l), \varphi_l^I(\zeta_l')]$ are driven out of the market. These firms may be able to substitute inputs in the general, multi-location case.

FIGURE 1.6. Optimal Sourcing Strategy



Notes: This figure illustrates sourcing modes from a given location l. Each curve displays expected *ex-ante* profits under a given strategy: sourcing directly from one $(D(S=1))$ or two $(D(S=2))$ suppliers, or sourcing indirectly (I). Firms are sorted by productivity on the x-axis. Firms on the gray segment do not source from l, those on the red segment source indirectly, and those on the blue segment source directly.

technology become more valuable when disruptions are more frequent, amortizing the cost of the brokerage fee. Finally, the most productive firms that continue to source directly have incentives to expand their supplier set. The relative value of backup suppliers increases for these firms, reducing the productivity cutoffs for multiple direct matches.

PROPOSITION 4. (RISK RESPONSES) *Given moderate disruption probabilities $\zeta_l \equiv \{\zeta_l^D, \zeta_l^I\}$ in source location l, a proportional increase in ζ_l:*

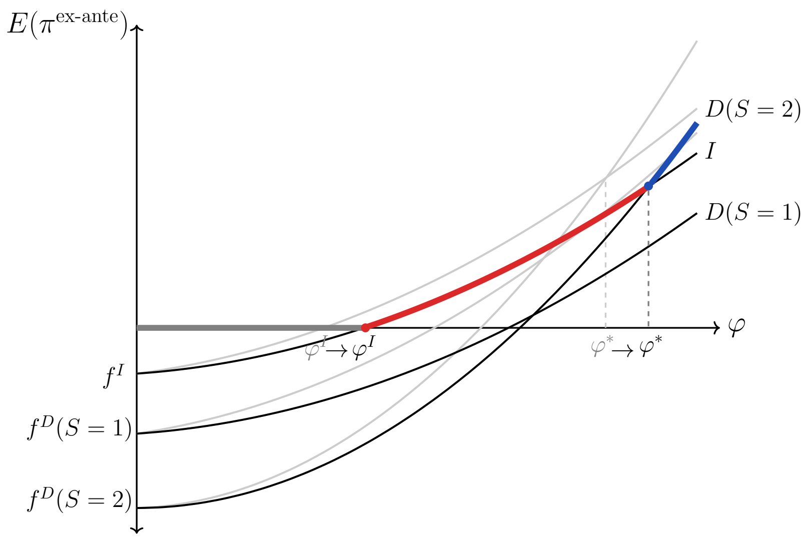
a. *Induces marginal firms sourcing indirectly to stop sourcing from l:* $\varphi^I(\zeta_l') \geq \varphi^I(\zeta_l)$
b. *Induces marginal firms sourcing directly to switch sourcing modes:* $\varphi^*(\zeta_l') \geq \varphi^*(\zeta_l)$
c. *Induces firms that keep sourcing directly to diversify suppliers:* $\varphi_S^D(\zeta_l') \leq \varphi_S^D(\zeta_l)$ *for* $S > 1$

Proof. *See Appendix A.3*.

Figure 1.7 illustrates these patterns. The slope of *ex-ante* profits under direct sourcing, for any given choice of direct suppliers, is larger than for indirect sourcing.[28] Higher supply chain risk pushes down *ex-ante* profits under both sourcing modes, but the slope difference between

[28] Formally, the difference in slopes between *ex-ante* profits under any given choice of direct suppliers and indirect sourcing is $m^*(\zeta_l) \equiv \left(1 - (\zeta_l^D)^{S_l^D} - \frac{1-(\zeta_l^I)^{S^I}}{\kappa^{\sigma-1}}\right)\left(p_{il}^x\right)^{1-\sigma}\varphi^{\sigma-1}B_i$. Note that, if $m^*(\zeta_l) < 0$ for all direct options, then indirect profits would exhibit both a lower intercept and a higher slope than direct alternatives, and all producers would source indirectly.

FIGURE 1.7. Higher Probability of Disruptions



Notes: This figure illustrates how *ex-ante* expected profits evolve with an increase in the probability of disruptions. Each curve represents a sourcing strategy: sourcing directly from one $(D(S=1))$ or two $(D(S=2))$ suppliers, or sourcing indirectly (I). The lighter curves indicate profits before the increase in supply chain risk. Firms are sorted by productivity on the x-axis. Firms in the gray segment do not source from l, those in the red segment source indirectly, and those in the blue segment source directly.

indirect profits and any direct option shrinks. This, in turn, moves both the productivity cutoff to start sourcing indirectly, $\varphi^I(\zeta)$, and the threshold where producers switch from indirect to direct sourcing, $\varphi^*(\zeta)$, to the right. These responses affect the use of intermediaries in opposite directions, while the compositional shift among indirect buyers pushes up intermediation, as switching producers are larger than those exiting. The net effect on the total use of intermediaries is thus ambiguous. Note that these responses reflect complementarities between resilience investments and supply chain risk: accessing more suppliers and trimming disruption probabilities through intermediaries make a greater contribution when risk is higher.[29]

1.3.5. Optimal Sourcing with Multiple Locations

I now consider firms' global sourcing strategy when they can access inputs from multiple locations. While the main results for the role of intermediation services and supply chain risk carry over, additional cross-country complementarities emerge. A sourcing strategy is a triplet $\{L(\omega), M_l(\omega), S_l^D(\omega)\}$ that includes the producer's set of source locations $L(\omega) \in \mathcal{L}$, the sourcing mode at each location, and the number of suppliers per location under direct sourcing. Producers thus have an additional margin of adjustment to supply chain risk, as they trade off

[29] In principle, these results hold as long as the probability of disruptions is not particularly high: as shown in Appendix A.3, $\zeta_l \leq 0.5$ is a sufficient condition for Proposition 4. However, under any realistic calibration of the intermediation technology, the results are valid even for higher disruption probabilities.

input prices $p_{il}^{x,M}$ and disruption probabilities ζ_l^M when selecting source locations.

As before, producers make decisions in two steps, defining their sourcing strategies before disruptions materialize, and making input purchases and production decisions after disruptions. The *ex-post* solution is analogous to the single-location case (1.7), but the producer's input cost incorporates the prices obtained in each operational location, as described by (2.4). Therefore, producers' *ex-post* profits can be expressed as:

$$\pi_i^{\text{ex-post}}\left(\omega \,\middle|\, L, M_l, S_l^D, Z_l\right) = \begin{cases} \varphi(\omega)^{\sigma-1}\left(\sum_{L(\omega)}\left(p_{il}^{x,M}(\omega)\right)^{1-\eta}\right)^{\frac{1-\sigma}{1-\eta}} B & \text{if operational} \\ 0 & \text{otherwise} \end{cases} \tag{1.12}$$

where $B \equiv \frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} P_i^{\sigma-1} E_i$ and $\eta > 1$ is the elasticity of input substitution across locations. Given this *ex-post* solution, the producer's *ex-ante* problem is:

$$\begin{aligned} \max_{\substack{L(\omega)\in\mathcal{L} \\ \{M_l(\omega)\in\{D,I\}\} \\ \{S_l^D(\omega)\in\mathcal{S}_l\}}} \quad & \pi_i^{\text{ex-ante}}\left(\omega, L, M_l, S_l^D, Z_l\right) = \mathbb{E}_{Z_l}\left[\pi_i^{\text{ex-post}}\left(\omega, L, M_l, S_l^D, Z_l\right)\right] \\ & - \sum_{L(\omega)} \mathbb{I}_{\{M_l(\omega)=D\}} f_l^D\left(S_l^D(\omega)\right) - \sum_{L(\omega)} \mathbb{I}_{\{M_l(\omega)=I\}} f_l^I \end{aligned} \tag{1.13}$$

In the spirit of Antràs et al (2017), expected *ex-post* profits are an increasing function of the producer's *expected sourcing capability*:

$$\mathbb{E}_{Z_l}\left[\pi_i^{\text{ex-post}}\left(\omega, L, M_l, S_l^D, Z_l\right)\right] = \varphi(\omega)^{\sigma-1}\, \mathbb{E}_{Z_l}\left[\Theta\left(\omega, L, M_l, S_l^D, Z_l\right)^{\frac{\sigma-1}{\eta-1}}\right] B \tag{1.14}$$

where $\Theta \equiv \sum_L \left(p_{il}^{x,M}\right)^{1-\eta}$. Sourcing decisions influence this capability through various channels. At the outer level, a larger set of locations generates input variety gains and increases network operability, with more efficient and less risky locations making a greater contribution. At the inner level, the sourcing mode affects expected input prices as in the one-location case. However, the global sourcing problem entails interdependent decisions, as the choices made in locations l and l' jointly determine producers' expected marginal costs.

Producers' *ex-ante* global sourcing problem is a high-dimensional, combinatorial discrete-choice problem. In the one-location case, there are $2^{|\mathcal{S}_l|+2}$ possible choices, which reduce to $|\mathcal{S}_l|+2$ when suppliers are perfectly substitutable. With multiple locations, the number of choices expands to $\prod_{l\in\mathcal{L}}\left(|\mathcal{S}_l|+2\right)$. Proposition 5 characterizes producers' optimal sourcing strategies.

Proposition 5. (global sourcing) *Producers' global sourcing problem is such that:*

a. *The expected sourcing capability is non-decreasing in firm productivity:* $\mathbb{E}_{Z_l}\left[\Theta(\varphi^H)^{\frac{\sigma-1}{\eta-1}}\right] \geq \mathbb{E}_{Z_l}\left[\Theta(\varphi^L)^{\frac{\sigma-1}{\eta-1}}\right]$ *for* $\varphi^H \geq \varphi^L$.

b. *If* $\sigma > \eta$, *the optimal sets of source locations and direct suppliers per location are non-contracting in firm productivity:* $\mathcal{L}(\varphi^L) \subseteq \mathcal{L}(\varphi^H)$, $S_l^D(\varphi^L) \leq S_l^D(\varphi^H)$ *for* $\varphi^H \geq \varphi^L$.

c. *If* $\sigma > \eta$, *the choice of direct sourcing at each location (weakly) increases with firm productivity:* $\mathbb{1}_{\{M_l=D\}}(\varphi^H) \geq \mathbb{1}_{\{M_l=D\}}(\varphi^L)$ *for* $\varphi^H \geq \varphi^L$.

Proof. *See Appendix A.3.*

The choices made by high-productivity firms grant them a greater *expected sourcing capability*, which in turn amplifies their productivity advantage. In particular, more productive firms select a larger number of locations and direct suppliers per location, and are more likely to source directly. This occurs when $\sigma > \eta$, meaning that final goods are closer substitutes in consumption than intermediate inputs in production, generating complementarities in sourcing decisions. As in previous models of global sourcing, producers follow a *pecking order* of locations (Antràs et al. 2017; Huang et al. 2024), but this ranking now considers both input costs and disruption probabilities. The increasing number of direct suppliers based on firm productivity is consistent with the skewness of trade and production networks (Bernard et al. 2018c, 2022a), while the choice of sourcing modes resembles canonical intermediation models where less productive firms sort into intermediaries (Ahn et al. 2011; Bernard et al. 2015).

Given an optimal sourcing strategy and a particular realization of disruptions, one can compute producers' input purchases from each operational location:

$$\tilde{X}_{il}^{M}(\omega) = \Big(\varphi(\omega)\Big)^{\sigma-1}\Big(p_{il}^{x,M}(\omega)\Big)^{1-\eta}\Big(\Theta(\omega)\Big)^{\frac{\sigma-\eta}{\eta-1}}(\sigma-1)B \tag{1.15}$$

and therefore producers' global input purchases:

$$\tilde{X}_{i}(\omega) = c(\omega)q(\omega) = \Big(\varphi(\omega)\Big)^{\sigma-1}\Big(\Theta(\omega)\Big)^{\frac{\sigma-1}{\eta-1}}(\sigma-1)B \tag{1.16}$$

More productive firms face greater final demand, which increases input purchases from all their operational locations (1.15). They also have greater incentives to transact with multiple suppliers per location and to avoid the brokerage fee, since *ex-ante* profits (1.13) are supermodular in productivity and the *expected sourcing capability*, and the latter increases monotonically with productivity. This monotonic relationship also ensures that mid-productivity firms switch from direct to indirect sourcing when faced with increased risk. The mechanisms driving sourcing mode decisions in the one-location case are thus amplified in the global sourcing setting.

1.3.6. Imperfect Supplier Substitution

Until now I have assumed that suppliers are identical and perfectly substitutable within locations, selling the local input x_l at the location-specific price $p^x_{il} = \tau_{il}\alpha_l$. Under this assumption, supply chain risk is the only reason for producers to match with multiple suppliers, and operational suppliers fully compensate for disrupted ones. It also implies that producers consider the number but not the identity of suppliers at each location, reducing the dimensionality of the combinatorial problem. To incorporate imperfect supplier substitution in a tractable manner, I now consider suppliers that are *ex-post heterogeneous* but remain *ex-ante homogeneous*.

I assume that each x_l is now a unit-measure bundle of intermediate varieties v, with constant elasticity of substitution $\lambda > 1$, such that the cost of x_l under sourcing mode M is:

$$p^{x,M}_{il} = \left(\int_0^1 p^{x,M}_{il}(v)^{1-\lambda}\, dv \right)^{\frac{1}{1-\lambda}}$$

Suppliers in l can produce all local varieties $v \in [0,1]$ at the location-specific costs $\tau_{il}\alpha_l$ plus a supplier-variety specific cost $\xi_s(v)$ that is revealed after supply links are formed. I treat the vector of variety-specific costs as independent realizations from a Fréchet distribution with dispersion parameter $\theta > 0$, which governs the degree of substitution across suppliers.[30] The price set by supplier s for variety v is then:

$$p^x_{sl}(v) = \tau_l\, \alpha_l\, \xi_s(v) \qquad \Pr(\xi_s(v) \geq t) = e^{-t^{\theta}} \tag{1.17}$$

Under direct sourcing in location l, producers purchase each variety from their lowest-cost operational supplier $S^{O,D}_l(\omega)$. Similarly, under indirect sourcing, the intermediary buys each variety from its lowest-cost operational option in $S^{O,I}_l$ on behalf of the producer.

$$p^{x,D}_{il}(v) = \min_{s \in S^{O,D}_l(\omega)} \left\{ \tau_{il}\, \alpha_l\, \xi_{sl}(v) \right\} \qquad p^{x,I}_{il}(v) = \kappa \min_{s \in S^{O,I}_l} \left\{ \tau_l\, \alpha_l\, \xi_{sl}(v) \right\}. \tag{1.18}$$

Since variety-specific costs are *iid* over a continuum of measure one, the share of inputs sourced from each operational supplier is given by the probability that a supplier is the lowest-cost option. Using the properties of the Fréchet distribution, the average prices faced by the producer

[30] Note that *ex-ante* supplier heterogeneity can be incorporated by adding supplier-level production costs α_{ls}, or by including a supplier-specific technological parameter T_s in the Fréchet distribution.

in location l can be expressed as:

$$p_{il}^{x,D} = \gamma\, \tau_l\, \alpha_l \left(S_l^{O,D}(\omega)\right)^{-1/\theta} \qquad p_{il}^{x,I} = \gamma\, \tau_l\, \alpha_l \left(\frac{S_l^{O,I}}{\kappa_l^{\theta}}\right)^{-1/\theta} \tag{1.19}$$

where γ is a constant defined by the gamma function $\Gamma(\cdot)$.[31]

Allowing for imperfect supplier substitution gives rise to three additional results. First, producers benefit from a larger supply network not only by hedging disruptions but also by having additional cost draws, which reduces input prices through better matches. Second, since suppliers are not perfectly interchangeable, supply chain disruptions are costly for producers even if their overall network remains operational. Third, producers' optimal risk responses are shaped by the degree of substitution across suppliers within locations (θ) and across inputs from different locations (η). Intuitively, when supply chain risk increases in a location, producers have stronger incentives to diversify there if suppliers are more homogeneous or if other locations specialize in different products.

1.3.7. General Equilibrium

In equilibrium, free-entry implies that *ex-ante* expected profits must equal the fixed cost of entry, f_i^e, such that only producers above a productivity threshold $\overline{\varphi}_i$ begin operations.

$$\int_{\overline{\varphi}_i}^{\infty} \mathbb{E}\left(\pi_i^{\text{ex-ante}}(\varphi)\right) dG_i(\varphi) = w_i f_i^e \tag{1.20}$$

It can be shown that equation (1.20) delivers a unique demand shifter B_i, and that producers' combinatorial discrete choice problem has a unique solution given B_i.The equilibrium mass of producers in country i is then given by:

$$N_i = \frac{\beta L_i}{\sigma\left[\int_{\overline{\varphi}_i}^{\infty} \sum_{l \in \mathcal{L}(\varphi)} \left(\mathbb{1}_{\{M_l(\varphi)=D\}}\, f_l^D\left(S_l^D(\varphi)\right) + \mathbb{1}_{\{M_l(\varphi)=I\}}\, f_l^I\right) dG_i(\varphi) + f_i^e\right]} \tag{1.21}$$

where $\mathbb{1}_{\{M_l(\varphi)\}}$ are indicator variables for the selected sourcing modes at each location l in the sourcing set $\mathcal{L}(\varphi)$ of a producer with productivity φ.

[31] As in Eaton and Kortum (2002a), $\gamma = \left[\Gamma\left(\frac{\theta+1-\lambda}{\theta}\right)\right]^{\frac{1}{\lambda-1}}$ so I need $\lambda < \theta + 1$ to have a well-defined price index. As long as this restriction is satisfied, λ appears only in a constant term without affecting any relevant outcomes.

1.3.8. Model Extensions

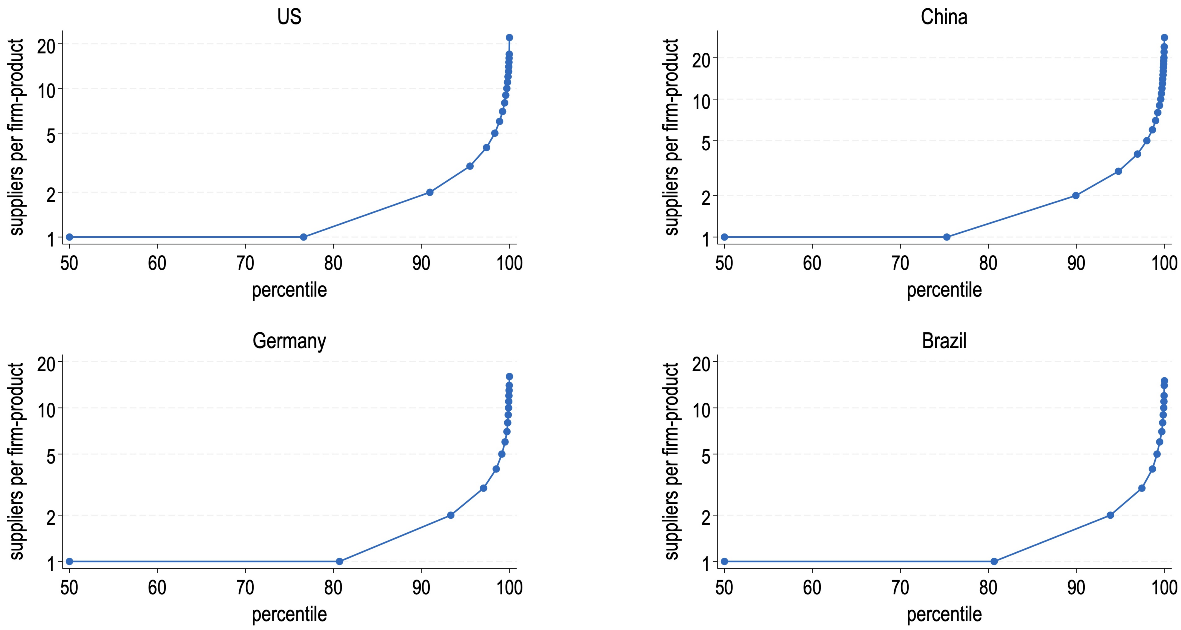
While the baseline model abstracts away from the market structure of the intermediation sector, its main mechanisms and results would continue to hold in an extended framework with market clearing in that sector. For example, the equilibrium brokerage fee could be chosen by monopolistically competitive wholesalers that specialize in different origin countries and industries. Intermediaries would take into account how their brokerage fee influences their set of customers and downstream input demand, with no qualitative effect on producers' sourcing strategies. However, counterfactuals not directly targeting intermediaries may also impact equilibrium brokerage fees in this extension, affecting producers' sourcing outcomes.

I have also assumed that producers face independent disruptions on their supply links. Although the data suggest a low correlation across link separations, it is evident that some real-world shocks operate at a broader level. In practice, it is straightforward to incorporate location-level disruptions with some exogenous probability, introducing a correlation across disruptions within locations. More generally, it can be shown that model propositions remain valid under shock structures satisfying three conditions: a regularity condition ensuring that network operability increases with the number of suppliers, a supermodularity condition on expected profits for disruption and suppliers (such that extra suppliers are more valuable when risk increases), and a weak independence condition ruling out the possibility that adding a location changes the probability of disruptions in other places. The results on intermediated sourcing are thus more general than implied by a setting with idiosyncratic disruptions.

1.4. Reduced-Form Evidence

The model in Section 1.3 can rationalize the systematic rise in intermediated imports under higher origin country risk (Fact 1), with producers trading off risk and efficiency in choosing their input source locations and sourcing mode. In particular, the model shows that intermediaries' wider portfolio of suppliers (Fact 2) and lower supplier separation rates (Fact 3) make them an attractive sourcing technology, particularly for risky origins and for less productive firms. I now provide additional empirical evidence consistent with this key model mechanism. I first document the heterogeneity in direct sourcing activity across firms, and the relationship between the number of direct suppliers and input cost volatility. I then establish that fewer firms opt to source directly when supply chain risk rises, but those who do choose to expand their supplier base. These results support the role of both in-house diversification and access to intermediation services in minimizing the impact of supply chain disruptions on input costs.

Figure 1.8. Number of Direct Suppliers in Selected Countries



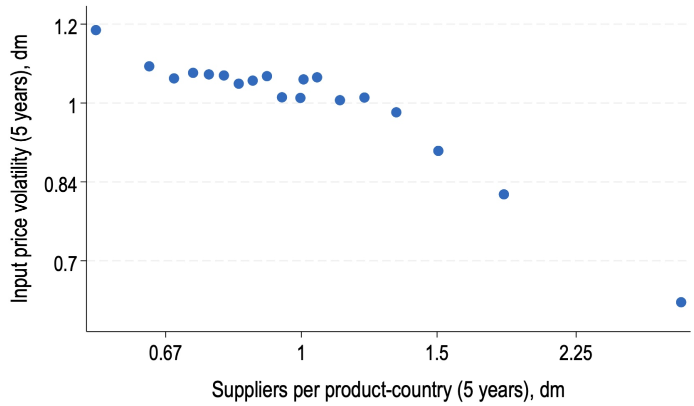
Notes: This figure plots the distribution of the number of suppliers at the firm-product level, considering the main source locations for Chilean importers. The sample includes all Chilean producers importing directly in 2019.

1.4.1. Direct Supplier Diversification and Input Cost Volatility

Figure 1.8 plots the distribution of the number of suppliers at the firm-product level, considering the top origin countries for Chilean producers: the United States, China, Germany, and Brazil. The data reveals that about 20% of producers source products from multiple suppliers, while a few producers have many supply relationships. In turn, the subset of producers multisourcing in the same location accounts for two-thirds of total imports, indicating that they are larger on average. These numbers align with recent evidence for US firms, where 21% of importers source from multiple suppliers in the same origin country and account for three-quarters of imports (Blaum et al. 2023). They are also consistent with data on Colombian importers, where the share of firms with more than one supplier is around 30% (Bernard et al. 2018a). My evidence confirms the skewness of the number of suppliers in the Chilean data when only producers are considered in the sample. Moreover, these patterns are consistent with the presence of sizable matching costs preventing direct supplier diversification.

In the model, the combination of a discrete set of suppliers and independent disruptions across supply links imply that input cost volatility decreases with a firm's number of suppliers. Figure 1.9 confirms this relationship in the Chilean data. The x-axis displays the average number of suppliers firms have for a given product and origin country over a 5-year period (2014–2019), while the y-axis shows input price volatility, measured by the standard deviation of unit values

FIGURE 1.9. Number of Direct Suppliers and Input Cost Volatility



Notes: Firms are sorted into 20 equal-sized bins. The x-axis shows the average number of suppliers that a producer has for a given product and origin country over a 5-year period. The y-axis displays the corresponding standard deviation of input prices over the same period. Both variables are demeaned using product-origin country fixed effects. The linear slope is -0.33.

over the same period. Firms are grouped into 20 equal-sized bins, with dots indicating values for a representative firm. Both variables are demeaned using product-origin country fixed effects. The figure reveals a clear negative relationship between the number of suppliers and input cost volatility, with a linear slope of -0.33. This supports the idea of producers mitigating disruptions by maintaining multiple supply relationships.

1.4.2. Direct Supplier Diversification and Input Location Risk

I examine the risk responses of heterogeneous producers sourcing directly. Specifically, I assess how producers adjust the number of direct suppliers for a given location (origin country-HS6 product) as risk increases over time, incorporating interactions with terciles of firm size, defined by total imports in the initial period. The empirical strategy is analogous to that in Section 1.2, but implemented at the firm-country-product level using stacked data for periods t and $t + 5$.[32] Table 1.6 shows a negative main effect for changes in *Trade Volatility*, while other risk measures have insignificant coefficients. However, interactions by firm size reveal that large producers increase the number of suppliers in response to both *Geopolitical Risk* and *Trade Volatility*, while the effect of *Economic Uncertainty* is insignificant. Note that country-product fixed effects ensure that comparisons are made within the same location over time, while firm fixed effects subsume the level effects of size dummies and cross-sectional heterogeneity among

[32] Since the analysis is conducted at a more granular level, employing long-differences would require that the same firm sources the same input from the same origin country over five years, significantly reducing observations. Instead, I use stacked periods and include fixed effects to control for product, origin country, and firm characteristics.

producers. Overall, these results support that large producers are the only ones that can afford precautionary diversification.

Table 1.6. Number of Direct Suppliers by Producer Size

	(log) # direct suppliers					
	Geopolitical Risk		Economic Uncertainty		Trade Volatility	
	(1)	(2)	(3)	(4)	(5)	(6)
Supply chain risk	-0.058	-0.068	-0.022	-0.019	-0.024***	-0.026***
	(0.049)	(0.047)	(0.025)	(0.024)	(0.005)	(0.005)
× 2nd size tercile	0.041**	0.042**	0.018	0.018	0.025***	0.025***
	(0.018)	(0.018)	(0.025)	(0.025)	(0.004)	(0.004)
× 3rd size tercile	0.069***	0.070***	-0.010	-0.009	0.062***	0.062***
	(0.017)	(0.018)	(0.031)	(0.031)	(0.008)	(0.008)
Origin country - product FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-country productivity	No	Yes	No	Yes	No	Yes
Origin-country trade costs	No	Yes	No	Yes	No	Yes
Product total imports	No	Yes	No	Yes	No	Yes
Observations	269,913	269,251	235,431	235,431	269,958	268,416

Notes: All regressions consider the (log) number of direct suppliers at the firm-product-origin country-year level, stacking periods t and $t + 5$. Size terciles are defined using total imports at the firm level in period t. Supply chain risk is measured by the Geopolitical Risk (GPR) and Economic Policy Uncertainty (EPU) indexes at the origin-country level, and by Trade Volatility at the origin country-product level. Controls include changes in total factor productivity, trade procedures, and total imports by product. The sample includes all import transactions by Chilean producers for years 2014 and 2019. Standard errors are clustered at the level of the risk measure.

1.4.3. Sourcing Mode and Input Location Risk

The model predicts that fewer firms source directly from riskier origin countries and rely instead on intermediaries. To assess this implication, Table 1.7 examines how the number of producers sourcing directly from a given location (origin country-HS6 product) varies with risk shocks over a 5-year period, replicating the approach used in Section 1.2. As predicted, I find that the count of direct importers systematically decreases with all measures of supply chain risk. These results are robust to controlling for changes in origin-country productivity and trade costs, as well as changes in total imports by product to account for downstream conditions.[33] Overall, these findings are consistent with changes in the use of intermediation services due to

[33] There were no significant changes in import tariffs in Chile during the analysis period. Meanwhile, time-constant trade barriers such as distance and cultural differences are absorbed by using long differences at the origin country-product level.

the selection of producers into different sourcing modes.[34]

Table 1.7. Number of Producers Importing Directly

	Δ (log) # Direct Importers					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Geopolitical Risk	-0.037***	-0.035***				
	(0.009)	(0.012)				
Δ Economic Policy Uncertainty			-0.041***	-0.044***		
			(0.010)	(0.015)		
Δ Trade Volatility					-0.007**	-0.005*
					(0.003)	(0.003)
Δ Origin-country productivity	No	Yes	No	Yes	No	Yes
Δ Origin-country trade costs	No	Yes	No	Yes	No	Yes
Δ Product total imports	No	Yes	No	Yes	No	Yes
Observations	33,074	32,768	23,791	23,791	35,155	34,393

Notes: All regressions consider changes in the (log) number of direct producers within origin country-products over a 5-year period. Supply chain risk is measured by the Geopolitical Risk (GPR) and Economic Policy Uncertainty (EPU) indexes at the origin-country level, and by Trade Volatility at the origin-product level. Controls include changes in total factor productivity, the number of trade procedures, and total imports by product. The coefficients are normalized to reflect the effect of one standard deviation. The sample includes all import transactions in Chile for years 2014 and 2019. Standard errors are clustered at the level of the risk measure.

1.5. Quantitative Analysis

The theory developed in Section 1.3 allows me to quantify the role of trade intermediation in mitigating supply chain disruptions. Leveraging the detailed microdata at hand, I operationalize this setting for Chile, five source regions (Latin America, China, the United States, Europe, and Rest of the World), and one sector per region. My main result is that intermediaries substantially reduce the impact of disruptions for producers in the middle of the size distribution, which access foreign inputs but lack the scale to diversify directly. I also show that changes in brokerage fees influence the use of intermediaries and therefore their contribution to supply chain resilience. This suggests that industrial policy in the wholesale sector can have broader effects on the economy.

[34]An additional empirical test would be to examine whether the probability of producers switching to intermediaries increases with supply chain risk. This requires information on VAT domestic transactions between producers and intermediaries, contained in Form 29 of the Tax Authority of Chile. While access to this data has been requested, it is not yet operational and represents a natural next step for this project.

1.5.1. Numerical Solution

To solve the model numerically, the first challenge is the dimensionality of the choice set. In principle, the firm's maximization problem (1.13) involves decisions over $|\mathcal{L}|$ locations and $2^{|\mathbb{S}_l|+2}$ options at each of them. However, the assumption of *ex-ante* homogeneous suppliers reduces the latter to $|\mathbb{S}_l| + 2$ options. Even in a tractable setting with 5 locations and 4 suppliers per location, this contracts the choice set from nearly a billion combinations to less than ten thousand. I further reduce dimensionality using the model. The *equivalent* number of suppliers $\tilde{S}_l^I$ defined in (1.11) allows me to compare direct choices with the intermediation technology, ruling out strictly dominated options at each location.[35] Finally, I apply a squeezing procedure to avoid evaluating all remaining options, following recent methods for combinatorial discrete choice problems (Arkolakis et al. 2023a; Huang et al. 2024).[36]

The second challenge is that forward-looking producers anticipate the occurrence of disruptions, which involves a high-dimensional expectation over each choice. There are up to $|\mathbb{S}_l| + 1$ possible realizations at each location l in $L(\omega)$, which jointly determine producer ω's expected sourcing capability in (1.14). I address this issue by approximating these complex expectations using Monte Carlo simulations. As shown in (1.9) and (1.10), the pattern of disruptions implies that, given a set of potential suppliers at l, the number of operational suppliers follows a Binomial distribution. I use these distributions to generate random draws under each possible sourcing strategy and compute expected profits.[37]

1.5.2. Estimation Strategy

Elasticities. I calibrate the parameters governing substitution across final goods in consumption (σ), across inputs from different locations in production (η), and across suppliers within locations (θ). I take $\hat{\sigma} = 5$ as a median estimate from the trade literature (Broda and Weinstein 2006a; Feenstra and Romalis 2014; Antràs et al. 2017) and infer η and θ using model-consistent equations.

First, I consider a log-linear version of (1.15) indicating firm f's input purchases from

[35] In the model, I assumed $f_l^D(\cdot) \leq f_l^I$ ensuring that matching with $S_l^D \leq \tilde{S}_l^I$ direct suppliers cannot be optimal. In the numerical solution, however, I allow for heterogeneous matching costs that exceed f_l^I on average (Section 1.5.2). In this case, the discard rule becomes more nuanced, depending on how f_l^I compares to $f_l^D(\cdot)$ for direct choices near $\tilde{S}_l^I$. Firms with high matching costs still reduce their choices as before, intermediation is ruled out for firms with very low matching costs, while it is not always possible to reduce choices for firms in between.

[36] A key condition for this procedure is that producers' *ex-ante* expected profits satisfy single-crossing differences. In the next section, I show that the parametric condition $\sigma > \eta$ holds for standard values of σ and the estimated value of η, ensuring single-crossing differences from below.

[37] I use 100,000 simulations when estimating the model and implementing counterfactuals.

source location l, conditional on direct sourcing:

$$\log \tilde{X}^D_{fl} = (\sigma - 1)\log \varphi_f + (1-\eta)\log p^{x,D}_{fl} + \left(\frac{\sigma - \eta}{\eta - 1}\right)\log \Theta_f + \log\left(\sigma - 1\right)B$$

To back out η, I take the following empirical counterpart to the data:

$$\log \tilde{X}^D_{flt} = \delta_{ft} + (1-\eta)\log p^{x,D}_{flt} + u_{flt} \tag{1.22}$$

where δ_{ft} absorbs differences in producers' marginal costs due to their core productivity and sourcing capability. Identification then comes from price variation across locations for the same firm and year. To address reverse causality concerns, I also estimate (1.22) for the last sample year (2019) using geographic distance from Chile as an instrument for input prices.[38] Table A9 reports estimates around $\hat{\eta} = 1.3$, which is similar to values typically used in the trade literature (Atkeson and Burstein 2008a; Edmond et al. 2015a).

For θ, I consider a log-linear version of (1.19) that relates input prices to firms' number of suppliers under imperfect substitution, expressed empirically as:

$$\log p^D_{flt} = \delta_{lt} - \frac{1}{\theta}\log S^D_{flt} + u_{flt} \tag{1.23}$$

where δ_{lt} captures location-specific trade and production costs. Identification thus arises from variation in the number of suppliers across firms sourcing from the same location (origin country - HS6 product) and year, and I also include firm-year fixed effects to account for changes in firm-level conditions.[39] Table A10 presents results considering the full panel (2005–2019) and the last sample year, with values for $\hat{\theta}$ ranging from 3.4 to 3.9, where the upper bound is equivalent to the estimates in Huang et al. (2024).

Panel A of Table 1.8 summarizes the estimated elasticities. There is greater substitution across inputs in production relative to final goods in consumption ($\sigma > \eta$), which is consistent with sourcing complementarities. Furthermore, substitution is easier among suppliers within locations than across different input locations ($\theta > \eta$).

[38] In the model, input prices are unaffected by the amount purchased by atomistic producers. In reality, producers may obtain quantity discounts, or their purchases may affect market prices when they are large players. While tariffs are a standard time-varying instrument in the trade literature, their flat structure in Chile prevents their use. I then exploit geographic distance from Chile, which is positively related to import prices and unlikely to be correlated with other origin country conditions.

[39] The main econometric concern is that input prices influence firms' supplier choices through their impact on firms' sourcing capabilities. In a time-varying specification, this concern is reduced to the extent that moderate price changes are less likely to induce discrete changes in suppliers, especially in the presence of sizable matching costs. Moreover, the results in Table 1.8 also include δ_{ft} to absorb changes in firm-level conditions.

TABLE 1.8. Estimation Parameters

Panel A. Elasticities of substitution

σ *(final goods)*	5	η *(input locations)*	1.3	θ *(suppliers)*	3.6

Panel B. Input costs, disruption probabilities, and suppliers per region

	LAT	CHN	USA	EUR	ROW
$\tau_l\alpha_l$: *trade and production costs*	2.7	3.1	16.1	16.4	10.2
ζ_l^D: *direct disruption probability*	0.23	0.26	0.19	0.18	0.22
ζ_l^I: *indirect disruption probability*	0.17	0.21	0.13	0.13	0.16
$\mathcal{S}_l$: *(potential) direct suppliers*	4	4	4	4	4
S_l^I: *(intermediary) indirect suppliers*	3	4	3	3	3

Panel C. Sourcing costs and demand shifter

κ *(brokerage fee)*	1.2	β^0	1.39	$\beta^{Institutions}$	-2.79
ψ *(indirect contracting)*	0.05	$\beta^{Distance}$	3.07	$\beta^{Suppliers}$	9.49
$\beta^{Dispersion}$	1.02	$\beta^{Language}$	0.96	B *(final demand)*	1.11

Notes: This table summarizes the calibrated parameters used in the quantification. Panel A presents the elasticities of substitution. Panel B reports input costs, disruption probabilities, and supplier sets across regions. Panel C provides the demand shifter and sourcing costs, including the brokerage fee, (relative) indirect contracting costs, and the matching cost parameters from (1.27). Additionally, I assume a Pareto shape parameter of 1.5 for the distribution of producers, with the scale parameter normalized to 1.

Location Input Costs. Consider the cost structure defined in (1.17), which separates the cost of input varieties into location ($\tau_l\,\alpha_l$) and supplier-variety ($\xi_s(v)$) multiplicative factors. I assume that the average price charged by a foreign supplier to Chilean buyers follows this structure, and exploit the time dimension of the data to infer the location-specific component. The empirical specification is:

$$\log \bar{p}_{slt} = \delta_{lt} + \delta_{st} + e_{slt} \tag{1.24}$$

where δ_{lt} is interpreted as the average trade and production cost in each location (origin country - HS6 product) and year, which are then aggregated to source regions. The normalized version of these estimates (relative to Chile) is reported in Panel B of Table 1.8 for the last sample year (2019).[40] As expected, the estimated costs are significantly higher in Europe and the US

[40] Since domestic input sourcing is not observed, I assume similar production costs in Chile and Latin America, attributing all differences to iceberg trade costs. These costs are estimated to be around a factor of 2.7, following Anderson and Van Wincoop (2004a). To facilitate comparisons, I normalize input costs in Chile to 1, such that, by construction, Latin America has an input cost of 2.7 in Table 1.8.

compared to Latin America and China. Table A11 reports the raw cost estimates in USD and examines a longer time period, revealing similar patterns.

Disruption Probabilities. I parameterize the probability that producer-supplier links break in a given location using a nonlinear (logit) functional form. Specifically, I consider a vector of observable location characteristics, Z_l, which includes the supply chain risk indexes from Section 1.2 (*Geopolitical Risk*, *Economic Uncertainty*, and *Trade Volatility*), and a set of dummies classifying countries into low-, middle-, and high-income levels. This allows countries at different stages of development to differ in baseline probabilities, which then vary based on the risk measures within groups. Additionally, I include a vector D_b to control for changes in buyer-level downstream conditions, which are then excluded from the projected probabilities.[41] The empirical specification is:

$$\mathbb{D}(separation)_{bslt} = \frac{e^{Z'_{lt}\gamma + D'_{bt}\delta}}{1 + e^{Z'_{lt}\gamma + D'_{bt}\delta}} \tag{1.25}$$

where $\mathbb{D}(separation)_{bslt}$ is a dummy that equals 1 when a bs-link in location l and period t will break in $t + 1$.

Table 1.8 presents the results aggregated at the level of source regions. Direct disruption probabilities range from 0.18 to 0.26, with Europe being the safest region and China the riskiest for Chilean producers. More generally, disruption probabilities are higher in regions with lower input costs, posing an efficiency-risk tradeoff in the choice of source locations.[42] Table A12 reports the estimates for vectors Z_l and D_b. All coefficients are statistically significant and operate in the expected direction: the frequency of disruptions increases with the risk measures, and decreases in more developed countries or when buyers experience favorable downstream conditions.

For indirect disruption probabilities, I compare the supplier separation rates of producers and intermediaries in each source region. As in Section 1.2, the analysis considers supply links within the same product and origin country (when there is more than one country in the region), while incorporating the demand controls mentioned above. Table A13 reports these results, which are then used to adjust the direct probabilities. As shown in Table 1.8, indirect

[41] Following the analysis in Section 1.2, I include the changes in producers' total imports and number of suppliers from period $t - 1$ to t. Without controlling for these factors, I find similar relative patterns for disruption probabilities across locations, but the average probability is about 9 pp higher.

[42] In the baseline scenario, I consider disruptions in global sourcing but *safe* domestic links. This can be rationalized as producers facing lower matching costs in the home country, allowing them to find replacements within a reasonable time frame. However, it is straightforward to incorporate risk in the home country. The probability of disruptions in Chile could be inferred by extrapolating the coefficients estimated in (1.25). Alternatively, this probability can be estimated using VAT data on domestic transactions.

disruptions are about 6 pp less likely on average, representing a 25% reduction in the probability of disruptions relative to direct sourcing.[43]

Suppliers per Location. I use import transactions to compute the number of indirect suppliers offered by intermediaries. Specifically, I compute the average number of suppliers that wholesalers have per product (HS6)-region, weighting by wholesalers' import shares. Table 1.8 reports that the intermediation technology exhibits multisourcing in all regions: when producers source indirectly, they access 4 suppliers per product in China and 3 in the remaining regions. On the other hand, I assume that producers can match with up to 4 suppliers per region when sourcing directly. This corresponds to the 95th percentile in the distribution of direct suppliers per producer, and allows producers to build a diversified network if they can afford the associated matching costs.

Brokerage Fee. In principle, one would like to observe the prices charged by import intermediaries to local producers and compare them to those charged by foreign suppliers in the same industry. I take a similar approach by using customs data on Chilean exports, which allows me to compare the prices charged by producers and export intermediaries for the same destination and sector.[44] I run the following empirical specification:

$$\log p_{flt}^{Exp} = \delta_{lt} + (\kappa - 1)\, D^{Exp}(Intermediary = 1)_{ft} + \epsilon_{flt} \tag{1.26}$$

where p_{flt}^{Exp} denotes the price charged by firm f in location l (destination-sector), and $D(\mathrm{Intermediary} = 1)_{ft}$ is a dummy indicating whether the exporter is an intermediary. I find intermediation markups to be around 11%. This is similar to the *accounting* markups documented in the US wholesaler sector (13.5%), although theory-consistent estimates suggest markups up to 30% in that market (Ganapati 2024). Likewise, recent evidence from microdata in Canada finds wholesale markups above 30% (Alexander et al. 2024). Thus, I take a middle point in the baseline estimation ($\kappa = 1.2$) and then evaluate scenarios with lower and higher markups.

Matching Costs and Demand Shifter. The last objects to estimate are the aggregate demand shifter B, the matching costs of sourcing directly in each region $f_l^D(S_l^D)$, and the costs of

[43] These differences are smaller than those reported in Section 1.2 due to the demand-side controls. However, I consider my approach to be conservative in terms of the resilience advantage of intermediaries, as these buyer-level controls may partially absorb supply-side conditions.

[44] The transactions between import intermediaries and local producers are observable in the VAT data from the Tax Authority, which has been requested but is not yet operational. Once available, the estimates for the brokerage fee in Chile can be further refined.

contracting with intermediaries f_l^I. To reduce the parameter space, I assume the intermediation costs are a constant share ψ of the cost of matching directly with suppliers. I then parameterize matching costs as a function of the number of direct suppliers and proxies for shipping, communication, and contracting costs: bilateral distance, common language, and control of corruption. These costs are drawn from a log-normal distribution with dispersion parameter β^{Disp} and the following scale parameter:[45]

$$\log f_l^D\left(S_l^D\right) = \log \beta^0 + \beta^{Dist} \log \mathrm{Dist}_l + \mathrm{Lang}_l \cdot \log \beta^{Lang} + \beta^{Inst}\, \mathrm{Inst}_l + \beta^{Supp} \log S_l^D \quad (1.27)$$

I estimate the vector of 8 parameters $\Omega \equiv \{B, \psi, \beta_0, \beta^{Dist}, \beta^{Lang}, \beta^{Inst}, \beta^{Supp}, \beta^{Disp}\}$ using the Simulated Method of Moments (SMM). For any initial guess, the algorithm solves buyers' optimal sourcing strategy, computes the implied model moments, and iterates until the solution produces moments close to the data. I target a vector M of 8 moments: (1) the overall share of Chilean producers importing directly, (2) - (6) the shares of Chilean producers importing directly from each region, (7) the share of Chilean producers diversifying suppliers, and (8) the share of Chilean producers sourcing indirectly. Intuitively, (1) helps identify the aggregate demand shifter and the baseline matching cost, (2) - (6) account for variation in matching costs across regions, (7) captures how matching costs vary with the number of suppliers, and (8) identifies the relative cost of contracting with intermediaries.[46]

Panel C in Table 1.8 presents the estimates for Ω. As expected, matching costs increase with distance and decrease with common language and institutional quality. Moreover, these costs grow exponentially with the number of suppliers, indicating that diversification is much costlier than simply importing, while contracting with intermediaries is substantially cheaper than direct supplier matching. Table 1.9 reports the model fit for targeted moments. The model captures the relative importance of different source regions and the shares of producers sourcing directly and indirectly. However, the model overpredicts the share of firms sourcing from multiple suppliers, suggesting additional barriers to diversification. This implies that the role of disruptions and intermediaries is likely greater than indicated by the subsequent counterfactual analysis.

[45]This specification allows matching costs to vary across producers, rationalizing deviations from the strict sorting patterns predicted by the model for direct and indirect sourcing. On the other hand, Pareto draws for producers' productivity are taken using stratified random sampling, ensuring that more points are sampled on the right tail of the distribution.

[46]I describe the algorithm to solve the model numerically and implement the Simulated Method of Moments in Appendix A.4. Note that I use the identity matrix for weights in the minimization problem, following evidence on a better fit for import shares (Antràs et al. 2017; Huang et al. 2024).

Table 1.9. Empirical and Simulated Moments

Moments	Data	Model
% producers importing directly	0.039	0.057
% producers importing directly per region:		
– Latin America	0.012	0.012
– China	0.020	0.045
– United States	0.014	0.021
– Europe	0.017	0.014
– Rest of the world	0.006	0.004
% producers with multiple suppliers	0.206	0.312
% producers importing indirectly	0.061	0.053

Notes: This table reports the model fit for the eight empirical targets used in the Simulated Method of Moments (SMM). This procedure estimates the vector Ω containing the demand shifter, indirect contracting costs, and the six parameters characterizing direct matching costs.

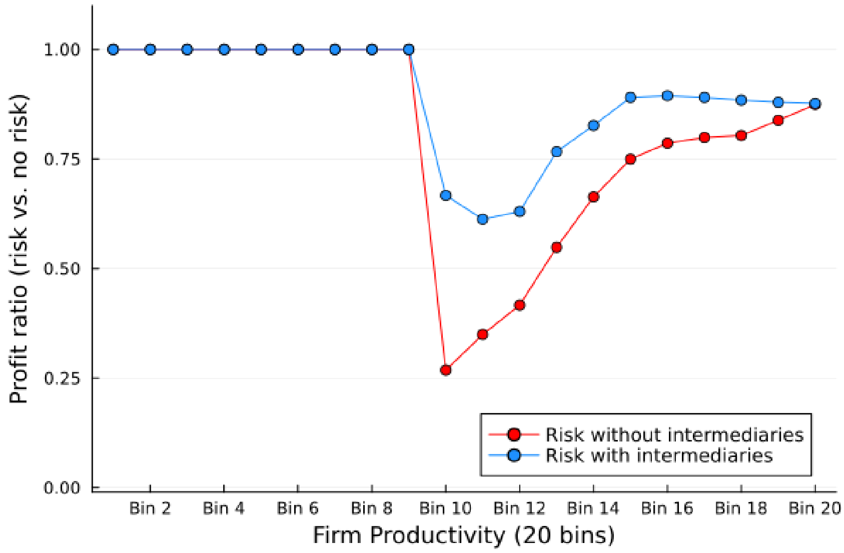
1.5.3. Counterfactuals

Having estimated the model, I perform counterfactuals to quantify the role of trade intermediation in mitigating disruptions. I first evaluate how supply chain risk affects the performance of heterogeneous producers relative to a scenario without disruptions. I then examine how the intermediation technology reduces the impact of disruptions across the firm size distribution. Finally, I consider changes in intermediation markups, assessing to what extent industrial policy encouraging competition in this sector can enhance resilience in input sourcing.

The Impact of Disruptions. I compute firm profits in the baseline model with the estimated probability of disruptions, and in a counterfactual scenario where these probabilities are set to zero under both sourcing modes. The analysis is conducted for a sample of 1,200 producers, which are then divided into 20 equal-sized bins sorted by productivity. The blue line in Figure 1.10 plots the ratio of firm profits with and without risk, showing the average value for firms in each bin. The results indicate that supply chain disruptions have a greater impact on mid-size firms. Larger firms source from more locations and suppliers per location, ensuring network operability, while smaller firms source primarily domestically and are unaffected by foreign disruptions. Table 1.10 presents the average effect by size group: supply chain disruptions reduce the profits of mid-size producers by nearly 20%, compared to 16% for large firms.[47]

[47] I consider the last two bins (19–20) to be large firms, the remaining importers (10–18) to be mid-size firms, and firms sourcing only domestically (1–9) to be small. Alternative thresholds would alter group effects without changing the overall pattern. Figure 1.10 helps visualize the effects across the distribution, but the mapping into aggregate measures is not direct. First, producers' Pareto draws are taken using stratified random sampling, ensuring more points in the right tail of the distribution. Additionally, aggregation must consider the relative

Figure 1.10. Supply Chain Disruptions and Trade Intermediaries



The Role of Intermediaries. I repeat the analysis for scenarios with and without risk, considering a counterfactual where the intermediation technology is not available. This case is represented by the red line in Figure 1.10. The impact of disruptions increases across the firm distribution, but the effect is more pronounced among mid-size firms. While these producers are large enough to import, they lack the scale to diversify suppliers and protect from disruptions on their own. Shutting down intermediation is especially severe for firms on the lower end of the mid-size spectrum, which typically enter a single import market and supplier, meaning that disruptions could prevent their access to foreign inputs altogether. Table 1.10 shows that, on average, intermediaries reduce the impact of disruptions for mid-size firms by 20 percentage points, while their contribution is negligible for large firms. These effects are sizable, implying that the profit losses from disruptions would double for this group without access to intermediaries.

Changes in Intermediation Markups. Figure 1.11 displays the baseline model ($\kappa = 1.2$) alongside counterfactual scenarios with lower ($\kappa = 1.1$) and higher ($\kappa = 1.3$) brokerage fees. The results show that reducing markups improves the disruption buffer for mid-size producers, decreasing the impact of disruptions by 5.4 percentage points, as intermediation becomes more accessible across locations. Conversely, increasing intermediation markups to the levels observed in developed countries (Ganapati 2024; Alexander et al. 2024) hurts mid-size firms, raising the impact of disruptions by 3.2 percentage points. Overall, these results indicate that brokerage fees play a significant role in determining the contribution of intermediaries. This

weight of each bin, with higher bins accounting for a larger share of profits.

Table 1.10. Effect of Supply Chain Disruptions

	Baseline (Intermediation)	No Intermediation	Lower Brokerage Fee	Higher Brokerage Fee
Panel A. Profit ratio relative to no-risk scenario				
Mid-size firms	0.799	0.601	0.853	0.768
Large firms	0.836	0.835	0.838	0.835
Panel B. Difference to baseline (pp)				
Mid-size firms	–	-0.199	0.054	-0.032
Large firms	–	-0.001	0.002	-0.001

Notes: Panel A reports the ratio of firm profits with and without supply chain risk, considering four scenarios: the baseline model, a model without intermediaries, lower brokerage fees (κ = 1.1), and higher brokerage fees (κ = 1.3). Panel B displays percentage point differences relative to the baseline model. Firms are classified as in Figure 1.10. Among 20 size bins in the baseline distribution, the last two correspond to large firms (19 - 20), the remaining importers are classified as mid-size firms (10 - 18), while small firms source only domestically and are omitted from the table (1 - 9).

suggests that industrial policies in sectors instrumental to trade, such as wholesaling, could have meaningful effects on resilience, given evidence of high intermediation markups.

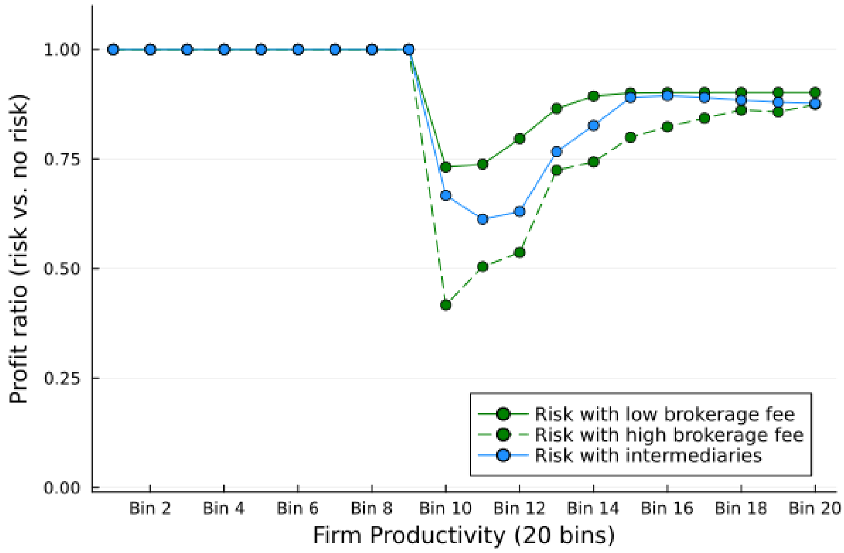
1.6. Conclusion

Firms often face disruptions in international supply chains that affect their operations. While producers could protect themselves through supplier diversification, evidence on trade and production networks suggests high matching costs, making this strategy prohibitive for many of them. This chapter combines rich Chilean data on firms' supply networks with a quantitative model of global sourcing to examine a novel risk management strategy: the use of specialized intermediaries for input sourcing.

Three key takeaways emerge from this study. First, an effective approach to resilience must account for firm heterogeneity, as feasible adaptive responses differ across the firm size distribution. Second, intermediaries possess a resilience advantage that can relax efficiency-risk trade-offs despite imposing higher input markups. Third, intermediation services are quantitatively important for resilience, especially for mid-size producers that engage in offshoring but are unable to diversify. This points to a broader role of intermediaries in trade and development, especially in contexts where firms are constrained to make resilience investments.

My findings shed light on market responses to supply chain risk and suggest that policies

Figure 1.11. Changes in Intermediation Markups



targeting wholesale markups can enhance resilience. The design of such policies would benefit from further research into the business models of intermediaries and the factors driving their market power. More broadly, the distribution sector plays a pivotal role for resilience, and future research could explore how intermediaries interact with inventory management and transportation logistics. Ultimately, optimal adaptive strategies depend on the nature of disruptions, where our theoretical and empirical understanding remains preliminary.

Chapter 2

Productivity, Matchability and Intermediation in Production Networks

2.1. Introduction

Firm production networks have transformed global economic activity, and become focal to policy objectives of growth and stability. Despite dramatic declines in transportation and communication costs in recent decades, driven by both policy advancements and technological innovations, buyer-supplier networks remain sparse and dominated by few, highly connected large firms. These patterns suggest that significant barriers to network formation persist, limiting firms' potential to benefit from globalization. Of special interest is whether network connectivity is subject to market frictions that warrant policy intervention. This underpins the active arena of trade promotion and facilitation, especially in developing countries that are highly reliant on international trade but burdened by poor infrastructure.

Key to these questions are the costs of firm network formation and operation, and the market solutions that emerge to facilitate buyer-supplier interactions. The nature of search, match and transaction costs matters for how firms and countries participate in production networks, how this impacts firm profits and consumer welfare, and how firms prepare for and respond to shocks or policy reforms. By easing firm transactions, specialized intermediaries can importantly reshape these network patterns and consequences. Indeed, wholesalers mediate a significant share of global trade, accounting for example for 50% of imports and 14% of exports in Chile. Yet little is known about the essence of firm network costs and the role of intermediaries in buyer-supplier links.

This chapter examines intermediation in production networks to unpack the firm attributes and matching costs that govern firm-to-firm networks and the gains from trade. Exploiting rich customs data for Chile, we show that exporters of all sizes use intermediaries, mix trade modes across buyers, and set lower prices on intermediated flows. We rationalize these facts in a model of network formation with suppliers of heterogeneous productivity and matchability, buyers of heterogeneous productivity, and intermediaries that reduce matching costs for a brokerage fee. Empirical evidence on trade activity across firms and countries corroborates the model, and informs how geographic distance, logistics and customs efficiency, formal institutions, and cultural-linguistic similarity shape network costs. Model estimation reveals that sellers' attributes are negatively correlated, such that intermediaries enable highly productive sellers with low matchability to reach smaller buyers. This amplifies the welfare gains from intermediation due to wider and deeper network connectivity.

Our first contribution is to unveil empirical facts about direct and intermediated trade in firm networks. We exploit comprehensive Chilean data on the universe of firm-to-firm import transactions, matched to tax records that report firm size and business activity. This allows us to identify foreign exporters, domestic producers, and import intermediaries.[1] We also classify foreign suppliers according to their trade strategy: purely direct exporters that sell only directly to manufacturers, purely indirect exporters that transact only with wholesalers, and mixed exporters that pursue both trade modes.

We document three stylized facts. First, exporters across the size distribution use all three trading strategies, with bigger exporters less likely to trade purely directly, more likely to mix trade modes, and similarly likely to trade purely indirectly. This sharply contrasts with existing intermediation models, in which all sellers above (below) a productivity cutoff sort into direct (indirect) trade, and points to the need to consider supplier heterogeneity along two, imperfectly correlated dimensions. Second, exporters frequently mix trade modes within narrow products and regardless of product rank. Mixed suppliers split product-level exports evenly between direct and intermediated sales, with negligible variation across their core and peripheral products. This suggests that buyer heterogeneity is also needed to rationalize intermediation patterns. Third, exporters charge wholesalers lower prices than producer buyers. Purely indirect suppliers set lower prices than purely direct and mixed suppliers, and mixed suppliers set lower prices on their indirect transactions. This result informs rent sharing with wholesalers, and therefore the trade-off faced by exporters when choosing their optimal sales strategy.

[1] We use "wholesaler" and "intermediary" interchangeably. The data distinguishes between wholesalers that conduct firm-to-firm transactions and retailers that mediate firm-to-consumer sales. We restrict our analysis to wholesalers to study intermediation in production networks as distinct from intermediation chains to consumers. We capture the vast majority of cross-border flows, as retailers account for less than 10% of total imports in Chile.

Our second contribution is to develop a general-equilibrium model of network formation with trade intermediation that is motivated by the empirical facts. In the model, upstream suppliers choose their optimal set of downstream buyers, trade mode with each buyer, and sales value, price and quantity in each match. Upstream suppliers are heterogeneous along two dimensions: productivity, which pins down their marginal production cost, and matchability, which determines their fixed cost of searching, matching and transacting directly with a buyer. Downstream firms are heterogeneously productive in assembling inputs into final goods. Finally, specialized wholesalers facilitate buyer-supplier transactions at a lower match-specific fixed cost, and charge a fee for their services by capturing a share of the trade surplus from each match under Nash bargaining with the supplier. The general equilibrium is characterized by a fixed point for link functions that describe all direct and indirect matches.

This model illustrates novel economic mechanisms, and delivers rich predictions for the pattern of global production networks. Along the extensive margin, the set of ultimate customers widens with a seller's productivity and matchability, where these attributes jointly determine the profitability of each potential buyer under direct and indirect trade and thereby the seller's total sales. There can thus be purely direct, purely indirect, and mixed sellers along the entire seller size distribution. Given productivity (matchability), suppliers with higher matchability (productivity) are less likely to sell exclusively indirectly and more likely to sell exclusively directly. Moreover, mixed suppliers optimally serve buyers above (below) a cutoff productivity directly (indirectly). Along the intensive margin, bilateral sales conditional on a match increase with both seller and buyer productivity, because buyer's input demand is higher when inputs are cheaper and when final demand is greater due to cheaper output. The trade mode also matters, as a seller's price and revenue are lower when serving a buyer through an intermediary.

Intermediaries thus widen production networks by enabling more firm links, especially for smaller buyers and for productive suppliers with low matchability. Intermediaries also deepen production networks, as higher buyer connectivity endogenously increases input purchases through lower input costs and higher final demand.

Our third contribution is to provide empirical evidence that corroborates the model and informs the nature of network transaction costs. At the micro level, we show that the median number of direct buyer links varies little across supplier size bins, while the link distribution overlaps greatly across bins. This is in line with two-dimensional seller heterogeneity in the model, and inconsistent with strict monotonicity predicted by frameworks with a single seller attribute. We also confirm that direct buyer-seller matches exhibit negative degree assortativity such that suppliers with more producer buyers on average sell to producers with fewer suppliers. Analogously, more connected producers on average source from less connected suppliers. While negative degree assortativity has previously been reported in firm networks, we document it specifically for direct links that differ conceptually from intermediated links.

We then examine the variation in trade intermediation across countries exporting to Chile at the sector level. Using GDP per capita as a proxy for average productivity, we document that the shares of intermediated trade and of indirect suppliers fall with origin income, consistent with model implications for the seller productivity distribution. We also analyze a series of country characteristics that capture three potential types of average matching and transaction costs across suppliers: shipping and logistics; customs and red tape; and contracting frictions. This informs what barriers challenge buyer-supplier link formation, but are possible for specialized wholesalers to alleviate. Our results suggest that intermediaries primarily help producers in arranging shipping logistics and transacting with customers when informal contracting institutions are weak: they mediate a greater share of trade flows emanating from distant countries with unreliable shipping arrivals, low trust in foreigners, and limited religious similarity. By contrast, trade intermediation varies little with customs efficiency, linguistic proximity, or the quality of formal contracting institutions at the origin.

Our final contribution is to quantify the welfare effects of trade intermediation and the role of two-dimensional supplier heterogeneity. We develop a method for estimating the model based on simulated method of moments. Two main results emerge from the quantification exercise. First, intermediation reduces matching costs by 26% relative to average direct matching costs. Second, we find a negative correlation between supplier productivity and matchability, i.e. highly productive suppliers have higher direct matching costs on average. While we do not investigate the origins of this correlation, it could arise, for example, due to imperfect or incomplete labor markets, such as information frictions in the market for sales managers or span of control issues inside the firm.

We conclude with two counterfactual exercises. First, shutting down intermediation raises the consumer final-goods price index (CPI) by 3.3%, implying that the welfare gains from intermediation are around 3%. Intuitively, many firm-to-firm links are broken, with small, less productive buyers and high-productivity, low-matchability sellers affected the most. This speaks to policies that improve access to cross-border intermediation services, such as domestic competition policy in the services sector or multilateral deep integration that spans goods and services trade liberalization. Second, moving from negatively correlated to uncorrelated seller attributes decreases the CPI by 3.4%. Intuitively, highly productive firms are no longer hindered by high direct matching costs on average, almost never sell purely indirectly, and their inputs are more likely to reach final producers. This signals how the gains from intermediation may vary across sectors or countries with different distributions of firm-to-firm matching costs. Both counterfactuals reveal differential impacts across the seller and buyer distributions.

Related Literature. This chapter bridges and advances two parallel literatures on buyer-supplier networks and on trade intermediation. On the one hand, research on global value chains and production networks has made important advances in documenting and understanding their complexity (Baldwin (2015), Bernard and Moxnes (2018a), Antras and Chor (2022)). This literature has examined the role of global input sourcing and roundabout production for firms' productivity, quality, innovation and profitability, and thereby for the gains from trade (Goldberg et al. (2010a), Manova and Zhang (2012), Gopinath and Neiman (2014), Caliendo and Parro (2015), Antràs et al. (2017), Amiti and Konings (2007a), Halpern et al. (2015a), Bøler et al. (2015a), Blaum et al. (2018a), Boehm and Oberfield (2020), Bloom et al. (2021)). Frontier work highlights the roles of two-sided buyer- and seller heterogeneity and imperfect competition for endogenous network formation, performance across the firm size distribution, and the gains from trade (Chaney (2014a), Carballo et al. (2018), Bernard et al. (2018c), Bernard et al. (2019a), Huang et al. (2024), Eaton et al. (2022a), Bernard et al. (2022a), Fontaine et al. (2023)). While this literature is interested in how firms match and how idiosyncratic shocks propagate to shape aggregate fluctuations, it typically treats network formation and operation costs as a black box, and abstracts away from trade intermediation (Acemoglu et al. (2012), Baqaee and Farhi (2019), Carvalho et al. (2021a), Elliott et al. (2022), Lim (2018)).

A separate strand of research has explored the role of intermediaries in facilitating commerce. Intermediaries are believed to reduce the fixed costs of trade (Ahn et al. (2011), Bernard et al. (2015), Blum et al. (2009)), although their market power can diminish the gains from intermediation (Dhingra and Tenreyro (2020), Ganapati (2024), Grant and Startz (2022)). Early theoretical work examined the choice of direct vs. indirect exports of heterogeneous final producers (Antràs and Costinot (2011), Ahn et al. (2011)), which counterfactually predicts that sellers above (below) a productivity threshold sort strictly into direct (indirect) sales. Data limitations also restricted early empirical analysis to comparing the exports of manufacturers and intermediaries (Bernard et al. (2010), Bernard et al. (2015)), rather than the direct and indirect exports of manufacturers as dictated by theory. Current work highlights the role of intermediaries in production networks. Allowing for both seller and buyer productivity heterogeneity can accommodate suppliers with purely direct, purely indirect, and mixed sales strategies, and has implications for aggregate productivity and shock transmission downstream (Blum et al. (2024)). Yet, it cannot fully rationalize the prominent prevalence we document for all three sales modes across the firm size distribution.

We advance this line of work by analyzing network formation between heterogeneous sellers and buyers with two-dimensional seller heterogeneity and access to intermediation. We establish the relevance of supplier productivity and matchability both empirically and quantitatively, and show that their joint distribution shapes the welfare gains from intermediation. We also study the direct and intermediated exports of manufacturers, and exploit their variation across origin countries to inform the role of the productivity distribution and to unpack country drivers of firm networking costs.

More generally, our research speaks to the interdependence of manufacturing and services sectors, in that wholesale services directly shape seller-buyer production networks. While we focus on the use of intermediation by suppliers seeking to broaden their sales network, in complementary work Perello (2024) explores how downstream producers choose to source upstream inputs directly or through intermediaries to guard against supply network disruptions. Implicitly, this body of evidence indicates to what extent the market for intermediation services has responded to meet the needs of manufacturing firms. This informs thinking about trade promotion and facilitation that many developing-country governments undertake and international organizations support, as well as discussions of geopolitical reorganization of production networks.

The rest of the chapter is organized as follows. Section 2 introduces the data and stylized facts. Section 3 develops the general equilibrium model of trade intermediation and two-sided firm heterogeneity in production networks. Section 4 presents empirical evidence for trade patterns across firms and origin countries, and unpacks drivers of implied network costs. Section 5 provides model quantification and welfare counterfactuals. The last section concludes.

2.2. Stylized Facts

2.2.1. Data

We exploit rich data for Chile that allows us to examine the universe of firm-to-firm import transactions and detailed characteristics of domestic firms. We obtain the value, quantity, and unit value for all import flows from the Chilean Customs Service for the 2005-2019 period. These records identify the origin country, HS 6-digit product, foreign seller, and domestic buyer for each transaction. We also collect information on firm size and primary industry of activity from the Business Statistics maintained by the Chilean Tax Authority for the same period. We match these datasets based on a unique firm tax identifier. Below we report results for the most recent cross-section in the data, year 2019; all patterns hold in the cross-section for other years and in the pooled panel with year fixed effects.

We classify Chilean firms into three types based on their main business activity: producers, wholesalers, and retailers. The Chilean Tax Authority closely follows the *International Standard Industrial Classification* (ISIC, rev. 4) for the wholesale and retail sectors. Wholesalers specialize in the "resale without transformation of new and used goods to retailers, to industrial commercial, institutional or professional users, or to other wholesalers". Wholesale operations can include services incidental to trade, such as sorting, packaging, or storage. Retailers, on the other hand, specialize in the resale of goods to the general public for personal or household consumption. Thus, wholesalers intermediate firm-to-firm transactions, while retailers focus on firm-to-consumer transactions.

Table 2.1 provides summary statistics for the activity of these three types of Chilean firms. Overall, there are 13,524 producer-importers, who represent 45% of all importers and capture 46% of imports by value. Wholesaler-importers number 8,980 (30%), and account for a disproportionately large share of imports (44%). Retailer-importers are likewise numerous at 7,851 (25%), but contribute only 10% to aggregate imports. Given our interest in firm-to-firm production networks, we focus exclusively on Chilean producers and wholesalers, and omit retailers from the analysis. For convenience, we will use "wholesaler" and "intermediary" synonymously.

TABLE 2.1. Summary statistics by firm type

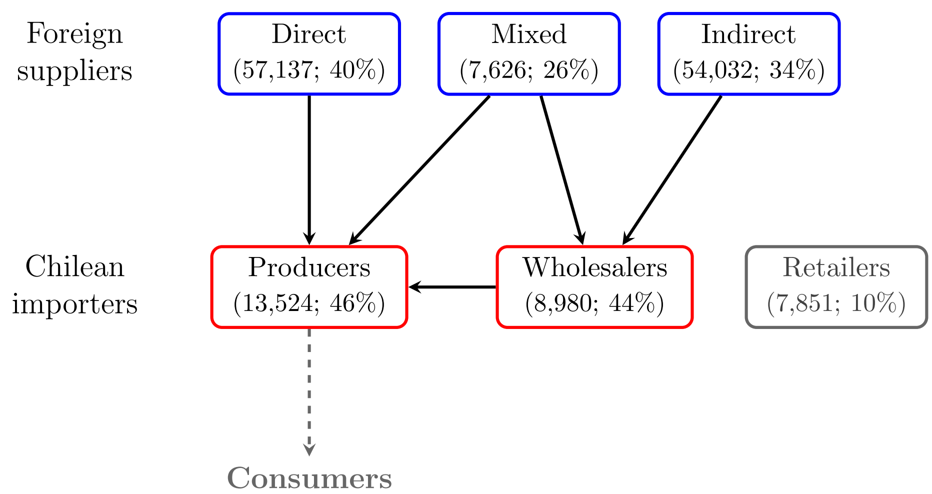
	N	%	trade value	% trade value
Chilean importers				
Producers	13,524	0.45	28,105,142	0.46
Wholesalers	8,980	0.30	26,866,504	0.44
Retailers	7,851	0.25	6,540,562	0.10
Foreign suppliers				
Direct suppliers	57,137	0.48	20,226,218	0.40
Indirect suppliers	54,032	0.45	16,858,178	0.34
Mixed suppliers	7,626	0.07	13,167,955	0.26

Note: Summary statistics are reported for the universe of Chilean importers, and for the subset of foreign suppliers trading with producers and wholesalers. Foreign suppliers transacting with retailers are excluded from the analysis. The table displays cross-sectional data for 2019.

We distinguish between three types of foreign firms exporting to Chile based on their trade strategy: Direct suppliers sell exclusively to producers, indirect suppliers transact only with wholesalers, and mixed suppliers sell both to producers and to wholesalers. In some empirical exercises, we also consider suppliers' trade mode within a particular product, in recognition of the large role of multi-product exporters in the data.

We display summary statistics for foreign suppliers in the bottom half of Table 2.1, and visualize the relationship between foreign suppliers and domestic buyers in Figure 2.1. Chile receives imports from 57,137 purely direct foreign suppliers from 141 countries of origin, 54,032 purely indirect suppliers from 148 origins, and 7,626 mixed suppliers from 78 countries. Direct and indirect exporters represent respectively 48% and 45% by count, but are responsible for only 40% and 34% of total trade value (approximately 20% less than their weight in the pool of exporters). Instead, the 7% suppliers with a mixed sales strategy conduct 26% of all exports to Chile, which is almost 4 times their weight by number.

FIGURE 2.1. Bi-partite network of foreign suppliers and Chilean importers



Note: Numbers in parenthesis correspond to the count of firms, while percentages indicate trade shares and add up to 1 in each row. The figure displays cross-sectional data for 2019.

2.2.2. Facts on Intermediated Export Transactions

We establish three stylized facts about trade intermediation using the detailed Chilean records. These empirical regularities go against theoretical predictions in the prior literature that have not been confronted with disaggregated data on firm-to-firm transactions, and motivate key ingredients of the novel model we propose in Section 3.

Stylized Fact 1: *Exporters across the size distribution use trade intermediation. Bigger exporters are less likely to trade purely directly, more likely to mix trade modes, and similarly likely to trade purely indirectly.*

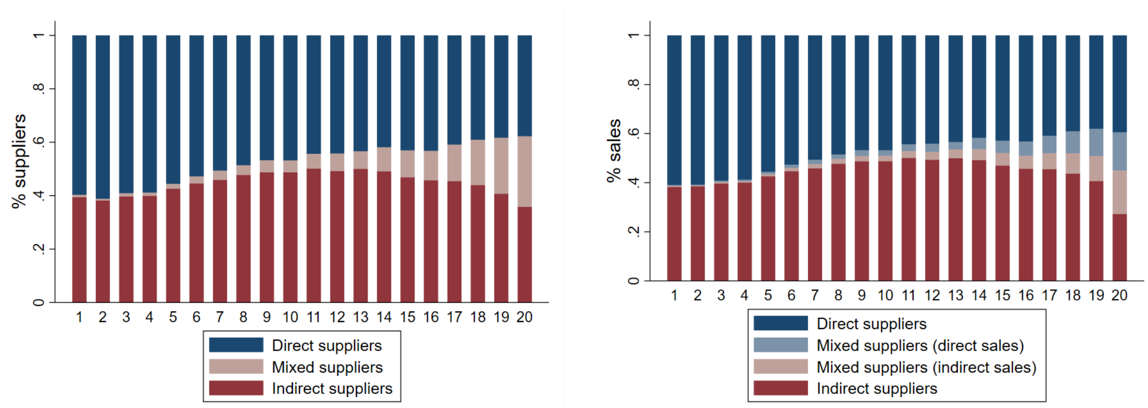
Figure 2.2A documents the use of different sales strategies across 20 size bins of exporters to Chile. We measure a seller's size with its total exports to Chile, and summarize trade activity pooling across sellers from all origin countries. The share of suppliers that transact only directly with downstream producers falls systematically with supplier size, from approximately 60% in the bottom 5% to fewer than 40% in the top 5%. The share of suppliers that trade exclusively through wholesalers remains close to 40% across the size distribution, with some indication of an inverse U-shape. Finally, the share of suppliers that pursue both direct and intermediated sales rises monotonically with firm size, from negligible levels among the smallest 5% to about 30% among the biggest 5%.

Intermediated trade is not only often used by suppliers big and small, but it also accounts for a large portion of aggregate trade flows. Figure 2.2B decomposes the value of total exports to Chile in each exporter size bin into direct exports by purely direct suppliers, direct exports by mixed suppliers, indirect exports by mixed suppliers, and indirect exports by purely indirect suppliers. Intermediated trade contributes 40-50% of aggregate exports across the board.

Figure 2.3 confirms that similar patterns hold when we consider one origin country at a time. We plot the breakdown of export strategies across 20 size bins separately for suppliers from Brazil, China, Germany, and the US. These countries are not only among Chile's most important trade partners, but they also represent a mix of developed and developing economies, near and far. Each sees notable activity under all three trade modes.

Fact 1 sharply contrasts key predictions of existing models of trade intermediation. Such models feature seller heterogeneity, whereby all exporters above a productivity cutoff sort exclusively into direct exporting, and all exporters below that cutoff trade only through intermediaries (Ahn et al. (2011), Akerman (2018), Felbermayr and Jung (2011)). The new empirical regularity we uncover points to the need to consider supplier heterogeneity along two, imperfectly correlated dimensions; in our model, these will be seller productivity and matchability.

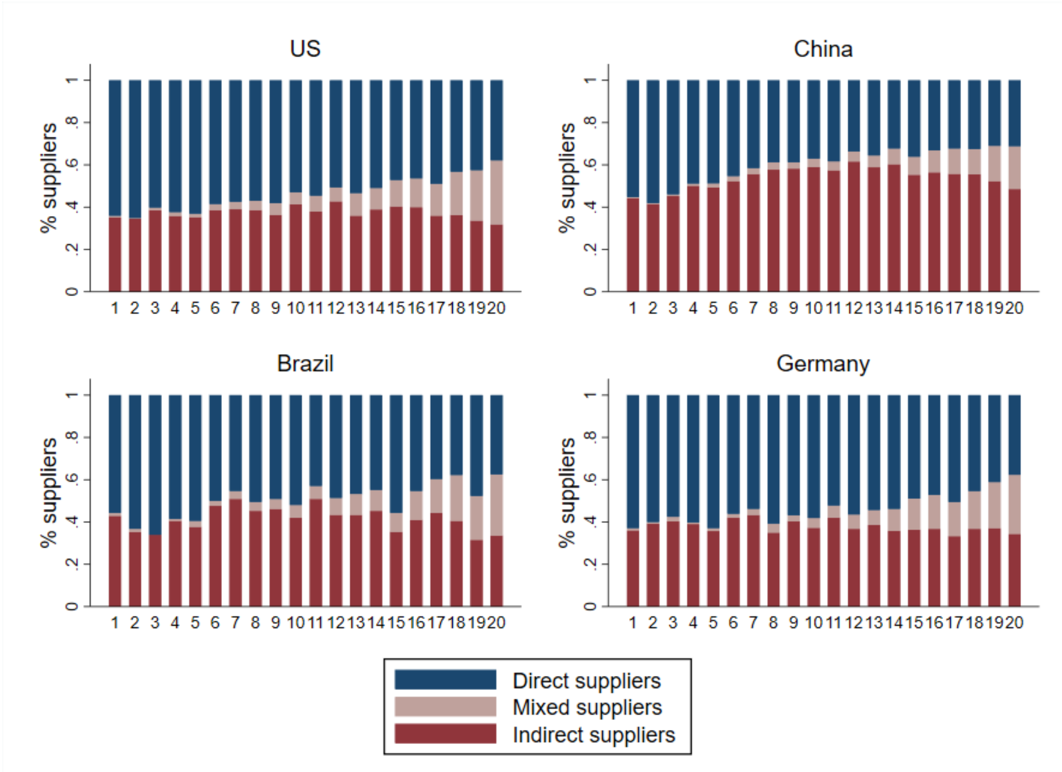
Figure 2.2. Trade strategy across the supplier size distribution



(A) Share of suppliers by trade mode

(B) Share of trade value by trade mode

FIGURE 2.3. Suppliers' trade strategy for top origin countries



Stylized Fact 2: *Exporters mix trade modes within narrowly defined products, regardless of the exporter's product scope or product rank.*

Table 2.2 demonstrates that mixed suppliers are not simply multi-product firms that sell each product under a single trade mode but adopt different strategies across products. Instead, mixed suppliers routinely market the same finely disaggregated HS 6-digit product both directly and through wholesalers. Fully 65% of all mixed suppliers mix trade modes within at least one of their products, with the average mixed supplier transacting both directly and indirectly in 31% of their products. Revenues from such mixed-mode products are moreover not trivial, but amount to 45% of total firm sales on average.

Table 2.2 also documents that these patterns hold for suppliers of different product scope. We distinguish between mixed exporters with 1, 2, 3, or at least 4 products in their sales portfolio. The share of exporters that mix sales modes within at least one product is always above 50% and generally rises with product scope; this share is definitionally 100% for single-product mixed sellers. Suppliers with a bigger product range tend to mix sales modes for a smaller share of their varieties that in turn generate a smaller share of total revenues, but both shares remain high at 15% and 35% on average, respectively.

Finally, mixed suppliers do not systematically vary their choice of trade mode across products based on the product's sales rank. For each mixed supplier that offers at least n products, we sort their products by export revenue, and assign $rank = 1$ to their core good and $rank = 2, 3, .., n-1, n+$ to their progressively more peripheral goods. We then calculate the share of a product's direct and indirect sales by product rank for each firm, and average these shares across firms. Figure 2.4 shows that among mixed suppliers of at least 4 products ($n = 4$), intermediated sales account for a remarkably flat 52% regardless of product rank. We have confirmed that the share of indirect sales remains similarly stable across core and peripheral goods when we consider subsamples of mixed suppliers with a more diversified product portfolio, such as $n = 5$ or $n = 10$.

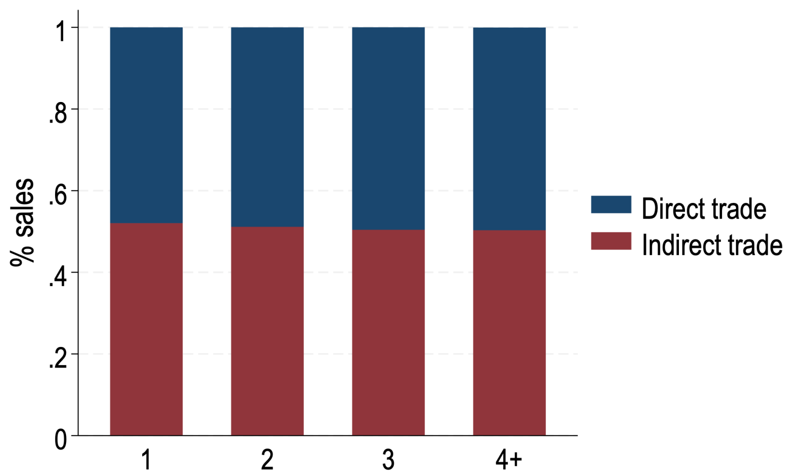
Fact 2 suggests that seller heterogeneity is not sufficient to rationalize the incidence of intermediated trade in the data. Existing models of multi-product firms typically combine heterogeneity in firm-wide efficiency across firms with dispersion in firm-product specific expertise across products within firms (Bernard et al. 2011; Manova and Yu 2017). Incorporating this insight into standard models of trade intermediation with only supply-side heterogeneity would imply that firms choose a single trade mode for each product and are systematically more likely to rely on wholesalers for more peripheral goods. Fact 2 indicates that both of these predictions are counterfactual. Instead, it points to a role for buyer heterogeneity as featured in some prior models of trade intermediation, whereby each exporter supplies a given product directly (indirectly) to buyers above (below) a productivity threshold.

In sum, Facts 1 and 2 together motivate a framework with two-dimensional seller heterogeneity (productivity and matchability) and buyer heterogeneity (productivity). Note that allowing for one-dimensional heterogeneity among both sellers and buyers would fail to explain the incidence of intermediated trade across the seller size distribution or across the product hierarchy within sellers.

Table 2.2. Trade strategy of mixed suppliers by product scope

Product scope	# Firms	% Firms mixing within product	% Products mixed	% Sales from mixed products
1	1,067	1	1	1
2	1,622	0.5	0.27	0.41
3	1,093	0.53	0.21	0.38
4+	3,844	0.64	0.15	0.35
Total	7,626	0.65	0.31	0.45

Figure 2.4. Trade strategy of multi-product suppliers by product rank



Stylized Fact 3: *Exporters charge wholesalers lower prices than producer buyers. Purely indirect exporters set lower prices than purely direct and mixed exporters, and mixed exporters set lower prices on their indirect transactions than on their direct transactions.*

Table 2.3 establishes that trade prices are systematically lower on sales to wholesalers than on sales to producer buyers. This pattern holds both across sellers with different trade strategies and across the buyers of sellers that mix trade modes, even within narrow product categories.

We first compare the prices charged by purely direct, purely indirect and mixed foreign suppliers of the same product.[2] In Column 1 of Table 2.3, we regress log unit value at the transaction level on dummies for seller type, conditioning on HS 6-digit product fixed effects. Compared to mixed suppliers, purely direct exporters set 50% higher prices on average, while purely indirect exporters receive 14% lower prices on average. These price differentials remain large at 28.5% and 25% respectively in Column 2, when we additionally control for seller, buyer and transaction attributes that may relate to bargaining power or volume discounts and thus capture economic forces other than trade intermediation. In particular, we condition on the size and connectivity of each trade partner, as well as the log transaction value.[3]

We then restrict the analysis to the subsample of mixed suppliers, and evaluate the prices charged by the same supplier across direct and indirect sales transactions for the same product.

[2]Table 2.3 shows results when mixed suppliers are defined at the firm-product level, such that suppliers are classified as mixed only for their mixed products. As reported in the Appendix, we find similar results when defining mixed suppliers at the firm level.

[3]The size of Chilean buyers is approximated by their total imports, while their connectivity is measured by their total number of international suppliers. The size and connectivity of foreign suppliers is defined analogously, but considering their sales and customers in Chile.

In Column 3, we now regress log unit values on a dummy for exports to a wholesaler, controlling for supplier-product pair fixed effects. In Column 4, we further condition on transaction value, buyer size and connectivity. Exporters consistently offer intermediaries 8.3%-9.6% lower prices compared to direct producer buyers.

TABLE 2.3. Direct and indirect prices

	All suppliers		Mixed suppliers	
	(1)	(2)	(3)	(4)
	log(Unit Value)	log(Unit Value)	log(Unit Value)	log(Unit Value)
D(Direct Supplier=1)	0.496***	0.285***		
	(0.030)	(0.042)		
D(Indirect Supplier=1)	-0.141***	-0.251***		
	(0.033)	(0.044)		
D(Wholesaler Buyer=1)			-0.096***	-0.083***
			(0.014)	(0.015)
Product FE	Yes	Yes	No	No
Supplier-Product FE	No	No	Yes	Yes
Transacted value	No	Yes	No	Yes
Supplier controls	No	Yes	No	No
Buyer controls	No	Yes	No	Yes
N	471,730	471,730	27,296	27,296

Note: All regressions are at the supplier-HS6 product-buyer level for year 2019. Columns 1-2 compare the prices charged by purely direct and purely indirect suppliers to those of mixed suppliers. Columns 3-4 compare the prices that mixed suppliers charge when exporting to wholesalers and to producer buyers. Buyer and supplier controls include firm size (total trade value) and connectivity (number of trade partners).

Fact 3 is informative of price setting in wholesale transactions, and can thus discriminate between different conceptualizations of the seller-wholesaler relationship in the prior literature. This in turn informs the trade-off faced by exporters when choosing their optimal sales strategy. The price discount on intermediated sales is inconsistent with the wholesaler engaging in double marginalization or charging a brokerage fee on the seller's variable profits, as in both cases the supplier would not price discriminate across customers. The evidence also speaks against a brokerage fee on the sales value of the transaction, which would manifest in higher, rather than lower prices on intermediated trade. Instead, the new fact we document suggests that suppliers and wholesalers may engage in Nash bargaining, whereby the fee for intermediation services depends on the wholesalers' relative market power.

2.3. Theoretical Framework

We develop a quantifiable model of endogenous network formation with trade intermediation. Models of trade and production networks typically abstract from distribution channels, while canonical models of intermediaries ignore their role in shaping firm-to-firm connections. Our framework blends these two approaches in a setting with two-sided firm heterogeneity and heterogeneous relationship capabilities.

2.3.1. Setup

Consider a world with multiple countries $j \in \mathcal{J}$ and three active sectors in each country: upstream suppliers $(\mathcal{U})$ who use labor to produce differentiated intermediate inputs, downstream producers $(\mathcal{D})$ who assemble intermediates into differentiated final goods, and wholesale intermediaries $(\mathcal{W})$ who can handle transactions between upstream suppliers and downstream producers. The upstream and downstream sectors are populated by a fixed mass of respectively $N_j(\mathcal{U})$ and $N_j(\mathcal{D})$ heterogeneous firms that engage in monopolistic competition. We study homogeneous intermediaries to focus on the sorting of heterogeneous manufacturers into different trade modes. We model intermediaries located in the destination market, as import intermediaries are observationally much more important than export intermediaries in the Chilean context. We use tilde-notation $\tilde{y}$ to denote variables related to final goods and standard notation y when referring to intermediate inputs, and suppress country subscripts when not of interest.

Upstream suppliers differ along two dimensions: productivity, which pins down their marginal production cost, and relationship capability (also called matchability), which determines their fixed cost of searching, matching and transacting directly with a customer. Downstream producers differ in their productivity in assembling inputs into final goods.[4] Intermediaries offer distribution services that reduce relationship-specific costs in exchange for an implicit brokerage fee that depends on their bargaining power. One can think of them as wholesalers that coordinate transportation, logistics, contracts, insurance, and customer communication. Thus, upstream suppliers choose whether to serve a given downstream producer directly, indirectly by hiring the services of an intermediary, or not at all.

We examine a bi-partite production network in order to characterize the impact of trade intermediation in a transparent and tractable way. In particular, we assume without loss of generality that downstream producers operate domestically, while upstream suppliers can serve both domestic and foreign markets. Incorporating trade in final goods, or the use of final goods

[4] We assume that sellers bear all relationship-specific costs in order to understand how upstream suppliers use intermediaries to trade with downstream producers. Section 4 discusses the role of heterogeneous seller matchability in fitting the model to the data.

in producing intermediates, would add network complexity without qualitatively affecting the novel mechanisms of interest.

2.3.2. Final Demand

Consumers in country j have Cobb-Douglas preferences over homogeneous and differentiated final goods. The homogeneous good $\tilde{q}_{j0}$ is freely traded and produced using labor under constant returns to scale, such that one unit of labor produces w_j units of output. Using the homogeneous good as numeraire sets wages to w_j in country j. Consumers exhibit CES preferences for varieties $\omega \in \Omega_j$ of the non-tradable differentiated good:

$$U_j = \tilde{q}_{j0}^{1-\beta} \left(\int_{\Omega_j} \tilde{q}_j(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\beta\sigma/(\sigma-1)},$$

where $\sigma > 1$ is the elasticity of substitution across varieties. Given aggregate expenditure $\tilde{E}_j$ and the price index $\tilde{P}_j \equiv \left(\int_{\Omega_j} \tilde{p}(\omega)^{1-\sigma} d\omega \right)^{1/(1-\sigma)}$ for differentiated goods, demand for variety ω with price $\tilde{p}(\omega)$ is:

$$\tilde{q}_j(\omega) = \tilde{p}_j(\omega)^{-\sigma} \tilde{P}_j^{\sigma-1} \left(\beta \tilde{E}_j \right). \tag{2.1}$$

2.3.3. Downstream Producers

Downstream producers sell to local consumers in country j. They own a blueprint for a single variety ω of final goods, and draw productivity $\zeta \in [\underline{\zeta}, \overline{\zeta}]$ from distribution $G(\zeta)$ with density $dG(\zeta)$. The downstream technology transforms intermediate inputs into final goods under constant returns to scale:

$$\tilde{q}(\zeta) = \zeta Q(\zeta), \qquad Q(\zeta) = \left(\int_{\Omega(\zeta)} q(v,\zeta)^{\frac{\eta-1}{\eta}} dv \right)^{\eta/(\eta-1)},$$

where $\eta > 1$ is the elasticity of substitution across intermediates, and $q(v,\zeta)$ is the quantity purchased of input variety v from the producer's set of upstream suppliers $\Omega(\zeta)$. The marginal cost of downstream producers thus depends on their own productivity and their input cost index $C(\zeta)$, which aggregates input prices $p(v,\zeta)$ across suppliers:

$$\tilde{c}(\zeta) = \frac{C(\zeta)}{\zeta}, \qquad C(\zeta) = \left(\int_{\Omega(\zeta)} p(v,\zeta)^{1-\eta} dv \right)^{1/(1-\eta)}. \tag{2.2}$$

Under monopolistic competition and CES final demand, downstream producers charge a constant markup $\tilde{\mu} = \frac{\sigma}{\sigma-1}$ over their marginal cost, such that $\tilde{p}(\zeta) = \tilde{\mu}\,\tilde{c}(\zeta)$. Thus, quantity sold by producer ζ in country j is given by (2.1), and its demand for intermediate variety v from country i is:

$$q_{ij}(v,\zeta) = p_{ij}(v,\zeta)^{-\eta} C_j(\zeta)^{\eta-1} X_j(\zeta), \tag{2.3}$$

where $X_j(\zeta)$ are the total input purchases of producer ζ. Note that the trade mode does not affect input demand beyond any effect it might have on prices. Furthermore, downstream producers incur no matching costs, and the efficiency gains from input variety therefore incentivize them to transact with all interested upstream suppliers $\Omega(\zeta)$.

2.3.4. Upstream Suppliers

Upstream suppliers sell to downstream producers both at home and abroad. They draw productivity $z \in [\underline{z}, \overline{z}]$ and matchability $f^D \in [\underline{f}^D, \overline{f}^D]$ from joint distribution $G(z, f^D) \equiv G(\lambda)$ with density $dG(\lambda)$, where productivity and matchability may be correlated. They use labor to produce a single variety v of intermediate goods under constant returns to scale, and face iceberg trade costs τ_{ij}. The marginal cost of upstream supplier $\lambda = (z, f^D)$ in country i selling to downstream producers in country j is thus:

$$c_{ij}(\lambda) = \frac{\tau_{ij} w_i}{z(\lambda)}. \tag{2.4}$$

Suppliers face relationship-specific fixed costs f^D (in units of labor) when trading directly with a downstream customer. Alternatively, they can delegate all relationship logistics to an intermediary. They would then incur a fixed cost f^I that does not depend on their matchability, in return for an implicit brokerage fee specified below that reduces their variable profits. One can micro-found this cost structure with intermediaries passing on some of their own fixed costs to the supplier, or as suppliers having to retain some degree of relationship management activities in-house.

Upstream supplier $\lambda = (z, f^D)$ will optimally choose the sets of downstream producers to serve directly $\{\zeta \epsilon D(\lambda)\}$ and indirectly $\{\zeta \epsilon \mathcal{I}(\lambda)\}$ and the price and quantity for each transaction to maximize global profits. The supplier's problem can be expressed as:

$$\max_{\mathcal{D}(\lambda), \mathcal{I}(\lambda), \{p^D(\lambda,\zeta), p^I(\lambda,\zeta), q^D(\lambda,\zeta), q^I(\lambda,\zeta)\}} \pi(\lambda) = \int_{\mathcal{D}(\lambda)} \pi^D(\lambda,\zeta) d\zeta + \int_{\mathcal{I}(\lambda)} \pi^I(\lambda,\zeta) d\zeta, \tag{2.5}$$

where $\pi^D(\lambda,\zeta)$ and $\pi^I(\lambda,\zeta)$ denote supplier profits when trading with producer ζ under each trade mode, and vector $\{p^D(\lambda,\zeta), p^I(\lambda,\zeta), q^D(\lambda,\zeta), q^I(\lambda,\zeta)\}$ indicates the bilateral prices and quantities offered in direct and indirect transactions.

2.3.5. Trade Intermediaries

Intermediaries specialize in operationalizing transactions between foreign suppliers and their matched domestic buyers. We abstract away from intermediary heterogeneity and matchmaking services, and focus on the role of homogeneous intermediaries in reducing relationship-specific costs associated for example with logistics, distribution, or communication.[5]

An import intermediary in country j receives and transfers goods from upstream supplier λ in country i intended for downstream producer ζ in j. The wholesaler incurs a fixed cost f^W per relationship, and charges the supplier a brokerage fee. Specifically, the wholesaler and the supplier engage in Nash bargaining over the trade surplus (or variable profits) from the transaction, with bargaining weights ϕ and $1 - \phi$ respectively. The wholesaler's profits are thus $\pi^W = \int_{\Omega^W}[B(\phi, \lambda, \zeta) - f^W]d(\lambda, \zeta)$, where Ω^W is its set of intermediated transactions, $p_{ij}^W(\lambda, \zeta)$ is the price it charges the final buyer, and the brokerage fee is $B(\phi, \lambda, \zeta) = \phi \left(p_{ij}^W(\lambda, \zeta) - c_{ij}(\lambda) \right) q_{ij}^I(\lambda, \zeta)$.

We make two assumptions about the market for intermediation services that grant the model transparency and tractability with little loss of generality. These assumptions ensure that the use of wholesale trade is determined solely by the upstream supplier, such that we can cleanly illustrate how access to intermediation reshapes production networks. We are able to characterize rich and empirically relevant sorting patterns, without having to consider an exhaustive taxonomy of cases.

First, we take the structure of the intermediation contract and the wholesaler's bargaining power ϕ as exogenous. However, these can be rationalized as equilibrium outcomes of the market for intermediation services, for example under free entry in the wholesale sector or when ϕ reflects a wholesaler's market share of aggregate (intermediated) trade.[6]

Second, we also assume that f^W is sufficiently small to guarantee that intermediaries are willing to carry out any transaction that is deemed profitable by upstream suppliers. Intuitively, this is consistent with specialized intermediaries having high relationship capability due to their established distribution network, streamlined contracting and logistics, and professionalized customer management.[7]

[5] The presence of multiple homogeneous intermediaries that offer identical service contracts could be justified with some degree of horizontal differentiation in intermediation services that is orthogonal to the buyer-supplier production network. For example, intermediaries may specialize in different geographic regions that have otherwise identical probabilistic buyer distributions, such that suppliers first choose intermediated buyer links and then transact with whichever wholesaler covers that buyer's region.

[6] For instance, ϕ would be pinned down by $\pi^W = 0$ under free entry into intermediation.

[7] Alternatively, one can think of intermediaries passing their relationship-specific costs onto suppliers in the form of non-linear pricing. The supplier fixed cost of indirect sales f^I would then encompass f^W.

2.3.6. Firm-to-Firm Sales

Upstream suppliers maximize global profits by making independent sales decisions across buyers.[8] The supplier problem (2.5) therefore reduces to a two-step optimization: (i) optimal match-specific prices and quantities conditional on a direct or indirect link, and (ii) optimal sets of direct and indirect links. We first characterize the intensive margin of firm-to-firm sales conditional on the network structure; the next section then describes the extensive margin of endogenous network formation.

Conditional on transacting with a given buyer, the supplier will choose the optimal bilateral price and quantity to maximize profits from that relationship, taking into account the chosen trade mode. The profit maximization problem of upstream supplier λ from country i selling directly to downstream producer ζ in market j would be:

$$\max_{p^D(\lambda,\zeta),q^D(\lambda,\zeta)} \pi_{ij}^D(\lambda,\zeta) = \left[p_{ij}^D(\lambda,\zeta) - c_{ij}(\lambda)\right] q_{ij}^D(\lambda,\zeta) - f^D(\lambda).$$

Given downstream input demand (2.3) and monopolistic competition upstream, suppliers would optimally charge all of their direct customers a constant markup $\mu = \frac{\eta}{\eta-1}$ above their marginal cost of production and delivery, such that $p_{ij}^D(\lambda,\zeta) = \mu c_{ij}(\lambda)$.

On the other hand, the profits of upstream supplier λ when serving the same downstream producer ζ indirectly would be:

$$\pi_{ij}^I(\lambda,\zeta) = (1-\phi)\left[p_{ij}^W(\lambda,\zeta) - c_{ij}(\lambda)\right] q_{ij}^I(\lambda,\zeta) - f^I,$$

where the first term reflects the share $(1-\phi)$ of the variable profits (or trade surplus) $\left(p_{ij}^W(\lambda,\zeta) - c_{ij}(\lambda)\right) q_{ij}^I(\lambda,\zeta)$ generated from an intermediated transaction between λ and ζ.

Given downstream input demand (2.3) and Nash bargaining between the wholesaler and the supplier, the wholesaler optimally charges the buyer the same price as under a direct transaction, $p^W(\lambda,\zeta) = p^D(\lambda,\zeta) = \mu c_{ij}(\lambda)$, so as to maximize the trade surplus to be shared with supplier λ. Thus, $B(\phi,\lambda,\zeta) = \phi\left(p_{ij}^D(\lambda,\zeta) - c_{ij}(\lambda)\right) q_{ij}^I(\lambda,\zeta)$ is the intermediary's brokerage fee, while $(1-\phi)\left(p_{ij}^D(\lambda,\zeta) - c_{ij}(\lambda)\right) q_{ij}^I(\lambda,\zeta)$ are the seller's variable profits.

The supplier's profit maximization problem under intermediated trade can therefore be expressed in terms of the implied price received on indirect transactions $p_{ij}^I(\lambda,\zeta)$:

$$\max_{p^I(\lambda,\zeta),q^I(\lambda,\zeta)} \pi_{ij}^I(\lambda,\zeta) = \left[p_{ij}^I(\lambda,\zeta) - c_{ij}(\lambda)\right] q_{ij}^I(\lambda,\zeta) - f^I,$$

[8] Interdependence could arise, for example, due to production capacity or credit constraints, or (dis)economies of scale in marketing and distribution.

where $p^I_{ij}(\lambda,\zeta)$ satisfies $\left(p^I_{ij}(\lambda,\zeta) - c_{ij}(\lambda)\right) = (1-\phi)\left(p^D_{ij}(\lambda,\zeta) - c_{ij}(\lambda)\right)$.

Suppliers will therefore price discriminate across customers, and offer intermediaries a lower price than direct producer buyers:

$$p^I_{ij}(\lambda,\zeta) = \left(\frac{\eta-\phi}{\eta}\right) p^D_{ij}(\lambda,\zeta) = \left(\frac{\eta-\phi}{\eta-1}\right) c_{ij}(\lambda). \tag{2.6}$$

Note that the wedge between the supplier's direct and indirect prices is shaped by the bargaining power of intermediaries: When $\phi \approx 1$, the wholesaler extracts all rents from the transaction and the supplier only covers its marginal costs, while when $\phi \approx 0$, the supplier gives no wholesaler discount. Therefore, upstream prices depend on both seller productivity and trade mode, but not on buyer productivity or any other match characteristic beyond iceberg trade costs. On the other hand, the ultimate buyer faces the same input price regardless of how the input reaches them, since wholesalers' double marginalization implies $p^W_{ij}(\lambda,\zeta) = p^D_{ij}(\lambda,\zeta)$.[9]

We can characterize seller-buyer trade flows $x_{ij}(\lambda,\zeta) \equiv p_{ij}(\lambda,\zeta)q_{ij}(\lambda,\zeta)$ by replacing optimal prices in the demand for intermediate goods (2.3):

$$x^D_{ij}(\lambda,\zeta) = \mu^{1-\eta}\left(\frac{\tau_{ij}w_i}{z(\lambda)}\right)^{1-\eta} C_j(\zeta)^{\eta-1}X_j(\zeta). \tag{2.7}$$

$$x^I_{ij}(\lambda,\zeta) = \left(\frac{\eta-\phi}{\eta}\right) x^D_{ij}(\lambda,\zeta). \tag{2.8}$$

Firm-to-firm sales depend on seller productivity (through marginal cost), buyer productivity (through total input purchases), and trade mode (through transaction price), but are unaffected by seller matchability.

Proposition 1. (Intensive margin) *Conditional on a seller–buyer match, sales from upstream supplier $\lambda = (z, f^D)$ to downstream producer ζ:*

(a) increase in seller productivity z but are independent of seller matchability f^D;

(b) increase in buyer productivity ζ;

(c) are lower and cheaper when intermediated.

Proof. *See Appendix B.2.*

[9] Alternative pricing schemes for intermediation services can induce different pricing patterns that contradict Fact 3 that suppliers charge lower prices on indirect transactions (see Appendix B.2 for details). For example, if intermediaries charge sellers an explicit brokerage fee γ as a share of variable profits, sellers would counterfactually charge the same price for direct and indirect transactions. Sellers would instead set higher indirect markups and prices if the wholesale fee is applied on transaction values. Fact 3 aside, one can also always find a level of wholesalers' market power ϕ that is consistent with γ.

Intuitively, more productive upstream suppliers set lower prices due to their lower marginal costs, which in turn increases demand from downstream producers. At the same time, any supplier would earn lower indirect than direct sales revenues because the intermediary holds market power and extracts a share of the supplier's markup on direct sales. Turning to buyer heterogeneity, more productive downstream producers have larger total input purchases, as their lower marginal cost of assembly attracts greater demand from final consumers. This implies larger purchases from each infra-marginal supplier (intensive margin). However, we show below that more productive downstream producers are profitable customers for a larger set of suppliers. This tends to lower their input cost index, but also raise their consumer appeal and thereby also their total input expenditure, with opposing effects on their input demand from each supplier (extensive margin). The relative strength of these forces depends on supply and demand elasticities.

2.3.7. Direct and Indirect Links

The second step in the supplier's problem is choosing which downstream producers to serve and via which trade mode. Given optimal firm-to-firm prices, quantities and sales in equations (2.7) and (2.8), the supplier's profits from potential match (λ, ζ) become:

$$\pi_{ij}^{D}(\lambda, \zeta) = \frac{x_{ij}^{D}(\lambda, \zeta)}{\eta} - f^{D}(\lambda), \tag{2.9}$$

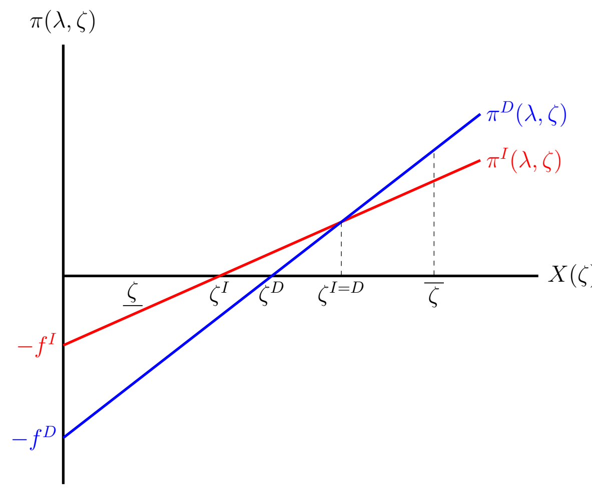
$$\pi_{ij}^{I}(\lambda, \zeta) = \left(\frac{\eta - \phi}{\eta}\right) \frac{x_{ij}^{D}(\lambda, \zeta)}{\eta} - f^{I}. \tag{2.10}$$

Upstream suppliers will pursue only partnerships that generate non-negative profits, and if both direct and indirect sales are individually profitable, they will pick the more profitable strategy. This gives rise to an endogenous network of direct and indirect links between upstream suppliers and downstream producers.

Figure 2.5 illustrates the supplier's problem. For a given upstream supplier $\lambda = (z, f^{D})$ in market i, we plot potential direct and indirect profits from transacting with downstream producers ζ in market j. Producers are indexed by their total input purchases $X_j(\zeta)$, so that $X_j(\underline{\zeta})$ and $X_j(\bar{\zeta})$ mark the location of the least and most productive potential customer.[10] We suppress origin and destination subscripts for legibility. Note that supplier productivity z affects the slope of both direct (2.9) and indirect (2.10) profits, but not their vertical intercept. By contrast, supplier matchability f^{D} determines the intercept for direct profits, but neither the

[10] Atomistic upstream suppliers take $X_j(\zeta)$ as given: The firm network determines downstream producers' input cost index, and thereby how much final demand they face and their total input purchases.

FIGURE 2.5. Direct and indirect supplier profits



intercept for indirect profits nor the slope of either profit line.

Upstream supplier λ faces a trade-off when choosing its optimal trade mode: Indirect transactions entail lower fixed costs $f^I < f^D(\lambda)$, but also lower variable profits as indirect prices are lower. At the same time, both direct and indirect profits increase linearly with the input purchases of downstream producers $X(\zeta)$, which below we establish increase with buyer productivity ζ. This implies that there are downstream productivity thresholds $\zeta^D(\lambda)$ and $\zeta^I(\lambda)$, above which direct and indirect sales are respectively profitable for upstream supplier λ. There is also a downstream productivity threshold $\zeta^{D=I}(\lambda)$, at which the supplier is indifferent between trade modes, and above which direct trade is strictly preferred. The following proposition formalizes these properties:

PROPOSITION 2. (PRODUCTIVITY THRESHOLDS) *For each upstream supplier* $\lambda = (z, f^D)$ *in market* i *selling to downstream producers in market* j*, there is a set of buyer productivity thresholds* $\zeta^D_{ij}(\lambda)$*,* $\zeta^I_{ij}(\lambda)$*, and* $\zeta^{D=I}_{ij}(\lambda)$ *such that:*

(a) $\pi^D_{ij}(\lambda, \zeta^D_{ij}(\lambda)) = 0$ *and* $\pi^D_{ij}(\lambda,\zeta) > 0$ *for* $\zeta > \zeta^D_{ij}(\lambda)$*;*
(b) $\pi^I_{ij}(\lambda, \zeta^I_{ij}(\lambda)) = 0$ *and* $\pi^I_{ij}(\lambda,\zeta) > 0$ *for* $\zeta > \zeta^I_{ij}(\lambda)$*;*
(c) $\pi^D_{ij}(\lambda, \zeta^{D=I}_{ij}(\lambda)) = \pi^I_{ij}(\lambda, \zeta^{D=I}_{ij}(\lambda))$ *and* $\pi^D_{ij}(\lambda,\zeta) > \pi^I_{ij}(\lambda,\zeta)$ *for* $\zeta > \zeta^{D=I}_{ij}(\lambda)$*.*

Proof. *See Appendix B.2.*

The optimal trade strategy for upstream suppliers can be fully characterized with these three buyer productivity cutoffs, which are implicit functions of supplier attributes and trade costs. Variation in the distribution of supplier and buyer attributes can thus rationalize heterogeneity in trade mode use across countries and sectors as observed in the data.

The model can accommodate four scenarios. First, the supplier will not trade with any customers when $\zeta^D(\lambda) > \overline{\zeta}$ and $\zeta^I(\lambda) > \overline{\zeta}$, since no buyer is productive enough to incentivize sales by λ. This would be the case if the supplier has both low productivity and low matchability. Second, seller λ will be a purely direct supplier, and transact directly with customers $\zeta \epsilon [max(\underline{\zeta}, \zeta^D(\lambda)), \overline{\zeta}]$ when $\zeta^D(\lambda) < \zeta^I(\lambda)$ and $\zeta^D(\lambda) < \overline{\zeta}$. This would be the case for suppliers with high productivity, high matchability, or both, such that profit curves intersect below the x-axis or not at all.[11] Third, seller λ will be a purely indirect supplier and serve all buyers $\zeta \epsilon [max(\underline{\zeta}, \zeta^I(\lambda)), \overline{\zeta}]$ through an intermediary when $\zeta^I(\lambda) < \overline{\zeta} \leq \zeta^{D=I}(\lambda)$. This might be the case for suppliers with either low productivity or low matchability in a market with few highly productive customers. Lastly, supplier λ will mix trade modes across buyers when $\zeta^I(\lambda) < \zeta^{D=I}(\lambda) < \overline{\zeta}$ and $\underline{\zeta} < \zeta^{D=I}(\lambda)$. Mixed sellers will directly supply sufficiently productive customers $\zeta \epsilon [\zeta^{D=I}(\lambda), \overline{\zeta}]$ that warrant the higher fixed costs, and serve a less productive segment of customers $\zeta \epsilon [max(\underline{\zeta}, \zeta^I(\lambda)), \zeta^{D=I}(\lambda))$ through a wholesaler. This is the case illustrated in Figure 2.5, and is likely to describe suppliers with intermediate levels of productivity and matchability.

The proposition below summarizes suppliers' optimal trade strategy:

Proposition 3. (Optimal trade strategy) *Consider the set of downstream buyers in market j with productivity support $[\underline{\zeta}_j, \overline{\zeta}_j]$. The optimal trade strategy for upstream supplier $\lambda = (z, f^D)$ from market i is:*

(a) No trade if $\zeta^D_{ij}(\lambda) > \overline{\zeta}_j$ and $\zeta^I_{ij}(\lambda) > \overline{\zeta}_j$;

(b) Direct trade with buyers $\zeta \in \left[\max(\underline{\zeta}_j, \zeta^D_{ij}(\lambda)), \overline{\zeta}_j\right]$ if $\zeta^D_{ij}(\lambda) < \zeta^I_{ij}(\lambda)$ and $\zeta^D_{ij}(\lambda) < \overline{\zeta}_j$;

(c) Indirect trade with buyers $\zeta \in \left[\max(\underline{\zeta}_j, \zeta^I_{ij}(\lambda)), \overline{\zeta}_j\right]$ if $\zeta^I_{ij}(\lambda) < \overline{\zeta}_j \leq \zeta^{D=I}_{ij}(\lambda)$;

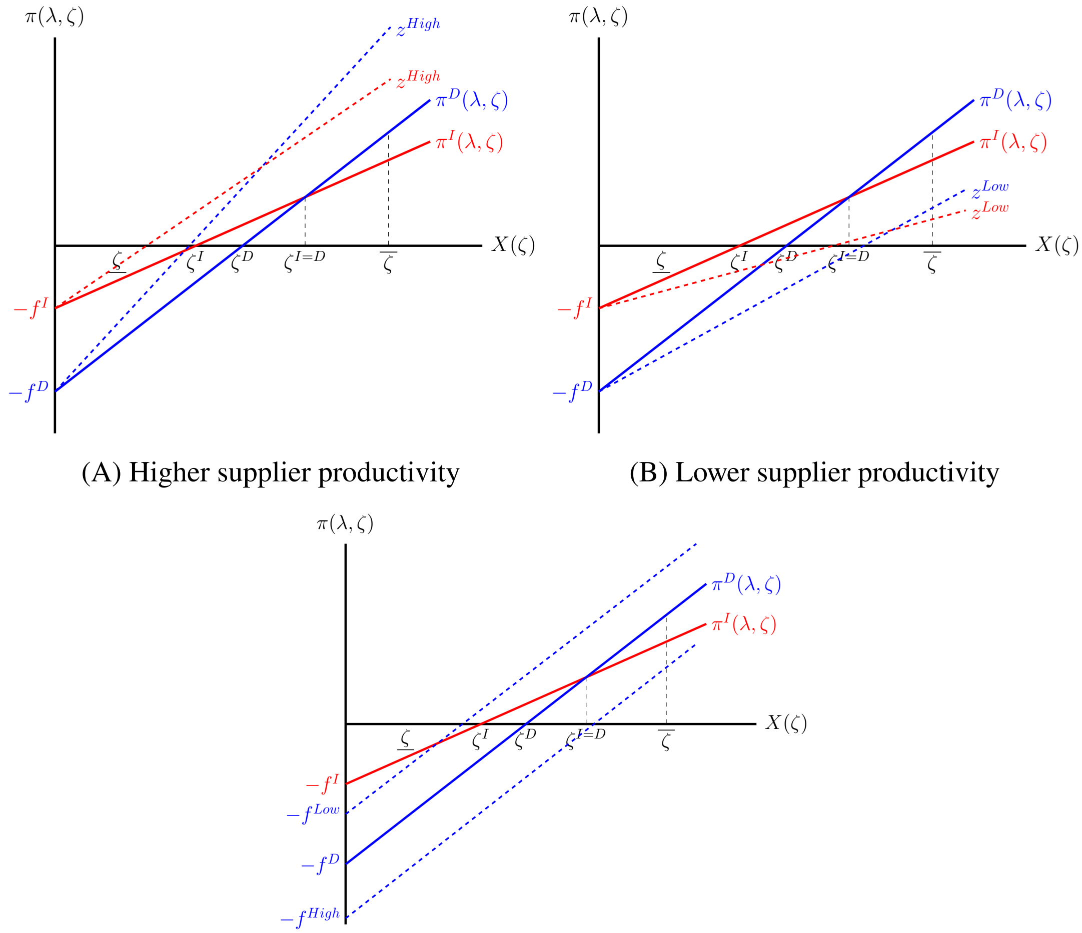
(d) Indirect trade with buyers $\zeta \in \left[\max(\underline{\zeta}_j, \zeta^I_{ij}(\lambda)), \zeta^{D=I}_{ij}(\lambda)\right)$ and direct trade with buyers $\zeta \in \left[\zeta^{D=I}_{ij}(\lambda), \overline{\zeta}_j\right]$ if $\zeta^I_{ij}(\lambda) < \zeta^{D=I}_{ij}(\lambda) < \overline{\zeta}_j$ and $\underline{\zeta}_j < \zeta^{D=I}_{ij}(\lambda)$.

Proof. *See Appendix B.2.*

To build intuition, we analyze the optimal trade mode of upstream suppliers when varying only one of their two dimensions of heterogeneity. Figures 2.6a and 2.6b compare suppliers of low, medium and high productivity levels, $z^{Low} < z < z^{High}$, but the same matchability. They all share the same intercepts for direct and indirect profits, but both profit lines are steeper for more productive suppliers. Holding matchability constant, more productive suppliers will thus serve more buyers and be more likely to transact directly. Suppliers with sufficiently high

[11] To be precise, there might be a fifth scenario where profit curves intersect above the x-axis, but the supplier still trades only directly (i.e., $\zeta^I(\lambda) < \zeta^D(\lambda)$ and $\zeta^{D=I} < \underline{\zeta}$). We assume that there is always a buyer with sufficiently low productivity to rule this out.

FIGURE 2.6. Supplier productivity and matchability



(A) Higher supplier productivity

(B) Lower supplier productivity

(C) Changes in supplier matchability

productivity will sell exclusively directly, suppliers with sufficiently low productivity will pursue only indirect trade, and suppliers with intermediate productivity levels will sell directly to their more productive customers and rely on intermediaries for an additional margin of less productive customers.

Figure 2.6c in turn compares two suppliers of the same production efficiency but different degrees of matchability, $f^{Low} < f^D < f^{High}$. While profits for indirect transactions are not affected by matchability, the profit lines for direct sales are parallel to each other at different intercepts, so that they cross the x-axis and π^I at different points. Suppliers with higher matchability will be more likely to have direct customer relationships. Suppliers with sufficiently low relationship costs will sell exclusively directly, and among purely direct sellers, those with higher matchability will have more customers. By contrast, suppliers with sufficiently high relationship costs will sell exclusively through intermediaries. Suppliers with moderate levels of matchability will target more productive buyers directly and reach additional customers through an intermediary. Conditional on productivity, all mixed suppliers will have the same number of ultimate buyers, but those with higher matchability will maintain a bigger share of direct links.

Proposition 4. (Extensive margin) *The set of direct and indirect buyers* $\zeta \in \{\mathcal{D}(\lambda) \cup \mathcal{I}(\lambda)\}$ *of upstream supplier* $\lambda = (z, f^D)$ *is non-contracting in supplier productivity* z *and matchability* f^D.

(i) Given matchability (or productivity), suppliers with higher productivity (or matchability) are more likely to sell exclusively directly and less likely to sell exclusively indirectly.

(ii) Suppliers with a mixed trade strategy serve buyers above (or below) a productivity threshold directly (or indirectly).

Proof. *See Appendix B.2.*

This endogenous network of direct and indirect buyer-supplier links implies negative degree assortativity along the extensive margin when supplier connectivity captures all ultimate customers. In particular, all upstream suppliers follow the same pecking order of downstream buyers based on buyer productivity, even if some of these transactions are performed indirectly through trade intermediaries. Holding matchability (productivity) constant, a more productive (matchable) supplier would thus serve the same customers as a less productive (matchable) supplier and further add an extra margin of less productive customers. Since buyer size and number of suppliers are monotonic in buyer productivity, the average ultimate customer of a more connected supplier will be smaller and less connected.

However, more connected suppliers need not be more connected in terms of direct links. This occurs because sellers' productivity and matchability jointly determine both the number of their total links and the number of their direct links, but these two numbers need not move proportionately or even in the same direction. This model can therefore rationalize deviations from strict negative degree assortativity in network data that ignores indirect linkages.

2.3.8. General Equilibrium

The general equilibrium of the model is a bipartite global network of upstream suppliers selling directly and indirectly to downstream producers, who in turn sell to final consumers. We first solve for the equilibrium conditional on a given network of matches, using firms' optimal sales prices and quantities for this network. We then use the formulation for suppliers' optimal direct and indirect matches to characterize the endogenous network as a fixed point that can be solved for numerically.

The network of firm-to-firm linkages can be summarized with two link functions: $l^D_{ij}(\lambda, \zeta)$ and $l^I_{ij}(\lambda, \zeta)$ for direct and indirect links, respectively. As described below, we follow Bernard et al. (2022a) and introduce an idiosyncratic match-specific component to a seller's matching cost in order to estimate the model in Section 2.5. Thus $l_{ij}^{D}(\lambda,\zeta)$ is the share of seller-buyer pairs (λ,ζ) between i and j that match directly, and $l_{ij}^{I}(\lambda,\zeta)$ is defined analogously for indirect connections. The total share of potential links that are activated is thus $l_{ij}(\lambda,\zeta)=l_{ij}^{D}(\lambda,\zeta)+l_{ij}^{I}(\lambda,\zeta)$. We will establish that the equilibrium is characterized by a single fixed point for $l_{ij}(\lambda,\zeta)$.

We first describe key outcomes for downstream producers. Taking the matching functions as given, and noting that producers perceive the same price under direct and indirect transactions, the input cost index (2.2) of final producer ζ is:

$$C_j^{1-\eta}(\zeta)=\sum_i \frac{N_i(\mathcal{U})}{(\mu w_i \tau_{ij})^{\eta-1}}\left(\int z(\lambda)^{\eta-1} l_{ij}^{D}(\lambda,\zeta)dG(\lambda)+\int z(\lambda)^{\eta-1} l_{ij}^{I}(\lambda,\zeta)dG(\lambda)\right) \tag{2.11}$$

where $N_i(\mathcal{U})$ is the mass of upstream suppliers in market i. The producer's input cost index depends on the productivity of all its direct and indirect suppliers. It is also implicitly affected by these suppliers' matchability, through the matching process that determines links $l_{ij}^{D}(\lambda,\zeta)$ and $l_{ij}^{I}(\lambda,\zeta)$. Producers' input costs $C_j^{1-\eta}(\zeta)$ in turn pin down their optimal output price $\tilde{p}_j(\zeta)$ and sales $\tilde{X}_j(\zeta)\equiv\tilde{p}_j(\zeta)\tilde{q}_j(\zeta)$.

We next relate the global sales of upstream suppliers to the equilibrium link functions. Suppliers' total sales are the sum of direct $S_i^{D}(\lambda)$ and indirect $S_i^{I}(\lambda)$ sales worldwide, which in turn summate sales $x_{ij}(\lambda,\zeta)$ to individual downstream producers. Aggregating direct (2.7) and indirect (2.8) bilateral sales across markets and customers, supplier λ's global sales are:[12]

$$S_i(\lambda)=\sum_j \frac{N_j(\mathcal{D})B_j z(\lambda)^{\eta-1}}{(\mu w_i \tau_{ij})^{\eta-1}}\left(\int \frac{\zeta^{\sigma-1}}{C_j(\zeta)^{\sigma-\eta}} l_{ij}^{D}(\lambda,\zeta)dG(\zeta)+\left(\frac{\eta-\phi}{\eta}\right)\int \frac{\zeta^{\sigma-1}}{C_j(\zeta)^{\sigma-\eta}} l_{ij}^{I}(\lambda,\zeta)dG(\zeta)\right) \tag{2.12}$$

where $N_j(\mathcal{D})$ is the mass of downstream producers in country j, and $B_j=\frac{\beta\tilde{E}_j\tilde{P}_j^{\sigma-1}}{\tilde{\mu}^{\sigma}}$ summarizes aggregate demand for final goods.

Suppliers' global sales depend on their own productivity $z(\lambda)$, as well as the productivity ζ and input costs $C_j(\zeta)$ of all their customers. Suppliers' relationship capability $f^{D}(\lambda)$ and the option of intermediation affect their sales through the matching functions $l_{ij}^{D}(\lambda,\zeta)$ and $l_{ij}^{I}(\lambda,\zeta)$, which reflect the extensive margins of direct and indirect customers. Access to wholesale services also affects the intensive margin of bilateral sales, since direct and indirect prices differ.

We can express the share of indirect trade for upstream supplier λ globally and within

[12] Producers' total input purchases scale up with their total sales, $X_j(\zeta)=\frac{\tilde{X}_j(\zeta)}{\tilde{\mu}}$, where $\tilde{\mu}$ is the markup for final goods. We use this relationship to express $X_j(\zeta)$ in equation (2.7) in terms of final demand for good ζ.

market j as:

$$\frac{S_i^I(\lambda)}{S_i(\lambda)} = \frac{\sum_j N_j(\mathcal{D}) B_j \tau_{ij}^{1-\eta} \left(\frac{\eta-\phi}{\eta}\right) \int \frac{\zeta^{\sigma-1}}{C_j^{\sigma-\eta}(\zeta)} l_{ij}^I(\lambda,\zeta) dG(\zeta)}{\sum_j N_j(\mathcal{D}) B_j \tau_{ij}^{1-\eta} \left(\int \frac{\zeta^{\sigma-1}}{C_j^{\sigma-\eta}(\zeta)} l_{ij}^D(\lambda,\zeta) dG(\zeta) + \left(\frac{\eta-\phi}{\eta}\right) \int \frac{\zeta^{\sigma-1}}{C_j^{\sigma-\eta}(\zeta)} l_{ij}^I(\lambda,\zeta) dG(\zeta)\right)}, \tag{2.13}$$

$$\frac{S_{ij}^I(\lambda)}{S_{ij}(\lambda)} = \frac{\left(\frac{\eta-\phi}{\eta}\right) \int \frac{\zeta^{\sigma-1}}{C_j^{\sigma-\eta}(\zeta)} l_{ij}^I(\lambda,\zeta) dG(\zeta)}{\int \frac{\zeta^{\sigma-1}}{C_j^{\sigma-\eta}(\zeta)} l_{ij}^D(\lambda,\zeta) dG(\zeta) + \left(\frac{\eta-\phi}{\eta}\right) \int \frac{\zeta^{\sigma-1}}{C_j^{\sigma-\eta}(\zeta)} l_{ij}^I(\lambda,\zeta) dG(\zeta)}. \tag{2.14}$$

Note that these indirect trade shares depend on the supplier's productivity and matchability both through their role in determining equilibrium linkages and through the value of direct vs. indirect bilateral sales conditional on a link. These shares also reflect the relative productivity and input costs of direct and indirect downstream customers, weighted by customers' market size and trade costs when aggregating across destinations.

Firm-to-firm matching in general equilibrium is determined in two steps. In the first step, suppliers determine whether direct or indirect sales dominate to a given seller, i.e. $k^* = \arg\max_{k\in\{D,I\}} \left[\tilde{\pi}_{ij}^k(\lambda,\zeta) - f^k(\lambda)\right]$, where $\tilde{\pi}_{ij}^k(\lambda,\zeta)$ is gross profits for a potential match using mode k. In the second step, we assume that suppliers observe an idiosyncratic multiplicative shock, ϵ, so that their total matching cost becomes $f^{k^*}(\lambda)\,\epsilon$. After observing ϵ, the supplier determines whether to match or not, i.e. whether $\tilde{\pi}_{ij}^{k^*}(\lambda,\zeta) - \epsilon f^{k^*}(\lambda) > 0$. Therefore, the share of seller-buyer pairs (λ,ζ) that trade with each other is:

$$l_{ij}(\lambda,\zeta) = \int I\left[\ln\epsilon < \ln\tilde{\pi}_{ij}^{k^*}(\lambda,\zeta) - \ln f^{k^*}(\lambda)\right] dH(\epsilon), \tag{2.15}$$

where $I[]$ is the indicator function and $dH(\epsilon)$ denotes the density of ϵ.

The link function is a fixed-point problem, as profits from a potential match determine the link probabilities according to equation (2.15), and the link probabilities in turn determine profits according to equations (2.11) and (2.12).[13] After solving for $l_{ij}(\lambda,\zeta)$, it is straightforward to back out direct $l_{ij}^D(\lambda,\zeta)$ and indirect $l_{ij}^I(\lambda,\zeta)$ links given the optimal trade strategies described above.

[13]While we do not provide a formal proof for the uniqueness and existence of the unconditional equilibrium, the fixed-point problem is numerically well-behaved and converges to the same solution under different starting values.

2.3.9. Role of Assumptions

We show numerically that a weakly negative correlation between seller productivity and matchability is necessary to account for the fact that exporters across the size distribution use trade intermediation, with larger suppliers being less likely to trade only directly, more likely to mix trade modes, and similarly likely to trade indirectly. By contrast, the share of purely direct (indirect) suppliers would counterfactually increase (decrease) with supplier size if supplier efficiency and relationship capability were uncorrelated or positively correlated. Reverting to one-dimensional seller heterogeneity in productivity alone would counterfactually imply that sellers sort monotonically into either purely indirect or mixed trade, and are never purely direct. Finally, suppressing productivity differences across buyers would remove suppliers' incentives to mix sales modes, and they would counterfactually sort monotonically into purely indirect or purely direct trade. These simulations are reported in Appendix B.2.

2.4. Reduced-Form Evidence

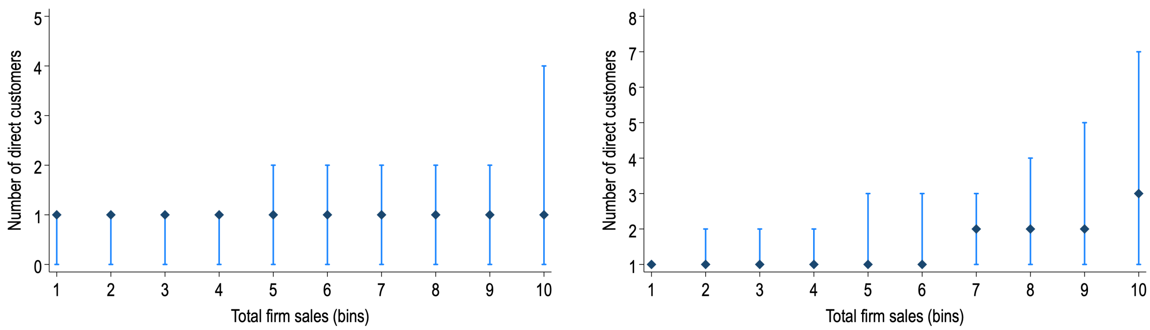
We next provide empirical evidence that corroborates the model and informs the nature of network transaction costs. We first validate theoretical predictions for the number of direct links across suppliers and the assortativity of buyers and suppliers in direct matches. We then show that the shares of intermediated trade and of indirect suppliers fall with origin-country GDP per capita, consistent with model implications for the seller productivity distribution. Lastly, we analyze how trade intermediation varies with different origin-country characteristics, to unpack the economic forces that drive firm-to-firm matching and transaction costs. This informs what barriers to buyer-supplier links are problematic but wholesalers can help overcome.

2.4.1. Network Connectivity

A key feature of the model is sellers' two-dimensional heterogeneity. Since we do not observe seller productivity and matchability in the data, we cannot directly assess their pattern across firms. However, we can evaluate the model's implication that the number of direct matches will generally not vary systematically with total sales across sellers, since neither is a sufficient statistic for sellers' vector of attributes. This contrasts with the prediction of strict monotonicity in standard models with unidimensional firm heterogeneity.

Figure 2.7 shows that the median number of direct buyer links indeed varies little across suppliers sorted into 10 bins by total sales. This holds not only when we pool all sellers in Panel A, but also when we focus on purely direct sellers in Panel B. Moreover, the distribution of direct connectivity across firms within a size bin overlaps greatly across bins, as illustrated by the 25th-75th interquartile ranges.

FIGURE 2.7. Number of direct customers by seller size



(A) All sellers (indirect, mixed, direct)

(B) Purely direct sellers

Since two-dimensional seller heterogeneity breaks the monotonicity of seller size and connectivity, the model implies negative degree assortativity in the production network in terms of firms' number of direct links and buyer size, but not necessarily in terms of seller size. Appendix Figure A1 reveals that, on average, suppliers with more direct connections in Chile on average sell to producers with fewer direct connections and lower imports. Analogously, more connected Chilean producers on average source directly from suppliers with fewer direct links and lower direct sales, but the latter relationship is significantly flatter as expected.

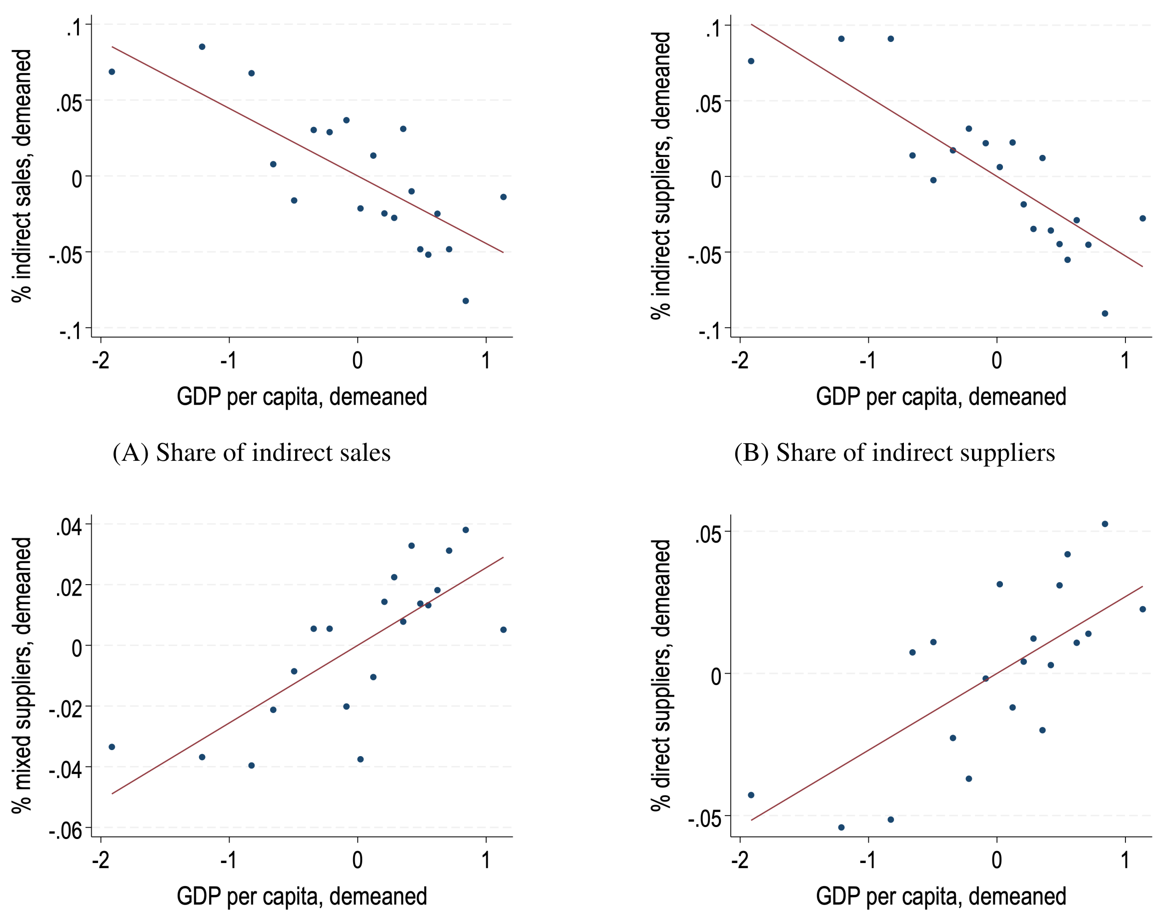
Note that while recent work has analyzed degree assortativity using the universe of transactions across or within countries (Bernard et al. (2018c), Bernard et al. (2019a), Bernard et al. (2022a)), we explicitly exclude intermediated transactions that may be aimed at multiple producers. We thus provide more accurate evidence for negative degree assortativity that in principle need not, but in practice does corroborate conclusions in the prior literature.

2.4.2. Average Productivity

We next exploit the variation in trade intermediation across origin countries exporting to Chile, in order to inform model predictions for the role of the seller productivity distribution. The model implies that conditional on matchability, more productive suppliers are more likely to sell directly and less likely to trade through intermediaries. We use origin GDP per capita as a proxy for average productivity across suppliers from that origin. Assuming that the shape of the matchability distribution is orthogonal to average productivity across countries (even if average matchability isn't), we can expect less use of intermediation services by exporters from richer origins.

Figure 2.8 confirms that intermediated exports are indeed more prevalent for origins with lower GDP per capita. We examine aggregate exports to Chile at the country-sector (HS 2-digit) level, demeaned by sector and sorted into 20 bins by origin income. Panel A shows that the share of intermediated sales to Chile systematically decreases with source-country GDP per capita. Panels B-D reveal that this pattern reflects the sorting of foreign suppliers into different trade modes. As origin income rises, there is a smaller share of purely indirect suppliers to Chilean buyers and bigger shares of purely direct and mixed suppliers.

FIGURE 2.8. GDP per capita and intermediation shares



(A) Share of indirect sales

(B) Share of indirect suppliers

(C) Share of mixed suppliers

(D) Share of direct suppliers

2.4.3. Matching Frictions

Finally, we analyze how intermediated trade varies with origin-country characteristics that may plausibly capture economic determinants of network matching and transaction costs. We consider country indicators for three types of potential costs: shipping and logistics, customs procedures, and contracting frictions. We view these country indicators as proxies for average matching costs across suppliers from that origin. Assuming that the shape of the productivity distribution is orthogonal to average matchability across countries (even if average productivity isn't), there is in principle more scope for trade intermediation for origins with higher matching costs. In practice, we can expect more use of intermediation for such origins only to the extent that intermediaries are able to offer specialized services targeted at these frictions.

We measure shipping and logistics costs with the distance between capital cities from CEPII and several indicators from the World Bank's *Logistics Performance Index,* such as the quality of logistic services, track and trace, the ease of arranging shipments, timely shipment arrival, and overall trade infrastructure. For customs procedures, we take the cost and time of border compliance, the cost and time of export documentation, and the number of trade procedures from the World Bank's *Doing Business Report*, as well as the overall customs efficiency component from the *Logistics Performance Index.* Lastly, we distinguish between formal and informal institutions that shape contracting costs. For formal contracting institutions, we study the control of corruption (World Bank's *Worldwide Governance Indicators*), the rule of law (World Bank's *World Development Indicators*), and an indicator for common legal origins with Chile (CEPII). For informal contracting institutions, we exploit measures of trust and cultural affinity. We consider the share of people who report complete trust in foreigners from the *World Values Survey*, and the share of people who share the same religion or language proximity with Chile based on ancestral roots (i.e., language trees) from CEPII.

Armed with these country indicators, we estimate variants of the following specification in the cross-section of origin countries c and sectors s:

$$Y_{cs} = \gamma_1\, Shipping_c + \gamma_2\, Customs_c + \gamma_3\, Formal_c + \gamma_4\, Informal_c + \gamma_5\, Productivity_c + \delta_s + \epsilon_{cs},$$

where the outcome variable is the share of intermediated trade by value or shares of exporters by sales mode. We condition on sector fixed effects δ_s and origin GDP per capita as a proxy for productivity in light of the analysis above. We first run separate horse-race regressions for each cost category that include all cost indicators from that category. Appendix Tables A1, A2 and A3 report these results. We then pool the leading, most significant cost measures across all categories into a holistic regression that we present in Table 2.4.

The results suggest that intermediaries primarily help producers in arranging shipping logistics and transacting with customers when informal contracting institutions are weak. In particular, intermediaries mediate a greater share of trade flows emanating from distant origins with unreliable shipping arrivals, low trust in foreigners, and limited religious affinity with Chile. A greater share of suppliers from such origin countries are either purely indirect or mixed exporters to Chile. On the other hand, we do not find that trade intermediation varies systematically with customs efficiency or the quality of formal contracting institutions at the source country.

Table 2.4. Matching frictions and intermediation shares

	(1) % Ind Trade	(2) % Ind Sellers	(3) % Mix Sellers	(4) % Dir Sellers
Shipping logistics (distance)	0.041***	0.051***	-0.045***	-0.005
	(0.013)	(0.014)	(0.013)	(0.017)
Customs efficiency (cost in border)	-0.024	-0.044	0.052	-0.008
	(0.088)	(0.092)	(0.073)	(0.109)
Formal contracting (control of corruption)	0.024	0.013	0.006	-0.018
	(0.017)	(0.019)	(0.013)	(0.020)
Informal contracting (trust in foreigners)	-0.432**	-0.420**	-0.014	0.435**
	(0.194)	(0.210)	(0.141)	(0.170)
Average productivity (GDP per capita)	-0.078**	-0.081**	0.034*	0.046
	(0.031)	(0.033)	(0.019)	(0.034)
HS2 sector FE	Yes	Yes	Yes	Yes
N	3,197	3,197	3,197	3,197

Note: All regressions are at the origin country - HS2 sector level for year 2019. The outcome variable is the share of imports intermediated by wholesalers in Column 1, and the shares of purely indirect sellers, mixed sellers, and purely direct sellers in Columns 2-4. Shipping logistics are proxied by the log-distance between the origin country and Chile (CEPII). Customs procedures are measured by the monetary cost at the border (World Bank's Doing Business). The ease of formal contracting is accounted for by the control of corruption (World Bank's Worldwide Governance Indicators). Informal contracting is measured by trust in foreigners (World Values Survey).

2.5. Quantitative Analysis

We estimate the model by simulated method of moments (SMM). This serves two purposes. First, the estimated parameters are of intrinsic interest, as they inform us about the nature of seller and buyer heterogeneity and about the economic costs and benefits of intermediation.

The results reveal that seller productivity and matchability are negatively correlated, which may suggest that there are frictions in the market for managers or span of control issues inside the firm.

Second, using the estimated model parameters, we can perform counterfactual analyses. In particular, we quantify the welfare gains from intermediation by shutting it down and the role of two-dimensional seller heterogeneity by imposing orthogonal productivity and matchability.

2.5.1. Simulated Method of Moments

Recall that the joint distribution of upstream suppliers' productivity z and matchability f^D is $G\left(z, f^D\right)$. We assume that this distribution is joint log-normal with expectations $\mu_{\ln z} = 0$ and $\mu_{\ln f^D}$, standard deviations $\sigma_{\ln z}$ and $\sigma_{\ln f^D}$, and correlation coefficient ρ. We also assume that the downstream producers' productivity distribution is log-normal with expectation $\mu_{\ln \zeta} = 0$ and standard deviation $\sigma_{\ln \zeta}$.[14] Together with the indirect cost f^I, this yields six unknown parameters to be estimated: $\Upsilon = \left\{\sigma_{\ln z}, \mu_{\ln f^D}, \sigma_{\ln f^D}, \rho, \sigma_{\ln \zeta}, f^I\right\}$.

In addition to these parameters, we need information about the elasticities of substitution σ and η and the bargaining weight ϕ. Since we have no direct evidence on the elasticities, we set $\sigma = \eta = 5$ in the baseline estimation to be consistent with prior estimates of trade elasticities (e.g., Broda and Weinstein (2006a)). Recall that ϕ is the share of variable profits generated from an intermediated transaction that accrues to the wholesaler. From the pricing rule in equation (2.6), the relative price of a direct to an indirect transaction is:

$$\frac{p^D}{p^I} = \frac{\eta}{\eta - \phi}.$$

Rearranging, the bargaining weight is $\phi = \eta\left(1 - p^I/p^D\right)$. From Table 2.3, the indirect to direct price ratio p^I/p^D is roughly 0.9 in the data, using our preferred estimate with supplier-product fixed effects in Column 3. Inserting $\eta = 5$, the bargaining weight is therefore $\phi = 0.5$.

The idiosyncratic matching cost ϵ is also assumed log-normal, with mean $\mu_{\ln \epsilon} = 0$ and standard deviation $\sigma_{\ln \epsilon}$. Following Bernard et al. (2022a), we set the standard deviation to $\sigma_{\ln \epsilon} = 4$.[15] Table 2.5 summarizes the external parameters of the model.

We choose in total 24 empirical moments to estimate Υ. The first two moments are the variance of log intermediate sales across sellers and the variance of log intermediate purchases across buyers. Intuitively, these moments map to the variance of suppliers' and downstream

[14]The normalizations $\mu_{\ln z} = 0$ and $\mu_{\ln \zeta} = 0$ are innocuous, as a shift in the productivity distribution would not affect firms' market shares or network connections.

[15]The role of ϵ is to make the objective function smooth in the parameters of the model. With a very low $\sigma_{\ln \epsilon}$, the SMM estimation procedure is not well-behaved using standard gradient-based methods.

Table 2.5. External model parameters

Parameter	Definition	Value	Source
ϕ	Intermediary bargaining weight	.5	$\phi = \eta\left(1 - \frac{p^I}{p^D}\right)$, p^I/p^D from Table 3 Column 3
σ	Elasticity of substitution across final goods	5	Broda and Weinstein (2006a)
η	Elasticity of substitution across intermediates	5	Assumption: $\eta = \sigma$
$\sigma_{\ln \epsilon}$	Pair matching cost dispersion	4	Bernard et al. (2022a)

producers' productivities z and ζ. The third moment is the average share of indirect to total sales across upstream suppliers, S^I/S. Intuitively, this moment relates to the indirect matching cost f^I. The fourth moment is the variance of S^I/S, calculated for each of the 20 sales bins (i.e., the bins from Figure 2.2), and then averaged across bins. This moment informs us about the variance of the direct matching cost f^D: If $\sigma_{\ln f^D} = 0$, then all firms in a bin would choose the same mode (direct, indirect or mixed), and as such $var\left(S^I/S\right) = 0$. Conversely, if $\sigma_{\ln f^D}$ is very high, we would expect high dispersion in S^I/S.

The last twenty moments are the shares of indirect and mixed firms for each sales decile (again, from Figure 2.2). These moments reflect $\mu_{\ln f^D}$ relative to indirect costs f^I, as well as the correlation coefficient ρ. With $\rho = 0$ or $\rho < 0$, we expect high-productivity suppliers to choose predominantly direct sales. With $\rho > 0$, however, we expect some high-productivity firms to choose indirect sales, as those firms face high direct matching costs f^D. This is consistent with the evidence in Figure 2.2: A high proportion of suppliers in the upper sales bins are either indirect or mixed suppliers.

Collecting the empirical moments in vector x and the simulated moments in vector $x^s(\Upsilon)$, the SMM estimates for Υ solve:

$$\arg\min_{\Upsilon} \left(x - x^s(\Upsilon)\right)' \left(x - x^s(\Upsilon)\right).$$

2.5.2. Estimation Results

The results from the SMM estimation procedure are reported in Column 2 of Table 2.6. Two take-aways stand out. First, there is a positive correlation between supplier productivity and direct matching costs ($\rho > 0$). In other words, on average highly productive suppliers have lower capabilities of matching with foreign buyers. This is consistent with the conclusion in Bernard et al. (2022a) for domestic production networks in Belgium. Interestingly, our identification of ρ is based on a completely different data context and set of moments, but we nevertheless arrive at the same qualitative result.

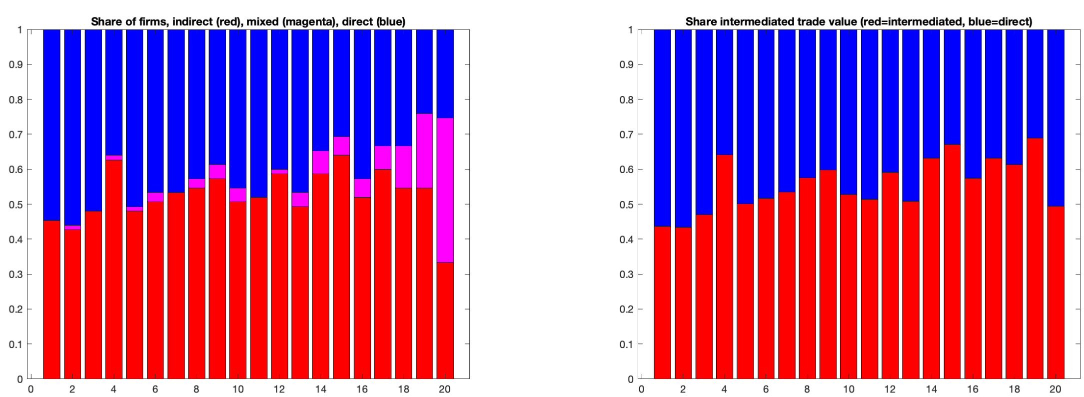
While we do not examine the origins of $\rho > 0$, we expect it arises from imperfect or incomplete labor markets, either inside the firm or external to the firm. One possibility is that firms need to hire production and sales managers, but either do not perfectly observe manager talent, or there are firm-manager match-specific shocks that are revealed only after hiring the manager. Another possibility is that firm CEOs have limited time resources, and face span of control issues when supervising both production and sales managers.

Our second take-away is that intermediation indeed lowers matching costs: $f^I = 0.74$, suggesting that using intermediation reduces matching costs by 26% relative to average direct matching costs. However, there is also large dispersion in direct matching costs, so that $f^I > f^D$ for some firms. According to our estimates, the fixed cost of indirect sales exceeds the fixed cost of direct sales for 39% of all firms.

Table 2.6 also reports targeted and untargeted moments. The SMM procedure is able to fit the first four moments quite well. The simulated share of indirect and mixed firms according to our estimates are shown in Figure 2.9a. Comparing these shares to the empirical counterpart in Figure 2.2, we observe that the fit is relatively good.

Turning to untargeted moments, Figure 2.9b reports the share of intermediated trade value to total trade for each sales bin according to the model. This is the model counterpart to the empirical patterns in Figure 2.2b. The model matches the data relatively well. Table 2.6 also reports three additional untargeted moments. On average, the share of intermediated trade value is slightly over-predicted. Dispersion in suppliers' sales, as indicated by the share of intermediate trade by the top 5% suppliers is also somewhat under-predicted. While not observed in the data, the simulated distribution of final good sales by downstream buyers seems comparable to that of intermediate sales by upstream suppliers, as reflected in the market share of the top 5% of final producers.

FIGURE 2.9. Estimated model: Trade strategy across the supplier size distribution



(A) Share of suppliers by trade mode

(B) Share intermediate/direct trade value

Table 2.6. SMM model fit

	Data (1)	Estimated model (2) Baseline
Estimated parameters:		
$\mu_{\ln F^D}$		1.48
$\sigma_{\ln z}$		0.44
$\sigma_{\ln F^D}$		1.49
ρ		0.32
$\sigma_{\ln \zeta}$		0.48
f^I		0.74
Targeted moments:		
$var\,(\ln Sales)$	4.86	4.86
$var\,(\ln Purchases)$	6.01	6.01
mean (indirect sales / total sales)	0.48	0.56
$var\left(S^I/S\right)$, average across bins	.24	.23
Share indirect firms, by sales decile (10 moments)	Figure 2a	Figure 2.9
Share mixed firms, by sales decile (10 moments)	Figure 2a	Figure 2.9
Non-targeted moments:		
Share intermediated trade value	.48	.54
Share intermediated trade value, by sales decile	Figure 2b	Figure 2.9b
Share sellers using intermediation	.52	.59
Share of intermediate trade, top 5% sellers	.82	.65
Share of final goods trade, top 5% buyers		.67

2.5.3. Counterfactuals

We end this section by performing two informative counterfactuals. The first counterfactual is to shut down intermediation completely, by setting $f^I = \infty$. Table 2.7 summarizes the results. With no access to wholesale services, the final goods price index increases by 3.3%, implying that the welfare gains from intermediation are around 3%. This occurs because many connections are broken in the absence of intermediation: The total number of buyer-seller links declines by more than 15%.

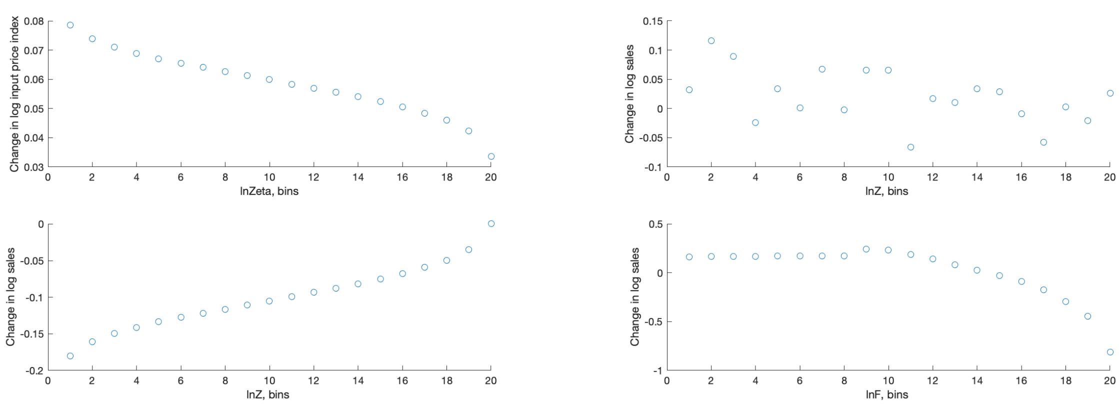
Figure 2.10a reports the change in the input price index $C(\zeta)$ and final-goods sales across 20 bins of the final-goods seller productivity distribution ζ. Small, low-productivity final-goods firms are most affected, with their input prices increasing by as much as 8% and sales declining by almost 20%. Intuitively, these producers rely heavily on intermediated trade, which is

Table 2.7. Counterfactual I: No intermediation

	Baseline (1)	Counterfactual (2)
Change in consumer price index		3.3%
Change in number of firm links		-15.3%
Share intermediated trade value	.54	0
Share sellers using intermediation	.59	0
Share of intermediate trade, top 5% sellers	.65	.66
Share of final goods trade, top 5% buyers	.67	.69

no longer available. Figure 2.10b reports changes in suppliers' sales across 20 bins of the productivity, z, and direct matching cost, f^D, distributions. Our results indicate that both low- and high-productivity suppliers are affected by intermediation, possibly because of the positive estimate for ρ. In addition, low-matchability sellers see the largest reduction in sales, as these use intermediation intensively in the baseline scenario.

Figure 2.10. Counterfactual I (no intermediation): Seller and buyer outcomes



(A) Buyer outcomes

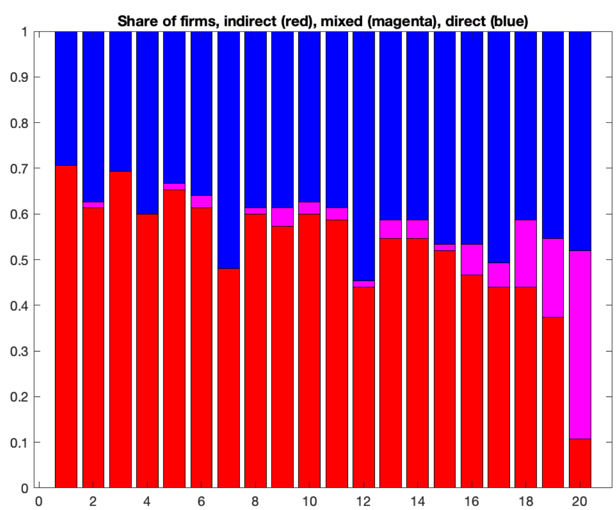
(B) Seller outcomes

In our final counterfactual, we explore the role of the correlation between productivity and matchability, by setting $\rho = 0$. Table 2.8 summarizes our findings. In this case, the consumer price index decreases by 3.4%, as highly productive suppliers are no longer penalized by having high direct matching costs on average. Interestingly, the total number of buyer-seller connections declines by 1.3%. Figure 2.11 reports the shares of direct, indirect and mixed suppliers in the counterfactual scenario. The largest suppliers are now almost completely absent among indirect firms. The reason is straightforward: Highly productive firms are now no longer burdened by low matchability, and therefore almost always sell directly to at least one customer. Nevertheless, we still observe many large mixed suppliers, as intermediation may still be the most profitable option when selling to small customers.

TABLE 2.8. Counterfactual II: Orthogonal seller attributes

	Baseline (1)	Counterfactual (2)
Change in consumer price index		-3.4%
Change in number of firm links		-1.3%
Share intermediated trade value	.54	.34
Share sellers using intermediation	.59	.59
Share of intermediate trade, top 5% sellers	.65	.69
Share of final goods trade, top 5% buyers	.67	.66

FIGURE 2.11. Counterfactual II (orthogonal seller attributes): Share of suppliers by trade mode



2.6. Conclusion

This paper examines the role of trade intermediaries in buyer-supplier networks and the implications for international trade and aggregate welfare. Using uniquely rich data for Chile, we establish novel stylized facts about seller-buyer interactions when suppliers can access wholesale services. We develop a general-equilibrium model of production networks with suppliers of heterogeneous productivity and relationship capability, buyers of heterogeneous productivity, and intermediaries that reduce relationship-specific costs in exchange for an implicit brokerage fee related to their bargaining power. This model with two-sided heterogeneity and two sources of supplier heterogeneity can rationalize how exporters optimally sort into different sales strategies. Intermediaries widen production networks by enabling more firm-to-firm links, especially for smaller buyers and for productive suppliers with low matchability. Intermediaries also deepen production networks, as higher buyer connectivity endogenously increases their input purchases through lower input costs and higher final demand. The presence of specialized intermediaries thus induces welfare gains and heterogeneous effects across firms.

Our work begins to unpack the nature of search, match and transaction costs that shape global value chains. This opens promising avenues for future research at the intersection of production networks and trade intermediation. Micro-foundations for the market power of wholesalers can provide additional insights on rent sharing, and inform policies aiming at a more competitive intermediation sector or denser production networks. The role of intermediaries in buyer-supplier links may also have important implications for shock transmission and the adjustment of firms' sourcing and sales decisions in response to trade reforms or macroeconomic movements. Further analysis can illuminate to what extent the market for intermediation services has responded to meet the needs of manufacturing firms, whether its market structure warrants policy intervention, and how trade promotion and facilitation policies implemented in developing countries can be most effective.

Chapter 3

Global Production Networks and Policy Reforms with Imperfect Competition

3.1. Introduction

Global value chains (GVCs) have transformed economic activity as firms today transact with upstream suppliers, downstream producers, and final consumers worldwide (e.g., Antràs et al. 2017; Bernard and Moxnes 2018b). These network linkages challenge policy making with their potential to alter the domestic and international effects of both trade agreements and behind-the-border reforms (e.g., Antràs and Staiger 2012; Grossman et al. 2021, 2023b; Antràs et al. 2024). In practice, the growth of GVCs has been accompanied by policy polarization: On the one hand, trade disintegration (e.g., Brexit, China-US trade war) and industrial policy acting as protectionism (Juhász et al. 2024). On the other hand, deeper integration with modern trade agreements that combine tariff cuts with regulatory harmonization, trade promotion, and competition or industrial policy, to facilitate firm entry and buyer-supplier transactions (Maggi and Ossa 2021).[1] While both market structure and network formation costs have been independently shown to affect firm performance and the gains from trade, understanding their interaction is essential for current policy design and impact evaluation.

This chapter studies the welfare effects of trade and competition reforms with global

[1] Competition policy is the most frequent provision in modern Preferential Trade Agreements (PTAs) according to the World Bank Deep Trade Agreements database (Hofmann et al. 2017). It is closely followed by policy coordination that lowers firm matching and transaction costs, such as policies on investment, capital and labor mobility, and intellectual property and environmental standards.

production networks and imperfect competition. Using French, Chilean and Chinese customs data, we show that import prices are lower with more Chinese suppliers; suppliers price discriminate across buyers; and diversified buyers pay lower prices. These facts motivate a model of network formation with two-sided firm heterogeneity, matching frictions, and oligopolistic competition upstream. More productive buyers match with more suppliers, spurring tougher supplier competition, lower input costs, and higher profits. Causal evidence confirms that French and Chilean firms (especially large ones) import higher quantities at lower prices as more Chinese suppliers enter, and suppliers charge diversified buyers lower markups. Finally, model quantification and counterfactual analysis reveal that entry upstream benefits high-productivity buyers, while lower trade or matching costs favor mid-productivity buyers. Package reforms that reduce matching costs or promote competition amplify the welfare gains from shallow trade agreements. Moreover, fixing trade networks or input markups dampen or nullify policy gains.

First, we establish three facts about production networks in customs data for China, Chile and France over 2000-2006. The network of upstream Chinese suppliers and downstream Chilean and French producers exhibits familiar sparsity, with skewed connectivity and pervasive concentration in input markets despite significant entry over time. Fact 1 documents that inputs sold by more suppliers trade at lower average prices. Fact 2 reveals that suppliers with more buyers vary prices significantly more across buyers within products. Lastly, Fact 3 uncovers that firms with more suppliers pay systematically lower input prices within products.

Second, we develop a new general-equilibrium model of global production networks with three key ingredients motivated by the facts above: (i) two-sided firm heterogeneity, (ii) matching frictions, and (iii) imperfect competition. In the model, heterogeneous buyers transact with heterogeneous suppliers in the presence of trade costs, match-specific cost shocks, oligopolistic competition upstream, and monopolistic competition downstream. At a higher fixed cost, a firm can meet more suppliers, which enables a better match for each input and lowers input markups due to tougher competition among suppliers.

The combination of endogenous network formation and imperfect competition upstream generates two-sided market power and a new channel through which production networks amplify firm heterogeneity. More productive firms optimally source from more suppliers, and therefore enjoy lower input costs and markups and higher sales, even though their marginal supplier is less productive. Respectively, more productive suppliers sell more to more buyers and earn higher revenues, with each supplier charging its less productive, less diversified marginal buyers higher markups. Thus buyers' and suppliers' market power varies across matches.

The model highlights novel distributional effects of local industrial policies and multilateral trade reforms. Industrial policy that triggers entry upstream in one country benefits sufficiently productive final manufacturers worldwide: Above a threshold, more productive firms expand their supplier set more aggressively and lower their input costs and markups by more. By contrast, tariff liberalization and trade promotion that reduce iceberg and matching costs, respectively, enable mid-productivity buyers that do not yet source from all suppliers to tap more suppliers. While lower trade costs raise profits for all buyers, those that add suppliers gain more.

The interaction of (i) two-sided firm heterogeneity, (ii) endogenous network formation, and (iii) imperfect competition is also necessary and sufficient to rationalize key data patterns that other frameworks cannot.[2] On necessity, models without (i) or (ii) cannot account for the variation in network activity across firms, across suppliers within buyers, and across buyers within suppliers. Models that feature (i) and (ii) but omit (iii) rule out price discrimination across buyers within suppliers, as well as differential effects of entry upstream across downstream firms. While models that combine (i) and (iii) without (ii) permit match-specific markups, fixing network links implies no cross-border spillovers of industrial policy or augmented effects of deep integration with trade facilitation relative to shallow integration without. On sufficiency, ours is the first within a potential class of data-consistent models that can accommodate the complexity of (i), (ii) and (iii), yet remain parsimonious and tractable.

As a third step, we provide causal evidence for the model in comprehensive production and customs data for France, Chile, and China in 2000-2006. We assess how the dramatic, exogenous expansion in firm entry and trade activity in China affected downstream producers in Chile and France, two economies of different size, development, and GVC position. For Chile, we exploit rich data on firm import transactions that identify the supplier, HS 6-digit product, value, price and quantity, matched to indicators for firm size bins. For France, we access analogous data without supplier identities, matched to detailed firm balance sheets. Finally, for China, we use matched data on firms' export transactions and balance sheets to characterize the set of Chinese suppliers to France, Chile, and the rest of the world (ROW) by HS-6 product.

Guided by the model, we proxy the set of potential Chinese suppliers by product and year with the number of Chinese exporters to ROW. We provide robust evidence using instead the actual number of Chinese exporters to Chile or France, which is arguably exogenous to atomistic buyers. We also instrument the latter with the number of Chinese exporters to ROW or to a comparable market (Pacific Alliance countries for Chile, USA for France). Given the importance of Chinese inputs to Chilean and French firms and the insignificance of the Chilean and French markets to China, our identification strategies permit causal interpretation.

We empirically establish that market structure upstream and buyer heterogeneity downstream shape global production networks in line with the model's predictions. On the buyer side, French

[2] We discuss the growing literature on production networks below.

and Chilean firms import greater values and quantities of Chinese inputs at lower unit prices as more Chinese suppliers enter over time. Moreover, bigger buyers adjust their sourcing strategy to a greater extent. These results condition on firm, product, and year fixed effects, as well as product-specific time trends. They are not driven by other supply conditions upstream, such as the distribution of supplier productivity and quality, the use of intermediated or processing trade, and the presence of multi-product and multinational suppliers. The patterns hold controlling for import tariffs and various aspects of the market structure downstream.

On the seller side, Chinese suppliers systematically vary prices across Chilean buyers in a way consistent with oligopolistic competition. Suppliers offer lower prices for the same product to producers that source that product from more Chinese providers. This result obtains in stringent specifications that account for suppliers' marginal cost and quality with supplier-product fixed effects and for downstream demand with buyer-product fixed effects.

Finally, we estimate the model to perform policy counterfactuals and assess the role of key model ingredients. We develop a novel estimation method for computationally demanding, high-dimensional models as ours, which tackles both the combinatorial multinomial discrete-choice problem of buyers' sourcing strategy and suppliers' buyer-specific pricing game. In particular, we build on techniques from the prior literature (Jia 2008; Antràs et al. 2017; Arkolakis et al. 2023b) to accommodate endogenous network formation and imperfect competition. We first directly estimate elasticity parameters and firm cost distributions, and then estimate aggregate demand and matching costs by simulated method of moments.

We consider (a) behind-the-border industrial or competition policy that supports firm entry upstream; (b) tariff liberalization that lowers iceberg trade costs; and (c) trade promotion and facilitation (or, equivalently, relaxation of non-tariff measures (NTMs)) that reduces fixed matching costs. We conduct the analysis for Chile and 5 regions that capture the geo-economic mix of its main trade partners: Latin America, USA, Europe, China, and ROW. We benchmark shock magnitudes to the actual expansion in Chinese suppliers to Chile over the 2000-2006 sample period and the Chile-China Preferential Trade Agreement (PTA) signed in 2006. We simulate policy packages motivated by the objectives of enhanced competition and lower firm networking costs in both the Chile-China PTA and the CPTPP that includes Chile.[3]

We show that (a) unilateral entry upstream, (b) lower bilateral trade costs, and (c) lower bilateral matching costs can each reduce buyers' input costs and either raise or lower total matching costs, with nuanced effects on sales and profits. This reflects how firms adjust their global sourcing due to input complementarities across regions. On net, (a) benefits only highly

[3]The Chile-China PTA includes a declaration of interest in the harmonization of SPS measures, firm dispute resolution, and trade promotion and facilitation for SMEs. Viewed as an archetype of modern trade agreements and deep integration (Maggi and Ossa 2021), the Comprehensive and Progressive Agreement for Trans-Pacific Partnership (CPTPP explicitly includes chapters on competition policy and state-owned enterprises.

productive buyers that expand their supplier portfolio, while (b) and (c) favor mid-productivity buyers that do so. Welfare gains are sizable with (a) and (b), but minimal with (c).

We also compare shallow integration (b) to deep integration (b+c) and package trade and industrial reforms (b+a). Both relaxing matching costs and facilitating entry upstream amplify the welfare gains from tariff liberalization in the baseline with endogenous markups and networks.

To illustrate how endogenous networks and imperfect competition interact, we finally contrast the baseline to scenarios with fixed production linkages or constant markups. Fixing the production network implies no effects of (a) or (c) on downstream firm sales and consumer prices and lower welfare gains from all other policy scenarios, as buyers can no longer re-optimize their suppliers. Similarly, fixing input markups significantly dampens gains from all interventions except (b) on its own, since firms reap no pro-competitive cost savings from adding suppliers, and all reforms except (b) feature important supplier-margin responses.

Related Literature. We advance several strands of literature. Most directly, we contribute to research on the determinants of global production networks and their implications for firm performance and aggregate welfare. Early studies showed that access to foreign inputs increases welfare and firm productivity, product quality, innovation, and profitability (Amiti and Konings 2007b; Goldberg et al. 2010b; Halpern et al. 2015b; Yu 2015; Bøler et al. 2015b; Manova et al. 2015; Blaum et al. 2018b). Recent advances emphasize how firm productivity and trade costs shape these outcomes (Antràs et al. 2017; Furasawa et al. 2018; Bernard et al. 2022b)

A growing research stream examines the role of firm heterogeneity in buyer-supplier production networks (Bernard and Moxnes 2018b). Bernard et al. (2019b) study the role of domestic supply links for firms' marginal cost and performance in Japan, whereas Bernard et al. (2018d), Eaton et al. (2022b), and Kramarz et al. (2022) explore the matching of exporters and importers in customs records for Norway, US-Colombia, and France, respectively. Bernard et al. (2022b) find that two-sided firm heterogeneity and match-specific shifters are key to firm-to-firm sales in the domestic production network in Belgium. Models of buyer-supplier networks generally feature constant markups in monopolistically competitive markets, often with one-sided firm heterogeneity (Chaney 2014b; Bernard et al. 2018d; Lim 2018; Oberfield 2018).

More broadly, we add to work on imperfect competition in trade. Classic paradigms with monopolistic competition typically require CES demand and Pareto-distributed productivity to generate gravity expressions for aggregate trade that permit welfare evaluation (Melitz 2003; Arkolakis et al. 2012; Head and Mayer 2014). Recent advances consider strategic interactions among firms in tractable oligopolistic environments (Bernard et al. 2003; Atkeson and Burstein 2008b; Edmond et al. 2015b; Neary 2016; Amiti et al. 2019). Concurrent work examines imperfect competition upstream, downstream or both in *fixed* production networks, and quantifies the welfare effect of markup dispersion across buyers (Morlacco 2020; Dhyne et al. 2022; Alviarez et al. 2023; Burstein et al. 2024). We contribute a tractable model of imperfect competition in which *endogenous* firm network formation under matching frictions can give rise to *endogenous* two-sided market power.

Our analysis has important policy implications for the gains from trade. First, existing studies evaluate trade policies in computable general equilibrium or quantitative trade models, which typically ignore production networks, firm granularity, and/or market power (Costinot and Rodríguez-Clare 2014; Ottaviano 2015). We evidence that taking these forces into account matters. Second, we illustrate the distinct benefits from lower trade costs and matching costs, as well as package reforms. This informs policies that target matching and transacting costs such as deep integration, trade promotion and facilitation, information technology, or international contract enforcement. Finally, we show that imperfect competition in global value chains gives rise to cross-border network spillovers from local industrial and trade policies.

Finally, we also shed light on how production networks shape the firm size distribution and shock propagation. Prior work indicates that the characteristics of firms' input suppliers contribute to the large and growing firm size dispersion (Melitz 2003; Sutton 2007; Bernard et al. 2022b). We show that endogenous match formation with imperfect competition is an additional channel through which buyer-supplier networks favor more productive firms and thereby amplify firm heterogeneity. Separately, input-output linkages in asymmetric networks have been found to enhance long-run growth and generate aggregate movements from firm-specific shocks (Acemoglu et al. 2012; Magerman et al. 2016; Baqaee 2018; Baqaee and Farhi 2019; Acemoglu and Azar 2020; Taschereau-Dumouchel 2020), while global production networks can transmit shocks across countries (Lim 2018; Boehm et al. 2019; Carvalho et al. 2021b; Dhyne et al. 2021). Our analysis suggests that the combination of imperfect competition and two-sided heterogeneity in global sourcing can strengthen these transmission mechanisms.

The chapter is organized as follows. Section 2 establishes stylized facts about pricing in buyer-supplier production networks. Section 3 presents the model of global sourcing with two-sided firm heterogeneity, endogenous network formation, and oligopolistic competition upstream. Section 4 introduces the data for France, Chile, and China, and provides causal empirical evidence for the model's predictions. Section 5 develops and implements the model estimation strategy, and performs counterfactual analyses. The last section concludes.

3.2. Stylized Facts

We establish three stylized facts about price dispersion in buyer-supplier networks, using rich transaction-level customs data for China, Chile, and France. We first briefly introduce the data and key features of the production networks between upstream Chinese suppliers and downstream Chilean and French buyers.

The raw data contains information about the universe of Chinese exports by firm, HS 6-digit product and destination; the universe of French imports by firm, HS-6 product and origin; and the universe of Chilean imports by firm, HS-6 product, origin, and supplier. Since the main empirical analysis in Section 3.4 identifies the impact of upstream entry in China on downstream sourcing activity in Chile and France, here we present systematic cross-sectional patterns in China-France and China-Chile trade relations for the year 2000, the first year in our panel.[4]

The network of upstream Chinese suppliers and downstream Chilean and French producers is sparse with a minority of highly connected firms, consistent with prior evidence for other countries (see Bernard and Zi 2022). Appendix Figure A1 illustrates the skewed distribution of buyer-supplier matches across firms. The median and modal Chilean importer use a single Chinese supplier per HS 6-digit input, with a long thin tail of wider sourcing. The median and modal Chinese supplier likewise serves a single Chilean buyer within a product. Similar patterns hold for the distribution of trade transactions between China and France.

This sparse production network is accompanied by pervasive concentration in input markets. Figure 3.1 displays the distribution of the number of Chinese exporters of a given HS-6 product to Chile and France. Approximately 80% of all inputs Chile imports from China are provided by fewer than 5 Chinese suppliers. This number stands at roughly 65% in the case of France.[5]

We now present three stylized facts about price dispersion in buyer-supplier networks, exploiting the Chilean customs data with trade partner identities. These facts point to a role for imperfect competition under two-sided firm heterogeneity and matching frictions, and motivate a novel model of global production networks with these three key ingredients.

Fact 1 (Average Input Prices and Competition): *Inputs sold by more suppliers trade at lower average prices.*

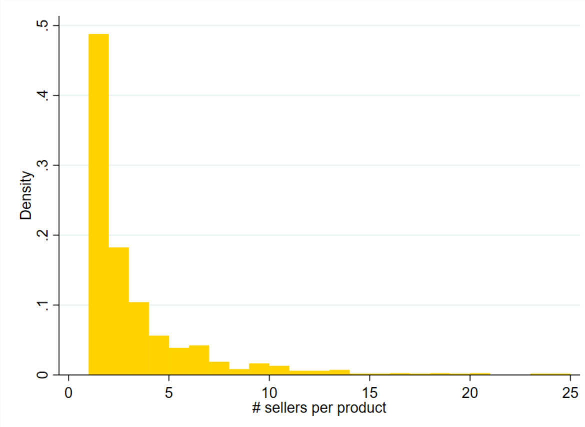
We present Fact 1 with a bin-scatter plot of the mean import price of an HS-6 product exported by Chinese firms to Chile in Figure 3.2. We group products into 20 bins by number of suppliers, and compute the simple average unit value across all import transactions. There is a

[4] Note China joined the World Trade Organization (WTO) in 2001. All facts hold for other years in our 2000-2006 panel.

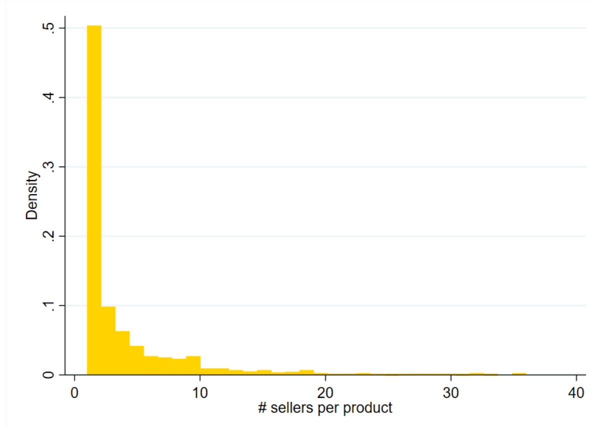
[5] These patterns mirror similar findings for the US and several European countries (Mayer and Ottaviano 2008; Bernard et al. 2018b).

FIGURE 3.1. Concentration Upstream

(A) Chinese suppliers to Chile per product



(B) Chinese suppliers to France per product

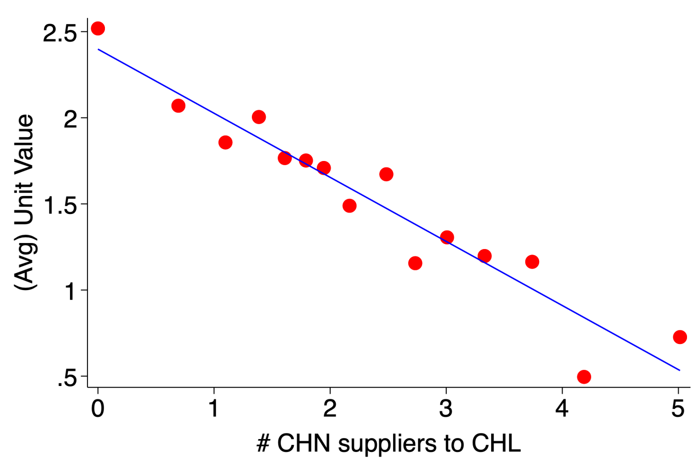


Note: Histograms of the number of Chinese suppliers (a) to Chile and (b) to France per HS6 product.

tight negative relationship, with slope coefficient of -0.39 for the fitted line.

Thus the first empirical pattern we highlight is that inputs sold by more suppliers generally trade at lower average prices. This pattern is consistent with more concentrated upstream markets featuring higher input prices for downstream manufacturers. It also aligns with prior research that documents how market structure shapes international trade prices (e.g., Atkeson and Burstein 2008b; Mayer et al. 2014; Edmond et al. 2015b).

FIGURE 3.2. Average Input Price



Note: Binscatter of the average log unit value for Chinese products exported to Chile (HS 6-digit), grouped into 20 bins sorted by the log number of Chinese exporters selling each product to Chile.

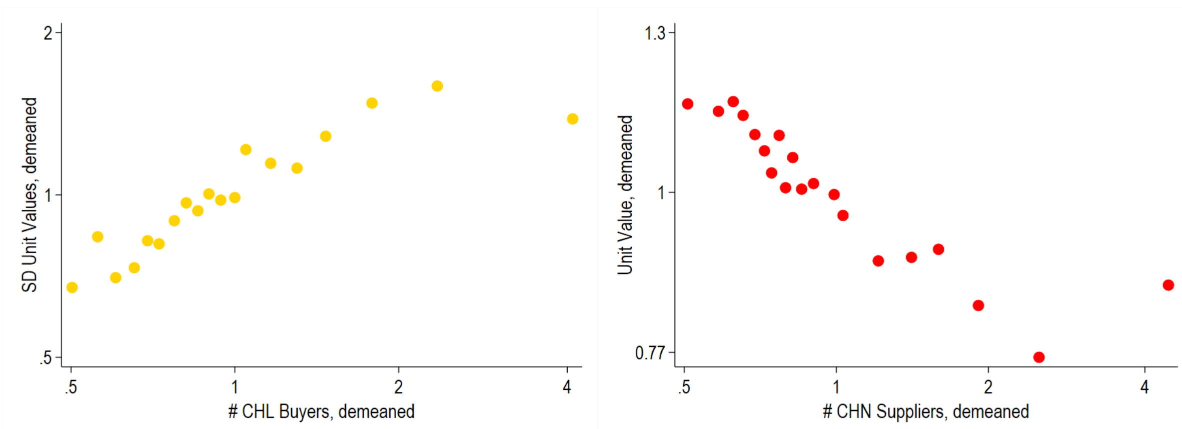
Fact 2 (Supplier Price Dispersion): *Suppliers with more buyers vary prices more across buyers within products.*

We demonstrate Fact 2 with the bin-scatter plot in Figure 3.3A, where each dot corresponds to a representative supplier in one of 20 bins. We first measure price dispersion within a Chinese exporter and HS-6 product pair across Chilean buyers with the standard deviation of transaction unit values, and demean by product. We then group exporter-product pairs into 20 bins based on their product-demeaned number of Chilean partners. For each bin, we finally construct a representative Chinese exporter with the bin-specific average price dispersion and number of Chilean buyers.

The second empirical fact we document is that Chinese suppliers with more Chilean buyers vary prices significantly more across their buyers. This variation suggests that suppliers may be able to price discriminate across their customers, consistent with evidence for French exporters in Fontaine et al. (2020). In particular, it is neither mechanical, nor consistent with models of constant markups across buyers within suppliers, which would imply a flat, rather than an upward-sloping relationship.[6]

Figure 3.3. Network Price Dispersion

(A) Price dispersion across buyers within suppliers (B) Average input price across buyers



Note: (a) Binscatter of the standard deviation of log unit values within Chinese suppliers across Chilean buyers, for 20 bins of Chinese exporters by number of Chilean buyers. (b) Binscatter of average log unit value of Chinese imports, for 20 bins of Chilean importers by number of Chinese suppliers. All values demeaned by HS-6 product.

Fact 3 (Buyer Pro-competitive Diversification): *Buyers with more suppliers enjoy lower average input prices within products.*

We illustrate Fact 3 with the bin-scatter plot in Figure 3.3B, where each dot represents a typical buyer in one of 20 bins. We first calculate the average unit value each Chilean importer pays for a given HS-6 product across its Chinese suppliers, and demean by product. We then

[6]Since the HS 6-digit product classification is somewhat coarse, the price dispersion we measure may under- or overstate the true variation (e.g., Fontaine et al. 2020; Burstein et al. 2024). This is irrelevant for Facts 2 and 3 to the extent that such measurement error is orthogonal to the number of buyers.

group importer-product pairs into 20 bins based on their product-demeaned number of Chinese partners. For each bin, we construct a representative Chilean importer with the bin-specific average demeaned unit value and number of Chinese suppliers.

The third empirical regularity we establish is that Chilean buyers with more Chinese suppliers pay systematically lower average input prices.[7] This indicates that buyers may enjoy pro-competitive gains from diversifying their supplier portfolio.[8] Once again, this pattern is not mechanical, and is inconsistent with models with no supplier heterogeneity that imply a flat relationship. It is also inconsistent with models of endogenous networks with two-sided heterogeneity and constant markups, which predict the opposite relationship: In these models, negative degree assortativity implies that more diversified buyers source from increasingly less productive, higher-cost suppliers, and pay higher average input prices.[9]

3.3. Theoretical Framework

We develop a quantifiable general equilibrium model of global sourcing in which heterogeneous buyers match with heterogeneous suppliers in the presence of trade and matching costs. We examine the impact of matching frictions and oligopolistic competition upstream on the sourcing behavior of monopolistically competitive firms downstream. We characterize the endogenous formation of the global production network and key outcomes at the firm- and firm-to-firm transaction levels. Detailed proofs are relegated to Appendix C.1.

3.3.1. Final Demand

Consumers in J countries have Cobb-Douglas preferences over homogeneous and differentiated goods. In each country i, wages w_i are pinned down by a sector that produces a freely tradable and homogeneous good produced under constant returns to scale. Consumers exhibit CES preferences for available varieties $\omega \in \Omega_i$ of the non-tradable differentiated final good:

$$U_i = Q_0^{1-\alpha}\left[\int_{\omega\in\Omega_i} q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega\right]^{\frac{\alpha\sigma}{\sigma-1}}, \ \sigma > 1,$$

[7] Our findings are consistent with the evidence in (e.g., Burstein et al. 2024) of substantial variation across Chilean firms in the prices they pay for domestic inputs. We instead focus on imported inputs and explicitly link input price variation to the number of suppliers.

[8] We emphasize how the extensive margin of sourcing from more suppliers correlates with inputs prices, which we later attribute to oligopolistic competition among suppliers in setting buyer-specific markups. This is distinct from, and complements prior evidence that the intensive margin of a supplier's input cost share shapes bargaining power and thereby match-specific markups (e.g., Fontaine et al. 2020; Dhyne et al. 2022; Alviarez et al. 2023).

[9] This interpretation would be more nuanced with quality heterogeneity across suppliers. We explicitly control for average supplier quality in the empirical analysis in Section 3.4.

where Q_0 is consumption of the homogeneous good, α is the expenditure share on differentiated goods, and σ is the elasticity of substitution across varieties. Given aggregate expenditure E_i and price index P_i for differentiated goods, demand for variety ω with price $p_i(\omega)$ is:

$$q_i(\omega) = E_i P_i^{\sigma-1} p_i(\omega)^{-\sigma}. \tag{3.1}$$

3.3.2. Downstream Producers

In each country, a continuum of monopolistically competitive downstream firms assemble domestic and imported inputs into differentiated goods. Given the CES demand (3.1), firms optimally set a constant markup above their marginal production cost $c_i(\omega)$ to maximize profits:

$$p_i(\omega) = \frac{\sigma}{\sigma - 1} c_i(\omega). \tag{3.2}$$

Upon paying an entry cost of $w_i f_i$, downstream firms draw core productivity φ from distribution $G_i(\varphi)$ with support $[\overline{\varphi}_i, \infty)$. They combine a unit measure of input varieties $v \in [0,1]$, produced by upstream suppliers in countries $j \in \mathcal{J} = \{1, ..., J\}$ and sectors $k \in \mathcal{K} = \{1, ..., K\}$. The elasticities of substitution across input varieties from the same country-sector and across country-sectors are $\lambda > 1$ and $\eta > 1$, respectively. The marginal cost of downstream firm φ is thus given by:

$$c_i(\varphi) = \frac{1}{\varphi} \left(\sum_{j=1}^{J} \sum_{k=1}^{K} I_{ijk}(\varphi) c_{ijk}(\varphi)^{1-\eta} \right)^{\frac{1}{1-\eta}}. \tag{3.3}$$

Here $I_{ijk}(\varphi)$ is an indicator equal to 1 if the firm sources sector k inputs from country j, and $c_{ijk}(\varphi)$ is the composite cost index of jk inputs:

$$c_{ijk}(\varphi) = \left(\int_0^1 z_{ijk}(\varphi, v)^{1-\lambda} \, dv \right)^{\frac{1}{1-\lambda}}, \tag{3.4}$$

which aggregates the costs of upstream input varieties v to producer φ, $z_{ijk}(\varphi, v)$. Note that input costs can vary across producers due to their endogenous choice of suppliers $\mathcal{S}_{ijk}(\varphi)$ and suppliers' endogenous choice of buyer-specific markups.

Buyer φ receives a match-specific cost shock $\xi_{ijks}(\varphi, v)$ for variety v after matching with supplier s and observing that supplier's price, $p_{ijks}(\varphi)$. This shock can be seen as the cost of adapting an input to the firm's production process or the cost equivalent of a quality defect. Conditional on sourcing inputs from a given country-sector, the buyer optimally purchases variety v from the lowest-cost upstream supplier within the set of suppliers it has matched with:

$$z_{ijk}(\varphi, v) = \min_{s \in \mathcal{S}_{ijk}(\varphi)} \left\{ \tau_{ijk} \cdot p_{ijks}(\varphi) \cdot \xi_{ijks}(\varphi, v) \right\}, \tag{3.5}$$

where τ_{ijk} is an iceberg trade cost of shipping sector-k inputs from country j to i. The presence of match-specific cost shocks implies that equally productive buyers matched with the same set of suppliers may choose different suppliers for the same input variety. Following Antràs et al. (2017), we assume that $1/\xi_{ijks}(\varphi, v)$ is Fréchet distributed: $\Pr(\xi_{ijks}(\varphi, v) \geq t) = e^{-t^{\theta}}$. A larger shape parameter θ corresponds to a wider dispersion of shocks and a higher elasticity of substitution across suppliers within country-sector.

3.3.3. Upstream Suppliers

A discrete number of upstream suppliers S_{jk} produce differentiated inputs in country j and sector k, and each supplier can produce all varieties in a given sector. In order to sell to downstream buyers in country i, they have to pay $w_j f^U_{ijk}$ (U denotes upstream), which can be thought of as the registration fee to attend a trade fair in a convention center. This fixed cost will imply that only the most productive suppliers select into exporting.

Suppliers matched to a downstream buyer compete oligopolistically among themselves, and set optimal match-specific prices to maximize profits $\pi^U_{ijks}(\varphi)$ separately for each relationship:[10]

$$\max_{p_{ijks}(\varphi)} \pi^U_{ijks}(\varphi) = Q_{ijks}(\varphi)(p_{ijks}(\varphi) - c_{jks}), \tag{3.6}$$

where c_{jks} is the constant marginal cost of jk input supplier s, and $Q_{ijks}(\varphi)$ is the expected residual demand of buyers with productivity φ.

3.3.4. Buyer-Supplier Matching

Let S_{ijk} suppliers in country-sector jk be productive enough to export to country i. We assume that there are many rooms in a convention center that runs trade fairs where buyers and suppliers can meet and form trading relationships. Each room can be equipped with seats for up to S_{ijk} suppliers. A buyer from country i can use a room with S seats to hold a bidding game among S suppliers, but it has to pay a higher fixed cost $w_i f^D_{ijk}(S)$ to use a bigger room, i.e. $f^D_{ijk}(S_{ijk}) > f^D_{ijk}(S_{ijk} - 1) > \cdots > f^D_{ijk}(1) > 0$ (D denotes downstream). These matching costs

[10] In the spirit of Neary (2016), the suppliers are large for an individual buyer, but small for the downstream sector as a whole. Consequently, they take downstream aggregate variables as given when setting prices.

can be thought of as combining a flat registration fee with room rental fees and labor costs for a team of sourcing managers, accountants and lawyers that scale up with the number of suppliers.

We assume that upstream firms enter each bidding room sequentially in increasing order of marginal cost. This will ensure a unique matching equilibrium and grant significant tractability: Instead of facing a high-dimensional choice over $2^{S_{ijk}}$ possible sets of suppliers in country-sector jk, the buyer has to consider only $S_{ijk}+1$ options.[11] At the cost of $w_i f^D_{ijk}(S')$, a buyer can therefore match with the 'top' $S' \in S_{ijk}$ suppliers.

3.3.5. Sourcing Problem

Downstream firms optimize their global sourcing strategy in two steps. First, they select the optimal set of countries and sectors from which to purchase inputs, $\mathbb{I}_i(\varphi) = \{\mathcal{J}\otimes\mathcal{K} : I_{ijk}(\varphi) = 1\}$, and the optimal set of input suppliers from each origin country-sector, $\mathbb{S}_i(\varphi) = \{\mathcal{J}\otimes\mathcal{K} : S_{ijk}(\varphi) \in \{0, 1, ..., S_{ijk}\}\}$. Second, they determine their optimal sourcing intensity across suppliers given $\mathbb{I}_i(\varphi)$ and $\mathbb{S}_i(\varphi)$. We characterize these problems in reverse order.

Sourcing Conditional on Supplier Set

Buyers solve the optimal sourcing problem (3.5) to identify the cheapest provider of each variety in country-sector jk. The probability that supplier s is the lowest-cost supplier is:

$$\chi_{ijks}(\varphi) = \frac{p_{ijks}(\varphi)^{-\theta}}{\sum_{s'=1}^{S_{ijk}(\varphi)} p_{ijks'}(\varphi)^{-\theta}}. \tag{3.7}$$

With a continuum of varieties and i.i.d. cost shocks across matches, $\chi_{ijks}(\varphi)$ is also the share of supplier s in the buyer's expenditure on jk inputs.

A buyer's composite cost index for jk inputs is therefore:

$$c_{ijk}(\varphi) = \gamma\tau_{ijk}\left[\sum_{s=1}^{S_{ijk}(\varphi)} p_{ijks}(\varphi)^{-\theta}\right]^{-1/\theta}, \tag{3.8}$$

where $\gamma = \left[\Gamma\left(\frac{\theta+1-\lambda}{\theta}\right)\right]^{\frac{1}{\lambda-1}}$ is a constant given by the gamma function $\Gamma(\cdot)$.[12] A downstream

[11] The hierarchical pattern that emerges from this assumption is consistent with empirical evidence in, for instance, Bernard et al. (2019b). This assumption also underlies the solution concept in Atkeson and Burstein (2008b), Eaton et al. (2012) and Gaubert and Itskhoki (2021). It can, for example, be rationalized as the equilibrium of a matching game in which suppliers pay a higher room-specific fixed cost to meet with more buyers.

[12] As in Eaton and Kortum (2002b), we need $\lambda < \theta + 1$ for the price index to be well defined.

firm's total input costs, $C_i(\varphi)$, and demand for jk inputs, $Q_{ijk}(\varphi)$, can be expressed as:

$$C_i(\varphi) = q_i(\varphi)c_i(\varphi) = \left(\frac{\sigma - 1}{\sigma}\right)^{\sigma} E_i P_i^{\sigma-1} c_i(\varphi)^{1-\sigma}, \tag{3.9}$$

$$Q_{ijk}(\varphi) = \left(\frac{\sigma - 1}{\sigma}\right)^{\sigma} E_i P_i^{\sigma-1} \varphi^{\eta-1} c_i(\varphi)^{\eta-\sigma} c_{ijk}(\varphi)^{-\eta}. \tag{3.10}$$

From the perspective of upstream supplier s, the expected residual demand by buyer φ is $Q_{ijks}(\varphi) = Q_{ijk}(\varphi)\chi_{ijks}(\varphi)$, so that the supplier's problem (3.6) is:

$$\max_{p_{ijks}(\varphi)} \pi^U_{ijks}(\varphi) = Q_{ijk}(\varphi)\chi_{ijks}(\varphi)(p_{ijks}(\varphi) - c_{jks}), \; s = 1, ..., S_{ijk}(\varphi). \tag{3.11}$$

While a higher price boosts a supplier's profit margin, $p_{ijks}(\varphi) - c_{jks}$, it reduces its market share $\chi_{ijks}(\varphi)$ and residual demand $Q_{ijk}(\varphi)$ by raising the buyer's marginal cost $c_i(\varphi)$.

Proposition 1 summarizes the optimal pricing strategy of the suppliers.

Proposition 1. *There exists a unique Nash Equilibrium with supplier s prices*

$$p_{ijks}(\varphi) = \frac{\varepsilon_{ijks}(\varphi)}{\varepsilon_{ijks}(\varphi) - 1} c_{jks}, \tag{3.12}$$

where $\varepsilon_{ijks}(\varphi) = \left[\sigma\delta_{ijk}(\varphi) + \eta\left(1 - \delta_{ijk}(\varphi)\right)\right]\chi_{ijks}(\varphi) + \theta\left[1 - \chi_{ijks}(\varphi)\right]$ *is the elasticity of residual demand, and* $\delta_{ijk}(\varphi)$ *is the share of country-sector jk in buyer* φ*'s input purchases.*

Proof. *See Appendix C.1.*

Suppliers can price discriminate, and optimally charge buyer-specific markups, $\mu_{ijks}(\varphi) = \frac{\varepsilon_{ijks}(\varphi)}{\varepsilon_{ijks}(\varphi)-1}$. Suppliers set higher markups when they have a larger market share in the buyer's input basket, provided that $\rho_{ijk}(\varphi) \equiv \theta - \eta + (\eta - \sigma)\delta_{ijk}(\varphi) > 0$. We assume that this condition holds in light of the prior literature (Amiti et al. 2019; Dhyne et al. 2022).[13] This implies that downstream firms with more diversified sourcing and lower average $\chi_{ijks}(\varphi)$ enjoy lower input markups. Suppliers have less market power and charge lower markups when buyers face more elastic final demand (higher σ), and when inputs are more substitutable across and within countries and sectors (higher η and θ).[14]

Proposition 2 describes the benefits associated with sourcing from more suppliers.

[13]As shown in Appendix C.1, $\partial\mu_{ijks}(\varphi)/\partial\chi_{ijks}(\varphi) = \rho_{ijk}(\varphi)/(\varepsilon_{ijks}(\varphi) - 1)^2$. We also show that $\rho_{ijk}(\varphi) > 0$ implies strategic complementarity in pricing among upstream firms (Amiti et al. 2019).

[14] With no match-specific shocks and $\theta \to \infty$, the model collapses to classic Bertrand competition with $p_{jks}(\varphi) = c_{jks}$. With a continuum of suppliers and no matching frictions, the model instead collapses to monopolistic competition with ubiquitous sourcing: As $S_{ijk}(\varphi) \to \infty$, we have $\chi_{ijks}(\varphi) \to 0$ and $\mu_{ijks}(\varphi) \to \frac{\theta}{\theta-1}$.

Proposition 2. *An increase in the number of country-sector jk suppliers to a buyer* $S_{ijk}(\varphi)$*:*
(a) reduces the market shares $\chi_{ijks}(\varphi)$*, markups* $\mu_{ijks}(\varphi)$*, and prices* $p_{ijks}(\varphi)$ *of all infra-marginal jk suppliers to the buyer;*
(b) lowers the buyer's input cost index across jk inputs $c_{ijk}(\varphi)$*.*

Proof. *See Appendix C.1.*

These results reflect several forces that operate through sourcing interdependence conditional on the set of input origins. Along the extensive margin, higher $S_{ijk}(\varphi)$ increases the probability that the buyer finds a better-matched and therefore lower-cost supplier for any input variety. Along the intensive margin, higher $S_{ijk}(\varphi)$ intensifies competition among matched suppliers, and lowers the markup on each incumbent variety. These beneficial effects outweigh a counteracting one on the extensive margin: Given sequential supplier entry in bidding rooms, expanding the supplier set means adding progressively less productive suppliers.[15]

Proposition 2 indicates that buyers can effectively exert market power in the input market by endogenously choosing their supplier set. Endogenous network formation can thus be seen as providing micro-foundations for endogenous two-sided market power in buyer-supplier transactions, even when there is oligopolistic competition only upstream. Moreover, both buyers and suppliers can have heterogeneous market power, and their market power can vary across their matches. We will see that more productive buyers and suppliers will enjoy greater market power, the former due to their bigger supplier portfolio, and the latter due to their bigger share in buyers' input purchases.

Optimal Supplier Set

Downstream firms optimally choose their set of country-sector origins $\mathbb{I}_i(\varphi)$ and suppliers $\mathbb{S}_i(\varphi)$ by maximizing total profits, given the final demand shifter $B_i = \frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} E_i P_i^{\sigma-1}$:

$$\max_{\substack{I_{ijk}(\varphi)\in\{0,1\}_{j=1,k=1}^{J,K} \\ S_{ijk}(\varphi)\in\{0,1,2,\ldots,S_{ijk}\}_{j=1,k=1}^{J,K}}} \pi_i^D(\varphi) = B_i c_i(\varphi)^{1-\sigma} - \sum_{j=1}^{J}\sum_{k=1}^{K} I_{ijk}(\varphi) w_i f_{ijk}^D(S_{ijk}(\varphi)). \quad (3.13)$$

Note that the firm's marginal cost $c_i(\varphi)$ decreases with its *sourcing capability* $\Theta_i(\varphi)$ since $\eta > 1$, where $\Theta_i(\varphi)$ is akin to an endogenous input cost index and thus captures the firm's

[15] All these effects operate within an origin-sector. When a buyer adds its first supplier from a new country-sector, they reap additional gains due to this extensive margin.

ability to source inputs from low-cost suppliers:

$$c_i(\varphi) = \frac{\gamma}{\varphi}\Theta_i(\varphi)^{\frac{1}{1-\eta}}, \qquad \Theta_i(\varphi) \equiv \sum_{j=1}^{J}\sum_{k=1}^{K} I_{ijk}(\varphi)\tau_{ijk}^{1-\eta}\left[\sum_{s=1}^{S_{ijk}(\varphi)} p_{ijks}(\varphi)^{-\theta}\right]^{-\frac{1-\eta}{\theta}}.$$

While there is no closed-form solution to the combinatorial multinomial discrete choice problem (3.13), we can characterize key properties of the optimal sourcing strategy:

Proposition 3. *Downstream buyers' optimal sourcing strategy is such that:*
(a) the set of input suppliers is non-contracting in φ *if* $\sigma > \eta$ *and* $\rho_{ijk}(\varphi) > 0$*, i.e.,* $I_{ijk}(\varphi_H) \geq I_{ijk}(\varphi_L)$ *and* $S_{ijk}(\varphi_H) \geq S_{ijk}(\varphi_L)$ *for* $\varphi_H \geq \varphi_L$*;*
(b) buyer sourcing capability $\Theta_i(\varphi)$ *is non-decreasing in* φ*.*

Proof. *See Appendix C.1.*

Result (a) implies that downstream firms observe a pecking order of input sourcing across country-sectors and across suppliers. This holds as long as final goods are closer substitutes in consumption than intermediate inputs in production, $\sigma > \eta$, and upstream suppliers' pricing features strategic complementarity, $\rho_{ijk}(\varphi) > 0$. When these two parameter restrictions hold, we say there is *sourcing complementarity* for downstream buyers.

The model thus delivers negative degree assortativity among buyers and suppliers on the extensive margin, in line with prior evidence (Bernard and Moxnes 2018b; Bernard et al. 2022b). More productive buyers purchase inputs from more countries in more sectors. They also transact with more suppliers within each country-sector, and include less productive suppliers on the margin. Analogously, more productive suppliers serve a wider range of progressively less productive buyers, compared to their less productive competitors.

Taken together with Proposition 2, Proposition 3 implies that more productive buyers have endogenously greater market power in input markets, because they choose to transact with more suppliers and thereby obtain their inputs at lower markups and prices. Endogenous production networks thus amplify the inherent advantage of more efficient downstream firms. This prediction is consistent with the prior literature on the contribution of production networks to the firm size dispersion (Bernard et al. 2022b).

3.3.6. Trade Flows

Despite the presence of endogenous network formation and imperfect competition, the model delivers gravity relationships for trade flows at the firm-to-firm, firm, and sector levels. Total imports by buyer φ in country i across suppliers s of country-sector jk inputs are:

$$\begin{aligned} X_{ijk}(\varphi) &= \sum_{s=1}^{S_{ijk}(\varphi)} X_{ijks}(\varphi) \\ &= \gamma^{\eta-\sigma-\theta}(\sigma-1)B_i\varphi^{\sigma-1}\Theta_i(\varphi)^{\frac{\sigma-\eta}{\eta-1}}\tau_{ijk}^{-\theta}c_{ijk}(\varphi)^{\theta+1-\eta}\sum_{s=1}^{S_{ijk}(\varphi)}\mu_{ijks}(\varphi)^{-\theta}c_{jks}^{-\theta}, \end{aligned} \tag{3.14}$$

Firm purchases of jk inputs thus increase with aggregate final demand B_i and with the firm's productivity φ and sourcing capability $\Theta_i(\varphi)$, and decrease with iceberg trade costs τ_{ijk}. Note that $X_{ijk}(\varphi)$ increases with the endogenous choice of suppliers $S_{ijk}(\varphi)$ both directly and indirectly through lower supplier markups $\mu_{ijks}(\varphi)$.

The model can accommodate positive assortativity among buyers and suppliers on the intensive margin, consistent with prior work (Benguria 2021; Bernard and Moxnes 2018b; Sugita et al. 2023). Firm-to-firm sales $X_{ijks}(\varphi)$ rise with supplier productivity, as a lower marginal cost c_{jks} increases a supplier's market share in a buyer's input purchases, and also drives up the buyer's overall input demand. How firm-to-firm sales vary with buyer productivity depends on the net effect of two opposing forces. On the one hand, more productive buyers face higher output demand and need more intermediates. This scale effect is amplified by their endogenously higher sourcing capability. On the other hand, more productive buyers source from more suppliers, and this competition effect reduces input demand per supplier.

Aggregating across firms, imports by country i of jk inputs are $X_{ijk} = \int_{\overline{\varphi}_{ijk}}^{\infty} X_{ijk}(\varphi)dG_i(\varphi)$, where $\overline{\varphi}_{ijk}$ is the least productive downstream buyer in i that sources jk inputs.

3.3.7. Equilibrium

We close the model with entry and market clearing conditions. Downstream, free entry implies that expected profits from entry must equal the fixed cost of entry, $\int_{\overline{\varphi}_i}^{\infty} \pi_i^D(\varphi)dG_i(\varphi) = w_i f_i$. Thus only buyers above a threshold productivity $\overline{\varphi}_i$ produce, and their equilibrium mass Δ_i scales with population L_i. Upstream, input suppliers below a marginal cost cut-off will be able to sell to downstream buyers. This selection results from the combination of fixed export costs per destination and sequential entry into bidding rooms. The number of suppliers from j to i in sector k, S_{ijk}, is determined by the marginal supplier $\bar{s}$ that earns non-negative net profits:

$$\Pi_{ijk\bar{s}}^U(S_{ijk}) = \Delta_i \int_{\overline{\varphi}_{ijk\bar{s}}}^{\infty} \pi_{ijk\bar{s}}^U(\varphi)dG_i(\varphi),\ \Pi_{ijk\bar{s}}^U(S_{ijk}) \geq w_j f_{ijk}^U,\ \Pi_{ijk\bar{s}}^U(S_{ijk}+1) < w_j f_{ijk}^U, \tag{3.15}$$

where $\overline{\varphi}_{ijk\bar{s}}$ is the marginal downstream buyer in country i that buys jk inputs from $\bar{s}$.

3.3.8. Comparative Statics

We now characterize the impact of supplier entry upstream, tariff reduction, and lower matching costs on firms' sourcing strategy. First, consider an increase in the number of potential suppliers from S_{ijk} to $S_{ijk}{'}$, for example, due to a lower fixed cost of entry f^U_{ijk} in upstream country-sector jk. Exogenous deregulation that lowers barriers to entry into production or exporting would, for instance, enable a new margin of suppliers from the left of the productivity distribution. From Proposition 2, sourcing from more suppliers $S_{ijk}(\varphi)$ reduces buyer φ's input cost index $c_{ijk}(\varphi)$. Not all buyers find it profitable to transact with the new suppliers, however, as they face a trade-off between lower marginal costs and higher matching costs: from Proposition 3, more productive buyers are more likely to expand their pool of suppliers.

Figure 3.4. Firm Productivity and # Suppliers: Comparative Statics

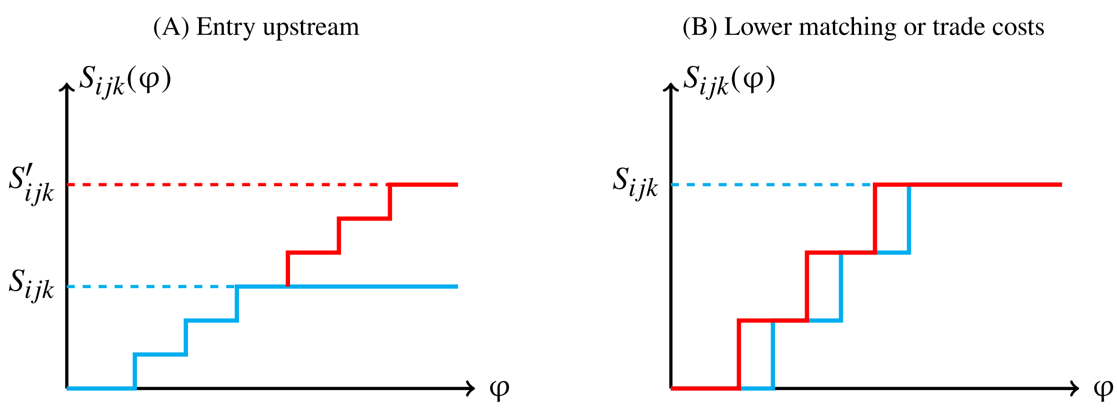


Figure 3.4a visualizes the impact of the upstream market structure in origin j on downstream firms' sourcing from j, where the optimal supplier set is a step function of buyer productivity. Low-productivity firms will not adjust their sourcing strategy. Sufficiently productive buyers will, however, choose to climb higher as the stairs get taller with entry upstream, and will thereby enjoy lower marginal costs and higher revenues and profits (at somewhat higher matching costs). As we show in Section 3.5, sourcing complementarity will imply that upstream entry in one origin may induce some buyers to also expand suppliers from other origins and further magnify their gains. Overall, upstream entry therefore amplifies performance dispersion between high- and low-productivity firms. Proposition 4 summarizes these insights:

Proposition 4. *Under sourcing complementarity and fixed market demand B_i, a rise in the number of potential suppliers S_{ijk} due to lower upstream entry costs:*
(a) weakly increases buyers' number of jk suppliers $S_{ijk}(\varphi)$;
(b) weakly reduces buyers' input price index $c_{ijk}(\varphi)$ and weakly increases its input quantities

$Q_{ijk}(\varphi)$ and purchases $X_{ijk}(\varphi)$ of jk inputs;
(c) exerts larger effects on marginal costs, revenues, and profits on more productive buyers.

Proof. *See Appendix C.1.*

Next, we evaluate the impact of trade liberalization that reduces bilateral iceberg trade costs τ_{ijk}. The productivity cut-off that buyers in i need to clear to warrant any set of suppliers from j falls, as illustrated by a leftwards shift in the sourcing strategy stairs in Figure 3.4B. Assuming that the most productive buyers had already tapped all potential suppliers, it is buyers in the middle of the productivity distribution that may be induced to expand their supplier portfolio.[16] The least productive final producers would still not find it optimal to buy intermediates from j.

Trade liberalization thus cuts downstream firms' marginal costs through two channels: lower import duties on the intensive margin for all firms already sourcing from abroad, and greater input variety and pro-competitively lower input markups on the extensive margin for those that grow their supplier roster. Reductions in marginal costs in turn boost revenues and profits.

Lastly, we study the effects of lower buyer-supplier matching costs, for example due to technological change that facilitates partner search and transactions. Whether bilateral or global for all country-sectors, this reduction in matching costs shifts sourcing productivity cut-offs much as trade liberalization does in Figure 3.4B, with sourcing complementarity across origins acting as an amplification force. Mid-productivity firms once again enlarge their supplier sets. While all globally sourcing firms will see their profits rise due to lower fixed matching costs, those that initiate new supplier relationships will enjoy additional profit gains due to lower inputs costs and higher sales. Proposition 5 formalizes these comparative statics.

Proposition 5. *Under sourcing complementarity and fixed market demand B_i, a reduction in iceberg trade costs τ_{ijk} or matching costs $f^D_{ijk}(S_{ijk})$:*
(a) weakly expands buyers' sourcing strategy $\mathbb{I}_i(\varphi)$ and $\mathbb{S}_i(\varphi)$;
(b) weakly reduces buyers' input price index $c_{ijk}(\varphi)$ and weakly increases their input quantities $Q_{ijk}(\varphi)$ and purchases $X_{ijk}(\varphi)$ of jk inputs;
(c) exerts bigger effects on marginal costs, revenues and profits on mid-productivity buyers.

Proof. *See Appendix C.1.*

[16] Sourcing productivity cut-offs for other origins may also fall due to sourcing complementarity across origins.

3.4. Reduced-Form Evidence

3.4.1. Institutional Context

We evaluate the empirical relevance of the model by examining the relationship between the upstream market structure in China and the downstream sourcing behavior in Chile and France over the 2000-2006 period. All three countries trade intensively and occupy different segments of the global value chain, with China known as factory of the world providing inputs and assembly to manufacturers in both developed and developing economies. In turn, Chile and France exemplify economies of very different market sizes, economic development, institutional strength, and economic geography. Finding consistent evidence across both can thus reveal the ubiquity and significance of the mechanisms of interest.

China experienced dramatic export growth after joining the World Trade Organization (WTO) in 2001, gradually relaxing various barriers to entry, developing trade-oriented special economic zones, and shoring up physical and institutional infrastructure to support trade activity. This made China an important input supplier to French and Chilean firms, with its share of total imports roughly doubling from 3.2% to 5.7% for France and from 5.6% to 9.9% for Chile between 2000 and 2006. By contrast, France and Chile are not key export markets for Chinese producers, with their respective market shares stable at around 1.4-1.5% and 0.2-0.3%. This makes China-France and China-Chile trade relations ideal contexts for identifying the role of upstream entry on downstream sourcing.

3.4.2. Identification Strategy

Proposition 4 delivers sharp predictions for the impact of the upstream market structure in China on the sourcing of Chinese inputs by downstream French and Chilean firms. We evaluate these predictions for the value, quantity and unit price of imports from China by firm f of HS-6 product p in year t with variants of the following specification:

$$\left\{\ln X_{fpt}, \ln Q_{fpt}, \ln p_{fpt}\right\} = \beta \ln S_{CHN\rightarrow ROW,pt} + \Gamma\Omega_{CHN,pt} + \delta_f + \delta_p + t\delta_p + \delta_t + \varepsilon_{fpt}. \quad (3.16)$$

We proxy unit prices with the average unit value across all input purchases from China at the fpt level. We also present robust results for model-consistent CES import price indices that weight import transactions by value, scaled by Broda-Weinstein elasticities of substitution.

Proposition 4 indicates that the observed number of Chinese exporters of product p to Chile or France in year t, $S_{CHN\rightarrow CHL,pt}$ or $S_{CHN\rightarrow FRA,pt}$ respectively, is the metric of Chinese upstream market structure relevant to Chilean or French buyer f. Even if $S_{CHN\rightarrow CHL,pt}$ or

$S_{CHN \to FRA,pt}$ endogenously responded to aggregate import demand downstream, this would be consistent with our general-equilibrium model of global sourcing and not invalidate causal interpretations at the level of individual firms. However, $S_{CHN \to CHL,pt}$ and $S_{CHN \to FRA,pt}$ may fail to capture the set of prospective upstream suppliers, or their correlation with downstream sourcing outcomes may in principle be driven by forces outside our model.

To alleviate such concerns, our baseline proxy for the number of potential Chinese suppliers to Chile (to France) is the number of Chinese exporters to the rest of the world excluding Chile (France), by product p and year t—labeled $S_{CHN \to ROW,pt}$ for both Chile and France for convenience. Guided by the model, we provide consistent evidence using the actual number of Chinese exporters to Chile $S_{CHN \to CHL,pt}$ (to France $S_{CHN \to FRA,pt}$), which is arguably exogenous from the perspective of atomistic buyers. We also instrument the latter either with $S_{CHN \to ROW,pt}$ or with the number of Chinese exporters to a larger yet comparable market: the Pacific Alliance countries (Colombia, Mexico, Peru) for Chile, and the USA for France.

We condition on a full set of firm, product, and year fixed effects, as well as on product-specific time trends, δ_f, δ_p, δ_t, and $t\delta_p$. We therefore identify coefficient β purely from the impact of changes in the Chinese market structure within downstream firms over time. We also guard against omitted variable bias by including product-year specific controls, $\Omega_{CHN,pt}$, which ensure that the market structure indicators do not capture trade costs or other supply conditions in China, as discussed below. We cluster standard errors by product-year (the level of the main variable of interest) to account for common supply and demand shocks across firms.

The theoretical model also characterizes the variation in trade activity across buyers from the perspective of suppliers. Proposition 1 implies that a Chinese supplier will price discriminate across its customers depending on their number of Chinese suppliers of the same product. We confront this prediction with data using variants of the following regression:

$$\ln p_{sfpt} = \beta \ln S_{CHN \to fpt} + \delta_{sp} + \delta_{fp} + \delta_{pt} + \varepsilon_{sfpt}, \tag{3.17}$$

where $\ln p_{sfpt}$ is the log unit value Chinese supplier s charges when selling HS-6 product p to downstream firm f, and $\ln S_{CHN \to fpt}$ is the log number of Chinese suppliers of input p to f, both at time t. We estimate this specification on the Chilean transaction-level data, which identifies foreign suppliers (unlike the French customs registry). We condition on supplier-product pair fixed effects to account for variation in marginal costs and quality at that level. Coefficient β thus captures the variation in markups across buyers within a supplier-product, on the assumption of minimal product customization across partners. In progressively more stringent specifications, we further add year fixed effects, or both product-year and buyer-product fixed effects. We conservatively cluster standard errors ε_{sfpt} at the product-year level.

3.4.3. Data and Key Trends

We exploit rich production and trade data for the near universe of Chilean, French and Chinese firms. For Chile and France, we obtain the value, quantity and price (unit value) of all import transactions at the firm - origin country - HS 6-digit product level from their respective customs agency. In the case of Chile, these records report the identity of the foreign supplier, which makes it possible to trace the bi-partite network of supplier-buyer matches. For France, we use detailed accounting statements and the main industry of activity for all firms from FICUS, and match these to the customs declarations based on unique firm identifiers. From the Chilean tax authority, we observe the primary output industry of each firm, as well as information on the size category it belongs to (13 tiers based on sales).

For China, we use comprehensive information on the universe of export transactions at the firm - destination country - HS 8-digit product level from the Chinese Customs Trade Statistics (CCTS), which we aggregate up to HS-6 products. CCTS reports additional information that we employ in robustness checks. It identifies firm ownership type (private domestic, state-owned, joint venture, or foreign multinational affiliate), and permits the classification of trade intermediaries from firm names and a standard word filter. At the transaction level, CCTS distinguishes between processing and ordinary trade, where the former entails exports produced on behalf of a foreign party using imported inputs. We match CCTS to accounting statements from the Chinese Annual Survey of Industrial Enterprises (ASIE) using a standard algorithm based on firm names, zip code, and phone number.

Since import transactions are recorded inclusive of cost, insurance and freight, we are careful to consider changes in trade duties over time. For Chile, MFN import tariffs on Chinese products remained unchanged throughout the 2000-2006 sample. These will therefore be subsumed by product fixed effects in the analysis.[17] For France, China was subject to the EU's GSP program, and hence faced zero or very low tariffs for most of its goods, with little variation over time. We nevertheless account for any gradual relaxation of import barriers with time-varying EU tariffs on China from UN WITS. We use applied ad-valorem tariffs at the HS-6 level, and take the maximum value if there are multiple tariff lines within a product code, $lmaxtariff_{pt} = \ln\left(1 + max\_rate/100\right)$; all results are robust to simple averages instead.

Panel A in Appendix Table A1 overviews the variation in Chinese market structure across traded products, and illustrates the dramatic trend in entry over time. In 2000, China exported 2,139 HS 6-digit products to France. The average number of suppliers per product was 16.9, with a median of 5 and standard deviation of 38.3. By 2006, China shipped 2,954 distinct products to France, from 37.7 suppliers on average, with a median of 8 and standard deviation

[17] Chile and China enforced a Preferential Trade Agreement in October 2006, towards the end of our sample.

of 92.3. A similar expansion is observed in China's exports to Chile over this period. The total number of products shipped grew from 1,431 to 2,388, while the average number of exporters per product jumped from 12.4 (standard deviation 23.5) to 21.4 (standard deviation 43.8).

Panel B demonstrates that rapid firm entry changed the composition of Chinese exporters in several respects. We locate each Chinese exporter of an HS-6 product p in ASIE, obtain relevant firm attributes, and report statistics at the product level by aggregating across all firms exporting p. China experienced secular productivity growth, with a steady increase in average value added per worker and measured average TFP, along with a rise in productivity dispersion. Average product quality remained stable, as proxied by firms' imported-input price index constructed from import transactions in CCTS. Also relatively stable were the shares of Chinese exports performed by trade intermediaries, multinational affiliates, or multi-product exporters. Effectively applied EU tariffs on Chinese products fell from 3.9% to 2.8% on average, while the overall share of processing trade declined from 36% to 26%.

Panel C summarizes the extent of downstream firm heterogeneity in Chile and France. Between 2000 and 2006, the number of producers sourcing inputs from China more than doubled in both France (from 12,571 to 25,737) and Chile (from 2,525 to 6,519). Worldwide firm imports also increased on average, and this partly reflects China's growing share in their import portfolio. Consistent with both less productive firms beginning to import on the extensive margin and growth in firm-level imports on the intensive margin, the median sales per worker across firms importing from China remained stable as the number of importers grew.

Panel D summarizes the bipartite network of Chinese supplier-Chilean buyer links. Between 2000 and 2006, the average number of Chilean buyers per product remained stable for Chinese suppliers. Similarly, the average number of Chinese suppliers per product shows little variation for Chilean producers. This is consistent with the significant entry by Chinese suppliers upstream, coupled with the sharp increase in the number of Chilean producers sourcing from China in Panel A. Of note, there was a rise in the dispersion of trade values and unit prices both across Chilean buyers within Chinese suppliers, and vice versa, in line with negative degree assortativity and price discrimination in the network.

3.4.4. Upstream Market Structure and Downstream Sourcing

Table 3.1 presents baseline results for the impact of the upstream market structure in China on the sourcing behavior of downstream firms in Chile (Columns 1-2) and in France (Columns 3-4), based on Proposition 4 and estimating equation (3.16). Panel A examines how the log number of Chinese exporters of an HS-6 product to the rest of the world in a given year, $\ln S_{CHN \to ROW,pt}$, affects the log value of imports from China by a Chilean or French firm for that product and year, $\ln X_{fpt}$. Panels B and C decompose $\ln X_{fpt}$ to repeat the analysis for the log quantity and log unit value of imports from China by downstream firm-product-year. Trade quantities are systematically recorded in kilograms for all products in the French customs data and in natural units of accounting that vary across products in the Chilean records. Any such heterogeneity is absorbed by product fixed effects.

Table 3.1. Baseline Results

	Chile		**France**	
	(1)	(2)	(3)	(4)
Panel A. (log) Import Value$_{fpt}$				
(log) # CHN → ROW Exporters$_{pt}$	0.028**	0.095**	0.085***	0.222***
	(0.014)	(0.039)	(0.010)	(0.029)
R2	0.003	0.553	0.008	0.585
Panel B. (log) Import Quantity$_{fpt}$				
(log) # CHN → ROW Exporters$_{pt}$	0.209***	0.232***	0.140***	0.285***
	(0.021)	(0.066)	(0.013)	(0.032)
R2	0.011	0.558	0.006	0.605
Panel C. (log) Import Unit Value$_{fpt}$				
(log) # CHN → ROW Exporters$_{pt}$	-0.181***	-0.137***	-0.055***	-0.063***
	(0.017)	(0.053)	(0.010)	(0.015)
R2	0.037	0.727	0.005	0.714
N	306,857	306,857	897,091	897,091
Year FE	YES	YES	YES	YES
HS-6 Product FE		YES		YES
HS-6 Product Trend		YES		YES
Firm FE		YES		YES
Product × Year Controls		YES		YES

Note: This table examines the effect of the market structure upstream on sourcing activity downstream. The dependent variable is the log value, quantity, or unit value of imports from China by Chilean or French firm, HS-6 product, and year. Upstream market structure is measured by the log # Chinese exporters to ROW by product and year. Product×year controls: log # Chilean or French importers from ROW; EU ad-valorem import tariffs on China (Columns 3, 4); mean and variance of Chinese exporters' productivity; mean input quality of Chinese exporters; value shares of Chinese processing and intermediated exports; shares of state owned, foreign-owned and multi-product Chinese exporters. Singletons dropped and standard errors clustered by HS-6 product × year. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We consistently find that more competition upstream induces downstream buyers in both Chile and France to expand their input expenditure and purchase higher input quantities, while enjoying lower input prices. Through the lens of the model, the pro-competitive effect of upstream competition on input prices lowers downstream firms' marginal production costs, which raises final demand for their output and in turn boosts their input demand. Together, these pro-competitive and scale effects result in higher import values. This evidence is consistent with tougher competition incentivizing Chinese suppliers to lower markups and cut prices.

These findings obtain both when we adopt a flexible specification with year fixed effects only (Columns 1, 3), and when we consider the most stringent variant of specification (3.16) with a full set of buyer firm, year and product fixed effects, along with product-specific time trends and additional controls (Columns 2, 4). The results can thus not be attributed to time-invariant buyer characteristics, global shocks, or persistent or trending product features. They also do not reflect the role of other product-year specific supply conditions in China, as we control for the average and the variance of the productivity of Chinese exporters (based on log value added per worker in the matched ASIE-CCTS data) and a proxy for the average output quality of Chinese exporters (based on the average unit value of each exporter's imported inputs). We also include the log number of Chilean or French importers of the same HS-6 product from the rest of the world to capture potentially relevant differences in downstream demand and market structure. We further condition on five value shares of Chinese exports conducted respectively by trade intermediaries, under the processing trade regime, by foreign-owned exporters, by state-owned enterprises, and by multi-product exporters. Finally, the regression for France controls for changes in the ad-valorem EU import tariff on Chinese goods.

Quantitatively, we estimate economically significant effects of the upstream market structure on downstream outcomes. For illustration, suppose the (log) number of potential upstream suppliers in China increased by 1 standard deviation (SD). Our results imply that French firms' import values would increase by 11.8% of a SD, total quantity would grow by 13.3% of a SD, and prices would fall by 6.4% of a SD. The corresponding numbers for Chilean buyers are 4.9%, 10.3% and -8.9%. Alternatively, take the actual rise in the number of Chinese exporters to ROW over the sample period. It can account for French firms' adjusting import values, quantities and prices by 22%, 28.1% and -6.1%, respectively, with analogous changes of 10.9%, 26.8% and -15.9% for Chilean producers.

Table 3.2 confirms that these baseline results survive a series of robustness checks. We first explore different sub-samples of firms. In Column 1, we drop upstream suppliers identified as wholesalers. This lowers all point estimates and makes the results for French import prices weakly insignificant, suggesting that large wholesalers play an important role in the context of imperfect competition upstream. In Column 2, we remove instead wholesale buyers downstream. If anything, this increases coefficient magnitudes in the case of Chile and slightly dampens those for France. Together, these results are consistent with interdependent price setting across suppliers within a buyer but not across buyers within a supplier. Ignoring important suppliers can thus underestimate the impact of upstream competition, while omitting individual buyers does not, with the caveat that the model predicts bigger effects on larger, more productive downstream firms, which we evaluate below.

TABLE 3.2. Robustness

Reported Regressor: (log) # CHN→ROW Exporters$_{pt}$	No Wholesalers: Upstream	No Wholesalers: Downstream	CES Import Price Index	Regressor: CHN→CHL/FRA Exporters: OLS	IV: # CHN→ROW Exporters	IV: # CHN→PA/US Exporters
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Chile						
(log) Import Value$_{fpt}$	0.063**	0.160***		0.055***	0.071	0.101
(log) Import Quantity$_{fpt}$	0.133***	0.315***	0.274***	0.069***	0.256**	0.425***
(log) Import Unit Value$_{fpt}$	-0.070*	-0.155**	-0.189***	-0.014	-0.185*	-0.324***
N	306,857	154,226	306,762	296,957		
KP-Stat					130	162
Panel B. France						
(log) Import Value$_{fpt}$	0.129***	0.136**		0.116***	0.268***	0.124***
(log) Import Quantity$_{fpt}$	0.124***	0.186***	0.296***	0.150***	0.359***	0.219***
(log) Import Unit Value$_{fpt}$	0.005	-0.050*	-0.082***	-0.034***	-0.091***	-0.095***
N	897,091	134,482	897,091	887,062	887,062	879,879
KP-Stat					606	350
Firm, Year, HS-6 Product FE	YES	YES	YES	YES	YES	YES
HS-6 Product Trend	YES	YES	YES	YES	YES	YES
Product × Year Controls	YES	YES	YES	YES	YES	YES

Note: This table examines the robustness of the baseline effect of the market structure upstream on sourcing activity downstream in Table 2. Columns 1 and 2 excludes respectively wholesale exporters and wholesale importers. Column 3 uses CES import price indices and quantities instead of simple averages. Columns 4-6 measure the upstream market structure with the actual number of Chinese exporters to Chile or France, instrumented with the number of Chinese suppliers to ROW in Column 5 and to the Pacific Alliance or the USA in Column 6. Singletons dropped and standard errors clustered by HS-6 product × year. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In Column 3, we consider alternative measures of import prices and quantities. We construct CES indices—instead of simple averages—of unit values and quantities at the firm-product-year level from the underlying transaction-level data, using product-specific elasticities of substitution from Broda and Weinstein (2006b). These model-consistent measures can in principle more accurately capture the impact of the upstream market structure, as they recognize that downstream firms can reallocate expenditure shares across inputs due to input price changes. Indeed, using these CES indicators produces highly significant estimates of higher magnitude than the baseline. We have confirmed that all other robustness checks likewise deliver stronger results with CES price and quantity measures. Since CES metrics require additional parametric assumptions, however, we have opted for conservative simple averages in the baseline.

In Columns 4-6, we explore alternative proxies for the upstream market structure in China. From the perspective of individual buyers in Chile or France, the overall number of Chinese exporters to their country can be considered exogenous. Moreover, it may better reflect the set of potential suppliers to their market, given differences in market size, proximity and institutional context that drive the export decisions of Chinese suppliers. Column 4 establishes that $\ln S_{CHN\rightarrow CHL,pt}$ and $\ln S_{CHN\rightarrow FRA,pt}$ indeed generate robust results in line with the baseline estimates. Column 5 provides additional corroborative evidence when instrumenting the actual number of Chinese exporters to Chile or France with the baseline number of Chinese exporters to ROW, excluding Chile or France respectively. Column 6 applies a more fine-tuned instrument that is meant to reflect Chinese export entry into markets similar to Chile and France rather than all of ROW. We consider Chile's neighbors and co-signatories to the Pacific Alliance organization, and use the USA as a benchmark for France. The results remain qualitatively unchanged.

Finally, we present several additional specification checks in Appendix Table A2. First, in Column 1, we restrict the sample to a balanced set of Chilean or French firms that are active in every period in the 2000-2006 panel. This reduces the number of observations significantly, but the estimates remain stable. Second, in Column 2, we define quantities and unit values in the French data based on supplementary information on different units of accounting (instead of kilograms), available for a subset of products. This exercise does not apply to the Chilean data, which enters with the natural unit of accounting already in the baseline.

Third, although we control for the number of Chilean or French importers in any HS-6 downstream industry throughout, this may not fully rule out other potential effects of the downstream market structure. We therefore include output industry-year fixed effects in Column 3. In Columns 4-5, we ensure instead that changes in upstream competition in other products that a firm sources do not confound our estimates: We control alternatively for the log (import-value weighted) average number of Chinese suppliers in a buyer's products other than p, or for the log number of Chinese exporters in the HS 4-digit category p belongs to.

Finally, in Column 6 we restrict the French sample to importers who do not source from Eastern Europe throughout our sample period. The findings confirm that we have not falsely assigned the effects of structural changes in Eastern Europe that took place during our sample period to increased competition in China.

3.4.5. Downstream Firm Heterogeneity

Table 3.3 demonstrates that bigger downstream buyers adjust their sourcing behavior more in response to greater competition upstream, in line with Proposition 4. We group buyers into three size terciles, using either total sales or total imports to proxy size. We then add to specification (3.16) interactions of indicators for buyers in the middle and top tercile with the measure of market competition upstream.[18] The main effect of $\ln S_{CHN\rightarrow ROW,pt}$ now identifies the impact

[18]We categorize firms on a yearly basis to maximize the number of observations in the regressions. Firms rarely switch across tercile groups, and the results are similar for a balanced sample with a fixed assignment in 2000.

on the bottom tercile, while the interaction terms pick up differential effects on mid-size and large buyers. We report results for both simple averages and CES price and quantity indices.

Table 3.3. Downstream Heterogeneity

	Chile				France			
Importer Size Measure	Sales		Total Imports		Sales		Total Imports	
	Baseline	CES Index	Baseline	CES Index	Baseline	CES Index	Baseline	CES Index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. (log) Import Value$_{fpt}$								
(log) # CHN→ROW Exporters$_{pt}$	0.088**		-0.040		0.196***		0.122***	
	(0.039)		(0.039)		(0.030)		(0.029)	
× 2nd Down Size Tercile Dummy	0.007**		0.088***		0.019***		0.027***	
	(0.003)		(0.002)		(0.005)		(0.007)	
× 3rd Down Size Tercile Dummy	0.007		0.153***		0.049***		0.105***	
	(0.005)		(0.003)		(0.006)		(0.008)	
R2	0.553		0.557		0.588		0.590	
Panel B. (log) Import Quantity$_{fpt}$								
(log) # CHN→ROW Exporters$_{pt}$	0.215***	0.255***	0.090	0.104	0.268***	0.271***	0.172***	0.168***
	(0.066)	(0.069)	(0.065)	(0.069)	(0.033)	(0.034)	(0.033)	(0.033)
× 2nd Down Size Tercile Dummy	0.016***	0.018***	0.096***	0.114***	0.015***	0.021***	0.036***	0.044***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)	(0.006)	(0.007)	(0.007)
× 3rd Down Size Tercile Dummy	0.021***	0.023***	0.161***	0.193***	0.048***	0.059***	0.119***	0.138***
	(0.005)	(0.006)	(0.004)	(0.004)	(0.007)	(0.008)	(0.008)	(0.009)
R2	0.558	0.527	0.561	0.531	0.607	0.598	0.609	0.601
Panel C. (log) Import Unit Value$_{fpt}$								
(log) # CHN→ROW Exporters$_{pt}$	-0.128**	-0.175***	-0.130**	-0.144**	-0.071***	-0.079***	-0.050***	-0.047***
	(0.053)	(0.057)	(0.053)	(0.057)	(0.015)	(0.016)	(0.015)	(0.016)
× 2nd Down Size Tercile Dummy	-0.009***	-0.011***	-0.009***	-0.032***	0.003	-0.004	-0.009***	-0.020***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
× 3rd Down Size Tercile Dummy	-0.013***	-0.018***	-0.008***	-0.050***	0.001	-0.014***	-0.014***	-0.041***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
R2	0.727	0.688	0.727	0.688	0.713	0.693	0.714	0.694
N	306,857	306,762	306,857	306,762	836,678	836,678	893,300	893,300
Firm, Year, HS-6 Product FE	YES	YES	YES	YES	YES	YES	YES	YES
HS-6 Product Trend	YES	YES	YES	YES	YES	YES	YES	YES
Product × Year Controls	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table examines the heterogeneity of the effect of the market structure upstream on sourcing activity downstream across buyer size terciles. Firm size terciles are based on total sales or total imports as indicated in the column headings. Odd (even) columns use simple average (CES) input price indices. Singletons dropped and standard errors clustered by HS-6 product × year. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The evidence indicates that bigger downstream buyers benefit more from tougher competition upstream than their smaller peers: They enjoy even lower input prices, source even higher input quantities, and have even higher imported input purchases overall. Through the lens of the model, these patterns are consistent with bigger buyers incurring higher matching costs to transact with more suppliers, and reaping pro-competitive gains from lower markups.

The results are economically and statistically more significant when using worldwide imports to measure buyers' size, compared to using firm sales. This is consistent with the drivers of suppliers' price setting in the model: A buyer's total input purchases determine the supplier's expected profits from the relationship and therefore the optimal input price. The buyer's output sales are only relevant to the extent that they are monotonic in firm productivity and thereby in total input purchases. This raises the possibility that global sourcing decisions may vary across firms for reasons outside our model that are not fully captured by total sales. The total amount of imported inputs may thus more accurately reflect firms' ability to match with more suppliers that is relevant to the competition forces in our model.

3.4.6. Upstream Price Discrimination

The findings above establish the impact of the upstream market structure on sourcing outcomes downstream. We complement this analysis with direct evidence on the pricing strategy of Chinese exporters across Chilean buyers. The results strongly support Proposition 1, namely that suppliers charge more diversified buyers lower markups and prices, even within finely disaggregated product categories. This is in line with suppliers engaging in price discrimination across buyers depending on the extent of competition they face from other suppliers to that buyer.

TABLE 3.4. Upstream Price Discrimination

	Chile			
	(log) UV$_{sfpt}$ (1)	(log) UV$_{sfpt}$ (2)	(log) UV$_{sfpt}$ (3)	(log) UV$_{sfpt}$ (4)
(log) # CHN Suppliers$_{fpt}$	-0.033***	-0.029***	-0.017***	-0.019***
	(0.003)	(0.003)	(0.004)	(0.004)
R2	0.860	0.892	0.928	0.928
N	330,381	326,594	285,335	285,335
Year FE	YES			
Supplier × HS-6 Product FE	YES	YES	YES	YES
HS-6 Product × Year FE		YES	YES	YES
Buyer × HS-6 Product FE			YES	YES
ROW Suppliers Control				YES

Note: This table examines price discrimination upstream and the pro-competitive effects of diversified sourcing. The dependent variable is the log unit value a Chinese supplier charges a Chilean importer for a given HS-6 product and year. The level of Chinese competition faced by the Chinese supplier is measured by the log number of Chinese suppliers of the same product to that buyer in that year. Column 4 controls for the log number of ROW suppliers of the same product to that buyer in that year. Singletons dropped and standard errors clustered by HS-6 product × year.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3.4 presents results from estimating specification (3.17) at the most granular level of Chinese supplier - Chilean buyer - HS-6 product - year transactions. Column 1 includes supplier-product and year fixed effects, such that the impact of the buyer's supply portfolio is identified from the variation within a supplier across buyers of the same product. Column 2 replaces the year fixed effects with product-year fixed effects that more flexibly control for product-specific changes in supply and demand conditions. Column 3 further adds a stringent set of buyer-product fixed effects, such that the main coefficient of interest is now identified from changes in sourcing strategy within buyer-product input lines over time. Finally, Column 4 additionally controls for the buyer's log number of non-Chinese suppliers of the relevant product. This implicitly accounts for changes in supply conditions in ROW, as well as for potential strategic interactions among suppliers from different origins outside our model.

The evidence consistently points to upstream Chinese suppliers offering lower prices to downstream buyers that source from more Chinese suppliers, product by product. This lends strong empirical support to the role of imperfect competition upstream in the model and the resultant pro-competitive effects that upstream entry can exert on sourcing outcomes downstream.

3.5. Quantitative Analysis

Our theoretical framework permits the assessment of several topical policy interventions. We conclude by quantifying the effects of market entry upstream, matching cost reductions, and lower trade barriers on firm performance and consumer welfare. We interpret upstream entry as the result of behind-the-border industrial or competition policy that supports firm entry in supplier countries. We view reductions in matching costs as arising from unilateral or bilateral trade promotion and facilitation, or equivalently the relaxation of non-tariff measures (NTMs). Finally, we see lower trade barriers as standard tariff liberalization. To guide the counterfactual magnitudes, we use the actual expansion in Chinese suppliers to Chile during the 2000-2006 sample period, as well as the Chile-China Preferential Trade Agreement (PTA) signed in 2006.

Importantly, we consider these policies as both stand-alone and *package* reforms to illustrate how policies interact and how sourcing complementarity generates cross-country spillovers. We also analyze the mediating roles of firm heterogeneity, endogenous network formation, and endogenous markups: We compare the baseline model to alternatives with a different productivity dispersion downstream, fixed buyer-supplier links, or constant markups for intermediates.

We estimate a single-sector version of the model for 1 home country (Chile), 5 upstream origin regions (the United States (USA), Europe (EUR), Latin America (LATAM), China (CHN), and Rest of the World (ROW)), and 4 or 5 suppliers per region (set to the regional mean in the data). This setup balances policy relevance with computational tractability, and reflects the geo-economic mix of Chile's main trade partners.

3.5.1. Estimation

The quantification proceeds in three steps. First, we estimate price elasticity parameters by exploiting the pricing equation for upstream suppliers. Next, we calibrate the supplier cost distribution for each region using the estimated elasticities and observed price distributions. Finally, we estimate the aggregate demand shifter and fixed matching costs to match the observed sourcing patterns of Chilean buyers.

Elasticities We start with the elasticities of substitution across final goods and input varieties, σ and η, and the Fréchet parameter governing match-specific cost shocks, θ. Consider supplier s from country c selling product p to buyer b. We log-linearize the supplier's pricing equation (3.12), and estimate it with supplier-product fixed effects to absorb marginal costs c_{scp}:

$$\ln p_{scpb} = \ln c_{scp} + \ln \frac{\varepsilon_{scpb}}{\varepsilon_{scpb} - 1}. \tag{3.18}$$

The markup $\frac{\varepsilon_{scpb}}{\varepsilon_{scpb}-1}$ depends on the residual demand elasticity faced by supplier s, $\varepsilon_{scpb} = \left[\sigma\delta_{cpb} + \eta\left(1 - \delta_{cpb}\right)\right]\chi_{scpb} + \theta\left[1 - \chi_{scpb}\right]$. We take $\hat{\sigma} = 5$ as a center value from the literature (Burstein et al. 2020; Gaubert and Itskhoki 2021). Given σ and the residuals from regression (3.18), we can estimate θ and η by non-linear least squares using observed input expenditure shares δ_{cpb} and χ_{scpb}. We construct $\chi_{scpb} = \frac{m_{scpb}}{m_{cpb}}$ as the share of supplier s in buyer b's imports m_{cpb} of input p from country c. In the absence of data on domestic inputs, we proxy the share of cp inputs in the buyer's input basket with the share of imports m_{cpb} in buyer b's total imports m_b, $\delta_{cpb} = \frac{m_{cpb}}{m_b}$.

Estimating (3.18) on the Chilean import data for the last year in our sample, 2006, we obtain $\hat{\eta} = 1.4$ and $\hat{\theta} = 3.9$, consistent with the theoretical assumption of sourcing complementarity $\sigma > \eta$ (i.e., inputs are more complementary in production than outputs in consumption).[19] Moreover, these estimates imply that the condition $\rho_{cpb} = \theta - \eta + (\eta - \sigma)\delta_{cpb} > 0$ is empirically satisfied for the vast majority of origin-product-buyer triplets in the data, as it is equivalent to $\delta_{cpb} < \frac{\theta-\eta}{\sigma-\eta} \approx 0.694$. This ensures that markups rise with the supplier's share in a buyer's purchases, and firms' sourcing decisions are strategic complements across countries and suppliers.

Cost Distributions We assume that suppliers in origin region j draw marginal costs $c \in (0, c_{M_j}]$ from region-specific discrete Pareto distributions $G(c) = (c/c_{M_j})^{k_j}$, where c_{M_j} is the upper bound and k_j the shape parameter (Eaton et al. 2012; Gaubert and Itskhoki 2021). We exploit properties of the Pareto distribution for the 1^{st} and 10^{th} percentiles, $c_{1,j}$ and $c_{10,j}$:

[19] The estimated $\hat{\eta} = 1.4$ is close to Antràs et al. (2017)'s estimate of 1.8. The estimated firm-to-firm trade elasticity $\hat{\theta} = 3.9$ is close to the aggregate trade elasticity in the literature (e.g., Simonovska and Waugh 2014).

$(c_{1,j}/c_{M_j})^{k_j} = 1/100$, $(c_{10,j}/c_{M_j})^{k_j} = 1/10$, and hence $(c_{10,j}/c_{1,j})^{k_j} = 10$. We estimate the Pareto shape parameters as $\hat{k}_j = \frac{\ln 10}{\ln c_{10,j} - \ln c_{1,j}}$ and the upper bounds as $\hat{c}_{M_j} = 100^{1/\hat{k}_j} c_{1,j}$, where the suppliers' marginal costs are proxied with the fixed effects estimated in (3.18).

Panel A of Table 3.5 shows that the estimated Pareto shapes are around 1, in line with the prior literature. For example, we compute 1.27 for Chinese exports to Chile in 2006, close to the 1.367 estimate in Head et al. (2014) for Chinese exports to Japan in 2000. The Pareto upper bounds for Europe and USA significantly exceed those for China and Latin America, consistent with the former having higher production costs. Since we do not observe domestic input sourcing from Chilean suppliers, we assume that Chile shares a common Pareto distribution with other Latin American countries, and discount the upper bound by the headline iceberg trade cost estimate of 2.70 in Anderson and Van Wincoop (2004b).

For Chilean downstream firms, we assume a Pareto productivity distribution with shape parameter 1.5 and scale parameter 1. Later, we vary the shape parameter in the counterfactual analysis to explore the implications of buyer heterogeneity.

TABLE 3.5. Estimated Parameters

Panel A. Supplier cost distributions			**Panel B. Demand shifter and matching costs**		
Region	Pareto shape $\hat{k}_i$	Pareto upper bound $\hat{c}_{M_i}$	Variable	Parameter	Estimate
Chile	1.25	1.19	Demand shifter	B_{Chile}	1.351
LATAM	1.25	3.23	Base cost	β_0	1.652
USA	0.93	38.76	Distance	β_1	4.908
EUR	1.09	17.03	Common language	β_2	0.961
CHN	1.27	4.69	Control of corruption	β_3	-2.082
ROW	1.20	7.38	# Suppliers	β_4	3.959

Note: This table reports the estimated parameters for the quantification: Pareto parameters for supplier marginal costs by region, the demand shifter for Chile, and the parameters of the matching cost function in equation (3.19).

Demand Shifter and Matching Costs Lastly, we estimate aggregate Chilean demand B_{Chile} and the matching costs of Chilean buyers b. Following Antràs et al. (2017), we parameterize the fixed cost of buying inputs from region j as a function of exogenous shipping, communication, and contracting costs, proxied respectively by bilateral distance $dist_j$, common language $comlang_j$, and control of corruption as an index of institutional strength, $ControlCorrupt_j$. Importantly, we depart from prior work to further allow this fixed sourcing cost to increase with the endogenous number of suppliers $S_b \geq 1$:

$$\ln(f_j(S_b)) = \ln(\beta_0) + \beta_1 \ln dist_j + \ln \beta_2 comlang_j + \beta_3 ControlCorrupt_j + \beta_4 \ln(S_b). \quad (3.19)$$

We impose that fixed sourcing costs drop to zero if b has no suppliers.[20] Gravity variables by region are constructed as weighted averages of country measures from CEPII (Conte et al. 2022) and World Bank Open Data.

We estimate the vector of 6 parameters $\Phi = \{B_{Chile}, \beta_0, \beta_1, \beta_2, \beta_3, \beta_4\}$ with the Simulated Method of Moments (SMM) applied to a set of informative target moments. We first generate 3,000 samples of buyers and suppliers.[21] For a guess Φ', we solve for buyers' optimal global sourcing strategy for each supplier cost draw, compute the implied model moments, and iterate until a solution $\hat{\Phi}$ produces model moments that closely match the corresponding data moments.

We identify the 6 parameters in Φ using 7 empirical moments that capture key features of Chilean firms' import behavior. First, origin-specific gravity components in matching costs shape firms' incentives to source from different regions. To help identify $\{\beta_1, \beta_2, \beta_3\}$, we therefore target the share of Chilean firms that import from each of the 5 foreign regions (Moments I). Second, within each region, transacting with a larger set of suppliers is more costly and profitable only for buyers above a higher productivity threshold. Since the Pareto productivity distribution implies that ever fewer firms source from a larger number of suppliers, we target the linear slope of the share of Chilean firms with respect to the (log) number of regional suppliers (=1, 2, 3, 4+) to help identify β_4 (Moment II).[22] Lastly, the final demand shifter B_{Chile} and the baseline fixed matching cost β_0 are common across buyers and key to whether sourcing inputs from abroad can ever be profitable. We thus use the share of Chilean firms that import any inputs as the final target moment (Moment III).

We face two computational challenges in implementing the SMM. First, sourcing complementarity creates choice interdependence across origins and suppliers, which leads to exponentially increasing complexity. For example, a setting with 6 regions and 5 suppliers per region implies $6^6 = 46,656$ possible sourcing strategies, since buyers choose to source from 0, 1, ..., 5 suppliers per region. This dwarfs the dimensionality of standard multinomial choice models with independent alternatives (Anderson et al. 1992). Second, input prices are determined in

[20] Our choice of functional form and gravity variables follows Antràs et al. (2017), but our firm-specific component is deterministic and dependends on S_b, while theirs is a random draw independent of S_b.

[21] Following (Antràs et al. 2017), we use stratified random sampling of Chilean buyers with 12 intervals, 10 draws per interval, and more draws in the right tail. We sample supplier marginal costs from 25 random draws. To reduce the computational burden, we do not estimate the Pareto shape for Chilean buyers, but conduct sensitivity analysis in Section 3.5.2.

[22] The relationship between supplier numbers and firm shares is very similar across origin regions and well approximated by a linear functional form, in line with Pareto distributed firm productivity.

strategic games played by a buyers' matched suppliers. Evaluating a firm's sourcing strategies thus requires repeatedly solving such pricing games, which further adds to the computational burden. This contrasts with frameworks where input prices are fixed or uniform across buyers in the absence of upstream market power or price discrimination (Antràs et al. 2017).

We develop methods to address the above two challenges, which can be used to solve other similar high-dimensional discrete-choice problems. To tackle the first challenge of combinatorial complexity, we extend the bounding algorithm in Jia (2008), Antràs et al. (2017) and Arkolakis et al. (2023b) for binary discrete-choice problems to *multinomial* discrete-choice problems. This algorithm eliminates sub-optimal choices from the overall choice set by exploiting single-crossing properties of common profit functions. Arkolakis et al. (2023b) show that when these properties hold, it is sufficient to examine the profitability of tapping a given supplier to rule out sub-optimal strategies, without having to evaluate and compare each sourcing profile with brute force. Starting from the smallest and largest possible supplier sets, one can therefore compute whether adding or removing a supplier raises buyer profits, and iteratively "squeeze" the set of potentially optimal choices. In Appendix C.2, we establish this approach for a multinomial choice problem without first transforming it into a series of binary choices that span all possible pairs of choices within the multinominal set.

To overcome the second challenge of solving pricing games, we decouple this step from the SMM estimation. From Proposition 1, the outcome of any pricing game depends only on the relevant set of suppliers, but not on the demand shifter, matching costs, or buyer identity per se. We therefore solve the pricing game only once for each possible supplier set and use the result for all buyers, rather than repeatedly for every buyer considering that same supplier set.

Together, these two techniques yield an efficient algorithm for computationally feasible SMM estimation of large-scale sourcing models with oligopolistic competition. We estimate Φ by solving the following problem with this algorithm in Appendix C.2:

$$\min_{\Phi} y_t = (\tilde{\mathrm{m}}(\Phi) - m)\mathrm{W}(\tilde{\mathrm{m}}(\Phi) - m)', \tag{3.20}$$

where $\tilde{\mathrm{m}}(\Phi)$ are the model moments, and W is the weighting matrix.[23]

Table 3.6 demonstrates that our SMM algorithm delivers an effective model fit to the data. The estimated model matches very well Moment I (the progressive selection of fewer and fewer buyers into wider supplier portfolios within origins; slope -1.56 in the data and -1.75 in the model) and Moment III (the share of Chilean firms that import inputs; 7.6% in the data and 7.65% in the model). The model also captures well several aspects of Moment II across origins:

[23] We use the identity matrix $W = I$ as in Antràs et al. (2017). The resulting estimates are consistent but might not be efficient. Following Jalali et al. (2015), we therefore normalize each moment by its mean.

Table 3.6. Target Moments and Model Fit

Moments		Data	Model
Regional importer share	LATAM	3.14%	7.65%
	USA	3.42%	7.65%
	EUR	3.11%	7.54%
	CHN	2.62%	1.36%
	ROW	2.98%	1.65%
Slope of importer share wrt # suppliers		-1.56	-1.75
Aggregate importer share		7.60%	7.65%

Note: This table reports model fit by targeted moment. The final moment is based on a regression of the share of importers with a given number of suppliers on the log number of suppliers.

the similar share of firms sourcing from Latin America, USA and Europe; the similar share of importers from China and ROW; and the fact that the former exceeds the latter. We surmise that the model slightly overpredicts the former and slightly underpredicts the latter due to the low cap of 4 or 5 potential suppliers from each region.

The estimated parameters of the matching cost function in Panel B of Table 3.5 are economically meaningful, and illustrate the role of granularity upstream. The matching cost rises with bilateral distance; falls with strong control of corruption at the origin; and is 4% lower when partners share a language ($1-\hat{\beta}_2 \approx 0.04$). Notably, the matching cost increases quickly with the number of suppliers, jumping $2^{\hat{\beta}_4} = 2^{3.959} \approx 15.5$ times every time a buyer doubles its supplier count. This is key to rationalizing sparse production networks: The share of Chilean importers with 1 supplier per country-product (80%) is over 4 times the share with 2 suppliers and 30-40 times the share with 3 suppliers.

3.5.2. Counterfactuals

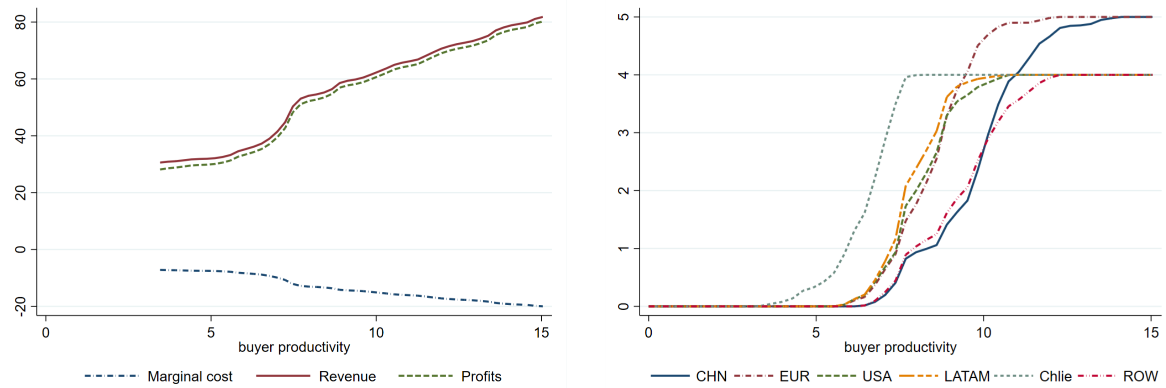
Having structurally estimated the model, we perform counterfactual analyses for Chile to assess the impact of different industrial and trade policies on firm performance and the consumer price index (CPI), which corresponds to welfare given normalized wages.

Baseline Economy We construct a baseline economy by simulating the model 20 times for 1,500 buyers, and report average firm outcomes across simulations in Figure 3.5.[24] Figure

[24]We fix the demand shifter in Chile, consistent with wages being set in an outside sector, and abstract from buyer and supplier entry as in Chaney (2008).

FIGURE 3.5. Baseline Model Economy

(A) Buyer performance (B) Buyer sourcing strategy



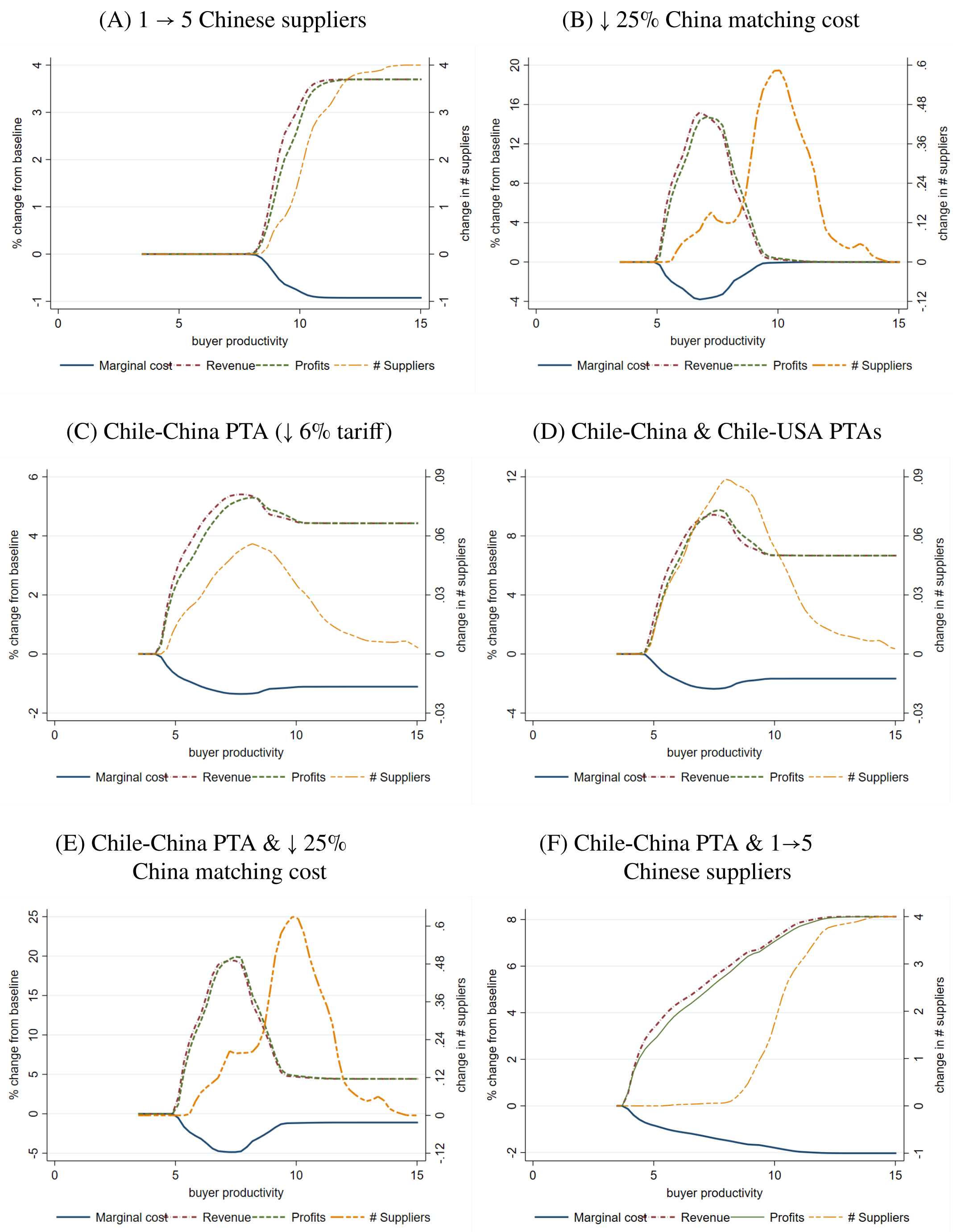
Note: This figure plots the simulated baseline economy, averaged across simulation samples.

3.5A confirms that more productive buyers have lower marginal costs, higher revenues, and greater profits. Figure 3.5B in turn demonstrates the selection of more productive buyers into sourcing from more regions and more suppliers within each region, with the granularity in matches corresponding to kinks in the cost, revenue, and profit curves.[25] Endogenous network formation thus amplifies the underlying buyer heterogeneity. The simulations also reveal a pecking order of productivity cut-offs for sourcing across regions in line with the regional variation in distance and average supplier cost: Chilean buyers find it most beneficial to source domestically, followed by nearby Latin America and the USA, distant Europe with strong institutions and familial languages, and finally physically and linguistically distant China and ROW.

Stand-alone Policy Reforms We first consider a counterfactual rise in the number of potential suppliers in China from 1 to 5, to illustrate the pro-competitive gains downstream from entry and tougher competition upstream. Consistent with Proposition 4, we see in Figure 3.6A that Chilean buyers above a certain productivity threshold opt to pay higher fixed matching costs to expand their supplier portfolio. The most productive among them add 4 more suppliers, to enjoy almost 1% lower marginal costs and more than 3.5% higher revenues and profits. Sourcing complementarity induces some buyers that match with new Chinese suppliers to also expand their sourcing network in other regions where they had not previously tapped all potential suppliers (Appendix Figure A2). Lower marginal costs for final producers in turn imply lower prices for consumers: As Column 1 in Panel A of Table 3.7 indicates, the CPI falls by 0.92%.

[25]Note that averaging across model simulations smooths kinks in these graphs.

FIGURE 3.6. Counterfactual Scenarios: Firm Response



Note: This figure reports the average counterfactual percentage change in buyers' marginal cost, revenue and profits (left axis) and the absolute change in buyers' number of suppliers worldwide (right axis) in response to: (a) entry upstream: number Chinese suppliers rises from 1 to 5; (b): lower matching costs: 25% reduction in β_0 and β_4 with China; (c): Chile-China Preferential Trade Agreement (PTA): 6% lower tariffs; (d): Chile-China and Chile-USA PTA: 6% lower tariffs; (e) policy package (b)+(c); (f) policy package (a)+(c).

We next assess the impact of lower bilateral matching costs by reducing parameters β_0 and β_4 in the matching cost function (3.19) for Chilean buyers sourcing from China by 25%. In line with Proposition 5, Figure 3.6B illustrates that this boosts the performance of mid-productivity firms the most, by incentivizing them to expand their supplier portfolio and thereby enjoy marginal cost cuts and greater sales. More precisely, the buyer productivity cut-offs for sourcing from any given number of Chinese suppliers fall, as do cut-offs for other origin regions due to sourcing complementarity. While all buyers benefit from lower matching costs on infra-marginal suppliers, the most productive buyers already trade with all suppliers and only mid-productivity buyers can profitably add suppliers. Since these firms have small market shares in consumer spending, the associated welfare gains are minimal (Column 2 in Panel A of Table 3.7).

Finally, we study the impact of a 6% bilateral tariff reduction on trade between Chile and China in Figure 3.6C. This corresponds to the average tariff cut in the PTA these countries introduced in October 2006. Consistent with Proposition 5, lower variable trade costs reduce marginal costs and increase revenues and profits for all firms that use foreign inputs. On the one hand, these cost savings are larger for more productive buyers who already source more intensively. On the other hand, sourcing complementarity induces mid-productivity buyers to further expand their supplier set despite higher fixed matching costs. These two forces account for the hump-shaped curve for the percentage change in profits. Overall, there is a sizable gain in Chile's welfare of 1.10% (Column 3 in Panel A of Table 3.7).

Package Policy Reforms We now turn to package deals that build on the Chile-China PTA. Chile signed an independent PTA with the USA in 2003 that also brought about an average tariff reduction of 6%. We consider the impact of these two simultaneous trade reforms in Figure 3.6D. While the driving mechanisms and overall patterns remain the same, sourcing complementarity roughly doubles the impact on firm performance in terms of costs, revenues, and profits across the firm size distribution. This can be attributed to an approximate tripling of the expansion in the supplier margin. As a result, consumer prices decline by 1.65% in Chile, or about 50% more than with a single reform (Column 4 in Panel A of Table 3.7).[26]

We also compare shallow and deep bilateral trade agreements, where we conceptualize the latter as a reduction in both tariffs and fixed matching costs on trade between Chile and China. Figure 3.6E illustrates that facilitating buyer-supplier matches amplifies the gains from lower iceberg costs most dramatically for mid-productivity buyers who widen their supply network. This adds little to the total PTA welfare gains, however, as these firms once again make only a modest contribution to the consumption basket (Column 6 in Panel A of Table 3.7).

Lastly, we study the combination of bilateral tariff cuts between Chile and China (by 6%)

[26]We have also simulated a Chile-USA PTA on its own. Its effect on the CPI is about -0.56%.

TABLE 3.7. Ciile-China Counterfactual Scenarios: Consumer Price Index

	(1)	(2)	(3)	(4)	(5)	(6)
Scenario	Upstream market entry in CHN	Lower matching costs with CHN	China PTA			
			Baseline	+USA PTA	+upstream market entry in CHN	+lower matching costs with CHN
Panel A. Buyer Pareto shape parameter = 1.5						
Δ CPI	−0.92%	−0.00%	−1.10%	−1.65%	−2.01%	−1.10%
Panel B. Buyer Pareto shape parameter = 2.5						
Δ CPI	−0.27%	−0.23%	−1.13%	−1.70%	−1.40%	−1.36%
Panel C. Buyer Pareto shape parameter = 2.5, Fixed Production Network						
Δ CPI	−0.00%	−0.00%	−1.09%	−1.64%	−1.08%	−1.09%
Panel D. Buyer Pareto shape parameter = 2.5, Constant Markup						
Δ CPI	−0.09%	−0.16%	−1.13%	−1.69%	−1.22%	−1.30%

Note: This table presents changes in consumer welfare measured in terms of consumer price index. Buyers are sampled from Pareto distributions with shape parameter 1.5 in Panel A and 2.5 in Panel B-D. Same as the baseline economy, Panels A and B conduct simulations under endogenous production network and variable markup. Panel C conducts simulations after fixing buyer firms' sourcing strategies to baseline economy ones. Panel D conducts simulations assuming supplier firms charge a constant markup of $\theta/(\theta-1)$.

and entry upstream in China (from 1 to 5 suppliers). This can be interpreted as another form of deep integration that relaxes export barriers in China, or alternatively as a standard shallow PTA at a time of industrial policy in China after it joined the WTO in 2001. Figure 3.6F reveals large amplification effects of this reform package, with a significant profit uplift across the buyer productivity distribution. More productive firms grow their supplier base more aggressively, and add suppliers globally due to sourcing complementarity across regions (Appendix Figure A2F). This results in a welfare gain of 2.01%, the highest across all scenarios we have examined (Column 5 in Panel A of Table 3.7).

Firm Heterogeneity, Production Networks, and Markups We conclude the counterfactual analysis by assessing the role of buyer heterogeneity, endogenous production networks, and endogenous markups due to imperfect competition.

First, since policy shocks exert differential effects across buyers, their aggregate welfare effect depends on the distribution of buyer productivity. In Panel B of Table 3.7, we increase the Pareto shape parameter from the baseline of 1.5 to 2.5, tilting the distribution of final producers towards the low-productivity end, and lowering average productivity. This amplifies the welfare gains from reforms that disproportionately benefit low- and mid-productivity firms, and conversely dampens gains from reforms that favor high-productivity firms. In particular, the CPI drop afforded by upstream entry alone or in combination with a PTA is significantly reduced, from 0.92% to 0.27% in Column 1 and from 2.01% to 1.40% in Column 5, respectively. By contrast, the CPI falls considerably more after a cut in matching costs, from around zero to 0.23% in Column 2, and from 1.10% to 1.36% when combined with a PTA in Column 6.

To highlight the role of endogenous production networks, in Panel C of Table 3.7 we repeat the counterfactual exercises with a buyer Pareto shape parameter of 2.5, but fix each buyer's supplier set at its baseline. Welfare gains from all policy counterfactuals are significantly lower when firms cannot re-optimize their supplier portfolio. By construction, entry upstream or lower matching costs now have no effects on downstream firms or consumers, as shown in Columns 1 and 2. Moreover, there are also no amplification effects when trade policy is coupled with upstream entry or lower matching costs in Columns 5 and 6, as firms reap no pro-competitive cost savings from expanding their supplier portfolio.

As a final exercise, we examine the role of oligopolistic competition and endogenous mark-ups. In Panel D of Table 3.7, we re-run the counterfactuals for buyer Pareto shape parameter of 2.5, assuming that suppliers charge a constant markup of $\theta/(\theta - 1)$ as under monopolistic competition. Since sourcing from more suppliers no longer brings gains from tougher competition among them, buyers have less incentives to adjust their supply network. The welfare effects of upstream entry and lower matching costs are thus substantially diminished in Columns 1 and 2. At the same time, variable markups appear to play a secondary role in the transmission of trade policy changes into consumer prices (Columns 3 and 4), unless trade reforms are coupled with upstream entry or lower matching costs (Columns 5 and 6). Intuitively, tariff reductions affect primarily the intensive margin of sourcing through lower variable costs, while upstream entry and matching costs move primarily the extensive margin of suppliers, and this latter margin brings smaller CPI reductions under constant markups.

3.6. Conclusion

This chapter examines the role of firm heterogeneity and imperfect competition for the formation of global production networks and the gains from trade. We develop a quantifiable trade model with (i) two-sided firm heterogeneity, (ii) matching frictions, and (iii) oligopolistic competition upstream. Combining highly disaggregated data on firms' production and trade transactions for China, Chile, and France, we present empirical evidence in line with the model that cannot be rationalized without features (i)-(iii). Downstream French and Chilean buyers import higher volumes and quantities at lower prices when upstream Chinese markets become more competitive. These effects are stronger for larger, more productive buyers. Moreover, Chinese suppliers price discriminate across buyers, charging more diversified downstream producers lower input markups and prices.

Our analysis indicates that global production networks amplify the gains from trade liberalization, and induce important policy interactions through the complementarity in firms' sourcing decisions across origin countries. Buyer-supplier linkages thus mediate international spillovers from national industrial and trade policy. In particular, lower barriers to entry upstream, lower matching costs, and lower trade costs improve firm performance downstream and generate aggregate welfare gains for consumers. Heterogeneous adjustments in sourcing strategy across the buyer productivity distribution imply that policy packages can significantly amplify the overall rise in real income.

Our work opens several promising avenues for future research. Incorporating imperfect competition both upstream and downstream could provide valuable insights into sourcing patterns and gains from trade. While we have studied matching frictions and imperfect competition in a bipartite network of buyers and suppliers, future work could broaden the analysis to complete networks with multiple production stages and roundabout production. Studying the role of reputational contracts and arm's-length vs. intra-firm offshoring would further improve understanding of rent sharing and shock transmission in global value chains.

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Statement of Joint Work

Chapter 1, "Trade Intermediation and Resilience in Global Sourcing," is single-authored by Oscar Perelló. Chapter 2, "Productivity, Matchability and Intermediation in Production Networks," was originally submitted by Oscar Perelló for the Upgrade Seminar at the MPhil in Economics and is now co-authored with Kalina Manova and Andreas Moxnes. Chapter 3, "Global Production Networks and Policy Reforms with Imperfect Competition," is co-authored with Hanwei Huang, Kalina Manova, and Frank Pisch. In the co-authored chapters, all authors have made proportional contributions.

Appendix A

Supplementary Materials for Chapter 1

A.1. Anecdotal Evidence

"Our global supply chain connects thousands of suppliers and vendors with leading brands and retailers, all with the goal of meeting consumer demand. We focus on managing complexity and risk to maximize your profitability."

– Li & Fung, leader intermediary in apparel [link]

"Safety and compliance are the foundation of our supply chain network. We pride ourselves on taking proactive measures to help reduce supplier risk and ensure continual supply of products to our customers."

– Univar Solutions, leader intermediary in chemicals [link]

"Life goes on in these (high-risk) countries despite repeated riots, crises, etc... but we don't establish ourselves there and we remember to put in a buffer on the delivery time."

– Interviews with clothing supply chain actors using intermediaries,
Vedel & Ellegaard (2013) [link]

"Distributors play a critical role in the economy, and this role was elevated during recent unpredictable demand fueled by COVID and the subsequent supply-chain disruptions."

– Article on industrial intermediaries, Boston Consulting Group (2023) [link]

FIGURE A1. Li & Fung – Annual Report (2015)

Our supply chain

We believe in building sustainable supply chains that create value for our customers, factories, workers and communities. We partner with customers and suppliers who share this commitment and collaborate with industry stakeholders to further positive change.

15,000+
SUPPLIERS WORLDWIDE

THREE LARGEST SOURCING MARKETS

1. China
2. Vietnam
3. Bangladesh

At Li & Fung we manage complex and unique supply chains in over 40 economies around the world for our customers. Our global supplier network has been evolving for over 100 years. While over 80% of our sourcing business is with a core group of strategic suppliers, our network also allows us the flexibility to move production across markets, balance capacity constraints and respond to demand, while meeting specific customer needs, such as proximity to the end-consumer or technical expertise and distribution. By sourcing from multiple factories across multiple markets, we can also activate business contingency plans when unexpected issues occur and continue production for our customers.

Our Vendor Support Services (VSS) unit focuses on the needs of our global supplier base as it addresses the challenges facing the industry. In 2015 we developed services to support suppliers to enhance productivity, operational and resource efficiencies and product testing, and to capture performance data along the supply chain. We want to help suppliers mitigate the increasing costs of labor and other inputs by better managing material and resource usage, production swings, operations and logistics.

Addressing challenges and opportunities in our supply chain is integral to our Sustainability Strategy. Our initiatives focus on three areas:

- Managing risk and furthering compliance in our supply chains
- Sourcing responsibly
- Collaborating with customers and partners to build sustainable supply chains

Supply Chain Compliance

Improving workplace conditions and overall factory management practices brings benefits to workers, suppliers, factories and communities. Each of the locations in our supply chain has a unique set of challenges that we manage through our network of on-the-ground teams and in collaboration with industry and non-profit organizations and local authorities.

Managing our supply chain risk starts with strategic sourcing decisions by our customers and/or sourcing teams and our continuing efforts to direct business to suppliers that share our commitment to compliance and enhancing sustainability performance. Our Vendor Compliance & Sustainability (VCS) team assesses supplier risk and compliance and supports factories to continually improve performance.

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Figure A2. Univar Solutions – End of Year Note to Customers (2021)

Managing supply through a resilient and reliable network

Looking ahead to a new year

It's hard to believe another year is coming to an end. While 2021 had more than its share of challenges, the growth in our customer and supplier relationships will serve us all well in the new year. We are hopeful we will put many of the supply challenges behind us in 2022.

While many factors have created widespread product availability issues in 2021, the situation allowed our team to work with existing suppliers in creative new ways to ensure supply continuity by securing supply routes and finding new sources to keep customers running. Pairing our domestic and global network of manufacturers with our local sales and technical teams proved invaluable to keeping our customers supplied. We plan to keep those communications channels open in the new year and provide our customers with the products and services needed to help keep our communities healthy, fed, clean, operating and safe.

As your partner, we will continue leveraging our extensive geographic footprint and premier producer partners to give our customers an advantage in situations such as supplying materials that require steel drums. We will also remain vigilant in managing supply through reliable freight deliveries, reliable/sustainable packaging, warehousing/inventory, and secure supply routes from our supplier network.

While no one can fully predict what 2022 will bring, Univar Solutions takes pride and is in a position to help our customers operate, overcome and plan for the challenges that remain in place going into 2022, as well as new challenges that arise to minimize disruptions. We are here for our customers, providing continuity to your business with teams of logistics experts, an extensive distribution network comprised of a significant private truck fleet, account managers, product managers, scientists, chemists and technical advisors to find your next solution.

2021 has taught us a lot about the global production base and supply chains. We have been nimble and challenged like most; but we have learned a lot in the process. We are using those learnings and focusing on improving your customer experience.

The new year will start fast as it always does. Your Univar Solutions team will be ready. Please work with your representative early to help you get what you need when you need it.

Thank you for the trust you place in our team every day. We do not take it for granted.

Have a wonderful and safe holiday season!

Largest & Most Local Distribution Network (60 Minutes Away)

Our objectives are focused on customer success and include:

- **Safe handling and on-time delivery**
- **Leverage strong position with local manufacturing and supply chains**
- **Offer technical and application development expertise**
- **Expansion of key supplier relationships**
- **Enabling customers and suppliers ESG objectives**
- **Help customers unlock value using our Solution Centers**
- **Enabling sustainable solutions by offering more sustainably sourced, clean label products**

A.2. Empirical Appendix

Data Sources and Management

Firm-to-Firm Trade and Intermediaries

- Customs Service of Chile (*Servicio Nacional de Aduanas*)
  - Importer tax ID, foreign supplier name, origin country, product (HS6), value, quantity, and unit value for the universe of import transactions (2005–2019).
- Tax Authority of Chile (*Servicio de Impuestos Internos*)
  - Firm tax ID, industry, sub-industry, primary activity, size (sales bins), number of

employees, age, and location for the universe of Chilean firms (2005–2019).

- I merge these datasets using the unique tax identifier (RUT) for Chilean firms.

Cleaning Procedure for Supplier Names

To address misreporting and spelling mistakes in the digitalized names of foreign suppliers, I implement the following cleaning routine.

- Drop observations without a name (15%).
- Suppress non-numerical characters and spaces within names.
- Remove spaces at the beginning and end of each name
- Trim names to their 30 first characters.
- Harmonize common abbreviations for Limited, Corporation, Company, Incorporated, etc.
- Collapse suppliers with the same name within origin country-product-buyer combinations.

Risk Measures

- Geopolitical Risk Index (Caldara and Iacoviello 2022) and Economic Policy Uncertainty Index (Baker et al. 2016) by origin country and year (2010–2019).[1]
- Trade Volatility Index by origin country, product (HS6) and year, using data on global trade flows by origin country, product (HS6), destination, and year (2010–2019) from the *CEPII* database (Gaulier and Zignago 2010).

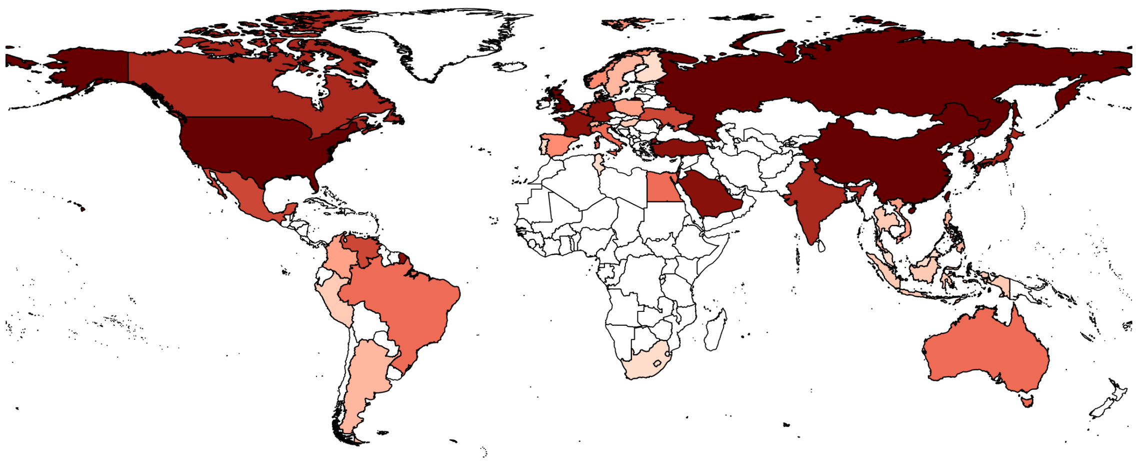
TABLE A1. Pairwise Correlations across Risk Measures (origin-country level)

	Geopolitical Risk	Economic Uncertainty	Trade Volatility
Geopolitical Risk	1.000	–	–
Economic Uncertainty	0.422	1.000	–
Trade Volatility	0.343	0.401	1.000

Notes: This table presents pairwise correlations for the three risk measures defined in Section 1.2.1 in year 2019. The Geopolitical Risk (GPR) and Economic Policy Uncertainty (EPU) indexes are defined at the origin-country level. Trade Volatility is built across origin-products and then aggregated at the country level to compute correlations.

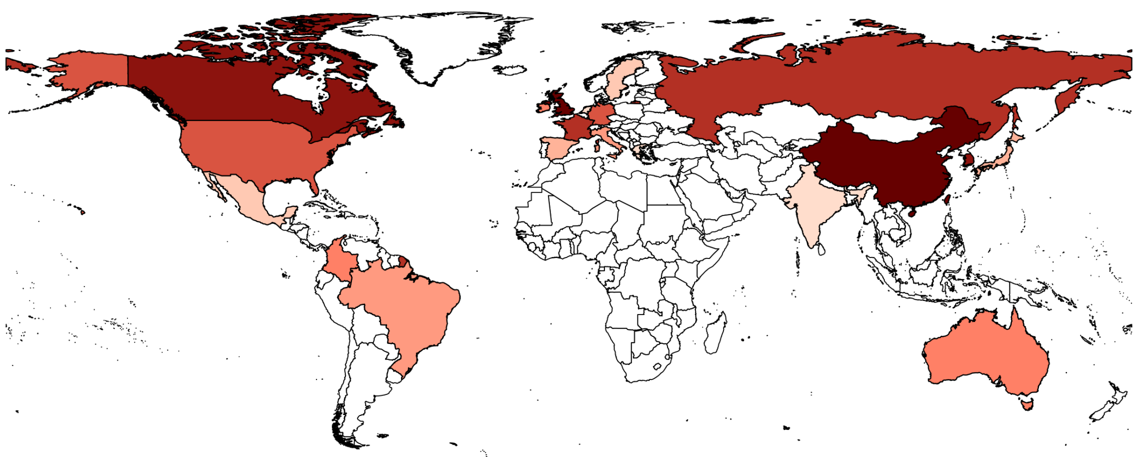
[1] The original monthly data is aggregated by year and each index is normalized between 0 and 1.

Figure A3. Geopolitical Risk Index (GPR)



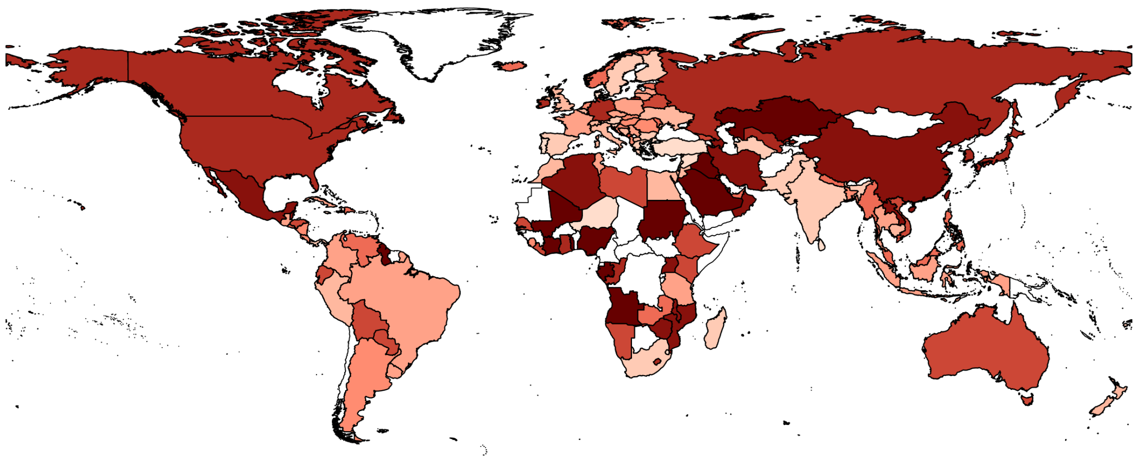
Notes: This figure displays a heat map for the Geopolitical Risk (GPR) index developed by Caldara and Iacoviello (2022), using data for 2019. The index is normalized between 0 and 1, and the map considers 10 levels of intensity.

Figure A4. Economic Policy Uncertainty Index (EPU)



Notes: This figure displays a heat map for the Economic Policy Uncertainty (EPU) index developed by Baker et al. (2016), using data for 2019. The index is normalized between 0 and 1, and the map considers 10 levels of intensity.

Figure A5. Trade Volatility Index



Notes: This figure displays a heat map for the Trade Volatility index developed in Section 1.2.1, considering data for 2019. The index is built across origin-products and then aggregated at the origin-country level. The map considers 10 levels of intensity.

Additional Data Sources

- Other country characteristics
  - Trade procedures and GDP per capita (World Development Indicators), and Total Factor Productivity (Penn World Table 9.1) by origin country and year (2010–2019).
- Data on export prices
  - I collect additional data from the Customs Service of Chile: exporter tax ID, destination country, product (HS6), and unit value for all transactions (2005–2019).

Additional Evidence on Stylized Facts

TABLE A2. Number and Concentration of Suppliers (homogeneous goods)

	(log) # suppliers		HHI suppliers	
	(1)	(2)	(3)	(4)
Intermediary Dummy	0.044***	0.036***	-0.016***	-0.012***
	(0.007)	(0.008)	(0.002)	(0.003)
Firm size (sales)	Yes	Yes	Yes	Yes
Imported value	Yes	Yes	Yes	Yes
Product - country FE	Yes	Yes	Yes	Yes
Observations	120,930	42,543	120,930	42,543

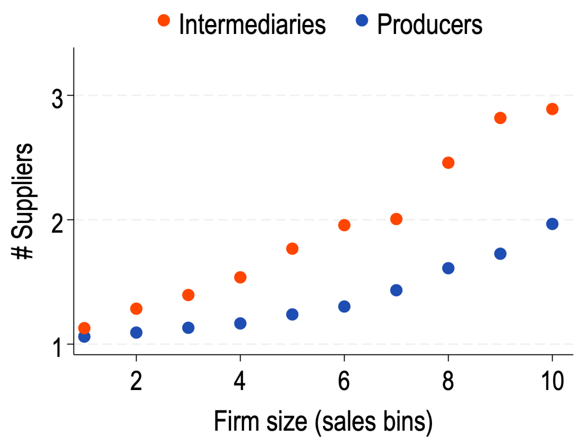
Notes: This table replicates Table 1.3 for the subsets of homogeneous goods according to the Rauch classification. Columns (1) and (3) exclude products classified as *differentiated* from the sample. Columns (2) and (4) consider only goods classified as *homogeneous* (i.e., goods traded on an organized exchange or where a reference price is available). All regressions are at the firm-product (HS6)-origin country level. The independent variable is a dummy indicating whether the buyer is a wholesaler. The sample includes all import transactions in Chile in 2019. Standard errors are clustered at the firm level.

TABLE A3. Probability of Supply Link Separations (demand controls)

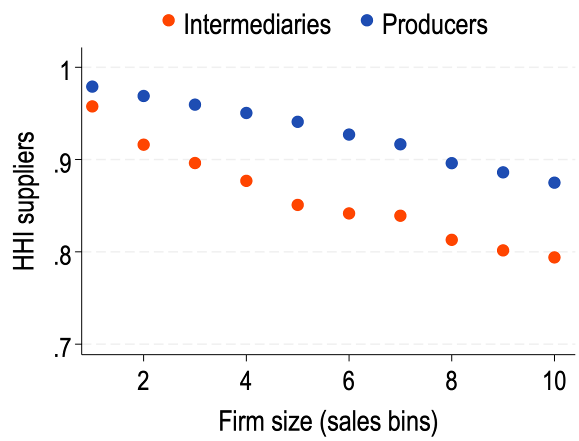
	Firm-product-country			Firm-product-country-supplier		
	(1)	(2)	(3)	(4)	(5)	(6)
Intermediary dummy	-0.078***	-0.063***	-0.061***	-0.060***	-0.048***	-0.046***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Δ Firm-level imports	Yes	No	Yes	Yes	No	Yes
Δ Firm-level suppliers	No	Yes	Yes	No	Yes	Yes
Firm size (sales)	Yes	Yes	Yes	Yes	Yes	Yes
Imported value	Yes	Yes	Yes	Yes	Yes	Yes
Number of suppliers	Yes	Yes	Yes	No	No	No
Product - country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	284,115	284,115	284,115	400,938	400,938	400,938

Notes: This table replicates Table 1.4 including controls for changes in demand conditions across buyers: changes in firm-level imports and suppliers. The dependent variable is a dummy indicating whether supply links break from period t to $t + 1$. The independent variable indicates whether the buyer is a wholesaler. The sample considers all import transactions in 2018 for firms active in both 2018 and 2019. Standard errors are clustered at the firm level.

FIGURE A6. Number and Concentration of Suppliers (weighted average)



(A) # suppliers per firm-product-origin



(B) Input Concentration across suppliers

Notes: Panel A displays the number of suppliers that a firm has per product (HS6) and origin country. Panel B computes a Herfindahl-Hirschman index (HHI) across suppliers. Each panel groups firms into 10 bins according to total sales (Tax Authority of Chile, SII). Within each bin, a dot represents the mean value of the variable on the y-axis. Since firms source multiple products from multiple countries, I consider the weighted-average across products and origin countries within a firm. Weights are determined by imported values, reducing the influence of peripheral inputs and markets. The figure considers cross-sectional data for year 2019.

A.3. Theory Appendix

Proof of Proposition 1

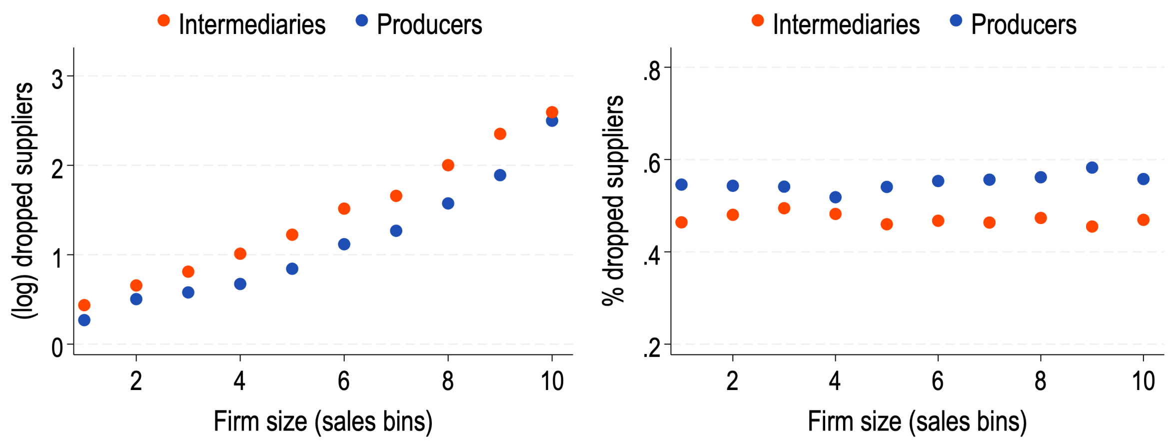
Let's first derive the expression for *ex-post* profits conditional on network operability. Recall the *ex-post* maximization problem of producer ω in the single-location case:

$$\max_{p_i(\omega), q_i(\omega), x_{il}(\omega)} \pi_i^{\text{ex-post}}\left(\omega \,\middle|\, M_l, S_l^D, Z_l\right) = \left[p_i(\omega) - c_i\left(\omega \,\middle|\, M_l, S_l^D, Z_l\right)\right] q_i(\omega)$$

Considering the linear production technology $q_i(\omega) = \varphi(\omega) x_{il}(\omega)$, input purchases are determined by downstream quantities. We then have the standard firm problem with monopolistic competition and CES demand $q_i(\omega) = p_i(\omega)^{-\sigma} P_i^{\sigma-1} E_i$, which can be expressed in terms of downstream prices alone. Omitting indexes, the first-order condition is $q(p) + pq'(p) - cq'(p) = 0$, and producers set a constant markup $p = \frac{\sigma}{\sigma-1} c$ such that:

$$\pi_i^{\text{ex-post}} = c(\omega)^{1-\sigma} \frac{1}{\sigma} \left(\frac{\sigma}{\sigma - 1}\right)^{1-\sigma} P_i^{\sigma-1} E_i$$

FIGURE A7. Number and Share of Dropped Suppliers (weighted average)



(A) # dropped suppliers per firm-product-origin (B) % dropped suppliers per firm-product-origin

Notes: Panel A displays the number of dropped suppliers per product (HS6) and origin country across firms. Panel B is analogous for the share of dropped suppliers. Drops are defined as links active in year t but not in $t+1$. Each panel groups firms into 10 bins according to total sales (Tax Authority of Chile, SII). Within each bin, a dot represents the mean value of the variable on the y-axis. Since firms source multiple products from multiple countries, I consider the weighted-average across products and origin countries within a firm. Weights are determined by imported values, reducing the influence of peripheral inputs and markets. The figure displays cross-sectional data for year 2019.

where the marginal cost is given by input prices in the single location available, $c(\omega) = \frac{p^{x,M}}{\varphi(\omega)}$. Thus, *ex-post* profits under indirect sourcing can be expressed as a fraction of those under direct sourcing:

$$\pi_i^{\text{ex-post}}(M_l = I) = \varphi(\omega)^{\sigma-1}(\kappa p^x)^{1-\sigma}\frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} P_i^{\sigma-1}E_i = \kappa^{1-\sigma}\pi_i^{\text{ex-post}}(M_l = D)$$

where $\kappa \geq 1$ and $\sigma > 1$.

For the second part, note that $\sigma > 1$ implies that *ex-post* profits are supermodular in firm productivity $\varphi(\omega)$ and a function $\phi(\kappa) \equiv \frac{1}{\kappa p^x}$, which is analogous to the *sourcing capability* defined in the multi-location case. This implies *complementarities* between $\varphi(\omega)$ and κ. Formally, the brokerage fee reduces *ex-post* profits $\left(\frac{\partial \pi_i^{\text{ex-post}}}{\partial \kappa} < 0\right)$, and this effect becomes more negative with higher productivity levels $\left(\frac{\partial^2 \pi_i^{\text{ex-post}}}{\partial \varphi\, \partial \kappa} < 0\right)$.

Table A4. Potential Mechanisms for Differences in Link Separations

	Firm-product-country-supplier				
	(1)	(2)	(3)	(4)	(5)
Intermediary dummy	-0.092***	-0.060***	-0.068***	-0.069***	-0.024***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Supplier FE	No	Yes	No	No	Yes
Share in supplier's sales	No	No	Yes	No	Yes
Supplier-product links	No	No	No	Yes	Yes
Firm size (sales)	Yes	Yes	Yes	Yes	Yes
Imported value	Yes	Yes	Yes	Yes	Yes
Product - country FE	Yes	Yes	Yes	Yes	Yes
Observations	406,481	352,770	406,481	406,481	352,770

Notes: This table explores mechanisms behind the lower supplier separation rates of intermediaries. Column (1) is identical to column (6) in Table 1.4. Column (2) includes supplier fixed effects to account for the possibility that intermediaries are better at screening suppliers. Column (3) controls for the share of buyers in suppliers' total sales to address whether intermediaries are more important customers. Column (4) defines supply links at the buyer-supplier-product level to assess if differences are driven by intermediaries sourcing multiple products per supplier. Column (5) combines all potential mechanisms.

Proof of Proposition 2

Part (a). Consider the probability that a supply network in location l is operational, $\Pr\left(S_l^O(\omega) \geq 1\right)$, conditional on a sourcing strategy $\left(M_l(\omega), S_l^D(\omega)\right)$. Under direct sourcing, we need this probability to increase with the number of direct links:

$$\Pr\left(S_l^O(\omega) \geq 1 \,\middle|\, D, S+1\right) > \Pr\left(S_l^O(\omega) \geq 1 \,\middle|\, D, S\right) \quad \forall S \in \mathcal{N}$$

Since links are disrupted with exogenous probability ζ_l^D, the number of *operational* suppliers $S_l^O(\omega)$ follows a Binomial distribution, such that:

$$\Pr\left(S_l^O(\omega) \geq 1 \,\middle|\, D, S\right) = 1 - \Pr\left(S_l^O(\omega) = 0 \,\middle|\, D, S\right) = 1 - \binom{S}{0}\left(1-\zeta_l^D\right)^0\left(\zeta_l^D\right)^S = 1 - \left(\zeta_l^D\right)^S$$

and we only need $\left(\zeta_l^D\right)^{S+1} < \left(\zeta_l^D\right)^S$ for all $S \in \mathcal{N}$, which holds trivially for $\zeta_l^D \in (0,1)$. Since additional direct matches do not affect input prices, this implies lower expected input costs.

Table A5. Number of Suppliers and Supply Chain Risk (Producers)

	(log) # suppliers					
	Geopolitical Risk		Economic Uncertainty		Trade Volatility	
	(1)	(2)	(3)	(4)	(5)	(6)
Supply Chain Risk	0.037***	0.043***	0.024***	0.021**	0.046***	0.056***
	(0.005)	(0.009)	(0.007)	(0.009)	(0.002)	(0.002)
Firm size	Yes	Yes	Yes	Yes	Yes	Yes
Imported value	Yes	Yes	Yes	Yes	Yes	Yes
Product FE (HS6)	No	Yes	No	Yes	No	Yes
Origin-country productivity	No	Yes	No	Yes	No	Yes
Origin-country trade costs	No	Yes	No	Yes	No	Yes
Observations	126,671	125,718	108,687	108,088	127,327	125,809

Notes: This table shows how the number of suppliers of producers varies with supply chain risk. All regressions are at the firm-product (HS6)-origin country level. Geopolitical Risk and Economic Policy Uncertainty are measured across origin countries, while Trade Volatility is at the origin-product level. Controls include firm sales (10 bins), imports per buyer-product-origin, and the origin country's total factor productivity and trade procedures. The sample includes all import transactions by wholesalers in 2019. Standard errors are clustered at the level of the risk measure.

Part (b). Using the probabilities for network operability derived above, the expected *ex-ante* profits of producer ω under the direct sourcing strategy $\left(D, S^D\right)$ are:

$$\begin{aligned}\mathbb{E}\left[\pi^{\text{ex-ante}}(\omega)\,\middle|\,D, S^D\right] &= \left[1-\left(\zeta^D\right)^{S^D}\right]\pi^{\text{ex-post}}(\omega, D) - f^D\left(S^D\right)\\ &= \chi(S^D)\,\varphi(\omega)^{\sigma-1}\left(p^x\right)^{1-\sigma}B - f^D\left(S^D\right)\end{aligned}$$

where $\chi(S^D) \equiv \left[1-\left(\zeta^D\right)^{S^D}\right]$ and $B \equiv \frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} P^{\sigma-1}E$. Consider two firms with productivity levels $\varphi^H > \varphi^L$ that, conditional on direct sourcing, choose to match with $S^{D,H}$ and $S^{D,L}$ suppliers. These choices are optimal if:

$$\chi(S^{D,H})\left(\varphi^H\right)^{\sigma-1}\left(p^x\right)^{1-\sigma}B - f^D\left(S^{D,H}\right) \geq \chi(S^{D,L})\left(\varphi^H\right)^{\sigma-1}\left(p^x\right)^{1-\sigma}B - f^D\left(S^{D,L}\right) \quad \text{(A1)}$$

$$\chi(S^{D,H})\left(\varphi^L\right)^{\sigma-1}\left(p^x\right)^{1-\sigma}B - f^D\left(S^{D,H}\right) \leq \chi(S^{D,L})\left(\varphi^L\right)^{\sigma-1}\left(p^x\right)^{1-\sigma}B - f^D\left(S^{D,L}\right) \quad \text{(A2)}$$

Combining inequalities (A1) and (A2) we get:

$$\left[\chi(S^{D,H}) - \chi(S^{D,L})\right]\left[\left(\varphi^H\right)^{\sigma-1} - \left(\varphi^L\right)^{\sigma-1}\right]\left(p^x\right)^{1-\sigma}B \geq 0 \quad \text{(A3)}$$

This implies that if $\varphi^H \geq \varphi^L$, then $\chi(S^{D,H}) \geq \chi(S^{D,L})$ and therefore $S^{D,H} \geq S^{D,L}$. Note that the number of suppliers affects expected profits through $\chi(S^D)$ but not p^x, which relies on perfect

Table A6. Number of Suppliers and Supply Chain Risk (Intermediaries)

	(log) # suppliers					
	Geopolitical risk		Economic uncertainty		Trade volatility	
	(1)	(2)	(3)	(4)	(5)	(6)
Supply chain risk	0.040**	0.054***	0.042***	0.032***	0.057***	0.066***
	(0.015)	(0.011)	(0.008)	(0.011)	(0.002)	(0.002)
Firm size	Yes	Yes	Yes	Yes	Yes	Yes
Imported value	Yes	Yes	Yes	Yes	Yes	Yes
Product FE (HS6)	No	Yes	No	Yes	No	Yes
Origin-country productivity	No	Yes	No	Yes	No	Yes
Origin-country trade costs	No	Yes	No	Yes	No	Yes
Observations	190,945	189,323	166,198	165,679	189,742	186,800

Notes: This table shows how the number of suppliers of intermediaries varies with supply chain risk. All regressions are at the firm-product (HS6)-origin country level. Geopolitical Risk and Economic Policy Uncertainty are measured across origin countries, while Trade Volatility is at the origin-product level. Controls include firm sales (10 bins), imports per buyer-product-origin, and the origin country's total factor productivity and trade procedures. The sample includes all import transactions by wholesalers in 2019. Standard errors are clustered at the level of the risk measure.

supplier substitution within locations. However, this result holds when relaxing this assumption, in which case additional suppliers can reduce input prices (e.g., due to better matches under search frictions or lower markups with imperfect competition) or increase them (e.g., due to less productive suppliers).[2]

Proof of Proposition 3

Part (a). For intermediation to increase operability, we need this probability to increase relative to sourcing directly from one supplier:

$$\Pr\left(S_l^O(\omega) \geq 1 \,\middle|\, I\right) > \Pr\left(S_l^O(\omega) \geq 1 \,\middle|\, D, 1\right), \text{ where } \Pr\left(S_l^O(\omega) \geq 1 \,\middle|\, I\right) = 1 - \left(\zeta_l^I\right)^{S_l^I}$$

Since the intermediation technology exhibits $\left\{S_l^I \geq S_l^D, \zeta_l^I \leq \zeta_l^D\right\}$, it follows $\left(\zeta_l^I\right)^{S_l^I} \leq \left(\zeta_l^D\right)$.[3]

Consider now the triplet $\mathcal{I} = \left\{S_l^I \geq 1, \zeta_l^I \leq \zeta_l^D, \kappa \geq 1\right\}$ containing the intermediation technol-

[2]The first case is considered in Section 1.3.6, where producers have two reasons to diversify: lower prices and risk mitigation. In the second case, the price effect reduces the incentives to diversify, but it remains true that more productive firms are more likely to afford it.

[3]Although this analysis considers independent disruptions on supply links, it is possible to incorporate correlated shocks. As discussed in the extensions, producers may face location-level disruptions affecting all l-suppliers with some probability ξ_l.

TABLE A7. Number of Suppliers and Supply Chain Risk (Interactions)

	(log) # suppliers					
	Geopolitical Risk		Economic Uncertainty		Trade Volatility	
	(1)	(2)	(3)	(4)	(5)	(6)
Intermediary Dummy	0.049**	0.049***	0.055***	0.054***	0.047***	0.048***
	(0.019)	(0.011)	(0.006)	(0.005)	(0.002)	(0.002)
Intermediary × Supply Chain Risk	0.040***	0.003	0.039***	0.015***	0.057***	0.011***
	(0.014)	(0.004)	(0.006)	(0.004)	(0.002)	(0.002)
Firm size (sales)	Yes	Yes	Yes	Yes	Yes	Yes
Imported value	Yes	Yes	Yes	Yes	Yes	Yes
Product FE (HS6)	Yes	No	Yes	No	Yes	No
Product - Country FE	No	Yes	No	Yes	No	Yes
Observations	317,239	299,476	274,470	264,208	316,783	295,383

Notes: This table shows how the number of suppliers of producers and intermediaries varies with supply chain risk, including interactions for intermediaries. All regressions are at the firm-product (HS6)-origin country level. Geopolitical Risk and Economic Policy Uncertainty are measured at the origin-country level, while Trade Volatility is at the origin country-product level. Controls include firm sales (10 bins), imports per buyer-product-origin, and the origin country's total factor productivity and trade procedures. The sample includes all import transactions by wholesalers in 2019. Standard errors are clustered at the level of the risk measure.

ogy and brokerage fee to access inputs in location l, and expected input costs $\mathbb{E}\Big[\big(p^x_{il}\big)^{1-\sigma}\,\big|\,M_l, S^D_l\Big]$ given a sourcing strategy $\{M_l, S^D_l\}$. I define a mapping $\tilde{S}^I_l$ that transforms $\mathcal{I}$ into an *equivalent* number of direct suppliers:

$$\tilde{S}^I_l(\mathcal{I}) \equiv \left\{S : \mathbb{E}\Big[\big(p^x_{il}\big)^{1-\sigma}\,\big|\,D, S\Big] = \mathbb{E}\Big[\big(p^x_{il}\big)^{1-\sigma}\,\big|\,I\Big]\right\}$$

Under independent disruptions across links the number of operational suppliers follows a Binomial distribution, such that:

$$\begin{aligned} \Big[1-(\zeta^D_l)^{\tilde{S}^I_l}\Big]\big(p^x_{il}\big)^{1-\sigma} &= \frac{\big[1-(\zeta^I_l)^{S^I_l}\big]}{\kappa^{\sigma-1}}\big(p^x_{il}\big)^{1-\sigma} \\ \iff \tilde{S}^I_l &= \frac{\ln\left(1-\dfrac{1-(\zeta^I_l)^{S^I_l}}{\kappa^{\sigma-1}}\right)}{\ln(\zeta^D_l)} > 0 \end{aligned} \tag{A4}$$

For the numerator in (A4) to be well-defined, we need $\left(1-\dfrac{1-(\zeta^I_l)^{S^I_l}}{\kappa^{\sigma-1}}\right) > 0$, which is always satisfied considering that $\kappa^{\sigma-1} \geq 1$ for $\sigma > 1$ and $\left(1-(\zeta^I_l)^{S^I_l}\right) \in (0,1)$. On the other hand, the

TABLE A8. Correlation across Supply Link Separations (firm-origin-product)

	Average correlation (ρ)				
	1 supplier	2 suppliers	3 suppliers	4 suppliers	5 suppliers
All firms	–	0.067	0.090	0.092	0.085
Producers	–	0.093	0.094	0.103	0.109
Wholesalers	–	0.051	0.088	0.085	0.071

Notes: This table reports the average correlation across link separations at the buyer-origin country-product (HS6) level. The analysis is conducted separately for observations with $N = \{2, 3, 4, 5\}$ suppliers. The probabilistic event is represented by a binary variable indicating whether a link active in period t will break in $t + 1$. Pairwise correlations are computed for each combination of links (i, j) given N, such that ρ reports the average across pairs. The sample includes all producers in 2018 that remain active in 2019.

denominator is well-defined for $\zeta_l^D \in (0, 1)$. Since both the numerator and denominator take negative values, we have $\tilde{S}_l^I > 0$. Intermediation then reduces (increases) expected input costs for firms that can match fewer (more) than $\tilde{S}_l^I$ suppliers directly.

Part (b). Consider two firms with productivity levels $\varphi^H > \varphi^L$ and sourcing modes M^H and M^L. The proposition requires that $M^H = I$ and $M^L = D$ cannot be optimal, which can be shown by contradiction. If $M^H = I$ and $M^L = D$ are optimal, they must satisfy the following conditions:

$$\chi(D, S^{D,H}) \left(\varphi^H\right)^{\sigma-1} \left(p^x\right)^{1-\sigma} B - f^D\left(S^{D,H}\right) \leq \chi(I) \left(\varphi^H\right)^{\sigma-1} \left(p^x\right)^{1-\sigma} B - f^I \tag{A5}$$

$$\chi(D, S^{D,L}) \left(\varphi^L\right)^{\sigma-1} \left(p^x\right)^{1-\sigma} B - f^D\left(S^{D,L}\right) \geq \chi(I) \left(\varphi^L\right)^{\sigma-1} \left(p^x\right)^{1-\sigma} B - f^I \tag{A6}$$

where $\chi(M, S^D) \equiv \left[1 - \left(\zeta^D\right)^{S^D}\right]$ under direct sourcing, $\chi(I) \equiv \frac{1}{\kappa^{\sigma-1}}\left[1 - \left(\zeta^I\right)^{S^I}\right]$ under indirect sourcing, and $S^{D,H}$ and $S^{D,L}$ are the best direct options for each firm. In the case of φ^H, this implies that $M^H = I$ is also preferred to $S^{D,L}$. Replacing this in (A5) we get:

$$\chi(D, S^{D,L}) \left(\varphi^H\right)^{\sigma-1} \left(p^x\right)^{1-\sigma} B - f^D\left(S^{D,L}\right) \leq \chi(I) \left(\varphi^H\right)^{\sigma-1} \left(p^x\right)^{1-\sigma} B - f^I \tag{A7}$$

and combining (A7) with the condition for φ^L to source directly (A6), we obtain:

$$\left[\chi(I) - \chi(D, S^{D,L})\right]\left[\left(\varphi^H\right)^{\sigma-1} - \left(\varphi^L\right)^{\sigma-1}\right]\left(p^x\right)^{1-\sigma} B \geq 0 \tag{A8}$$

The inequality (A8) requires $\chi(I) > \chi(D, S^{D,L})$. However, in that case it would not be optimal for φ^L to source directly in the first place: since $f^I < f^D(S)$, the condition (A6) would not be satisfied, leading to a contradiction.

I now derive the productivity threshold φ_l^* where producers switch from indirect to direct sourcing. Given the higher intercept of $\mathbb{E}\left[\pi_i^{\text{ex-ante}} \middle| I\right]$ and the monotonicity of expected *ex-ante* profits in φ, producers move to direct sourcing after the first direct curve $\mathbb{E}\left[\pi_i^{\text{ex-ante}} \middle| D, S_l^D\right]$ crosses the indirect curve from below. The intersections for each $S_l^D \in \mathcal{S}_l$ are:

$$\mathbb{E}\left[\pi_i^{\text{ex-ante}} \middle| D, S_l^D\right] = \mathbb{E}\left[\pi_i^{\text{ex-ante}} \middle| I\right]$$

$$\iff \varphi_l^*(S_l^D) = \left(\frac{f_l^D\left(S_l^D\right) - f_l^I}{\left(1 - (\zeta_l^D)^{S_l^D} - \frac{1-(\zeta_l^I)^{S^I}}{\kappa^{\sigma-1}}\right)\left(P_{il}^x\right)^{1-\sigma} B} \right)^{\frac{1}{\sigma-1}} \quad \text{for } S_l^D \in \mathcal{S}_l \tag{A9}$$

We can then define the switching threshold as the minimum of the thresholds in (A9):

$$\varphi_l^* = \min_{S_l^D} \varphi_l^*(S_l^D) \text{ for } S_l^D \in |\mathcal{S}_l| \tag{A10}$$

Note that $\varphi_l^* > 0$ if $\frac{1-(\zeta_l^I)^{S^I}}{1-(\zeta_l^D)^{S_l^D}} < \kappa^{\sigma-1}$ for some S_l^D, while all producers would source indirectly otherwise (i.e., indirect *ex-ante* profits do not intersect with any of the direct *ex-ante* profits for positive values of φ).

It can be shown that the following condition is required for both indirect and direct sourcing to take place:

$$\frac{\kappa^{\sigma-1} f_l^I}{f_l^D(S_l^D)} < \frac{1 - (\zeta_l^I)^{S^I}}{1 - (\zeta_l^D)^{S_l^D}} < \kappa^{\sigma-1} \quad \forall\, S_l^D \in \mathcal{S}_l$$

Consider a set of productivity cutoffs $\left\{\varphi_l^D(S_l^D)\right\}$ such that, under direct sourcing and a particular choice $S_l^D \in \mathcal{S}_l$, expected *ex-ante* profits are zero. Each cutoff is unique as *ex-ante* expected profits are monotonically increasing in φ.

$$\mathbb{E}\left[\pi_i^{\text{ex-ante}} \middle| D, S_l^D\right] = 0 \iff \varphi_l^D(S_l^D) = \left(\frac{f_l^D\left(S_l^D\right)}{\left(1 - (\zeta_l^D)^{S_l^D}\right)\left(P_{il}^x\right)^{1-\sigma} B} \right)^{\frac{1}{\sigma-1}} \quad \text{for } S_l^D \in \mathcal{S}_l \tag{A11}$$

Analogously, φ_l^I sets expected *ex-ante* profits to zero under indirect sourcing:

$$\mathbb{E}\Big[\pi_i^{\text{ex-ante}}\,\Big|\,I\Big]=0 \iff \varphi_l^I=\left(\frac{\kappa^{\sigma-1}f_l^I}{\Big(1-(\zeta_l^I)^{S^I}\Big)\Big(P_{il}^x\Big)^{1-\sigma}B}\right)^{\frac{1}{\sigma-1}} \tag{A12}$$

For a positive mass of producers to source indirectly, we need both $\mathbb{E}\big[\pi_i^{\text{ex-ante}}\,\big|\,I\big]>0$ and $\mathbb{E}\big[\pi_i^{\text{ex-ante}}\,\big|\,I\big]>\mathbb{E}\big[\pi_i^{\text{ex-ante}}\,\big|\,D,S_l^D\big]$ for all $S_l^D\in\mathcal{S}_l$ in some productivity range. The monotonicity of expected profits ensures that $\mathbb{E}\big[\pi_i^{\text{ex-ante}}\,\big|\,I\big]$ and each curve $\mathbb{E}\big[\pi_i^{\text{ex-ante}}\,\big|\,D,S_l^D\big]$ intersect at most once. Since $f_l^I\geq f_l^D(S_l^D)$ for all $S_l^D\in\mathcal{S}_l$, this can only occur if expected indirect profits reach the zero-profit threshold before all direct curves.[4] From (A11) and (A12) we have:

$$\varphi_l^I<\varphi_l^D(S_l^D)\ \ \forall\ S_l^D\in\mathcal{S}_l \iff \frac{1-(\zeta_l^I)^{S_l^I}}{1-(\zeta_l^D)^{S_l^D}}>\frac{\kappa^{\sigma-1}f_l^I}{f_l^D(S_l^D)}\ \ \forall\ S_l^D\in\mathcal{S}_l \tag{A13}$$

This provides a technological condition for intermediation to take place: the resilience of intermediated networks must be high enough to compensate for the brokerage fee, once adjusted for reductions in matching costs.

Proof of Proposition 4

Part (a). From Proposition 3, the productivity cutoff φ_l^I above which indirect sourcing generates positive expected *ex-ante* profits is given by (A12), which is a function of the indirect disruption probability ζ_l^I:

$$\varphi_l^I(\zeta_l^I)=\left(\frac{\kappa^{\sigma-1}f_l^I}{\Big(1-(\zeta_l^I)^{S^I}\Big)\Big(p_{il}^x\Big)^{1-\sigma}B}\right)^{\frac{1}{\sigma-1}}$$

Assuming that the technological condition for intermediation (A13) is satisfied, there is a positive mass of firms sourcing indirectly starting from this cutoff. Given final demand B, the

[4] If some direct curve reaches zero-profits before, then all producers opt for direct sourcing. The technological condition above guarantees that this is not the case.

change in φ_l^I with respect to small changes in ζ_l^I is:

$$\frac{\partial \varphi_l^I(\zeta_l^I)}{\partial \zeta_l^I} = \frac{1}{\sigma-1}\left(\frac{\kappa^{\sigma-1} f_l^I}{\left(1-(\zeta_l^I)^{S^I}\right)\left(p_{il}^x\right)^{1-\sigma} B}\right)^{\frac{1}{\sigma-1}-1} \frac{\partial\left(1-(\zeta_l^I)^{S^I}\right)^{-1}}{\partial \zeta_l^I} \frac{\kappa^{\sigma-1} f_l^I}{\left(p_{il}^x\right)^{1-\sigma} B}$$

$$= \frac{1}{\sigma-1}\, \varphi_l^I(\zeta_l^I)\, \frac{S^I(\zeta_l^I)^{S^I-1}}{1-(\zeta_l^I)^{S^I}} \quad > 0$$

This expression is positive given that $\sigma > 1$, $\zeta_l^I \in (0,1)$, $S^I \in \mathbb{N}^+$, and $\varphi_l^I(\zeta_l^I) > 0$. Thus, the threshold $\varphi_l^I(\zeta_l^I)$ increases and some indirect buyers stop sourcing indirectly.

Part (b). Consider now the productivity threshold where firms switch from indirect to direct sourcing, φ_l^*, as defined in (A9). This is a function of direct ζ_l^D and indirect ζ_l^I disruption probabilities:

$$\varphi_l^*(\zeta_l^D, \zeta_l^I) = \min_{S_l^D}\left[\frac{f_l^D(S_l^D) - f_l^I}{\left(1-(\zeta_l^D)^{S_l^D} - \frac{1-(\zeta_l^I)^{S^I}}{\kappa^{\sigma-1}}\right)\left(P_{il}^x\right)^{1-\sigma} B}\right]^{\frac{1}{\sigma-1}} \quad \text{for } S_l^D \in |\mathbb{S}_l|$$

As before, I assume that the technological condition for intermediation (A13) is satisfied, ensuring that a positive mass of firms sources indirectly. Similarly, I assume $\kappa^{\sigma-1} > \frac{1-(\zeta_l^I)^{S^I}}{1-(\zeta_l^D)^{S_l^D}}$, which ensures $\varphi^*(\zeta_l^D, \zeta_l^I) > 0$ and therefore a positive mass of direct buyers. Since ζ_l^D and ζ_l^I vary in the same proportion, we can write $\zeta \equiv \zeta_l^D$ and $\zeta_l^I = \mu\zeta$ for some factor $\mu \in (0,1)$. Considering $\tilde{S}_l^D$ as the number of direct suppliers that defines the cutoff $\varphi_l^*(\zeta_l)$ and differentiating with respect to ζ we get:

$$\frac{\partial \varphi_l^*(\zeta_l)}{\partial \zeta_l} = \frac{1}{\sigma-1}\left[\frac{f_l^D(\tilde{S}_l^D) - f_l^I}{A(\zeta_l)\left(P_{il}^x\right)^{1-\sigma} B}\right]^{\frac{1}{\sigma-1}-1} \frac{\partial A^{-1}(\zeta_l)}{\partial \zeta_l} \frac{\left(f_l^D(\tilde{S}_l^D) - f_l^I\right)}{\left(P_{il}^x\right)^{1-\sigma} B}$$

where the auxiliary mapping is $A(\zeta_l) \equiv \left(1-(\zeta_l)^{\tilde{S}_l^D} - \frac{1-(\mu\,\zeta_l)^{S_l^I}}{\kappa^{\sigma-1}}\right)$, such that:

$$\frac{\partial A(\zeta_l)}{\partial \zeta_l} = -\left(A(\zeta_l)\right)^{-2}\left(\frac{S_l^I\,(\zeta_l)^{S_l^I-1}\,\mu^{S_l^I}}{\kappa^{\sigma-1}} - \tilde{S}_l^D\,(\zeta_l)^{\tilde{S}_l^D-1}\right)$$

Since $\sigma > 1$, $f_l^D(S) > f_l^I$, and $A(\zeta_l) > 0$ under the condition for direct sourcing, we have that $\frac{\partial \varphi_l^*(\zeta)}{\partial \zeta_l} > 0$ when $\frac{\partial A(\zeta_l)}{\partial \zeta} > 0$. This requires the following condition to hold:

$$\left(\zeta_l\right)^{S_l^I - \tilde{S}_l^D} \left(\frac{S_l^I}{\tilde{S}_l^D}\right) < \left(\frac{\kappa^{\sigma-1}}{\mu^{S_l^I}}\right)$$

This is satisfied as long as the probability of disruptions ζ_L is not particularly high. In fact, noting that the RHS is always greater than one and defining $d \equiv S_l^I - \tilde{S}_l^D \geq 1$, a sufficient condition is $\zeta < \left(\frac{\tilde{S}_l^D}{\tilde{S}_l^D + d}\right)^{1/d}$. Since the upper bound increases with $\tilde{S}_l^D$ and d, we can set $\tilde{S}_l^D = d = 1$ to show that $\zeta_l < 0.5$ is sufficient (though not necessary) for $\frac{\partial A(\zeta)}{\partial \zeta} > 0$, in which case firms switch from direct to indirect sourcing in response to risk.

Part (c). Consider an arbitrary number of direct suppliers $S \in \mathcal{S}_l$ and define the productivity cutoff φ_{S+1}^D, which equalizes expected *ex-ante* profits for S and $S+1$ suppliers:

$$\varphi_{S+1}^D(\zeta_l^D) = \left(\frac{f_l^D(S+1) - f_l^D(S)}{\left(1 - (\zeta_l^D)^{S+1} - \left(1 - (\zeta_l^D)^S\right)\right)\left(p_{il}^x\right)^{1-\sigma} B}\right)^{\frac{1}{\sigma-1}} \tag{A14}$$

Following Proposition 2(b), producers with productivity above this cutoff prefer to source from $S+1$ rather than S direct suppliers, while the opposite is true for those below. Differentiating with respect to ζ_l^D we obtain:

$$\frac{\partial \varphi_{S+1}^D(\zeta_l^D)}{\partial \zeta_l^D} = \frac{1}{\sigma - 1}\left[\frac{f_l^D(S+1) - f_l^D(S)}{A(\zeta_l^D)\left(P_{il}^x\right)^{1-\sigma} B}\right]^{\frac{1}{\sigma-1}-1} \frac{\partial A^{-1}(\zeta_l^D)}{\partial \zeta_l^D} \frac{\left(f_l^D(S+1) - f_l^D(S)\right)}{\left(P_{il}^x\right)^{1-\sigma} B}$$

where the auxiliary mapping is now $A(\zeta_l^D) \equiv (\zeta_l^D)^S\left(1 - \zeta_l^D\right) > 0$ and:

$$\frac{\partial A(\zeta_l^D)}{\partial \zeta_l^D} = -\left(A(\zeta)\right)^{-2}\left(S(\zeta_l^D)^S - (S+1)(\zeta_l^D)^{S+1}\right) < 0 \quad \text{for } \zeta_l^D < \frac{S}{S+1}$$

Given that $\sigma > 1$ and $f_l^D(S+1) > f_l^D(S)$, we have that $\frac{\partial \varphi_{S+1}^D(\zeta_l^D)}{\partial \zeta_l^D} < 0$ if the probability of disruptions ζ_l^D is not particularly high. This implies that some producers sourcing directly expand their supply sets. In turn, this condition always holds if $\zeta_l^D < 0.5$, and it becomes more flexible as the number of suppliers increases.

Proof of Proposition 5

Part (a). The expected *ex-ante* profits of producer ω given a sourcing strategy $\vartheta(\omega) \equiv \{L(\omega), M_l(\omega), S_l^D(\omega)\}$ are:

$$\mathbb{E}\Big[\pi^{\text{ex-ante}}(\omega)\,\Big|\,\vartheta(\omega)\Big] = \varphi(\omega)^{\sigma-1}\mathbb{E}\Big[\Theta^{\frac{\sigma-1}{\eta-1}}\,\Big|\,\vartheta(\omega)\Big]\,B \\ - \sum_{L(\omega)} \mathbb{1}_{\{M_l(\omega)=D\}}\, f_l^D\big(S_l^D(\omega)\big) - \sum_{L(\omega)} \mathbb{1}_{\{M_l(\omega)=I\}}\, f_l^I$$

Consider two firms with productivity levels $\varphi^H > \varphi^L$. For readability, denote their sourcing strategies as ϑ^H and ϑ^L, and the associated fixed sourcing costs as $F(\vartheta^H)$ and $F(\vartheta^L)$. For these choices to be optimal, we require:

$$\big(\varphi^H\big)^{(\sigma-1)}\mathbb{E}\Big[\Theta^{\frac{\sigma-1}{\eta-1}}\,\Big|\,\vartheta^H\Big]\,B - F(\vartheta^H) \geq \big(\varphi^H\big)^{(\sigma-1)}\mathbb{E}\Big[\Theta^{\frac{\sigma-1}{\eta-1}}\,\Big|\,\vartheta^L\Big]\,B - F(\vartheta^L) \tag{A15}$$

$$\big(\varphi^L\big)^{(\sigma-1)}\mathbb{E}\Big[\Theta^{\frac{\sigma-1}{\eta-1}}\,\Big|\,\vartheta^H\Big]\,B - F(\vartheta^H) \leq \big(\varphi^L\big)^{(\sigma-1)}\mathbb{E}\Big[\Theta^{\frac{\sigma-1}{\eta-1}}\,\Big|\,\vartheta^L\Big]\,B - F(\vartheta^L) \tag{A16}$$

Combining both inequalities, we obtain:

$$\Big[\mathbb{E}\Big[\Theta^{\frac{\sigma-1}{\eta-1}}\,\Big|\,\vartheta^H\Big] - \mathbb{E}\Big[\Theta^{\frac{\sigma-1}{\eta-1}}\,\Big|\,\vartheta^L\Big]\Big]\Big[\big(\varphi^H\big)^{\sigma-1} - \big(\varphi^L\big)^{\sigma-1}\Big]B \geq 0 \tag{A17}$$

Since $\sigma > 1$, this implies that $\mathbb{E}\Big[\Theta^{\frac{\sigma-1}{\eta-1}}\,\Big|\,\vartheta^H\Big] \geq \mathbb{E}\Big[\Theta^{\frac{\sigma-1}{\eta-1}}\,\Big|\,\vartheta^L\Big]$ for $\varphi^H \geq \varphi^L$. Note that this result does not depend on the specific pattern of disruptions assumed.

Part (b). I first show that expected *ex-ante* profits satisfy increasing differences in the choice of source locations $(\mathbb{1}_l, \mathbb{1}_{l'})$, where $\mathbb{1}_l$ and $\mathbb{1}_{l'}$ are indicator variables for whether l and l' are included in the sourcing strategy. In the case without risk and parameter space $\sigma > \eta$, this holds trivially in the profit function $\pi(\mathbb{1}_l, \mathbb{1}_{l'}) = \varphi^{\sigma-1}\big(\Theta(\mathbb{1}_l, \mathbb{1}_{l'})\big)^{\frac{\sigma-1}{\eta-1}} B - F(\mathbb{1}_l, \mathbb{1}_{l'})$, which implies:

$$\pi(1,1) - \pi(0,1) \geq \pi(1,0) - \pi(0,0) \iff$$

$$\Theta(1,1)^{\frac{\sigma-1}{\eta-1}} - \Theta(0,1)^{\frac{\sigma-1}{\eta-1}} \geq \Theta(1,0)^{\frac{\sigma-1}{\eta-1}} - \Theta(0,0)^{\frac{\sigma-1}{\eta-1}}$$

To extend this result to the case with independent disruptions, consider χ_l and χ_l' as the probabilities that each location is operational. Expected profits satisfy increasing differences if:

$$\mathbb{E}\Big[\pi^{\text{ex-ante}}(1,1)\Big] - \mathbb{E}\Big[\pi^{\text{ex-ante}}(0,1)\Big] \geq \mathbb{E}\Big[\pi^{\text{ex-ante}}(1,0)\Big] - \mathbb{E}\Big[\pi^{\text{ex-ante}}(0,0)\Big] \iff$$

$$\chi_{l'}\chi_l\Theta(1,1)^{\frac{\sigma-1}{\eta-1}} + \chi_{l'}\big(1-\chi_l\big)\Theta(1,0)^{\frac{\sigma-1}{\eta-1}} + \big(1-\chi_{l'}\big)\chi_l\Theta(0,1)^{\frac{\sigma-1}{\eta-1}} + \big(1-\chi_{l'}\big)\big(1-\chi_l\big)\Theta(0,0)^{\frac{\sigma-1}{\eta-1}}$$

$$-\left\{\chi_l\Theta(0,1)^{\frac{\sigma-1}{\eta-1}} + \big(1-\chi_l\big)\Theta(0,0)^{\frac{\sigma-1}{\eta-1}}\right\} \geq \chi_{l'}\Theta(1,0)^{\frac{\sigma-1}{\eta-1}} + \big(1-\chi_{l'}\big)\Theta(0,0)^{\frac{\sigma-1}{\eta-1}} \iff$$

$$\chi_{l'}\chi_l\left[\Theta(1,1)^{\frac{\sigma-1}{\eta-1}} - \Theta(0,1)^{\frac{\sigma-1}{\eta-1}} - \Theta(1,0)^{\frac{\sigma-1}{\eta-1}} + \Theta(0,0)^{\frac{\sigma-1}{\eta-1}}\right] \geq 0$$

where $\chi_{l'}\chi_l > 0$ and the term in brackets is positive under increasing differences without risk, which is satisfied for $\sigma > \eta$. Note that, for simplicity but without loss of generality, I have abstracted from risk in locations other than l and l'.[5]

I next show that expected *ex-ante* profits satisfy increasing differences in the choice of direct suppliers $(S_l^D, S_{l'}^D)$. To ease notation, consider the following mapping:

$$\begin{aligned}\mathsf{K}(S',S) \equiv{}& \chi_{l'}(S')\chi_l(S)\big(\Theta(1,1)\big)^{\frac{\sigma-1}{\eta-1}} + \chi_{l'}(S')\big(1-\chi_l(S)\big)\big(\Theta(1,0)\big)^{\frac{\sigma-1}{\eta-1}} + \\ & \big(1-\chi_{l'}(S')\big)\chi_l(S)\big(\Theta(0,1)\big)^{\frac{\sigma-1}{\eta-1}} + \big(1-\chi_{l'}(S')\big)\big(1-\chi_l(S)\big)\big(\Theta(0,0)\big)^{\frac{\sigma-1}{\eta-1}}\end{aligned} \tag{A18}$$

where $\chi_{l'}(S')$ and $\chi_l(S)$ are the probabilities that locations l' and l are operational given choices S' and S.[6] For increasing differences to hold, we need:

$$\mathbb{E}\Big[\pi^{\text{ex-ante}}(S'+1,S+1)\Big] - \mathbb{E}\Big[\pi^{\text{ex-ante}}(S',S+1)\Big] \geq \mathbb{E}\Big[\pi^{\text{ex-ante}}(S'+1,S)\Big] - \mathbb{E}\Big[\pi^{\text{ex-ante}}(S',S)\Big]$$

$$\iff \mathsf{K}(S'+1,S+1) - \mathsf{K}(S',S+1) \geq \mathsf{K}(S'+1,S) - \mathsf{K}(S',S)$$

$$\iff \Big(\chi_{l'}(S'+1) - \chi_{l'}(S')\Big)\Big(\chi_l(S+1) - \chi_l(S)\Big) *$$

$$\left[\big(\Theta(1,1)\big)^{\frac{\sigma-1}{\eta-1}} - \big(\Theta(0,1)\big)^{\frac{\sigma-1}{\eta-1}} - \big(\Theta(1,0)\big)^{\frac{\sigma-1}{\eta-1}} + \big(\Theta(0,0)\big)^{\frac{\sigma-1}{\eta-1}}\right] \geq 0$$

[5]The assumption of independent disruptions adds tractability but is not necessary for this result. Intuitively, increasing differences in location choices without risk extend to the risk case as long as the contribution of additional locations does not reduce the contribution of current locations. This may not hold if sourcing from l' increases the probability of disruptions in l, but can accommodate global shocks to all locations. However, if shocks are more correlated, the benefits of diversification diminish.

[6]The number of suppliers enters only the probabilities and not the sourcing capability under perfect supplier substitution. However, it is straightforward to extend this result under imperfect supplier substitution as modelled in Section 3.6.

The first two terms are positive as the probability that a location is operational increases with the number of suppliers, while the square brackets contain the condition for increasing differences without risk, which holds for $\sigma > \eta$.

I have shown that expected *ex-ante* profits satisfy increasing differences in $(\mathbb{I}_l, \mathbb{I}_{l'})$ and $(S^D_{l'}, S^D_l)$, while increasing differences in $(\mathbb{I}_l, S^D_l)$ follow trivially. Given that for any choice $(\mathbb{I}_l, S^D_{l'}, \cdot)$ we have $\mathbb{E}\Big[\pi^{\text{ex-ante}}(\mathbb{I}_l, S^D_l, \cdot)\Big] = \varphi^{\sigma-1}\mathsf{K}(\mathbb{I}_l, S^D_l, \cdot)\, B - F(\mathbb{I}_l, S^D_l, \cdot)$, this function also satisfies increasing differences in $(\mathbb{I}_l, \varphi)$ and (S^D_l, φ) for $\sigma > \eta > 1$. Applying Topkis's monotonicity theorem, we have that $\mathbb{I}_l(\varphi^H) \geq \mathbb{I}_l(\varphi^L)$ and $S^D_l(\varphi^H) \geq S^D_l(\varphi^L)$ for $\varphi^H \geq \varphi^L$.

Part (c). From Proposition 3, we know that at any location l', there exists an equivalent number of direct suppliers $\tilde{S}_{l'}$ for the intermediation technology (A4). Only firms that can match with $S^D_{l'} > \tilde{S}_{l'}$ suppliers consider sourcing directly in l', and $S^D_{l'}$ is an increasing function of firm productivity φ. In the single-location case, this guarantees that a high-productivity firm φ^H would not resort to indirect sourcing if a low-productivity firm φ^L sources directly. With multiple locations, sourcing decisions in l' are affected by decisions in all locations through the expected sourcing capability, $\mathbb{E}\left[\Theta(\varphi)^{\frac{\sigma-1}{\eta-1}}\right]$. Parts (a) and (b) demonstrated that this object is an increasing function of φ and, if $\sigma > \eta$, this increases the optimal number of direct suppliers at any location. This monotonic relationship extends the result to the multi-location context.

I prove this by contradiction for the case with two locations, l' and l. To ease notation, I use the mapping $\mathsf{K}(S', S)$ defined in (A18) for choices S' and S in locations l' and l. If φ^H sources indirectly from l', and S^H_l is the corresponding choice in l, the following condition would be satisfied:

$$\left(\varphi^H\right)^{\sigma-1}\mathsf{K}\left(\tilde{S}_{l'}, S^H_l\right)B - f^I_{l'} - f^D_l(S^H_l) \geq \left(\varphi^H\right)^{\sigma-1}\mathsf{K}\left(S_{l'}, S_l\right)B - f^D_{l'}(S_{l'}) - f^D_l(S_l) \quad \forall S_{l'} \in \mathcal{S}_{l'}, S_l \in \mathcal{S}_l$$

where indirect sourcing in l' is *equivalent* to access $S' = \tilde{S}_{l'}$ direct suppliers. This implies:

$$\left(\varphi^H\right)^{\sigma-1}\mathsf{K}\left(\tilde{S}_{l'}, S^H_l\right)B - f^I_{l'} \geq \left(\varphi^H\right)^{\sigma-1}\mathsf{K}\left(S^H_{l'}, S^H_l\right)B - f^D_{l'}(S^H_{l'}) \tag{A19}$$

where $S^H_{l'}$ is the best direct alternative in l' given a choice S^H_l in l, and the fixed costs $f^D_l(S^H_l)$ offset each other. Analogously, if φ^L sources directly from $S^L_{l'}$ suppliers in l', and the corresponding choice in l is S^L_l, we have:

$$\left(\varphi^L\right)^{\sigma-1}\mathsf{K}\left(S^L_{l'}, S^L_l\right)B - f^D_{l'}(S^L_{l'}) - f^D_l(S^L_l) \geq \left(\varphi^L\right)^{\sigma-1}\mathsf{K}\left(\tilde{S}_{l'}, S_l\right)B - f^I_{l'} - f^D_l(S_l) \quad \forall S_{l'} \in S_l \in \mathcal{S}_l$$

which implies that:

$$\left(\varphi^L\right)^{\sigma-1}\mathsf{K}\left(S^L_{l'},S^L_l\right)B - f^D_{l'}(S^L_{l'}) \geq \left(\varphi^L\right)^{\sigma-1}\mathsf{K}\left(\tilde{S}_{l'},S^L_l\right)B - f^I_{l'} \tag{A20}$$

Combining inequalities (A19) and (A20) we get:

$$\begin{aligned} f^D_{l'}(S^H_{l'}) - f^D_{l'}(S^L_{l'}) \;\geq\; & \left(\varphi^H\right)^{\sigma-1}\Big(\mathsf{K}\left(S^H_{l'},S^H_l\right) - \mathsf{K}\left(\tilde{S}_{l'},S^H_l\right)\Big)B \\ & - \left(\varphi^L\right)^{\sigma-1}\Big(\mathsf{K}\left(S^L_{l'},S^L_l\right) - \mathsf{K}\left(\tilde{S}_{l'},S^L_l\right)\Big)B \end{aligned} \tag{A21}$$

However, if $S^H_{l'}$ is the best direct alternative in l' given a choice S^H_l in l, then we also have:

$$\left(\varphi^H\right)^{\sigma-1}\Big(\mathsf{K}\left(S^H_{l'},S^H_l\right) - \mathsf{K}\left(S^L_{l'},S^H_l\right)\Big)B \;\geq\; f^D_{l'}(S^H_{l'}) - f^D_{l'}(S^L_{l'}) \tag{A22}$$

which combined with inequality (A21) implies:

$$\left(\varphi^L\right)^{\sigma-1}\Big(\mathsf{K}\left(S^L_{l'},S^L_l\right) - \mathsf{K}\left(\tilde{S}_{l'},S^L_l\right)\Big)B \;\geq\; \left(\varphi^H\right)^{\sigma-1}\Big(\mathsf{K}\left(S^L_{l'},S^H_l\right) - \mathsf{K}\left(\tilde{S}_{l'},S^H_l\right)\Big)B \tag{A23}$$

We know that $\mathsf{K}\left(S^L_{l'},S^L_l\right) - \mathsf{K}\left(\tilde{S}_{l'},S^L_l\right) \geq 0$ since $f^D_{l'}(S^L_{l'}) \geq f^I_{l'}$ in (A20). However, $\mathsf{K}\left(S^L_{l'},S^H_l\right) - \mathsf{K}\left(\tilde{S}_{l'},S^H_l\right)$ is also positive and larger in magnitude since $S^H_l \geq S^L_l$ for $\varphi^H > \varphi^L$, which is driven by the increasing differences established in part (b). This leads to a contradiction.

A.4. Estimation Appendix

Solution Algorithm

I describe the algorithm to solve the model numerically and estimate direct matching costs ($f^D_l(S^D_l)$), contracting costs with intermediaries (f^I_l), and the demand shifter (B) using the Simulated Method of Moments. This algorithm is implemented after all other parameters have been separately estimated following Section 1.5.2: elasticities of substitution (σ,η,θ), location-specific input costs $(\tau_l\alpha_l)$, disruption probabilities by location and sourcing mode (ζ^M_l), number of indirect suppliers per location (S^I_l), number of potential direct suppliers per location (S^D_l), and brokerage fee (κ).

- **Step 1:** Draw N producers from a Pareto productivity distribution; each producer then draws its matching costs from a log-normal distribution.
- **Step 2:** Compute expected input costs for each possible choice of locations, sourcing mode at each location, and number of suppliers in direct locations: $\left\{L(\omega), M_l(\omega), S^D_l(\omega)\right\}$.

- The number of combinations equals $\prod_{l \in \mathcal{L}} \left(|\mathbb{S}_l| + 2 \right)$.
- Expectations are approximated by sampling 100,000 draws from the Binomial distribution describing the number of operational suppliers for each choice.

- **Step 3:** Guess an initial value for parameters to be estimated (Ω_0).
- **Step 4:** Solve the optimal sourcing problem for each producer.
  - Discard strictly dominated direct choices relative to indirect sourcing.
  - Discard indirect sourcing when strictly dominated by all direct options.
  - Apply squeezing method for discrete choice (Arkolakis et al. 2023a; Huang et al. 2024).
- **Step 5:** Compute simulated moments $M^{Model}(\Omega)$ given producers' optimal sourcing.
- **Step 6:** Compute Euclidean distance between simulated and data moments.

$$\min_{\Omega} Y_t = (M^{\text{Model}}(\Omega) - M^{\text{Data}})W(M^{\text{Model}}(\Omega) - M^{\text{Data}})', \quad W = I$$

- **Step 7:** Stop if $Y_t < \epsilon$; otherwise go back to Step 3 and evaluate a new guess Ω_{t+1}.

Estimation Results

Table A9. Elasticity of Substitution across Input Locations

	(log) Input purchases					1rst Stage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(log) Input prices	-0.248***	-0.224***	-0.251***	-0.404***	-0.378***		
	(0.002)	(0.002)	(0.008)	(0.082)	(0.074)		
(log) Distance						0.302***	0.338***
						(0.025)	(0.025)
Firm-Year FE	Yes	Yes	No	No	No	No	No
Firm FE	No	No	Yes	Yes	Yes	Yes	Yes
Country-Year FE	No	Yes	No	No	No	No	No
Country productivity	No	No	No	No	Yes	No	Yes
IV	No	No	No	Yes	Yes	Yes	Yes
Sample	2005-19	2005-19	2019	2019	2019	2019	2019
Observations	365,505	365,104	22,176	21,955	21,805	21,955	21,805

Notes: This table uses an empirical counterpart of equation (1.15) to estimate the elasticity of substitution across input locations (η). The dependent variable is (log) input purchases for a given buyer-origin country-year, the key regressor is (log) input prices, and the estimated coefficients correspond to $1 - \eta$. I include firm (firm-year) fixed effects, capturing variation for the same buyer across origins. Columns (1) and (2) use the full panel (2005–2019), column (3) considers the last year in the sample (2019), columns (4) and (5) instrument input prices with geographic distance from Chile, and columns (6) and (7) present first stages. The table reports robust standard errors.

Table A10. Elasticity of Substitution across Suppliers

	(log) Input prices			
	(1)	(2)	(3)	(4)
(log) # Suppliers	-0.256***	-0.279***	-0.266***	-0.295***
	(0.003)	(0.003)	(0.011)	(0.012)
Country-Product FE	No	No	Yes	Yes
Country-Product-Year FE	Yes	Yes	No	No
Firm FE	No	No	No	Yes
Firm-Year FE	No	Yes	No	No
Sample	2005-19	2005-19	2019	2019
Observations	1,954,843	1,917,790	115,483	112,903

Notes: This table uses an empirical counterpart of equation (1.19) to estimate the elasticity of substitution across suppliers within locations (θ). The dependent variable is (log) input prices for a given location (country - HS6 product) and year, the key regressor is the (log) number of suppliers, and the estimated coefficients correspond to $-1/\theta$. All regressions include location (location-year) fixed effects, capturing variation across buyers sourcing from the same market. Columns (1) and (2) consider the full sample of years, while columns (3) and (4) use the last year available (2019). The table reports robust standard errors.

Table A11. Location-Specific Trade and Production Unit Costs

	Raw estimates (USD)		Normalized (Chile=1)	
Region	All years (2005-19)	Only 2019	All years (2005-19)	Only 2019
CHN	12.67	17.31	1.93	3.12
EU	74.92	91.03	11.42	16.42
LAT	17.72	14.97	2.70	2.70
ROW	109.46	56.34	16.68	10.16
US	84.74	88.99	12.92	16.05

Notes: This table presents estimates for trade and production costs ($\tau_l \alpha_l$) across source regions. The raw estimates are in USD, and the normalized version is defined relative to input costs in Chile. Since domestic sourcing is not directly observed, I assume similar production costs in Chile and Latin America, attributing all differences to iceberg trade costs, which are estimated to be around a factor of 2.7 (Anderson and Van Wincoop 2004a). Thus, by construction, Latin America has an input cost of 2.7 in the last two columns.

Table A12. Estimated Parameters for Link Separation Probabilities

Dep. Variable: $\mathbb{D}(separation)_{bsl}$					
Location factors (Z_l)				Demand factors (D_b)	
Geopolitical risk	0.328***	Low-income dummy	-1.817***	Δ firm imports	-0.254***
	(0.033)		(0.066)		(0.066)
Economic uncertainty	0.180***	Mid-income dummy	-1.993***	Δ firm suppliers	-1.057***
	(0.027)		(0.063)		(0.018)
Trade volatility	0.052***	High-income dummy	-2.385***		
	(0.007)		(0.011)		

Notes: This table presents the estimates for vectors Z_l and D_b in the logit model (1.25) estimating the probability of link separations. The regressions are at the buyer-supplier-location level, where locations are defined at the origin country-HS6 product level. The dependent variable is a dummy that equals 1 when a buyer-supplier link in period t will be inactive in $t + 1$. The demand factors are excluded from the projected disruption probabilities. The sample considers all import transactions in 2018 for firms active in 2018 and 2019. The table reports robust standard errors clustered at the location level.

Table A13. Differences in Separation Rates by Region (Indirect vs. Direct)

	LAT	CHN	USA	EUR	ROW
	(1)	(2)	(3)	(4)	(5)
Intermediary dummy	-0.060***	-0.055***	-0.070***	-0.050***	-0.064***
	(0.015)	(0.012)	(0.013)	(0.012)	(0.018)
Firm size (sales)	Yes	Yes	Yes	Yes	Yes
Imported value	Yes	Yes	Yes	Yes	Yes
Number of suppliers	Yes	Yes	Yes	Yes	Yes
Product - country FE	Yes	Yes	Yes	Yes	Yes
Δ Firm-level imports	Yes	Yes	Yes	Yes	Yes
Δ Firm-level suppliers	Yes	Yes	Yes	Yes	Yes
Observations	29,694	72,881	49,715	87,922	43,868

Notes: This table compares supplier separation rates for producers and intermediaries in each source region: Latin America, China, the United States, Europe, and Rest of the World. For each group, the regressions are at the buyer-origin country-HS6 product level. The dependent variable is a dummy that equals 1 when the buyer has a separation from period t to $t + 1$. The independent variable is a dummy indicating whether the buyer is an intermediary. Controls for changes in demand conditions across buyers are included (firm-level imports and suppliers). The sample includes all import transactions in 2018 for firms active in both 2018 and 2019. Standard errors are clustered at the firm level.

Appendix B

Supplementary Materials for Chapter 2

B.1. Empirical Appendix

Table A1. Shipping logistics

	(1) % Ind Trade	(2) % Ind Sellers	(3) % Mix Sellers	(4) % Dir Sellers
(log) Distance	0.050***	0.062***	-0.057***	-0.006
	(0.013)	(0.012)	(0.007)	(0.014)
Logistic services	-0.059	0.061	-0.153	0.092
	(0.263)	(0.255)	(0.142)	(0.260)
Track and trace	0.298	0.143	0.123	-0.266
	(0.185)	(0.195)	(0.089)	(0.189)
Ease of arranging shipments	0.273	0.260	-0.040	-0.221
	(0.165)	(0.160)	(0.083)	(0.153)
Shipment arrivals (within time)	-0.613***	-0.578***	0.164	0.414*
	(0.187)	(0.176)	(0.124)	(0.218)
Trade infrastructure	-0.144	-0.208	0.191**	0.017
	(0.148)	(0.157)	(0.082)	(0.149)
(log) GDP per capita	-0.008	-0.002	-0.021*	0.023
	(0.023)	(0.023)	(0.012)	(0.024)
HS2 sector FE	Yes	Yes	Yes	Yes
N	4,008	4,008	4,008	4,008

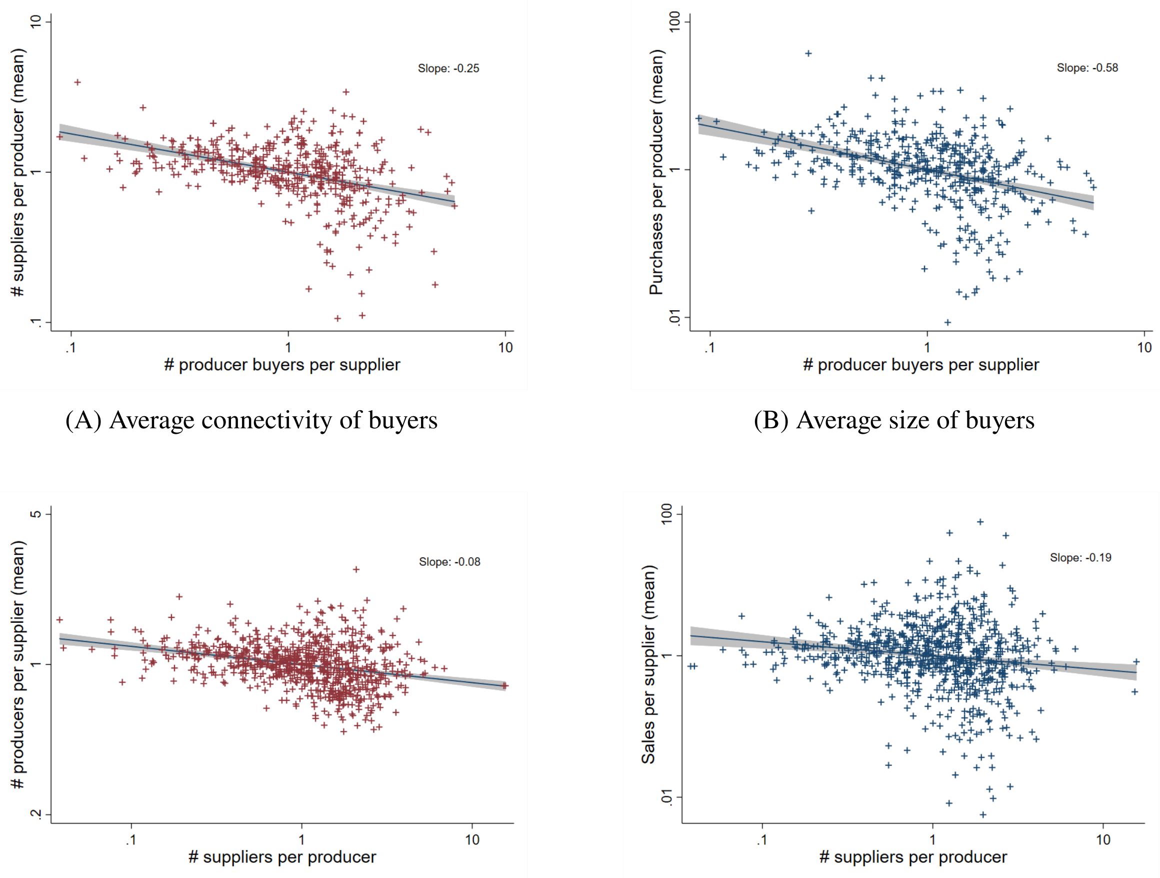
Table A2. Customs procedures

	(1) % Ind Trade	(2) % Ind Sellers	(3) % Mix Sellers	(4) % Dir Sellers
Border compliance: USD (0-1)	-0.035	-0.027	0.087	-0.060
	(0.119)	(0.112)	(0.097)	(0.130)
Border compliance: hours (0-1)	0.005	-0.054	0.011	0.043
	(0.198)	(0.190)	(0.093)	(0.177)
Export documentation: USD (0-1)	0.008	0.073	-0.161	0.088
	(0.297)	(0.324)	(0.223)	(0.299)
Export documentation: hours (0-1)	-0.117	-0.015	-0.213	0.228
	(0.253)	(0.261)	(0.140)	(0.238)
(log) # procedures	-0.051	-0.072	0.053	0.019
	(0.049)	(0.053)	(0.036)	(0.049)
Customs efficiency	-0.005	-0.052	0.072	-0.021
	(0.092)	(0.096)	(0.073)	(0.094)
(log) GDP per capita	-0.059**	-0.063**	0.017	0.046**
	(0.025)	(0.027)	(0.017)	(0.023)
HS2 sector FE	Yes	Yes	Yes	Yes
N	3,955	3,955	3,955	3,955

Table A3. Formal and informal contracting institutions

	(1)	(2)	(3)	(4)
	% Ind Trade	% Ind Sellers	% Mix Sellers	% Dir Sellers
Control of corruption	0.016	-0.000	0.022	-0.022
	(0.017)	(0.019)	(0.015)	(0.020)
Rule of law	-0.000	0.008	-0.026**	0.018*
	(0.012)	(0.014)	(0.012)	(0.010)
Common legal origins (=1)	0.023	0.015	0.022	-0.037
	(0.027)	(0.024)	(0.017)	(0.024)
Trust in foreigners (%)	-0.625***	-0.617***	0.089	0.528***
	(0.180)	(0.203)	(0.154)	(0.171)
Common religion (%)	-0.108***	-0.117***	0.047*	0.070**
	(0.040)	(0.040)	(0.028)	(0.034)
Language proximity (tree index)	0.032	0.043	-0.045	0.002
	(0.039)	(0.046)	(0.042)	(0.033)
(log) GDP per capita	-0.042	-0.045	0.026	0.019
	(0.030)	(0.033)	(0.024)	(0.033)
HS2 sector FE	Yes	Yes	Yes	Yes
N	3,104	3,104	3,104	3,104

Figure A1. Degree assortativity in direct transactions



(A) Average connectivity of buyers

(B) Average size of buyers

(C) Average connectivity of suppliers

(D) Average size of suppliers

B.2. Theory Appendix

Proof of Proposition 1

Part (a)

Consider a supplier $\lambda = (z, f^D)$ in market i selling to downstream producer ζ in market j. According to Equation (7), firm-to-firm sales conditional on a direct match are $x^D_{ij}(\lambda,\zeta) = \mu^{1-\eta}\left(\frac{\tau_{ij}w_i}{z(\lambda)}\right)^{1-\eta} C_j(\zeta)^{\eta-1}X_j(\zeta)$, where $\mu \equiv \frac{\eta}{\eta-1}$. Differentiating with respect to seller productivity we obtain $\frac{\partial x^D_{ij}(\lambda,\zeta)}{\partial z(\lambda)} = (\eta-1)^{\eta}\eta^{1-\eta}z(\lambda)^{\eta-2}\left(\tau_{ij}w_i\right)^{1-\eta} C_j(\zeta)^{\eta-1}X_j(\zeta)$, which is positive since $\eta > 1$ by assumption and all other terms are positive by definition. Under an indirect match, Equation (8) states that firm-to-firm sales are proportional to direct sales, $x^I_{ij}(\lambda,\zeta) = \left(\frac{\eta-\phi}{\eta}\right)x^D_{ij}(\lambda,\zeta)$, and considering that $\phi \in [0,1]$ we have that

$\frac{\partial x^I_{ij}(\lambda,\zeta)}{\partial z(\lambda)} = \left(\frac{\eta-\phi}{\eta}\right)\frac{\partial x^D_{ij}(\lambda,\zeta)}{\partial z(\lambda)}$ is also positive. Finally, note that neither $x^D_{ij}(\lambda,\zeta)$ or $x^I_{ij}(\lambda,\zeta)$ depend on seller matchability f^D.

Part (b)

Considering again Equation (7) for firm-to-firm sales under direct trade. Differentiating with respect to buyer productivity ζ we obtain $\frac{\partial x^D_{ij}(\lambda,\zeta)}{\partial\zeta} = \mu^{1-\eta}\left(\frac{\tau_{ij}w_i}{z(\lambda)}\right)^{1-\eta}\frac{\partial}{\partial\zeta}\left(C_j(\zeta)^{\eta-1}X_j(\zeta)\right)$, where total input purchases can be expressed as $X_j(\zeta) = \tilde{c}(\zeta)\tilde{q}(\zeta) = \zeta^{\sigma-1}C_j(\zeta)^{1-\sigma}\tilde{\mu}\tilde{P}_j^{\sigma-1}\beta\tilde{E}_j$ after replacing downstream demand (1) and the marginal cost (2). We then have that $\frac{\partial x^D_{ij}(\lambda,\zeta)}{\partial\zeta} = \left[(\sigma-1)\zeta^{\sigma-2}C_j(\zeta)^{\eta-\sigma} + (\eta-\sigma)\zeta^{\sigma-1}C_j(\zeta)^{\eta-\sigma-1}\frac{\partial C_j(\zeta)}{\partial\zeta}\right]\bar{K}_j$ where the last element is $\bar{K}_j \equiv \mu^{1-\eta}\left(\frac{\tau_{ij}w_i}{z(\lambda)}\right)^{1-\eta}\tilde{\mu}^{-\sigma}\tilde{P}_j^{\sigma-1}\beta\tilde{E}_j > 0$. For the case where elasticities are identical across final and intermediate goods ($\sigma = \eta$), this expression is always positive since $\sigma > 1$ and the second term cancels out, such that firm-to-firm sales increase with buyer productivity. The demonstration is analogous for the case of indirect trade using equation (8). For the case where $\sigma > \eta$, a sufficient condition is that the buyer's input cost index $C(\zeta)$ is decreasing in buyer productivity ζ, which ultimately depends on seller's endogenous matching decisions.

Part (c)

Conditional on a match (λ,ζ),the fact that firm-to-firm sales are lower under indirect mode is evident from Equation (8), where $x^I_{ij}(\lambda,\zeta) = \left(\frac{\eta-\phi}{\eta}\right)x^D_{ij}(\lambda,\zeta)$, $\eta > 1$ and $\phi \in [0,1]$. The fact that sales are cheaper follows from Equation (6), where $p^I_{ij}(\lambda,\zeta) = \frac{\eta-\phi}{\eta}p^D_{ij}(\lambda,\zeta)$.

Proof of Proposition 2

Part (a)

From Equation (9) we have that direct profits from upstream supplier $\lambda = (z, f^D)$ in market i selling in market j are $\pi^D_{ij}(\lambda,\zeta) = \frac{x^D_{ij}(\lambda,\zeta)}{\eta} - f^D(\lambda)$ for each potential buyer with productivity ζ. As shown in Proposition 1, $x^D_{ij}(\lambda,\zeta)$ is continuous and monotonically increasing in ζ. Also note that $x^D_{ij}(\lambda,\zeta) = 0$ when $\zeta = 0$, such that $\pi^D_{ij}(\lambda,\zeta) < 0$. Thus, there exists a unique threshold $\zeta^D_{ij}(\lambda)$ where the direct profits curve of supplier λ equals zero and $\pi^D_{ij}(\lambda,\zeta) > 0$ for $\zeta > \zeta^D_{ij}(\lambda)$.

Part (b)

From Equation (10) we can have that indirect profits of upstream supplier $\lambda = (z, f^D)$ in market i selling in market j are $\pi^I_{ij}(\lambda, \zeta) = \left(\frac{\eta - \phi}{\eta}\right)\frac{x^D_{ij}(\lambda,\zeta)}{\eta} - f^I$. Since $\eta > 1$ and $\phi \in [0, 1]$, the analysis is analogous to that of part (a) for direct profits: $x^D_{ij}(\lambda, \zeta)$ is continuous and monotonically increasing in ζ, so there exists a unique threshold $\zeta^I_{ij}(\lambda)$ where the indirect profits curve of supplier λ equals zero and $\pi^I_{ij}(\lambda, \zeta) > 0$ for $\zeta > \zeta^I_{ij}(\lambda)$.

Part (c)

Combining equations (9) and (10), we can define the curve $\pi^*_{ij}(\lambda, \zeta) = \pi^D_{ij}(\lambda, \zeta) - \pi^I_{ij}(\lambda, \zeta) = \left(\frac{\phi}{\eta}\right)\frac{x^D_{ij}(\lambda,\zeta)}{\eta} - \left(f^D(\lambda) - f^I\right)$, where $\frac{\phi}{\eta} \in [0, 1]$ since $\eta > 1$ and $\phi \in [0, 1]$. If direct matching costs are higher than contracting with intermediaries $(f^D(\lambda) - f^I > 0)$, then the analysis is analogous to that of parts (a) and (b): $x^D_{ij}(\lambda, \zeta)$ is continuous and monotonically increasing in ζ, so there exists a unique threshold $\zeta^{D=I}_{ij}(\lambda)$ where $\pi^*_{ij}(\lambda, \zeta) = 0$ and $\pi^D_{ij}(\lambda, \zeta) = \pi^I_{ij}(\lambda, \zeta)$, such that $\pi^*_{ij}(\lambda, \zeta) > 0$ and $\pi^D_{ij}(\lambda, \zeta) > \pi^I_{ij}(\lambda, \zeta)$ for $\zeta > \zeta^{D=I}_{ij}(\lambda)$. For suppliers with high matchability $(f^D(\lambda) - f^I < 0)$, then $\pi^*_{ij}(\lambda, \zeta) > 0$ and $\pi^D_{ij}(\lambda, \zeta) > \pi^I_{ij}(\lambda, \zeta)$ for any $\zeta > 0$.

Proof of Proposition 3

Part (a)

From Proposition 2a we know that $\pi^D_{ij}(\lambda, \zeta) < 0$ for $\zeta < \zeta^D_{ij}(\lambda)$, such that all potential direct matches in market j are unprofitable for seller λ when the highest-productivity buyer is $\overline{\zeta}_j < \zeta^D_{ij}(\lambda)$. Analogously, from Proposition 2b, $\pi^I_{ij}(\lambda, \zeta) < 0$ for $\zeta < \zeta^I_{ij}(\lambda)$, and all potential indirect matches are unprofitable for $\overline{\zeta}_j < \zeta^I_{ij}(\lambda)$. Thus, no-trade is the optimal strategy for seller λ.

Part (b)

Since $\zeta^D_{ij}(\lambda) < \overline{\zeta}_j$, there exists a set of potential buyers $[max(\underline{\zeta_j}, \zeta^D_{ij}(\lambda)), \overline{\zeta_j}]$ in market j that generates positive profits for seller λ under direct trade. If $\zeta^D_{ij}(\overline{\lambda}) < \zeta^I_{ij}(\lambda)$ then it must be the case that $\zeta^{D=I}_{ij}(\lambda) < \left\{\zeta^D_{ij}(\lambda), \zeta^I_{ij}(\lambda)\right\}$, because $f^D(\lambda) < f^I$ and both direct and indirect profit curves are monotonically increasing in buyer productivity (Propositions 2a and 2b), so direct profits can only reach zero from below before indirect profits if these curves already crossed each other. This implies that $\pi^D_{ij}(\lambda, \zeta) > \pi^I_{ij}(\lambda, \zeta)$ for all potential buyers that generate positive profits for seller λ, since direct and indirect profits cross only once (Proposition 2c). The optimal trade strategy is then to sell only directly to all potential buyers $\zeta \in [max(\underline{\zeta_j}, \zeta^D_{ij}(\lambda)), \overline{\zeta}_j]$.

Part (c)

Considering $\zeta^{I}_{ij}(\lambda) < \overline{\zeta}_j$, there exists a set of potential buyers $[max(\underline{\zeta_j}, \zeta^{I}_{ij}(\lambda)), \overline{\zeta}_j]$ in market j that generates positive profits for seller λ under indirect trade. Analogous to part (b), the fact that $f^D(\lambda) < f^I$ and that both profits curves are monotonically increasing implies that, if $\zeta^{I}_{ij}(\lambda) < \zeta^{D}_{ij}(\lambda)$, then it must be the case that $\zeta^{D=I}_{ij}(\lambda) > \left\{\zeta^{D}_{ij}(\lambda), \zeta^{I}_{ij}(\lambda)\right\}$ (i.e., if indirect profits reach zero from below before direct profits, then these curves must cross each other afterwards both curves generate positive profits). This implies that $\pi^{I}_{ij}(\lambda, \zeta) > 0$ and $\pi^{I}_{ij}(\lambda, \zeta) > \pi^{D}_{ij}(\lambda, \zeta)$ for buyers with productivity $[\zeta^{I}_{ij}(\lambda), \zeta^{D=I}_{ij}(\lambda)]$, while $\pi^{I}_{ij}(\lambda, \zeta) < \pi^{D}_{ij}(\lambda, \zeta)$ for buyers above $\zeta^{D=I}_{ij}(\lambda)$. In the case where $\zeta^{D=I}_{ij}(\lambda) > \overline{\zeta}_j$, there is no buyer in market j with a productivity large enough to induce seller λ to prefer direct over indirect trade. The optimal trade strategy is then to sell only indirectly to all potential buyers $\zeta \epsilon [max(\underline{\zeta_j}, \zeta^{I}_{ij}(\lambda)), \overline{\zeta}_j]$.

Part (d)

Starting from part (c), we now consider the case where $\zeta^{I}_{ij}(\lambda) < \overline{\zeta}_j$ and $\zeta^{D=I}_{ij}(\lambda) < \overline{\zeta}_j$. Analogously, this implies that $\zeta^{D=I}_{ij}(\lambda) > \left\{\zeta^{D}_{ij}(\lambda), \zeta^{I}_{ij}(\lambda)\right\}$ and $\pi^{I}_{ij}(\lambda, \zeta) > 0$ and $\pi^{I}_{ij}(\lambda, \zeta) > \pi^{D}_{ij}(\lambda, \zeta)$ for buyers with productivity $[\zeta^{I}_{ij}(\lambda), \zeta^{D=I}_{ij}(\lambda)]$, while $\pi^{I}_{ij}(\lambda, \zeta) < \pi^{D}_{ij}(\lambda, \zeta)$ for buyers above $\zeta^{D=I}_{ij}(\lambda)$. As long as $\zeta^{D=I}_{ij}(\lambda) > \underline{\zeta_j}$, the optimal trade strategy for seller λ is to mix trade modes, selling indirectly to buyers $\zeta \epsilon [max(\underline{\zeta_j}, \zeta^{I}_{ij}(\lambda)), \zeta^{D=I}_{ij}(\lambda)]$ and directly to buyers $\zeta \epsilon [\zeta^{D=I}_{ij}(\lambda), \overline{\zeta}_j]$. Note that the case where $\zeta^{D=I}_{ij}(\lambda) < \underline{\zeta_j}$ is analogous to part (b), and seller λ would sell directly to all potential buyers in market j, $\zeta \epsilon [\underline{\zeta_j}, \overline{\zeta}_j]$.

Proof of Proposition 4

Part (a)

From equation (9) and (10), we know that upstream supplier $\lambda = (z, f^D)$ in market i selling in market j obtains direct profits $\pi^{D}_{ij}(\lambda, \zeta) = \frac{x^{D}_{ij}(\lambda,\zeta)}{\eta} - f^D(\lambda)$ and indirect profits $\pi^{I}_{ij}(\lambda, \zeta) = \left(\frac{\eta-\phi}{\eta}\right)\frac{x^{D}_{ij}(\lambda,\zeta)}{\eta} - f^I$ when transacting with a buyer with productivity ζ. An increase in seller productivity z increases firm-to-firm sales under both trade modes as shown in Proposition 1a, and we have that $\frac{\partial x^{I}_{ij}(\lambda,\zeta)}{\partial z(\lambda)} = \left(\frac{\eta-\phi}{\eta}\right)\frac{\partial x^{D}_{ij}(\lambda,\zeta)}{\partial z(\lambda)}$ where $\left(\frac{\eta-\phi}{\eta}\right) < 1$ since $\eta > 1$ and $\phi \in [0, 1]$, such there is a greater increase in direct profits. Thus, given a matchability level $\bar{f}^D$, more productive sellers are more likely to trade directly. On the other hand, given a productivity level $\bar{z}$, a higher matchability level (i.e., lowerf^D) increase direct profits $\pi^{D}_{ij}(\lambda, \zeta)$ without affecting indirect profits $\pi^{I}_{ij}(\lambda, \zeta)$, such that sellers are more likely to trade directly.

Part (b)

The fact that mixed suppliers serve buyers above (below) a productivity threshold directly (indirectly) follows directly from Proposition 3d.

Alternative Pricing Schemes

Consider the following prices in each potential firm-to-firm transaction: (i) supplier λ charges $P^D(\lambda, \zeta)$ to buyer ζ under direct trade, supplier λ charges $P^I(\lambda, \zeta)$ to the wholesaler under indirect trade, and (iii) the wholesaler charges $P^W(\lambda, \zeta)$ to buyer ζ. Below we explore alternative pricing schemes for intermediaries, relative to the one presented in Section 3: Nash bargaining over the trade surplus (or variable profits) from the firm-to-firm transaction, with bargaining weights ϕ and 1 - ϕ, respectively.

Brokerage fee on variable profits

Consider that the intermediary takes a share $\gamma \in (0, 1)$ of supplier variable profits. The demand faced by supplier λ when selling indirectly to buyer ζ is $q^I(\lambda, \zeta) = \left(p^W(\lambda, \zeta)\right)^{-\eta} B$, and in the absence of double marginalization $p^W(\lambda, \zeta) = p^I(\lambda, \zeta)$

$$\begin{aligned}
\max_{p^I} \pi^I &= (1-\gamma)\left(p^I - c\right) q^I - f^I \\
&= (1-\gamma)\left(\left(p^I\right)^{1-\eta} B - c\left(p^I\right)^{-\eta} B\right) - f^I \\
FOC:\ (1-\eta)\left(p^I\right)^{-\eta} &+ \eta c\left(p^I\right)^{-\eta-1} = 0 \quad \Rightarrow p^I = \left(\frac{\eta}{\eta-1}\right) c
\end{aligned}$$

Note that firm-to-firm sales are independent of the trade mode: $x^I(\lambda, \zeta) = p^I(\lambda, \zeta) q^I(\lambda, \zeta) = x^D(\lambda, \zeta)$. The supplier charges the same price $p^I(\lambda, \zeta) = p^D(\lambda, \zeta)$, while $q^I(\lambda, \zeta) = q^D(\lambda, \zeta)$ because the buyer perceives the same price $p^W(\lambda, \zeta) = p^D(\lambda, \zeta)$

Brokerage fee on sales

Consider that the intermediary takes a share $\gamma \in (0, 1)$ of the supplier sales. As before, buyer demand is $q^I(\lambda, \zeta) = \left(p^I(\lambda, \zeta)\right)^{-\eta} B$ when the supplier sells indirectly because $p^W(\lambda, \zeta) = p^I(\lambda, \zeta)$ without double marginalization. The supplier's optimal indirect prices are then:

$$\max_{p^I} \pi^I = (1-\gamma)p^I q^I - cq^I - f^I$$
$$= (1-\gamma)\left(p^I\right)^{1-\eta} B - c\left(p^I\right)^{-\eta} B - f^I$$
$$FOC: \ (1-\gamma)(1-\eta)\left(p^I\right)^{-\eta} + \eta c\left(p^I\right)^{-\eta-1} = 0 \quad \Rightarrow p^I = \left(\frac{1}{1-\gamma}\right)\left(\frac{\eta}{\eta-1}\right)c$$

Indirect firm-to-firm sales are $x^I(\lambda,\zeta) = (1-\gamma)^{\eta-1} x^D(\lambda,\zeta) \ \Rightarrow \ x^I(\lambda,\zeta) < x^D(\lambda,\zeta)$. The supplier receives $p^I(\lambda,\zeta) > p^D(\lambda,\zeta)$, while $q^I(\lambda,\zeta) < q^D(\lambda,\zeta)$ because the buyer perceives $p^W(\lambda,\zeta) > p^D(\lambda,\zeta)$, and the reduction in buyer demand dominates. The intuition for this result is that the suppliers has a lower marginal revenue, similar to monopolist facing a less elastic demand.

Double marginalization

In thie case, the intermediary charges a markup $\mu^W > 1$ over the supplier price. The demand faced by supplier λ when selling indirectly is now $q^I(\lambda,\zeta) = \left(\mu^W p^I(\lambda,\zeta)\right)^{-\eta} B$, because the price perceived by the buyer is $p^W(\lambda,\zeta) = \mu^W p^I(\lambda,\zeta)$. The supplier's optimal indirect prices are then:

$$\max_{p^I} \pi^I = p^I q^I - cq^I - f^I$$
$$= \left(\mu^W\right)^{-\eta}\left(p^I\right)^{1-\eta} B - c\left(\mu^W p^I\right)^{-\eta} B - f^I$$
$$FOC: \ (1-\eta)\left(p^I\right)^{-\eta} + \eta c\left(p^I\right)^{-\eta-1} = 0 \quad \Rightarrow p^I = \left(\frac{\eta}{\eta-1}\right)c$$

Indirect firm-to-firm sales are $x^I(\lambda,\zeta) = \left(\mu^W\right)^{-\eta} x^D(\lambda,\zeta) \ \Rightarrow \ x^I(\lambda,\zeta) < x^D(\lambda,\zeta)$. The supplier charges same price for indirect and direct transactions $p^I(\lambda,\zeta) = p^D(\lambda,\zeta)$, but $q^I(\lambda,\zeta) < q^D(\lambda,\zeta)$ because the buyer perceives a higher price $p^W(\lambda,\zeta) > p^D(\lambda,\zeta)$.

Implications for Prices and Sales

The following table summarizes the implications for prices and sales under each pricing scheme, including the case with Nash bargaining considered in the model.

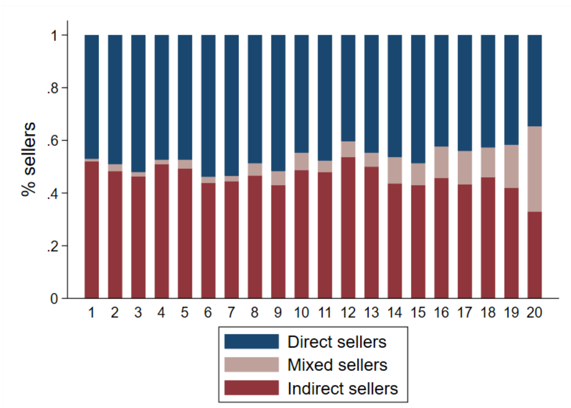
	p^D	p^I	p^W	Pricing	Sales
Fee on variable profits	$\left(\frac{\eta}{\eta-1}\right)c$	$\left(\frac{\eta}{\eta-1}\right)c$	$\left(\frac{\eta}{\eta-1}\right)c$	$p^D = p^I = p^W$	$x^I = x^D$
Fee on sales	$\left(\frac{\eta}{\eta-1}\right)c$	$\left(\frac{1}{1-\gamma}\right)\left(\frac{\eta}{\eta-1}\right)c$	$\left(\frac{1}{1-\gamma}\right)\left(\frac{\eta}{\eta-1}\right)c$	$p^I > p^D$, $p^W > p^D$	$x^I < x^D$
Double marginalization	$\left(\frac{\eta}{\eta-1}\right)c$	$\left(\frac{\eta}{\eta-1}\right)c$	$\mu^W\left(\frac{\eta}{\eta-1}\right)c$	$p^I = p^D$, $p^W > p^D$	$x^I < x^D$
Nash bargaining	$\left(\frac{\eta}{\eta-1}\right)c$	$\left(\frac{\eta-\phi}{\eta-1}\right)c$	$\left(\frac{\eta}{\eta-1}\right)c$	$p^I < p^D$, $p^W = p^D$	$x^I < x^D$

Role of Model Assumptions

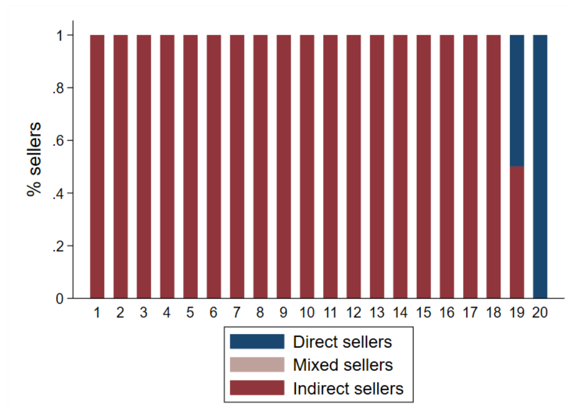
We simulate a simplified version of the model to inform the role played by different assumptions in matching the sorting of sellers into different trade modes. For this exercise, we assume that the productivity and matchability of upstream suppliers $\lambda = (z, f^D)$ are distributed joint log-normal with expectations $\mu_{ln\,z} = 0$ and $\mu_{ln\,f^D} = 1$, standard deviations $sd_{ln\,z} = 0.25$ and $sd_{ln\,f^D} = 1$, and a correlation coefficient of $\rho = -0.2$. We likewise assume that the productivity of downstream producers is log-normally distributed with parameters $\mu_{ln\,\zeta} = 0$ and $sd_{ln\,\zeta} = 0.25$. As standard in the trade literature, we set the elasticity of substitution for final goods to $\sigma = 5$, and we also use this value for the elasticity of substitution across intermediate inputs, η. Lastly, we let the fixed cost of trading indirectly f^I be 10% lower than the average relationship-specific cost f^D for direct transactions.

Figure A2 illustrates how the model is able to accommodate the sorting of exporters into different sales strategies. Panel A demonstrates that the model can reproduce Fact 1 under the assumed weakly negative correlation between seller productivity and matchability: Exporters across the size distribution use trade intermediation, with larger suppliers being less likely to trade only directly, more likely to mix trade modes, and similarly likely to trade indirectly. By contrast, Panel D indicates that the share of purely direct (indirect) suppliers would counterfactually increase (decrease) with supplier size if supplier efficiency and relationship capability were uncorrelated (or positively correlated). Panels B and C in turn show that alternative frameworks with no buyer heterogeneity or with one-dimensional seller heterogeneity cannot replicate Fact 1. Without productivity differences across buyers, there is no incentive for exporters to mix sales modes, and they sort monotonically into purely indirect or purely direct trade according to size. When suppliers instead differ only in productivity but not in matchability, they sort monotonically into purely indirect or mixed trade, with no purely direct sellers.

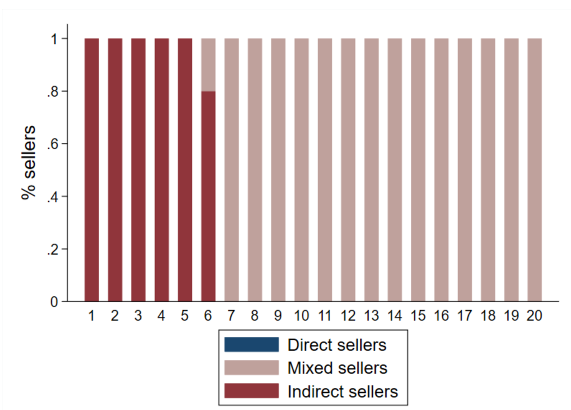
Figure A2. Direct and indirect sellers



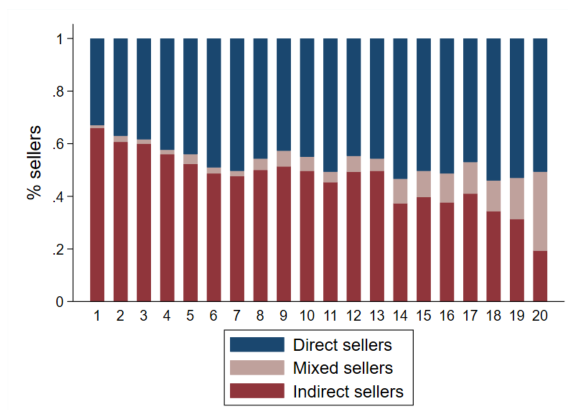
(A) Model simulation



(B) Homogeneous buyer productivity



(C) Homogeneous seller matchability



(D) Uncorrelated productivity and matchability

Appendix C

Supplementary Materials for Chapter 3

C.1. Theory Appendix

Proof of Proposition 1

According to equation (3.8), we have $\sum_{s=1}^{S_{ijk}(\varphi)} p_{ijks}(S_{ijk}(\varphi))^{-\theta} = c_{ijk}(\varphi)^{-\theta}\gamma^{\theta}\tau_{ijk}^{\theta}$. Therefore, we have

$$\chi_{ijks}(\varphi) = \frac{p_{ijks}(\varphi)^{-\theta}}{c_{ijk}(\varphi)^{-\theta}\gamma^{\theta}\tau_{ijk}^{\theta}} = \gamma^{-\theta}\tau_{ijk}^{-\theta}c_{ijk}(\varphi)^{\theta}p_{ijks}(\varphi)^{-\theta}. \tag{A1}$$

Substitute this result and equation (3.10) into the profit function of the upstream firm defined in problem (3.11), and we have

$$\pi_{ijks}^{U}(\varphi) = D_i(\varphi)\tau_{ijk}^{-\theta}c_{ijk}(\varphi)^{\theta-\eta}p_{ijks}(\varphi)^{-\theta}(p_{ijks}(\varphi) - c_{jks}),$$

where $D_i(\varphi) = \gamma^{-\theta}(\frac{\sigma-1}{\sigma})^{\sigma}E_iP_i^{\sigma-1}c_i(\varphi)^{\eta-\sigma}\varphi^{\eta-1}$ is the demand shifter for inputs by the downstream firm based in country i with productivity φ. When the upstream firm changes its price, it affects the price index of its own country-sector $c_{ijk}(\varphi)$ and the marginal cost of the downstream buyer $c_i(\varphi)$. The First Order Condition (FOC) $\frac{\partial\pi_{ijks}^{U}}{\partial p_{ijks}(\varphi)} = 0$ implies that

$$\frac{\partial\left(D_i(\varphi)c_{ijk}(\varphi)^{\theta-\eta}p_{ijks}(\varphi)^{-\theta}\right)}{\partial p_{ijks}(\varphi)}(p_{ijks}(\varphi) - c_{jks}) + D_i(\varphi)c_{ijk}(\varphi)^{\theta-\eta}p_{ijks}(\varphi)^{-\theta} = 0. \tag{A2}$$

For brevity, we ignore the functional argument φ from here on. It is easy to show that the FOC is equivalent to

$$\left(\frac{\partial(c_i^{\eta-\sigma}c_{ijk}^{\theta-\eta})}{\partial p_{ijks}}p_{ijks}^{-\theta} + c_i^{\eta-\sigma}c_{ijk}^{\theta-\eta}\frac{\partial p_{ijks}^{-\theta}}{\partial p_{ijks}}\right)(p_{ijks} - c_{jks}) + c_i^{\eta-\sigma}c_{ijk}^{\theta-\eta}p_{ijks}^{-\theta} = 0.$$

To proceed, we compute $\frac{\partial(c_i^{\eta-\sigma}c_{ijk}^{\theta-\eta})}{\partial p_{ijks}}$, which is

$$\begin{aligned}\frac{\partial(c_i^{\eta-\sigma}c_{ijk}^{\theta-\eta})}{\partial p_{ijks}} &= (\eta-\sigma)c_i^{\eta-\sigma-1}c_{ijk}^{\theta-\eta}\frac{\partial c_i}{\partial c_{ijk}}\frac{\partial c_{ijk}}{\partial p_{ijks}} + (\theta-\eta)c_i^{\eta-\sigma}c_{ijk}^{\theta-\eta-1}\frac{\partial c_{ijk}}{\partial p_{ijks}} \\ &= \frac{\partial c_{ijk}}{\partial p_{ijks}}c_i^{\eta-\sigma}c_{ijk}^{\theta-\eta}\left(\frac{\eta-\sigma}{c_i}\frac{\partial c_i}{\partial c_{ijk}} + \frac{\theta-\eta}{c_{ijk}}\right).\end{aligned}$$

Next, using the chain rule, we have

$$\frac{\partial c_{ijk}}{\partial p_{ijks}} = \frac{\partial c_{ijk}}{\partial \ln(c_{ijk})}\frac{\partial \ln(c_{ijk})}{\partial \ln(p_{ijks})}\frac{\partial \ln(p_{ijks})}{p_{ijks}} = \frac{c_{ijk}}{p_{ijks}}\frac{\partial \ln(c_{ijk})}{\partial \ln(p_{ijks})}.$$

Since $c_{ijk} = \gamma\tau_{ijk}(\sum_{s=1}^{S_{ijk}} p_{ijks}{}^{-\theta})^{-\frac{1}{\theta}}$ we have

$$\begin{aligned}\frac{\partial \ln(c_{ijk})}{\partial \ln(p_{ijks})} &= \frac{\partial \ln(c_{ijk})}{\partial \ln(\sum_{s=1}^{S_{ijk}} p_{ijks}{}^{-\theta})}\frac{\partial \ln(\sum_{s=1}^{S_{ijk}} p_{ijks}{}^{-\theta})}{\partial(\sum_{s=1}^{S_{ijk}} p_{ijks}{}^{-\theta})}\frac{\partial(\sum_{s=1}^{S_{ijk}} p_{ijks}^{-\theta})}{\partial p_{ijks}^{-\theta}}\frac{\partial p_{ijks}^{-\theta}}{\partial \ln(p_{ijks}^{-\theta})}\frac{\partial \ln(p_{ijks}^{-\theta})}{\partial \ln(p_{ijks})} \\ &= (-\frac{1}{\theta})\frac{1}{\sum_{s=1}^{S_{ijk}} p_{ijks}{}^{-\theta}}p_{ijks}^{-\theta}(-\theta) = \frac{p_{ijks}^{-\theta}}{\sum_{s=1}^{S_{ijk}} p_{ijks}{}^{-\theta}} = \chi_{ijks}.\end{aligned}$$

Therefore, we have

$$\frac{\partial c_{ijk}}{\partial p_{ijks}} = \frac{c_{ijk}}{p_{ijks}}\chi_{ijks}.$$

Similarly, we can show that $\frac{\partial c_i}{\partial c_{ijk}} = \frac{c_i}{c_{ijk}}\delta_{ijk}$. Substituting these results into $\frac{\partial(c_i^{\eta-\sigma}c_{ijk}^{\theta-\eta})}{\partial p_{ijks}}$, we get

$$\frac{\partial(c_i^{\eta-\sigma}c_{ijk}^{\theta-\eta})}{\partial p_{ijks}} = \frac{\chi_{ijks}c_i^{\eta-\sigma}c_{ijk}^{\theta-\eta}}{p_{ijks}}[(\eta-\sigma)\delta_{ijk} + (\theta-\eta)],$$

Substituting the above result back to the FOC we obtain

$$\left[\frac{\chi_{ijks}c_i^{\eta-\sigma}c_{ij}^{s\ \theta-\eta}}{p_{ijks}}((\eta-\sigma)\delta_{ijk}+(\theta-\eta))p_{ijks}^{-\theta}+c_i^{\eta-\sigma}c_{ijk}^{\theta-\eta}\frac{\partial p_{ijks}^{-\theta}}{\partial p_{ijks}}\right](p_{ijks}-c_{jks})$$
$$+c_i^{\eta-\sigma}c_{ijk}{}^{\theta-\eta}p_{ijks}^{-\theta}=0,$$

which can be simplified to

$$[(\eta-\sigma)\delta_{ijk}\chi_{ijks}+(\theta-\eta)\chi_{ijks}-\theta](p_{ijks}-c_{jks})+p_{ijks}=0.$$

Rearranging and solving for p_{ijks} yields

$$p_{ijks}=\frac{(1-\chi_{ijks})\theta+\chi_{ijks}[\sigma\delta_{ijk}+\eta(1-\delta_{ijk})]}{(1-\chi_{ijks})\theta+\chi_{ijks}[\sigma\delta_{ijk}+\eta(1-\delta_{ijk})]-1}c_{jks}. \tag{A3}$$

Since the residual demand faced by a supplier is given by

$$Q_{ijks}(\varphi)=\gamma^{-\theta}(\frac{\sigma-1}{\sigma})^{\sigma}E_iP_i^{\sigma-1}\varphi^{\eta-1}c_i(\varphi)^{\eta-\sigma}\tau_{ijk}^{-\theta}c_{ijk}(\varphi)^{\theta-\eta}p_{ijks}(\varphi)^{-\theta},$$

we have

$$\begin{aligned}\varepsilon_{ijks}(\varphi) &\equiv -\frac{\partial\ln(Q_{ijks}(\varphi))}{\partial\ln(p_{ijks}(\varphi))}=-\frac{\partial\ln(c_i(\varphi)^{\eta-\sigma}c_{ijk}(\varphi)^{\theta-\eta}p_{ijks}(\varphi)^{-\theta})}{\partial\ln(p_{ijks}(\varphi))}\\ &= -[(\eta-\sigma)\chi_{ijks}\delta_{ijk}+(\theta-\eta)\chi_{ijks}-\theta]. \end{aligned} \tag{A4}$$

Equation (A3) can therefore be rewritten as

$$p_{ijks}(\varphi)=\frac{\varepsilon_{ijks}(\varphi)}{\varepsilon_{ijks}(\varphi)-1}c_{jks}. \tag{A5}$$

We next establish the uniqueness of this equilibrium. Again, we ignore the functional argument φ to simplify the notation. Let $\Psi_{ijk}=[p_{ijk1}^{-\theta},p_{ijk2}^{-\theta},\cdots,p_{ijkS_{ijk}}^{-\theta}]'$ and

$$A_{ijk}=\begin{bmatrix}\chi_{ijk1}, & \cdots, & \chi_{ijk1}\\ \chi_{ijk2}, & \cdots, & \chi_{ijk2}\\ \vdots & \vdots & \vdots\\ \chi_{ijkS_{ijk}}, & \cdots, & \chi_{ijkS_{ijk}}\end{bmatrix}.$$

Then equation (3.7) can be written as

$$A_{ijk}\Psi_{ijk} = \Psi_{ijk}. \tag{A6}$$

Given that $\sum_{n=1}^{S_{ijk}} \chi_{ijks} = 1$, and $\chi_{ijks} > 0$ for $\forall n \in \{1, ..., S_{ijk}\}$, matrix A_{ijk} has a non-negative eigenvector with a corresponding eigenvalue $\lambda = 1$ according to the *Perron-Frobenius Theorem*. Consequently, there exists an equilibrium vector Ψ^*_{ijk} that satisfies equation (3.7). However, multiplying Ψ^*_{ijk} by any non-zero number and substituting it into equation (A6), the equation still holds, so that the eigenvector is not unique. Equation (A5) pins down the scale of the eigenvector, however. Formally, suppose Ψ^*_{ijk} and $\beta\Psi^*_{ijk}$ are both eigenvectors of A_{ijk}. According to equation (3.12), we have $p^*_{ijks} = \frac{\varepsilon_{ijks}}{\varepsilon_{ijks}-1} c_{jks}$ and $\beta p^*_{ijks} = \frac{\varepsilon_{ijks}}{\varepsilon_{ijks}-1} c_{jks}$. We therefore have $\beta = 1$ and the solution is unique.

Proof of Proposition 2

We prove the proposition for the case with one new supplier, since we can simply iterate the argument forward for cases with more than one supplier. For brevity, we simplify the notation here. Suppose a downstream buyer is matched with S upstream suppliers. The expenditure shares of the buyer for each supplier are denoted as $\chi_1, \chi_2, \ldots, \chi_S$ and we have $\sum_{n=1}^{S} \chi_n = 1$ before a new supplier enters the market. After matching with the entrant, suppose the suppliers' expenditure shares are $\chi'_1, \chi'_2, \ldots, \chi'_S, \chi'_{S+1}$ and satisfy $\sum_{n=1}^{S+1} \chi'_n = 1$. Since the market share of the entrant is positive, i.e., $\chi'_{S+1} > 0$, we have

$$\sum_{n=1}^{S} \chi'_n < 1 = \sum_{n=1}^{S} \chi_n. \tag{A7}$$

Therefore, the combined market shares of incumbents must decline. We next prove $\chi'_n < \chi_n$, for $1 \leq n \leq S$ by contradiction. Suppose there exists a firm n^* ($1 \leq n^* \leq S$) such that $\chi'_{n^*} \geq \chi_{n^*}$. Then there must be another firm j^* ($1 \leq j^* \leq S$) such that $\chi'_{j^*} < \chi_{j^*}$. Otherwise, inequality (A7) cannot hold. Using equation (3.7), we obtain

$$\chi'_{n^*} = \frac{{p'_{n^*}}^{-\theta}}{\sum_{n=1}^{S+1} {p'_n}^{-\theta}} \geq \chi_{n^*} = \frac{{p_{n^*}}^{-\theta}}{\sum_{n=1}^{S} {p_n}^{-\theta}}. \tag{A8}$$

The assumption that $\rho_{ijk}(\varphi) > 0$ implies $\frac{\partial \mu_{ijks}(\varphi)}{\partial \chi_{ijks}(\varphi)} > 0$: A higher market share leads to a higher markup. Then $\chi'_{n^*} \geq \chi_{n^*}$ implies $p'_{n^*} \geq p_{n^*}$, i.e., supplier n^* charges a higher markup as its market share increases. Rearranging inequality (A8), we have

$$\frac{\sum_{n=1}^{S} p_n{}^{-\theta}}{\sum_{n=1}^{S+1} p_n'{}^{-\theta}} \geq \left(\frac{p_{n^*}}{p'_{n^*}}\right)^{-\theta} \geq 1. \tag{A9}$$

On the other hand, given that $\chi'_{j^*} < \chi_{j^*}$, firm j^* would lower its price, so that we have

$$\begin{aligned} p'_{j^*} &< p_{j^*}, \\ \frac{p'_{j^*}{}^{-\theta}}{\sum_{n=1}^{S+1} p_n'{}^{-\theta}} &< \frac{p_{j^*}{}^{-\theta}}{\sum_{n=1}^{S} p_n{}^{-\theta}}. \end{aligned}$$

Combining the two inequalities, we have

$$\frac{\sum_{n=1}^{S} p_n{}^{-\theta}}{\sum_{n=1}^{S+1} p_n'{}^{-\theta}} < \left(\frac{p_{j^*}}{p'_{j^*}}\right)^{-\theta} < 1,$$

which contradicts inequality (A9). Therefore, there cannot be such a firm as n^* and we must have $\chi'_n < \chi_n$, for $1 \leq n \leq S$. Hence, the market share of all incumbents declines together with their markups and prices. This establishes part (a).

Input price indices are $c = \gamma\tau(\sum_{n=1}^{S} p_n^{-\theta})^{-\frac{1}{\theta}}$ and $c' = \gamma\tau(\sum_{n=1}^{S+1} p_n'^{-\theta})^{-\frac{1}{\theta}}$ before and after including the new supplier, respectively. Given part (a), we have $p'_n < p_n$, for $1 \leq n \leq S$. Therefore

$$\sum_{n=1}^{S} p_n'^{-\theta} > \sum_{n=1}^{S} p_n^{-\theta}.$$

As $p_{S+1}'^{-\theta} > 0$, we have $\sum_{n=1}^{S} p_n'^{-\theta} + p_{S+1}'^{-\theta} > \sum_{n=1}^{S} p_n'^{-\theta}$, which implies a decrease in the buyer's marginal cost when a new supplier is added:

$$c' < c. \tag{A10}$$

Proof of Proposition 3

Consider two buyer firms, one with higher productivity than the other, $\varphi_H > \varphi_L$. Denote their sourcing strategies as $\{\mathbb{I}_i(\varphi_H), \mathbb{S}_i(\varphi_H)\}$, and $\{\mathbb{I}_i(\varphi_L), \mathbb{S}_i(\varphi_L)\}$. For the high productivity firm to prefer $\{\mathbb{I}_i(\varphi_H), \mathbb{S}_i(\varphi_H)\}$ over $\{\mathbb{I}_i(\varphi_L), \mathbb{S}_i(\varphi_L)\}$, we need

$$\gamma^{1-\sigma} B_i \varphi_H^{\sigma-1} \Theta_i(\mathbb{I}_i(\varphi_H), \mathbb{S}_i(\varphi_H))^{\frac{\sigma-1}{\eta-1}} - w_i \sum_{j=1}^{J}\sum_{k=1}^{K} I_{ijk}(\varphi_H) f_{ijk}^{D}(S_{ijk}(\varphi_H))$$

$$> \gamma^{1-\sigma} B_i \varphi_H^{\sigma-1} \Theta_i(\mathbb{I}_i(\varphi_L), \mathbb{S}_i(\varphi_L))^{\frac{\sigma-1}{\eta-1}} - w_i \sum_{j=1}^{J} \sum_{k=1}^{K} I_{ijk}(\varphi_L) f_{ijk}^D(S_{ijk}(\varphi_L)). \quad \text{(A11)}$$

For the low productivity firm to prefer $\{\mathbb{I}_i(\varphi_L), \mathbb{S}_i(\varphi_L)\}$ over $\{\mathbb{I}_i(\varphi_H), \mathbb{S}_i(\varphi_H)\}$, we need

$$\gamma^{1-\sigma} B_i \varphi_L^{\sigma-1} \Theta_i(\mathbb{I}_i(\varphi_L), \mathbb{S}_i(\varphi_L))^{\frac{\sigma-1}{\eta-1}} - w_i \sum_{j=1}^{J} \sum_{k=1}^{K} I_{ijk}(\varphi_L) f_{ijk}^D(S_{ijk}(\varphi_L))$$
$$> \gamma^{1-\sigma} B_i \varphi_L^{\sigma-1} \Theta_i(\mathbb{I}_i(\varphi_H), \mathbb{S}_i(\varphi_H))^{\frac{\sigma-1}{\eta-1}} - w_i \sum_{j=1}^{J} \sum_{k=1}^{K} I_{ijk}(\varphi_H) f_{ijk}^D(S_{ijk}(\varphi_H)). \quad \text{(A12)}$$

Combining the two inequalities above, we obtain

$$\gamma^{1-\sigma} B_i (\varphi_H^{\sigma-1} - \varphi_L^{\sigma-1}) \left(\Theta_i(\mathbb{I}_i(\varphi_H), \mathbb{S}_i(\varphi_H))^{\frac{\sigma-1}{\eta-1}} - \Theta_i(\mathbb{I}_i(\varphi_L), \mathbb{S}_i(\varphi_L))^{\frac{\sigma-1}{\eta-1}} \right) > 0. \quad \text{(A13)}$$

Given that $\varphi_H > \varphi_L$, and $\sigma, \eta > 1$, the inequality above implies $\Theta_i(\mathbb{I}_i(\varphi_H), \mathbb{S}_i(\varphi_H)) > \Theta_i(\mathbb{I}_i(\varphi_L), \mathbb{S}_i(\varphi_L))$. Therefore, we establish result (b) that the buyers' sourcing capability is non-decreasing in φ.

We next prove result (a). Under our parameter restrictions that $\sigma > \eta$ and $\rho_{ijk}(\varphi) > 0$, we show that the profit function of the downstream firm in equation (3.13) features increasing differences in (I_{ijk}, I_{imn}), (S_{ijk}, S_{imn}) and (I_{ijk}, S_{imn}) for $\forall\ j \neq m$ or $\forall\ k \neq n$. In addition, it also has increasing differences in (I_{ijk}, φ) and (S_{ijk}, φ) for $\forall\ j$ and k. Therefore, according to the Topkis' Theorem, we have the following monotone comparative statics result: $I_{ijk}(\varphi_H) \geq I_{ijk}(\varphi_L)$ and $S_{ijk}(\varphi_H) \geq S_{ijk}(\varphi_L)$ for $\varphi_H \geq \varphi_L$.

To show these increasing differences properties of the profit function, we first invoke Proposition 2 and note that the country-sector input price index given in equation (3.8) is decreasing in the number of upstream firms within the sector if $\rho_{ijk}(\varphi) > 0$; that is $c_{ijk}(S_{ijk}+1) < c_{ijk}(S_{ijk})\ \forall S_{ijk} > 0$. We first show that the profit function is supermodular in (c_{ijk}, c_{imn}). We note that

$$\frac{\partial \pi_i^D}{\partial c_{ijk}} = (1-\sigma) B_i \frac{1}{\varphi} c_i(\varphi)^{1-\sigma} \Theta_i^{\eta} I_{ijk} c_{ijk}{}^{-\eta} = (1-\sigma)\gamma^{-\sigma} B_i \varphi^{\sigma-1} \Theta_i^{\frac{\sigma}{\eta-1}+\eta} I_{ijk} c_{ijk}{}^{-\eta}.$$

Therefore, we have

$$\frac{\partial^2 \pi_i^D}{\partial c_{ijk} \partial c_{imn}} = (1-\sigma)(1-\eta)\gamma^{-\sigma} \left(\frac{\sigma}{\eta-1} + \eta \right) B_i \varphi^{\sigma-1} \Theta_i^{\frac{\sigma}{\eta-1}+\eta-1} I_{ijk} c_{ijk}{}^{-\eta} I_{imn} c_{imn}{}^{-\eta}. \quad \text{(A14)}$$

It is easy to see that, under the parameter restriction $\sigma > \eta > 1$,

$$\frac{\partial^2 \pi_i^D}{\partial c_{ijk} \partial c_{imn}} \geq 0.$$

Therefore, the profit function features increasing differences in (c_{ijk}, c_{imn}):

$$\pi_i^D(c_{ijk}{}^H, c_{imn}{}^H) - \pi_i^D(c_{ijk}{}^L, c_{imn}{}^H) \geq \pi_i^D(c_{ijk}{}^H, c_{imn}{}^L) - \pi_i^D(c_{ijk}{}^L, c_{imn}{}^L),$$

for $c_{ijk}{}^H > c_{ijk}{}^L$ and $c_{imn}{}^H > c_{imn}{}^L$. Given that the country-sector price indices *decrease* in the number of upstream suppliers, we can re-write the inequality above by replacing arguments of the profit function: [1]

$$\pi_i^D(S_{ijk}{}^L, S_{imn}{}^L) - \pi_i^D(S_{ijk}{}^H, S_{imn}{}^L) \geq \pi_i^D(S_{ijk}{}^L, S_{imn}{}^H) - \pi_i^D(S_{ijk}{}^H, S_{imn}{}^H).$$

Multiplying both sides of the inequality by -1, we obtain

$$\pi_i^D(S_{ijk}{}^H, S_{imn}{}^H) - \pi_i^D(S_{ijk}{}^L, S_{imn}{}^H) \geq \pi_i^D(S_{ijk}{}^H, S_{imn}{}^L) - \pi_i^D(S_{ijk}{}^L, S_{imn}{}^L).$$

Therefore, the profit function also features increasing differences in the number of matched upstream firms (S_{ijk}, S_{imn}).

Finally, from equation (A14), it is obvious that the profit function has decreasing differences in (c_{ijk}, φ) and (c_{ijk}, I_{ijk}). Since c_{ijk} is decreasing in S_{ijk}, the profit function has increasing differences in (S_{ijk}, φ) and (S_{ijk}, I_{ijk}). To conclude, as long as $\sigma > \eta$, it is obvious that the profit function has increasing differences in (I_{ijk}, I_{imn}) and (I_{ijk}, φ).

Proof of Proposition 4

According to Proposition 3, we have $S_{ijk}(\varphi_H) \geq S_{ijk}(\varphi_L)$ for $\varphi_H > \varphi_L$. Therefore, firms that are sufficiently productive will be able to include the new entrants as suppliers. To be specific, before the entry of new suppliers, buyers with productivity $\varphi > \overline{\varphi}_{ij,S_{ijk}}$ can include the marginal upstream firm with the highest marginal cost as a supplier. When there are new entrants such that $S'_{ijk} > S_{ijk}$, then buyers with productivity $\varphi > \overline{\varphi}_{ij,S'_{ijk}}$ now source from $S_{ijk}(\varphi) = S'_{ijk}$ suppliers from country j in sector s, buyers with productivity $\overline{\varphi}_{ij,S'_{ijk}-1} < \varphi < \overline{\varphi}_{ij,S'_{ijk}}$ now source from $S_{ijk}(\varphi) = S'_{ijk} - 1$ suppliers, and buyers with productivity $\overline{\varphi}_{ij,S_{ijk}+1} < \varphi < \overline{\varphi}_{ij,S_{ijk}+2}$ now source from $S_{ijk}(\varphi) = S_{ijk} + 1$ suppliers. Finally, firms with productivity $\varphi < \overline{\varphi}_{ij,S_{ijk}+1}$ do not

[1] The number of upstream suppliers also affects the profit function through the fixed costs. Since they enter additively, however, they are differenced out.

change their sourcing strategy, as they cannot afford the higher fixed cost of more suppliers. In sum, firms with productivity higher than $\overline{\varphi}_{ij,S_{ijk}+1}$ increase the number of matched suppliers. Moreover, the higher a buyer's productivity, the more additional suppliers it adds to its portfolio. This establishes part (a) and (c).

Now we invoke result (b) of Proposition 2, which states that a higher number of upstream suppliers $S_{ijk}(\varphi)$ reduces the cost index $c_{ijk}(\varphi)$. Furthermore, it is easy to see from equations (3.10) and (3.15) that the quantity $Q_{ijk}(\varphi)$ and value $X_{ijk}(\varphi)$ of trade rise when the price index $c_{ijk}(\varphi)$ drops. According to result (a) above, downstream buyers weakly increase the matched number of upstream suppliers, with a larger magnitude for high-productivity firms. Naturally, this tends to reduce the price index $c_{ijk}(\varphi)$, increase trade quantity $Q_{ijs}(\varphi)$ and value $X_{ijk}(\varphi)$, with stronger effect for high productivity downstream firms.

Proof of Proposition 5

If sourcing decisions exhibit complementarity, the profit function specified in problem (3.13) features increasing differences between the sourcing decisions and the sourcing potential. Using Topkis's theorem, we have $\mathbb{I}_i(\varphi, \vec{\phi}_i(\varphi)) \subseteq \mathbb{I}_i(\varphi, \vec{\phi}_i{}'(\varphi))$, $\mathbb{S}_i(\varphi, \vec{\phi}_i(\varphi)) \subseteq \mathbb{S}_i(\varphi, \vec{\phi}_i{}'(\varphi))$, where $\vec{\phi}_i(\varphi) = \{\phi_{ijk}(\varphi)\}_{j=1,k=1}^{J,K}$ is the vector of sourcing potentials and $\phi_{ijk}(\varphi)' \geq \phi_{ijk}(\varphi)$ due to lower iceberg costs. The profit function also features increasing differences between the sourcing decisions and the matching friction. We have $\mathbb{I}_i(\varphi, \vec{f}_i) \subseteq \mathbb{I}_i(\varphi, \vec{f}_i{}')$, $\mathbb{S}_i(\varphi, \vec{f}_i) \subseteq \mathbb{S}_i(\varphi, \vec{f}_i{}')$, where $\vec{f}_i = \{f^D_{ijs}(S)\}_{j=1,k=1,s=1}^{J,K,S_{ijk}}$ and $f_{ijs}(S)' \leq f_{ijs}(S)$ for $S \geq 0$. However, the low-productivity firms will not be able to source from the additional suppliers. The most productive firms have already been matched with all potential suppliers. Therefore, it is the mid-productivity buyer firms that add additional suppliers and benefit the most.

Pricing of Upstream Firms

First, from equation (3.12), we know that an upstream supplier's markup when matched to a buyer with productivity is given by

$$\mu_{ijks}(\varphi) = \frac{\varepsilon_{ijks}(\varphi)}{\varepsilon_{ijks}(\varphi) - 1},$$

where $\varepsilon_{ijks}(\varphi) = -[(\eta - \sigma)\chi_{ijks}(\varphi)\delta_{ijk}(\varphi) + (\theta - \eta)\chi_{ijks}(\varphi) - \theta]$. Since $\frac{\partial \varepsilon_{ijks}(\varphi)}{\partial \chi_{ijks}(\varphi)} = -[(\eta - \sigma)\delta_{ijk}(\varphi) + (\theta - \eta)] = -\rho_{ijk}(\varphi)$, we have

$$\frac{\partial \mu_{ijks}(\varphi)}{\partial \chi_{ijks}(\varphi)} = \frac{-\frac{\partial \varepsilon_{ijks}(\varphi)}{\partial \chi_{ijks}(\varphi)}}{(\varepsilon_{ijks}(\varphi) - 1)^2} = \frac{\rho_{ijk}(\varphi)}{(\varepsilon_{ijks}(\varphi) - 1)^2}.$$

Next, we define an upstream firm's *competitor markup elasticities* (Amiti et al. 2019) as:

$$\Gamma_{-ijks}(\varphi) = \sum_{n \neq s, n=1,\ldots,S_{ijks}} \frac{\partial \mu_{ijks}(\varphi)}{\partial p_{ijkn}(\varphi)}.$$

If the markup elasticity with respect to competitor prices is *positive*, i.e., $\Gamma_{-ijks}(\varphi) > 0$, there are strategic complementarities in price setting among upstream firms: a supplier increases its markup in response to a competitor's price hike.

For brevity, we omit φ in the rest of the proof. Using equations (3.7) and (3.12), we find that

$$\begin{aligned}
\Gamma_{-ijks} &= \sum_{n \neq s, n=1,\ldots,S_{ijks}} \frac{\partial \mu_{ijks}}{\partial p_{ijkn}} = \sum_{n \neq s, n=1,\ldots,S_{ijks}} \frac{\partial \mu_{ijks}}{\partial \chi_{ijks}} \frac{\partial \chi_{ijks}}{\partial p_{ijkn}} \\
&= \frac{\rho_{ijk}}{(\varepsilon_{ijks} - 1)^2} \sum_{n \neq s, n=1,\ldots,S_{ijks}} \frac{\partial \chi_{ijks}}{\partial p_{ijkn}},
\end{aligned}$$

and

$$\begin{aligned}
\frac{\partial \chi_{ijks}}{\partial p_{ijkn}} &= \frac{-p_{ijks}^{-\theta}(-\theta p_{ijkn}^{-\theta-1})}{(\sum_n p_{ijkn}^{-\theta})^2} = \frac{\theta p_{ijks}^{-\theta}}{\sum_n p_{ijkn}^{-\theta}} \frac{p_{ijkn}^{-\theta}}{\sum_n p_{ijkn}^{-\theta}} p_{ijkn}^{-1} \\
&= \theta \chi_{ijks} \chi_{ijkn} p_{ijkn}^{-1}.
\end{aligned}$$

Combing the two results above, we find that

$$\begin{aligned}
\Gamma_{-ijks} &= \frac{\rho_{ijk}}{(\varepsilon_{ijks} - 1)^2} \sum_{n \neq s, n=1,\ldots,S_{ijks}} \theta \chi_{ijks} \chi_{ijkn} p_{ijkn}^{-1} \\
&= \frac{\rho_{ijk}}{(\varepsilon_{ijks} - 1)^2} \theta \chi_{ijks} \sum_{n \neq s, n=1,\ldots,S_{ijks}} \chi_{ijkn} p_{ijkn}^{-1}.
\end{aligned} \tag{A15}$$

Therefore, as long as $\rho_{ijk} > 0$, we have $\Gamma_{-ijks} > 0$ and upstream supplier pricing features strategic complementarity.

C.2. Estimation Appendix

Combinatorial Multinomial Discrete Choice Problem

We consider the following combinatorial multinomial discrete choice problem,

$$\max_{\mathcal{M} \in \mathbb{Z}^n} \pi(\mathcal{M}, \varphi), \tag{A16}$$

where a firm of productivity φ chooses a vector $\mathcal{M} = [M_1, M_2, ..., M_n]$ of non-negative finite integers $M_i \in \{0, 1, 2, ..., S_i\}$ and $i \in \{1, 2, ..., n\}$ to maximize the profit $\pi(\mathcal{M}, \varphi)$.[2] The collection of all permissible vectors is denoted by $\mathbb{Z}^n$, while S_i is the upper bound of option i and satisfies $1 \le S_i < \infty$. If $S_i = 1$ for all i, it is a binary choice problem.

We next discuss the algorithm to search for $\mathcal{M}^*$, the solution to the problem (A16). A brute force algorithm has a computational complexity of $\Pi_{i=1}^{n}(S_i + 1)$, which rises rapidly when the number of options n or the upper bound of each option S_i increases. To solve this problem, we extend the method of Jia (2008), Antràs et al. (2017) and Arkolakis et al. (2023b) for combinatorial *binary* choice problems to combinatorial *multinomial* choice problems. The key idea is to eliminate non-optimal choice sets without evaluating the profit function for all possible choices.

DEFINITION A1. *The marginal value operators, D_i^+ and D_i^- are defined as*

$$\begin{aligned} D_i^+ \pi(\mathcal{M}, \varphi) &= \pi([..., M_i + 1, ...], \varphi) - \pi([..., M_i, ...], \varphi), \ for \ M_i < S_i, \\ D_i^- \pi(\mathcal{M}, \varphi) &= \pi([..., M_i, ...], \varphi) - \pi([..., M_i - 1, ...], \varphi), \ for \ M_i > 0. \end{aligned}$$

Therefore, when we apply D_i^+ to the profit function $\pi(\mathcal{M}, \varphi)$, we obtain the marginal value of expanding option i of $\mathcal{M}$ by 1, while D_i^- pertains the marginal value of shrinking $\mathcal{M}$ by 1 for option i. The problem is combinatorial as long as the marginal values are not fully independent across options; otherwise, we can solve the problem option by option.

To reduce the choice set, we exploit two properties.

DEFINITION A2. *For any two decisions $\mathbf{0} \le \mathcal{M}_1 \le \mathcal{M}_2 \le \mathcal{S}$, the profit function $\pi(\mathcal{M}, \varphi)$ obeys single crossing differences from above (SCD-A) if for any option $i \in \{1, 2, ..., n\}$, we have*

$$D_i^+ \pi(\mathcal{M}_2, \varphi) \ge 0 \ \Rightarrow \ D_i^+ \pi(\mathcal{M}_1, \varphi) \ge 0, \tag{A17}$$

$$D_i^- \pi(\mathcal{M}_2, \varphi) \ge 0 \ \Rightarrow \ D_i^- \pi(\mathcal{M}_1, \varphi) \ge 0, \tag{A18}$$

[2] For example, firms in our model choose the number of suppliers to maximize profit in problem (3.13). It can also be a firm making decisions on the number of workers to hire for teams within the firm, or the number of stores to operate across locations.

and single crossing differences from below (SCD-B) if

$$D_i^{+}\pi(\mathcal{M}_1,\varphi)\geq 0 \quad\Rightarrow\quad D_i^{+}\pi(\mathcal{M}_2,\varphi)\geq 0, \tag{A19}$$

$$D_i^{-}\pi(\mathcal{M}_1,\varphi)\geq 0 \quad\Rightarrow\quad D_i^{-}\pi(\mathcal{M}_2,\varphi)\geq 0 \tag{A20}$$

where $\boldsymbol{0}=[0,...,0]$ *and* $\mathcal{S}=[S_1,S_2,...,S_n]$ *are the lower and upper bounds of the firm's choice.*

Therefore, if the profit function exhibits SCD-B, the marginal value of a larger choice ($\mathcal{M}_2$) is positive whenever the marginal value of a smaller choice ($\mathcal{M}_1$) is positive.[3] Intuitively, the choices are complementary. Similarly, under SCD-A, the choices are substitutes.

Next, we show that we can use a "squeezing procedure" to eliminate the non-optimal choices by iteration. For brevity, we demonstrate it for the scenario of SCD-B, the case of complementarity, which is what we focus on in this paper.

DEFINITION A3. *(Squeezing procedure) Suppose the profit function* $\pi(\mathcal{M}_1,\varphi)$ *exhibits SCD-B. Then for problem (A16), its bounding choices* $[\underline{\mathcal{M}}^{(k)},\overline{\mathcal{M}}^{(k)}]$ *are the output of the* k^{th} *application of the mapping of* S^B *given by*

$$S^B([\underline{\mathcal{M}}^{(k)},\overline{\mathcal{M}}^{(k)}])=[\underline{\mathcal{M}}^{(k+1)},\overline{\mathcal{M}}^{(k+1)}], \tag{A21}$$

such that

$$\begin{aligned}\underline{\mathcal{M}}^{(k+1)} &= \underline{\mathcal{M}}^{(k)}+[\mathbb{1}_1^{k+},\mathbb{1}_2^{k+},...,\mathbb{1}_n^{k+}],\\ \overline{\mathcal{M}}^{(k+1)} &= \overline{\mathcal{M}}^{(k)}-[\mathbb{1}_1^{k-},\mathbb{1}_2^{k-},...,\mathbb{1}_n^{k-}],\end{aligned}$$

where $\mathbb{1}_i^{k+}$ *and* $\mathbb{1}_i^{k-}$ *are indicators such that*

$$\mathbb{1}_i^{k+}=\begin{cases}1 & \text{if } D_i^{+}(\underline{\mathcal{M}}^{(k)})\geq 0,\\ 0 & \text{otherwise };\end{cases} \quad \text{and } \mathbb{1}_i^{k-}=\begin{cases}1 & \text{if } D_i^{-}(\overline{\mathcal{M}}^{(k)})<0,\\ 0 & \text{otherwise }.\end{cases} \tag{A22}$$

Every time the squeezing procedure is applied, it raises $\underline{\mathcal{M}}$ by increasing those options that have positive marginal value and decreases $\overline{\mathcal{M}}$ by reducing those options that have negative marginal value. By iteration, similar to Arkolakis et al. (2023b), the squeezing procedure converges to a fixed point that bounds the optimal solution in polynomial time, as established in the result below.

THEOREM A1. *Given the problem specified in (A16), if* $\pi(\mathcal{M},\varphi)$ *obeys SCD-B, successively applying* S^B *to* $[\boldsymbol{0},\mathcal{S}]$ *returns a sequence of bounding choices such that* $\underline{\mathcal{M}}^{(k)}\leq\underline{\mathcal{M}}^{(k+1)}\leq\mathcal{M}^*\leq$

[3] $\mathcal{M}_2\geq\mathcal{M}_1$ if every element of $\mathcal{M}_2$ is greater than, or equal to, the corresponding element of $\mathcal{M}_1$.

$\overline{\mathcal{M}}^{(k+1)} \leq \overline{\mathcal{M}}^{(k)}$ *in* $\mathcal{O}(n)$ *time.*

PROOF. We prove the theorem by induction. We apply S^B from $\underline{\mathcal{M}}^{(1)} = \mathbf{0}$, and $\overline{\mathcal{M}}^{(1)} = \mathcal{S}$. It is trivially true that $\mathbf{0} \leq \underline{\mathcal{M}}^{(1)}$ and $\overline{\mathcal{M}}^{(1)} \leq \mathcal{S}$. We first show that $\underline{\mathcal{M}}^{(1)} \leq \mathcal{M}^* \leq \overline{\mathcal{M}}^{(1)}$. By SCD-B and $\mathbf{0} \leq \underline{\mathcal{M}}^{(1)}$, we have $D_i^+\pi(\mathbf{0}, \varphi) \geq 0 \Longrightarrow D_i^+\pi(\underline{\mathcal{M}}^{(1)}, \varphi) \geq 0$. Since $D_i^+\pi(\underline{\mathcal{M}}^{(1)}, \varphi) \geq 0$ is true for any i, increasing any element of $\underline{\mathcal{M}}^{(1)}$ leads to an equal or higher profit. It must be that $\underline{\mathcal{M}}^{(1)} \leq \mathcal{M}^*$. Similarly, $D_i^-\pi(\mathcal{M}^*, \varphi) \geq 0$ by the optimality of $\mathcal{M}^*$. Then given $\overline{\mathcal{M}}^{(1)} \leq \mathcal{S}$ and SCD-B, we have $D_i^-\pi(\mathcal{S}, \varphi) \geq 0$ for any i; reducing any element of $\overline{\mathcal{M}}^{(1)}$ therefore leads to an equal or higher profit. Therefore, it must be that $\mathcal{M}^* \leq \overline{\mathcal{M}}^{(1)}$.

Suppose $\underline{\mathcal{M}}^{(k-1)} \leq \underline{\mathcal{M}}^{(k)} \leq \mathcal{M}^* \leq \overline{\mathcal{M}}^{(k)} \leq \overline{\mathcal{M}}^{(k-1)}$ for any $k > 1$. Given $\underline{\mathcal{M}}^{(k-1)} \leq \underline{\mathcal{M}}^{(k)} \leq \mathcal{M}^*$, it must be that $D_i^+\pi(\overline{\mathcal{M}}^{(k-1)}, \varphi) \geq 0$, i.e., raising any element of $\overline{\mathcal{M}}^{(k-1)}$ leads to an equal or higher profit. Then by SCD-B and $\underline{\mathcal{M}}^{(k-1)} \leq \underline{\mathcal{M}}^{(k)}$, we have $D_i^+\pi(\underline{\mathcal{M}}^{(k)}, \varphi) \geq 0$. Defining

$$\underline{\mathcal{M}}^{(k+1)} = \underline{\mathcal{M}}^{(k)} + [\mathbb{1}_1^{k+}, \mathbb{1}_2^{k+}, ..., \mathbb{1}_n^{k+}], \tag{A23}$$

we have $\underline{\mathcal{M}}^{(k)} \leq \underline{\mathcal{M}}^{(k+1)}$. Therefore, due to SCD-B, we have $D_i^+\pi(\underline{\mathcal{M}}^{(k+1)}, \varphi) \geq 0$, and that increasing any element of $\underline{\mathcal{M}}^{(k+1)}$ leads to an equal or higher profit. Naturally, $\underline{\mathcal{M}}^{(k+1)} \leq \mathcal{M}^*$, given the optimality of $\mathcal{M}^*$. Similarly, from $\mathcal{M}^* \leq \overline{\mathcal{M}}^{(k)} \leq \overline{\mathcal{M}}^{(k-1)}$, by the optimality of $\mathcal{M}^*$, we know that

$$D_i^-\pi(\overline{\mathcal{M}}^{(k)}, \varphi) \leq 0,$$

i.e., reducing $\overline{\mathcal{M}}^{(k)}$ by any element leads to a higher or equal profit.

If we define

$$\overline{\mathcal{M}}^{(k+1)} = \overline{\mathcal{M}}^{(k)} - [\mathbb{1}_1^{k-}, \mathbb{1}_2^{k-}, ..., \mathbb{1}_n^{k-}], \tag{A24}$$

we have $\overline{\mathcal{M}}^{(k+1)} \leq \overline{\mathcal{M}}^{(k)}$. Then, by SCD-B, we have

$$D_i^-\pi(\overline{\mathcal{M}}^{(k+1)}, \varphi) \leq 0.$$

Therefore, reducing any element of $\overline{\mathcal{M}}^{(k+1)}$ leads to a higher profit and we have $\mathcal{M}^* \leq \overline{\mathcal{M}}^{(k+1)}$ by the optimality of $\mathcal{M}^*$. Combing the results above, we have $\underline{\mathcal{M}}^{(k)} \leq \underline{\mathcal{M}}^{(k+1)} \leq \mathcal{M}^* \leq \overline{\mathcal{M}}^{(k+1)} \leq \overline{\mathcal{M}}^{(k)}$.

The above squeezing procedure stops within $\sum_{i=1}^n (S_i + 1)$ iterations, which is bounded by $n \cdot \max_{i=1,...,n}\{S_i + 1\}$. To see that, we note that the procedure does not decrease the lower bound choice or increase the upper bound choice, as evident in equations (A23) and (A24). □

The Estimation Algorithm

Here we describe the algorithm to estimate the demand shifter and fixed cost of sourcing by simulated method of moments.

- Step 1: draw K random samples of suppliers and marginal costs and N buyer firms and their productivity. We obtain $M = KN$ samples by interacting the two random samples, each with a particular productivity and supplier cost sample.
- Step 2: compute and save prices charged by suppliers for every possible supplier configuration for each supplier cost draw.
- Step 3: Guess an initial value for parameters to be estimated and denote it as Φ_0.
- Step 4: For a guess of Φ_t, use the extended algorithm in appendix section C.2 to solve the optimal sourcing problem for each downstream buyer for the drawn buyers and suppliers.
- Step 5: For each moment m_i, compute it as the sample average across the M samples of buyers and suppliers (denoted by $\tilde{\mathrm{m}}_i(\Phi_t)$).
- Step 6: Compute the Euclidean distance between the model moments and data moments for a given weighting matrix W:

$$y_t = (\tilde{\mathrm{m}}(\Phi_t) - m)\mathrm{W}(\tilde{\mathrm{m}}(\Phi_t) - m)', \tag{A25}$$

  where $\tilde{\mathrm{m}}(\Phi_t) = [m_1(\Phi_t), ..., m_S(\Phi_t)]$ are the set of targeted moments and $m = [m_1, ..., m_s]$ are the data counterparts.
- Step 7: Stop if $y_t < \epsilon$ where ϵ is a small positive number capturing the numerical precision. Otherwise, we go back to Step 3 and start with a new guess Φ_{t+1}.

Table A1. Summary Statistics

	2000				2006			
	N	Mean	St Dev	Median	N	Mean	St Dev	Median
Panel A. Market Structure (by HS-6 product)								
# CHN exporters to CHL	1,431	12.4	23.5	5	2,388	21.4	43.8	7
# CHN exporters to ROW w/o CHL	1,952	353	488	183	3,030	868	1,577	313
# CHL importers from CHN	1,954	14.8	29.8	4	3,034	22.9	46.8	6
# CHN exporters to FRA	2,139	16.9	38.3	5	2,954	37.7	92.3	9
# CHN exporters to ROW w/o FRA	2,865	272	426	124	3,695	729	1,452	231
# FRA importers from CHN	2,863	28.6	72.1	6	3,671	56.6	142.1	9
Panel B. Control Variables (by HS-6 product)								
applied EU import tariff (%)	2,899	3.9	7.5	1.5	3,600	2.8	7.1	0
mean VA / worker CHN exporters (log)	2,699	4.16	0.82	4.09	3,576	5.01	0.88	4.94
variance VA / worker CHN exporters (log)	2,546	7.23	2.23	7.31	3,454	9.30	2.27	9.35
mean TFP CHN exporters (log)	2,699	6.93	0.89	6.85	3,576	7.57	0.97	7.50
variance TFP CHN exporters (log)	2,546	13	2.22	13.2	3,454	14.7	2.25	14.7
mean input unit value CHN exporters (log), de-meaned	2,863	4.17	1.4	4.22	3,689	4.29	1.48	4.30
share CHN processing trade	2,865	0.36	0.32	0.29	3,695	0.26	0.27	0.16
share CHN trade intermediares	2,865	0.41	0.24	0.40	3,695	0.43	0.22	0.44
share CHN foreign-owned exporters	2,865	0.17	0.12	0.15	3,695	0.17	0.12	0.14
share CHN multi-product exporters	2,865	0.95	0.11	0.99	3,695	0.94	0.11	0.99
Panel C. Importer Characteristics (Firm-level)								
CHL sales (1m CHL Pesos)	2,164	20,681	55,141	1,050	6,488	16,173	48,987	1,050
CHL total imports (USD 1,000)	2,525	730	3,532	74	6,519	1,193	7,511	71
FRA sales (EUR 1,000)	11,319	59,600	609,900	4,000	22,790	48,400	574,300	3,200
FRA total imports (EUR 1,000)	12,571	785	7,088	43	25,737	864	7,631	32
FRA sales / worker (EUR 1,000)	10,679	460	2,854	215	20,860	466	3,530	222
Panel D. Chilean Sourcing Network with China								
# CHL importer - CHN exporter pairs (by HS-6 product)	1,954	26.1	67.5	5	3,034	37.3	91.5	8
trade value (by HS-6 product, USD 1,000)	1,954	439	1,848	37.2	3,034	1,122	5,124	99.3
unit value (by HS-6 product, USD 1,000)	1,954	1.1	37.4	0.005	3,034	3.6	120	0.005
# CHL importers (by exporter-HS-6 product)	37,954	1.3	1.5	1	89,714	1.3	1.3	1
trade value (by exporter-HS-6 product, USD 1,000)	37,954	22.6	106	2.9	89,714	37.9	272	3.78
unit value (by exporter-HS-6 product, USD 1,000)	37,954	0.14	10	0.004	89,714	0.38	23.1	0.005
# CHN exporters (by importer-HS-6 product)	28,940	1.8	2.0	1	69,542	1.6	1.8	1
trade value (by importer-HS-6 product, USD 1,000)	28,940	29.7	180	1.8	69,542	48.9	378	2.4
unit value (by importer-HS-6 product, USD 1,000)	28,940	0.14	9.9	0.003	69,542	0.46	28.4	0.005

Note: This table reports summary statistics for the upstream market structure and other characteristics in China across HS-6 products (Panels A-B), downstream Chilean and French firm characteristics (Panel C), and characteristics of the network of Chilean buyers and Chinese suppliers (Panel D).

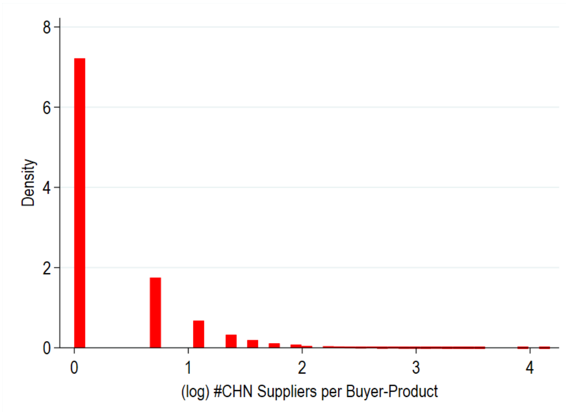
C.3. Additional Tables and Figures

Table A2. Additional Robustness

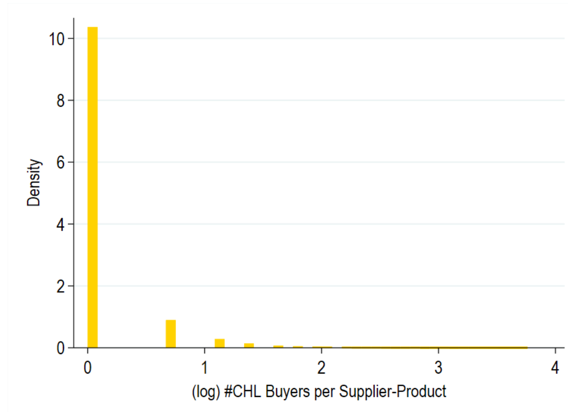
	Balanced Sample	Natural Quantity Units				No Eastern Europe Importers
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Chile						
(log) Import Value$_{fpt}$	0.021		0.089	0.089**	0.129***	
(log) Import Quantity$_{fpt}$	0.200***		0.231***	0.241***	0.317***	
(log) Import Unit Value$_{fpt}$	-0.179***		-0.140***	-0.152***	-0.188***	
N	169,436		294,149	301,370	306,857	
Panel B. France						
(log) Import Value$_{fpt}$	0.148***	0.277***	0.126***	0.125***	0.114***	0.094***
(log) Import Quantity$_{fpt}$	0.194***	0.356***	0.159***	0.160***	0.145***	0.126***
(log) Import Unit Value$_{fpt}$	-0.045***	-0.078***	-0.033***	-0.036***	-0.030***	-0.033***
N	486,849	308,718	829,308	803,363	887,062	319,098
Firm, Year, HS-6 Product FE	YES	YES	YES	YES	YES	YES
HS-6 Product Trend	YES	YES	YES	YES	YES	YES
Product × Year Controls	YES	YES	YES	YES	YES	YES
Downstr. Industry x Year FE			YES			
(log) # CHN→ROW Exporters$_{pt}$ other products				YES		
(log) # CHN→ROW Exporters$_{pt}$ in HS-4					YES	
Sample	(1)					(2)

Note: This table confirms the robustness of the results in Columns 2 and 4 of Table 1. Column 3 includes the (log) number of Chinese exporters to the rest of the world in all products of a firm other than p as a control. Columns 4 and 12 include the (log) number of Chinese exporters to the rest of the world in the HS 4 product to which p belongs. Sample (1) includes trade flows of firms that are present in all years. Sample (2) includes firms that never trade with Eastern European countries during our sample period. The product × year controls include the (log) number of French importers from ROW; the EU ad-valorem import tariff on Chinese exports; the average productivity of Chinese exporters, the variance of the productivity of Chinese exporters, the average quality of Chinese exporters; the value shares of processing trade, intermediated trade; and the share of foreign-owned, multi-product, state-owned firms in Chinese exports. Singletons are dropped, and standard errors are clustered by HS-6 product × year. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

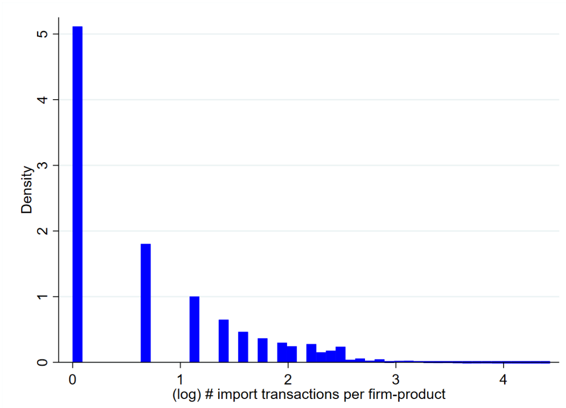
Figure A1. Sparse Production Networks



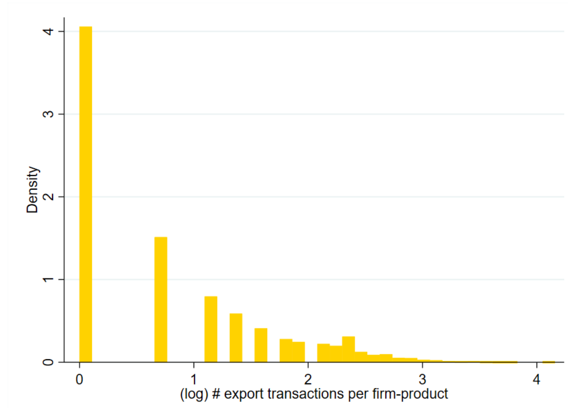
(A) Chinese suppliers per Chilean buyer



(B) Chilean buyers per Chinese supplier



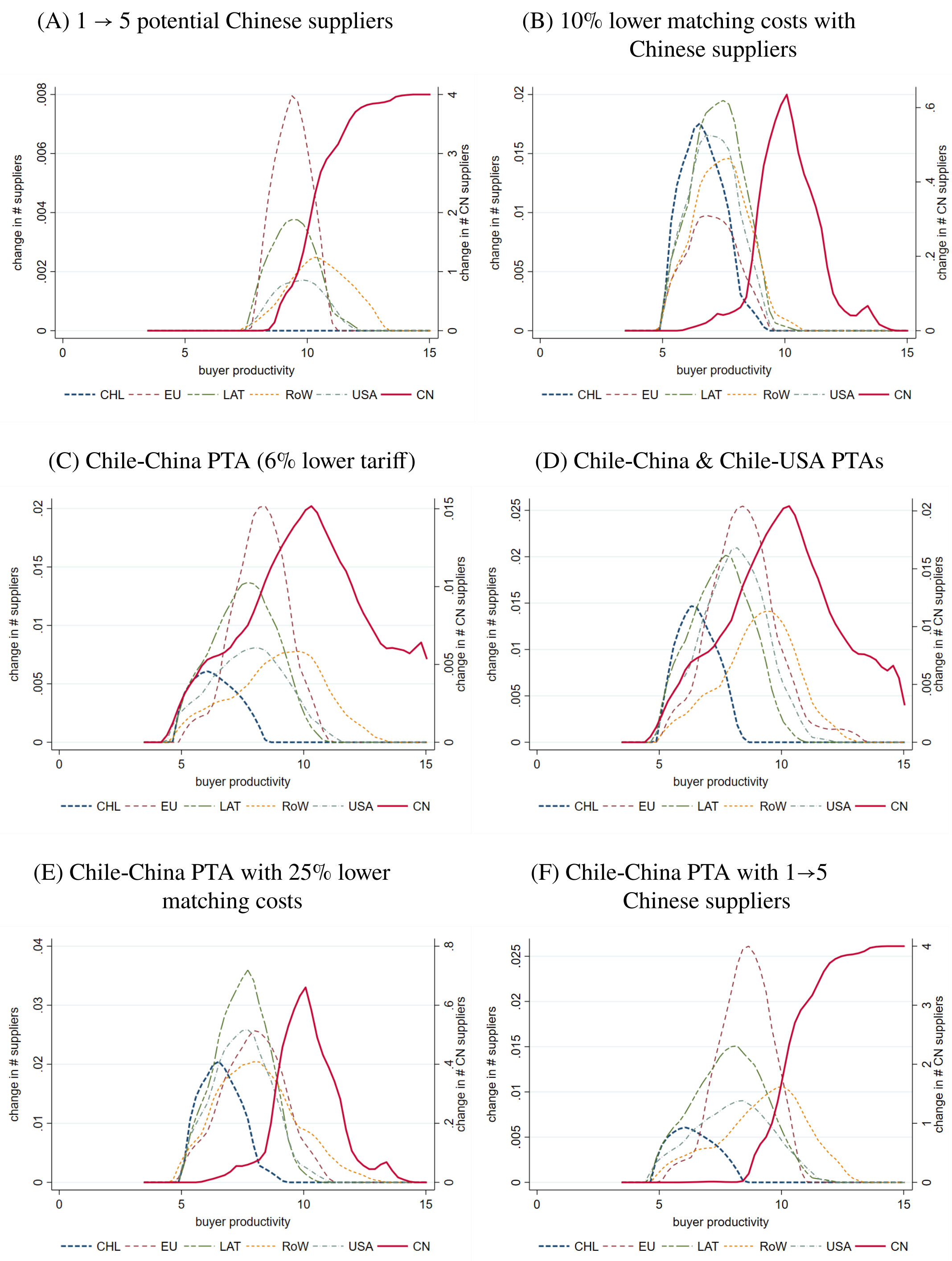
(C) Import transactions per French buyer



(D) Export transactions per Chinese supplier

Note: Histograms of log number of (a) Chinese suppliers per Chilean buyer-HS6 product, (b) Chilean buyers per Chinese supplier-product, (c) import transactions from China per French buyer-product, and (d) export transactions to France per Chinese supplier-product.

FIGURE A2. Change in the Number of Suppliers per Origin



Note: Figure shows comparisons between the baseline model and counterfactual simulations for the number of suppliers. Plot a) illustrates an increase in the # of potential Chinese suppliers from 1 to 5; plot B a 25% reduction in β_0 and β_4; plot c) a trade cost reduction of 6% with China; plot d) a 6% trade cost reduction vis-a-vis China and the USA; plot e) a 6% trade cost reduction with China and a reduction of β_0 and β_4 by 25%; plot f) a 6% trade cost reduction with China and an increase in the # of potential Chinese suppliers from 1 to 5.