Risky Global Agricultural Supply Chains: Evidence from Firm-to-Firm Trade*

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Abstract

Risks are inherent and increasingly recognized in global agricultural value chains; however, their effects and firm-level responses are poorly understood. Using novel global firm-to-firm trade data, we show that agricultural markets are highly concentrated and have sparse network structures, with buyers typically relying on a limited set of suppliers, and prices are shaped by the two-sided market power of both importers and exporters. We find that U.S. import prices are lower when importers account for a larger share of purchases, and that price volatility is reduced when firms diversify their foreign suppliers, for example in response to the Ukraine-Russia war. Motivated by these findings, we develop the first structural model of international sourcing under matching frictions and risk aversion applied to agricultural markets and global agricultural value chains. In this model, agri-food firms adjust along three margins: absorbing shocks, renegotiating with existing suppliers, or diversifying by switching to new suppliers. The relative importance of these adjustment strategies depends on relative Ricardian comparative advantage, risk aversion, and matching friction correlation across countries. Our simulated supply chain disruption counterfactual exercises show that policies promoting import-source diversification and reducing matching frictions enable importers to access new suppliers and help stabilize agricultural prices, especially with a more competitive upstream market structure.

Keywords: Agricultural Supply Chains; Firm-to-Firm Trade; Diversification; Ukraine-Russia War; Risk Management

JEL Classification: F10, Q17, L14

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1 Introduction

Global value chains can both buffer and amplify demand, supply, and policy shocks. For instance, in 2023, a historic drought cut Argentina's soy crop almost in half, but traders quickly took advantage of Brazil's record harvest to substitute and compensate for global supply shortfalls. On the other hand, when Russia invaded Ukraine in 2022, grain prices surged, and several North African countries experienced heightened food insecurity as wheat imports declined, recovering only two years later when shipments from Ukraine resumed. Importantly, global food supply chains do not merely propagate shocks; they also mediate them through firm-to-firm input–output networks, contracts, and market power. Local disruptions and policy shocks propagate both upstream and downstream, often with measurable macroeconomic effects. Building and adjusting global input–output networks involves costly search processes and durable yet renegotiable relationships under incomplete contracts. From a firm-level perspective, the reshaping of supply chains operates through two margins: renegotiation with incumbents and re-sourcing from new partners. At the same time, a firm's position in rivalry networks can confer pricing power, with central players sustaining higher markups, making network structure itself a determinant of shock propagation. When shocks strike, do agri-food supply chains renegotiate or rewire their networks? How does buyer diversification interact with seller market power? And which margin of adjustment moves first?

How do uncertainty and diversification shape the adjustment of agricultural trade to relative supply shocks? How do firms diversify suppliers to stabilize agri-food prices? Agriculture and food products are unique in that their production and prices are significantly more volatile than those of other tradable sectors, yet they are critical to global food security. Moreover, agricultural trade is highly concentrated (Crespi and MacDonald, 2022), with a small number of countries dominating global agricultural supply chains—especially in low-income countries.[1]

The international trade literature has traditionally focused more on manufacturing than on agriculture, even though agricultural trade is vital for national security and is not always well captured by standard trade theory, which often finds only small gains from trade (Arkolakis, Costinot and Rodríguez-Clare, 2012). Agricultural supply chains are uniquely exposed to geopolitical, climatic, and policy shocks, and they tend to be shorter and less complex. Moreover, agricultural trade data are relatively abundant, offering ample opportunities to analyze the distributional effects of trade policy. Yet agriculture remains underexplored in the literature on production networks and global value chains, which overwhelmingly centers on manufacturing. In particular, there is still a lack of firm-to-firm transaction-level evidence and systematic analysis

[1]Global agricultural supply chains are highly concentrated and vulnerable. Key commodities, such as soybeans, cocoa, palm oil, fertilizers, and seeds, are dominated by a few countries or firms. For example, China relies heavily on Brazil and the United States for soybean imports, leaving it exposed to trade tensions such as the U.S.–China trade war. Cocoa production depends largely on West Africa, raising concerns about supply shocks and ethical sourcing. Palm oil production is concentrated in Indonesia and Malaysia, as seen during the 2022 export bans. The fertilizer trade has been disrupted by geopolitical events such as the Ukraine–Russia war, threatening global food security. The seed industry is controlled by a few multinational firms, making supply chains less resilient.

of firm-level risk management strategies in agricultural trade.

We investigate the structure and resilience of global agricultural supply chains using firm-to-firm trade data. We develop a structural model that incorporates two central features: (i) imperfect competition, characterized by oligopoly and oligopsony power among dominant exporters and importers, and (ii) sourcing under uncertainty, where firms adopt diversification strategies in response to risk. Leveraging over 20 million detailed U.S. import transaction data from 2015 to 2024, we document new empirical facts on the concentration and diversification of agricultural trade at the firm level. Our analysis provides evidence that market power and geopolitical shocks significantly shape price formation and supply chain adjustments. We find that importers sourcing from major multinational firms (e.g., the so-called ABCDs [2]) pay higher prices, and that diversification enables firms to better absorb adverse shocks, stabilizing import volumes and prices. These findings highlight the interplay between market structure, risk, and firm behavior in shaping global food security and inform policy interventions aimed at enhancing supply chain resilience.

We begin by presenting several motivating facts using a global firm-to-firm agri-food trade dataset to analyze the agricultural trade network. Drawing on U.S. import lading data from 2015 to 2024, we find: (i) global agri-food supply chains are concentrated in a small number of one-to-one firm relationships; (ii) larger firms operate more diversified sourcing networks; (iii) market shares in both import and export markets are highly concentrated; (iv) long-term trade relationships are associated with lower import prices and greater resilience to supply chain disruptions; and (v) firms' contributions to the economy shrink with increased exposure to geopolitical shocks. These facts suggest that firms are substantially affected by supply chain shocks and actively manage supplier relationships and diversification, trading off risk against cost—reflecting both Ricardian disadvantages and market power considerations. For example, Domar weights for firms affected by shocks declined, and market shares shifted—potentially becoming more concentrated as fewer exporters or importers remained in the market, but with larger surviving agri-food firms. We also observe increased price volatility in agricultural commodities, closely tied to food security and the resilience of global supply chains, driven by changes in supplier and buyer shares across countries and products.

Second, to further illustrate the real-world impact of supply chain risk and diversification, we present empirical evidence on the consequences of the Ukraine-Russia war for global agricultural trade. This conflict constitutes a major exogenous shock to the agricultural supply network, given the central role of Ukraine and Russia as exporters of key commodities such as wheat, corn, sunflower oil, and fertilizers. By analyzing firm-to-firm trade data from before and after the onset of the war, we document how supply disruptions affected import prices, trade volumes, and the adjustment strategies of firms.

Third, we develop a firm-level sourcing model that incorporates uncertainty and risk aversion

[2]The term "ABCD companies" refers to four multinational corporations that dominate the global agricultural commodity trading market: Archer Daniels Midland (ADM), Bunge, Cargill, and Louis Dreyfus.

into the decision to diversify suppliers. In our framework, importers face both idiosyncratic and country-level shocks to input availability and prices, and must choose the set of suppliers and the allocation of purchases across them. The model extends standard Ricardian and CES trade models by introducing a portfolio choice problem, in which firms weigh the expected cost savings from sourcing from the most competitive suppliers against the risk of supply disruptions and price volatility. Risk-averse firms incur fixed costs to establish new supplier relationships, generating endogenous patterns of trade concentration and diversification. The optimal sourcing strategy depends on the correlation structure of shocks across suppliers and countries, the degree of risk aversion, and the cost of matching frictions. This framework allows us to analyze how diversification mitigates supply chain risk, how market structure shapes price formation, and how policy interventions—such as reducing matching frictions or promoting new supplier entry—can enhance supply chain resilience and global food security.

To evaluate the quantitative implications of agricultural supply chains formation, we calibrate our model to the observed international trade flows across countries and products between the United States and foreign countries. Our estimation strategy proceeds in two steps. First, we match key model moments—such as the average number of suppliers per importer, the distribution of bilateral concentration indices, and the variance of firm-level import shares—to their empirical counterparts in the data. Second, we estimate several structural parameters, including the trade elasticity, risk aversion, and correlation of shocks across suppliers, using the simulated moments of method (SMM). This approach captures the observed patterns of diversification, concentration, and price volatility in global agricultural supply chains. The calibration targets include: (i) the average and distribution of suppliers per importer, (ii) the Herfindahl-Hirschman Index (HHI) of import shares, (iii) the relationship between firm size and diversification, and (iv) the pass-through of supply shocks to import prices. By matching these moments, the model quantitatively rationalizes the empirical facts documented in Section 2, and provides a foundation for counterfactual analysis of supply chain disruptions and policy interventions.

The model formalizes the firm's sourcing decision as a trade-off between minimizing expected costs and hedging against risk, captured by the variance of profits. Firms choose both the set of countries from which to source and the number of suppliers per country, balancing Ricardian comparative advantage, risk aversion, and matching frictions. The key mechanism is that higher within-country shock correlation (*within-country risk correlation*) increases the variance of input costs, making concentrated sourcing riskier. Consequently, risk-averse firms optimally diversify across countries and suppliers to reduce exposure to correlated shocks. This theoretical prediction—that higher *within-country risk correlation* incentivizes cross-country diversification—is a central implication of the model. The framework further shows that the optimal number of suppliers per country declines as *within-country risk correlation* rises, whereas lower *cross-country risk correlation* encourages broader diversification.

These model implications align closely with the empirical facts documented earlier. First, the model predicts that risk aversion and exposure to shocks drive diversification—consistent

with the finding that larger firms and multinationals maintain more diversified supplier networks (Facts 1 and 2). Second, it shows that market concentration influences transaction prices, reflecting the interplay between market power and risk in supplier selection (Fact 3). Third, the model rationalizes the observed resilience of firms with diversified sourcing strategies during the Ukraine–Russia war, as those with broader supplier bases were better able to absorb shocks and sustain import volumes. Finally, the relationship between risk aversion, supplier diversification, and price volatility is supported by regression evidence indicating that firms exposed to riskier suppliers experience greater price fluctuations and higher rates of relationship breakdowns (Fact 4).

Finally, we use the calibrated model to study how the supply chain disruptions affect the formation of an agricultural firm-to-firm production networks with two different counterfactual analyses. In our first counterfactual simulation, we evaluate the impact of the recent Ukraine-Russia war on the two major agricultural commodity trades. Specifically, we simulate the observed shocks to wheat and oil imports from these countries, quantifying how the resulting reductions in U.S. imports altered sourcing patterns and prices.

In the second counterfactual, we analyze a subsidized import diversification policy, comparing its effects under risk-neutral and risk-averse sourcing strategies and across different market structures. Our results show that the welfare gains from such a policy are larger when upstream markets are more competitive and when firms account for risk aversion in their diversification decisions. These findings underscore that incorporating the endogenous formation of agricultural supply chains and matching costs leads to larger and more heterogeneous effects of international trade shocks.

Related Literature. This paper contributes to several strands of literature. First, in the literature on global value chains, limited attempts have been made to analyze the agricultural sector and how firms interact in ag-food trade. Adamopoulos and Leibovici (2024) studies trade and agricultural productivity, showing how trade integration affects farm-level outcomes and rural development. Hsiao, Moscona and Sastry (2024) analyzes food supply chains and the impact of shocks on food prices and security. Farrokhi and Pellegrina (2023) investigates trade costs and market access in agricultural supply chains, focusing on the role of infrastructure and policy. Nath (2025) examines climate risk and its effects on agricultural trade and supply chain resilience. Gollin et al. (2025) explores the dynamics of agricultural markets and the implications for development and food security. Bergquist et al. (2022) studies scaling and technology adoption in agriculture, with implications for supply chain efficiency. Sotelo (2020) analyzes domestic trade networks and their role in agricultural market integration. Gaigné and Gouel (2022) investigates trade and logistics in grain markets, emphasizing the importance of transportation costs. Kasahara and Li (2020) examines grain supply chains and the effects of trade policy on market concentration and efficiency. Our paper advances this literature by providing micro-level empirical evidence on the structure and resilience of global agricultural supply chains using

firm-to-firm trade data. We document new facts about concentration, diversification, and adjustment strategies in agricultural trade networks, and develop a theoretical model that incorporates risk aversion and matching frictions. By linking empirical findings to a structural framework, we offer insights into how market structure and risk shape sourcing decisions and supply chain outcomes, addressing gaps in the existing literature on agricultural global value chains.

Second, we contribute to the literature on market power in global agri-food value chains. A recent report commissioned by the EU parliament finds that approximately 70%-90% of international grain trade is concentrated in only four firms, often referred to as "ABCD" multinational firms (Wion et al., 2024). In spite of this stark market power, the literature on the concentration of grain trading firms is scarce, with only few studies analyzing their structural dominance in global agri-food trade (Barrett et al., 2022). Clapp (2015) emphasizes how these firms have evolved from commodity merchants to managers of vertically integrated agricultural value chains, consolidating control over both physical infrastructure and market information. Moreover, she documents the opaque practices and concentration risks posed by these firms, particularly in grain markets. Sexton (2013) discusses how oligopolistic behavior and logistical scale grant them persistent market power, suggesting asset intensity, information asymmetry, vertical integration, and policy leverage are drivers of the strong degree of concentration. We contribute to this literature by providing firm-to-firm level empirical evidence on the drivers and mechanisms that lead to power accumulation along international food trade.

Third, a growing body of work models production networks as the endogenous outcome of firm-level optimization under uncertainty, where firms choose suppliers by balancing cost, complementarity, and risk exposure (Kopytov et al., 2024; Baqaee and Farhi, 2024; Grossman, Helpman and Sabal, 2023; Elliott and Golub, 2022; Bernard et al., 2022; Lim, 2018). These models highlight how equilibrium network structures can be fragile due to underinvestment in redundancy, resulting in the concentration of supplier linkages that lead to the amplification of shocks throughout the network. Khanna, Morales and Pandalai-Nayar (2022), Handley, Kamal and Monarch (2024), and Huneeus (2018) provide country-focused empirical evidence on such endogenous network responses to large-scale disruptions remains scarce. Our paper contributes to this literature on the global level by providing micro-level evidence on the reconfiguration of global agricultural production networks in response to supply, demand and policy shocks. Recent literature focuses on how buyer-supplier relationships are formed and why these relationships end or change over time. By identifying both parties that are connected in buyer-supplier or importer-exporter relationships, these provide the opportunity to examine the formation and features of particular links within domestic and global supply chains.

Fourth, we contribute to the literature on resilience and risk management in global agricultural value chains. Existing research largely examines producer- and management-level strategies for addressing risks from weather, climate, and supply chain fragility. Some studies, such as Grossman, Helpman and Sabal (2023) and Grossman and Helpman (2020), analyze trade-policy tools like tariffs and subsidies to reduce risk through diversification, while others measure sup-

ply chain risk and study firm responses to disruptions—for example, Smirnyagin and Tsyvinski (2022) develops the U.S. Supply Disruptions Index, and Agca, Birge and Wu (2022) stresses the importance of local capacity in balancing efficiency and risk. Evidence also shows that vertical integration can reduce disruptions (Chatterji and Shibuya, 2025), and regional sourcing requirements can shift trade patterns toward nearby suppliers (Hsu, Li and Wu, 2022). Another approach, "relational value chains," focuses on stronger, longer-lasting buyer–supplier relationships; microdata reveal that many such links are short-lived—over half of new U.S. import relationships last less than a year (Monarch and Schmidt-Eisenlohr, 2017), though some persist for years (Martin, Mejean and Parenti, 2023), with higher survival rates for skill- or contract-intensive products (Monarch, 2022).

Fifth, the literature on agricultural trade, volatility, and food security offers a plenitude of insights relating to how trade policy shapes food price volatility (e.g., Dalheimer and Bellemare, 2023; Pieters and Swinnen, 2016; Schaefer and Wolf, 2025; Anderson and Nelgen, 2012). The larger part of this literature stops short at the phenomenon, while we provide evidence of one of the key mechanisms. At a more micro level, some studies focus on specific segments of the supply chain, such as transportation, wholesalers, and retailers, which are not the typical "stylized" agents in traditional trade models. Ardelean and Lugovskyy (2023) uses Chilean import port-to-port routes, finding that larger importers face lower maritime freight rates. Reducing market power distortion in the upstream sector (transportation) may amplify the informational friction distortion and price discrimination in the downstream sectors (importing industries). These findings contrast with the assumption of symmetric ad-valorem or specific trade costs on a given route. Most existing firm-to-firm empirical work on supply chain fragility and risk focuses on manufacturing (e.g. Fieler, Eslava and Xu, 2018). Food is a necessity good, while at the same time, food production and supply chains are subject to relatively riskier environments. AGVCs are notoriously subject to geographic and climate constraints (Dalheimer, 2025), perishability, seasonality, industry concentration (Stevens and Teal, 2024; Wahdat and Lusk, 2023; Ma and Lusk, 2021) and geopolitical sensitivity (Ubilava, 2024), exacerbating the profit maximization problem under uncertainty for agribusinesses. Several studies have analyzed domestic industry concentration and uncertain business environments (e.g. Richards, Ubilava and Polyviou, 2025) and globally, but at the country-level (Dalheimer, 2025; Beck, Lim and Taglioni, 2024). We take GAVCs into the framework of endogenous production networks and diversification theory and model risk-sensitive sourcing in a Ricardian setting and show that relationship-specific characteristics, such as supplier diversification, critically shape firm-level resilience.

The rest of the paper is organized as follows. Section 2 describes the data sources and presents motivating facts about global agricultural supply chains. Section 3 provides empirical evidence on the impact of the Ukraine–Russia war on firm-to-firm trade and supply chain adjustments. Section 4 develops a theoretical model of firm sourcing under uncertainty and diversification. Section 5 examines sourcing decisions under uncertainty. Section 6 discusses the quantitative estimation, and Section 7 presents the counterfactual analysis. Section 8 concludes.

2 Data and Motivating Facts

In this section, we analyze the structure and dynamics of global agricultural supply chains using firm-to-firm trade data. We document key patterns of concentration, diversification, and market share, focusing on how firms adjust their sourcing strategies in response to shocks. By leveraging detailed transaction-level data, we provide empirical evidence on the role of supplier networks, market power, and risk in shaping trade relationships and price formation.

2.1 Data

The main dataset we use for firm-to-firm trade is from Bill of lading data from S&P Panjiva. The dataset contains over one billion transaction-level records of goods traded across borders, including information on consignees and shippers, product descriptions, quantity, and, in limited cases, estimated values of shipment transactions in USD. We use the bill of lading data of US imports, which allows us to observe both imports and exports of goods for all trading partners.

The raw dataset for the U.S. contains approximately 200 million records, spanning from 2007 to the present. It primarily covers seaborne imports, accounting for about half of the overall U.S. imports. The dataset is based on bills of lading obtained from the U.S. Customs and Border Protection (CBP) under the Freedom of Information Act of 1966 (FOIA). A bill of lading is a legal document that serves as proof of shipment from its origin to its final destination. Each bill of lading includes various fields, such as the names and addresses of the shipper (exporter) and consignee (importer), descriptions of goods, vessel name, transport company name, ports of lading and unlading, weight, and container details. Panjiva supplements this information by imputing additional variables, such as shipment volume in twenty-foot equivalent units (TEUs), based on container details and other shipment attributes.

Table B.1 lists the key variables in the dataset. For more detailed information, refer to the data sample. (Flaaen et al., 2023) compares the bill of lading data with macro-level international trade data from UN Comtrade and demonstrates its consistency and accuracy in capturing trends in U.S. import data. The dataset contains over 20 million transaction-level records, capturing granular buyer-supplier relationships and product-level details for HS 2-digit codes 01–24. For this analysis, we focus on agricultural products, specifically HS codes 04, 07, 08, 10, 11, 12, 15, 19, and 21, as shown in Table 1.

2.2 Motivating Facts

We present several motivating facts about firm-to-firm trade networks. These networks consist of different types of linkages, including bilateral linkages, multilateral linkages, and indirect linkages. Bilateral linkages represent direct trade relationships between two firms, while multilateral linkages involve trade relationships among multiple firms. Indirect linkages refer to trade

Table 1: HS Chapters 01–24 (Ag-Food Sector)

HS	Title	HS	Title
01	Live animals	13	Lac; gums, resins, vegetable extracts
02	Meat and edible meat offal	14	Vegetable plaiting materials; n.e.s.
03	Fish, crustaceans, molluscs, etc.	15	Animal/vegetable fats & oils; waxes
04	Dairy produce; eggs; honey; other animal prod.	16	Preparations of meat or fish, etc.
05	Products of animal origin, n.e.s.	17	Sugars and sugar confectionery
06	Live trees, plants, cut flowers, foliage	18	Cocoa and cocoa preparations
07	Edible vegetables and certain roots/tubers	19	Preparations of cereals, flour, starch
08	Edible fruit and nuts; citrus/melon peel	20	Prep. of vegetables, fruit, nuts, plants
09	Coffee, tea, maté and spices	21	Miscellaneous edible preparations
10	Cereals	22	Beverages, spirits and vinegar
11	Milling products; malt; starch; inulin	23	Residues of food industry; animal fodder
12	Oil seeds; misc. grains; industrial plants	24	Tobacco and manufactured substitutes

Notes: This table lists the HS chapters included in our analysis. Specifically, we focus on products from HS codes 04, 07, 08, 10, 11, 12, 15, 19, and 21, which cover key agricultural and food-related sectors. All products with other HS codes are excluded from this study.

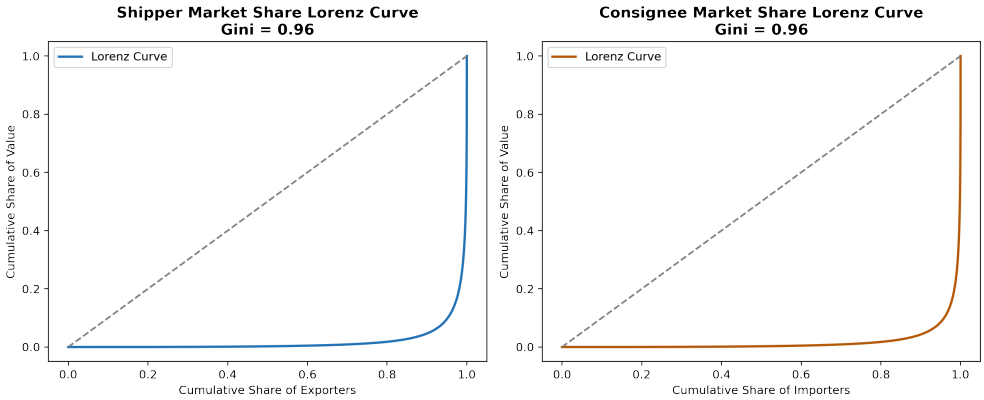
relationships that are not directly observed but can be inferred from the data.[3]

Fact 1: Global agricultural supply chains are highly concentrated and lack diversification. We present this fact with a distribution of the number of foreign exporters to the US importers. Table 2 highlights that U.S. importers typically rely on a small number of foreign exporters, with the average number of exporters per importer being only 2.68. Notably, the median importer sources from just one exporter, indicating a high degree of concentration. This lack of diversification underscores the vulnerability of agricultural supply chains to sudden disruptions, as many importers depend heavily on a limited set of suppliers.

We then use the Lorenz curve to show the level of market concentration. The Lorenz curve is a graphical representation of the distribution of trade shares, illustrating the degree of concentration in firm-to-firm agricultural trade. To compute the Lorenz curve, we first rank firms (exporters or importers) by their trade shares in ascending order. Next, we calculate the cumulative share of trade for each firm and plot this against the cumulative share of firms. A perfectly equal distribution would result in a 45-degree line, while deviations from this line indicate concentration. Figure 1 presents the Lorenz curve for exporters and importers in firm-to-firm agricultural trade. The results reveal a high degree of concentration, with a small number of firms accounting for a disproportionately large share of total trade. This highlights the oligopolistic

[3] Bernard and Moxnes (2018) provides a more comprehensive account of these facts on firm-to-firm trade: (1) Most exporters sell to a small number of foreign buyers, and most importers purchase from a small number of foreign sellers. (2) At least one party in any given firm-to-firm match tends to be a large firm; there are few links observed between small buyers and small sellers. (3) The set of buyer-supplier links features "negative degree assortativity", which can be explained as exporters that have few links (and are thus presumably smaller and less productive firms) tend on average to sell to importers that have many connections (and are thus presumably larger and more productive firms).

Figure 1: Cumulative Market Share Curve for Exporters and Importers



Notes: This figure plots the cumulative market share (Lorenz curve) for exporters and importers in firm-to-firm agricultural trade. The curve illustrates the degree of concentration, showing that a small number of firms account for a large share of total trade. Data are aggregated for agricultural products (HS codes 04, 07, 08, 10, 11, 12, 15, 19, and 21).

Table 2: Firm-to-Firm Linkages and Bilateral Shares

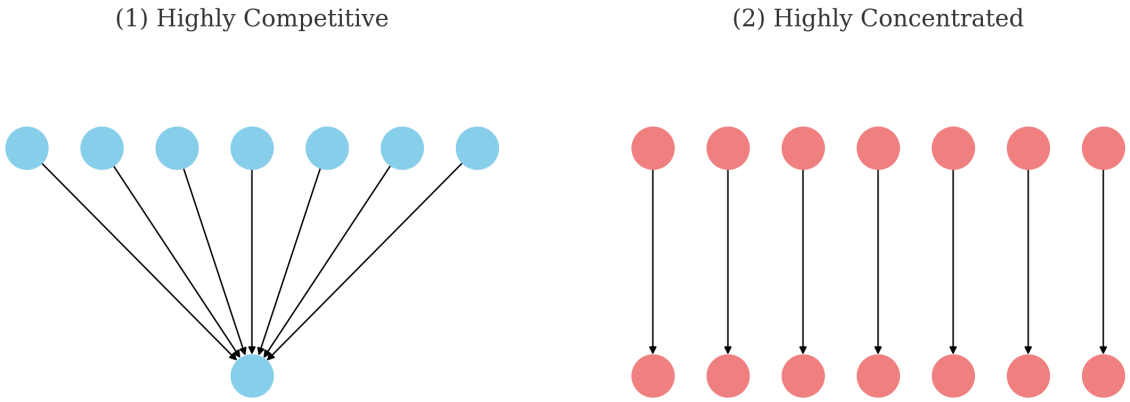
Variable	**Mean**	**Std. Dev.**	**p10**	**p50**	**p90**
Number of exporters per importer	2.68	8.91	1.00	1.00	4.00
Number of importers per exporter	2.59	7.78	1.00	1.00	5.00
Importer's supply share (x^h_{ijt})	0.43	0.43	0.00	0.22	1.00
Exporter's buyer share (s^h_{ijt})	0.48	0.42	0.01	0.35	1.00
Importer tenure (years)	4.04	2.99	0.00	3.00	8.00
Exporter tenure (years)	3.88	2.97	0.00	3.00	8.00
Longevity of trading relationships (years)	2.94	2.77	0.00	2.00	7.00

Notes: This table summarizes firm-to-firm linkages for HS codes 04, 07, 08, 10, 11, 12, 15, 19, and 21. Here, s^h_{ijt} is the share of exporter i in importer j's imports of product h at time t; x^h_{ijt} is the share of importer j in exporter i's total export quantity of product h to the U.S. at time t. Exporter (importer) experience is measured by the number of years since the exporter (importer) first started supplying (sourcing) product h. The longevity of the relationship is measured by the number of years since the foreign exporter first served the U.S. importer.

and oligopsonistic market structures along global agricultural supply chains.

Figure 2 illustrates highly competitive and highly concentrated trade structures as developed in (citation) in the left and right panels, respectively. In the left panel, exporters compete for access to a single importer, resulting in highly competitive environments. In the right panel, one-to-one matching between exporters and importers leads to lock-in effects and high concentration and a highly sparse production network. Fact 1 suggests that firm-to-firm trade of the US importers is closer to the situation depicted in the right side panel. By extension, in GAVCs, the concentration of both exporters and importers plays a critical role in determining transaction prices.

Figure 2: Market Structure in Global Agricultural Supply Chains



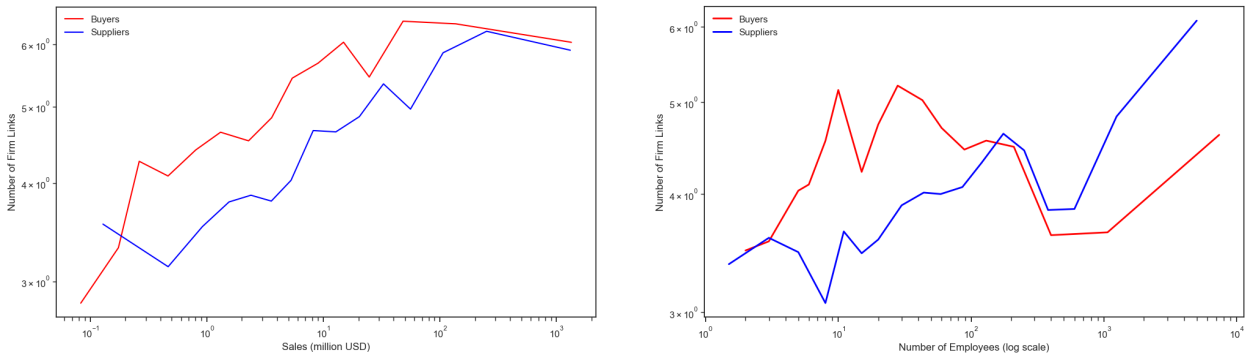
Notes: This figure illustrates the structure of firm-to-firm trade networks in global agricultural value chains. Exporters often compete for access to a single importer, resulting in highly competitive environments, while one-to-one matching between exporters and importers leads to lock-in effects and high concentration. In AGVCs, the concentration of both exporters and importers plays a critical role in determining transaction prices.

Fact 2: Larger firms tend to have more diversified trading relationships. Figure 3 provides evidence that larger firms, particularly multinationals, tend to have more diversified trading relationships. Panel (a) shows a positive correlation between firm sales and the number of suppliers and buyers, indicating that firms with higher sales are connected to more trading partners. Panel (b) demonstrates a similar pattern for firm employment, with larger firms (by workforce size) engaging with a greater number of suppliers and buyers. These results suggest that firm size is strongly associated with supply chain diversification, supporting the hypothesis that larger firms are in a better position to hedge against supply chain risks by sifting sourcing activities among their network of trading relationships.

Increasing supplier and buyer linkages in firm revenue is consistent with the findings in other contexts, such as in Japan (Bernard, Moxnes and Saito, 2019), Belgium (Bernard et al., 2022), Chile Arkolakis, Huneeus and Miyauchi (2023), and the United States (Lim, 2018).

Fact 3: Bilateral Shares and Prices in the Agricultural Value Chain. We next examine how market concentration on both the supplier and buyer sides shapes transaction prices in global agricultural supply chains. We begin by computing the average outdegree of a firm's suppliers. First, we calculate for each supplier i, the total value of sales from i to buyer j, relative to j's total purchases. We then add these shares across all buyers j of supplier i. Second, for each buyer j, we compute the average of these shares across all of their suppliers, which we define as the importer share, x^h_{ijt}. Similarly, we define the exporter share, s^h_{ijt}. This measure captures how nodal the suppliers of a given buyer j are. Higher numbers mean that suppliers of buyer j have more buyers, and represent a larger share of their buyers' purchases. We define bilateral market

Figure 3: Number of Suppliers and Buyers and Firm Size



(a) Sales and Number of Suppliers & Buyers

(b) Labor and Number of Suppliers & Buyers

Notes: Panel (a) shows the relationship between firm sales and the number of suppliers and buyers. Panel (b) shows the relationship between firm employment (labor size) and the number of suppliers and buyers. Both figures are based on firm-to-firm trade data for agricultural products (HS codes 04, 07, 08, 10, 11, 12, 15, 19, and 21), aggregated at the annual level.

shares as follows:

$$x_{ijt}^h = \frac{q_{ijt}^h}{\sum_{i'} q_{i'jt}^h}, \quad s_{ijt}^h = \frac{p_{ijt}^h q_{ijt}^h}{\sum_{j'} p_{ijt}^h q_{ij't}^h}, \tag{1}$$

where q_{ijt}^h is the quantity of product h traded between exporter i and importer j at time t.

Figure 4 illustrates the high degree of concentration in global agricultural supply chains. The average exporter and importer shares indicate that a small number of firms account for a large proportion of trade, while the cumulative market share curves (Lorenz curves) demonstrate that both exports and imports are dominated by a few major players. This pattern reflects a strongly oligopolistic and oligopsonistic market structure, where most trade value is controlled by a limited set of firms on both sides of the market.

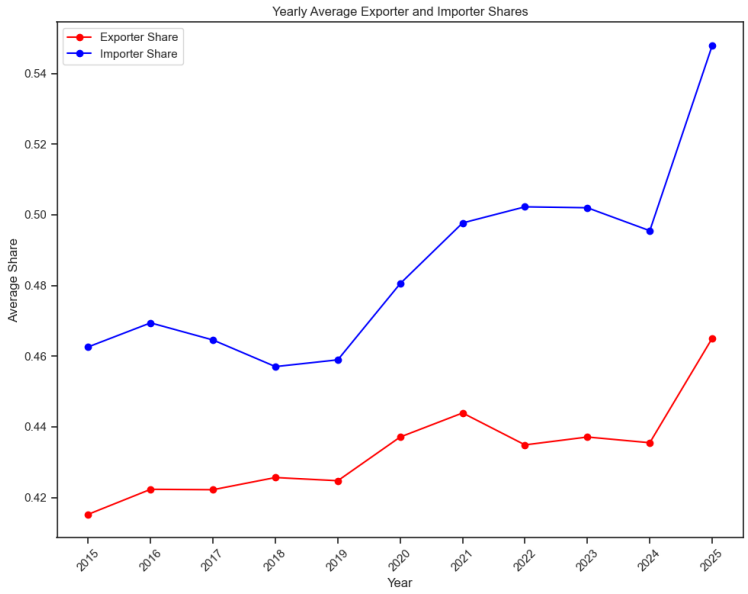
In agricultural markets, both exporters and importers may exert market power, resulting in price formation that reflects oligopoly and oligopsony dynamics. To quantify these effects, we estimate the pass-through of bilateral market shares to import prices, following the approach of Fontaine, Martin and Mejean (2020). Specifically, we estimate the following regression specification:

$$\ln p_{ijt}^h = \alpha + \beta_s s_{ijt}^h + \beta_x x_{ijt}^h + \mathbf{fi}' \mathbf{X}_{ijt}^h + \gamma_i + \delta_j + \lambda_{ht} + \epsilon_{ijt}^h, \tag{2}$$

where p_{ijt}^h denotes the price of product h imported by importer j from exporter i in year t; s_{ijt}^h is the share of exporter i in importer j's imports of product h; x_{ijt}^h is the share of importer j in exporter i's exports of product h; $\mathbf{X}_{ijt}^h$ is a vector of control variables; γ_i and δ_j are exporter and importer fixed effects; and λ_{ht} are product-by-year fixed effects.

The coefficients β_s and β_x capture the effects of supplier and buyer concentration, respec-

Figure 4: Average Exporter and Importer Shares

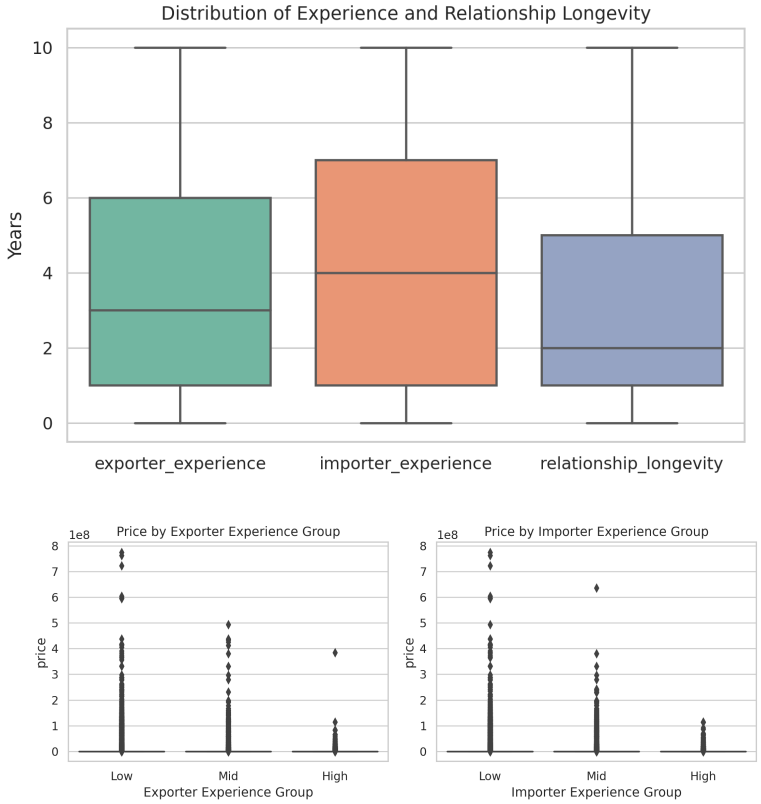


Notes: This figure shows the average share of exporters and importers in firm-to-firm agricultural trade. The exporter share is the proportion of an importer's purchases accounted for by each exporter; the importer share is the proportion of an exporter's sales accounted for by each importer. High average shares indicate concentration, with a few firms dominating trade flows. Data are aggregated for agricultural products (HS codes 04, 07, 08, 10, 11, 12, 15, 19, and 21).

tively. A positive β_s indicates that greater supplier market share is associated with higher prices, consistent with oligopoly pricing. Conversely, a negative β_x suggests that greater buyer market share leads to lower prices, reflecting buyer bargaining power. The coefficient estimates are depicted in Table 3 and suggest that prices increase with supplier concentration and decrease with buyer concentration, confirming standard mechanisms of market power and the role of market structure overall determining prices along the agricultural value chain.

Fact 4: Long-term relationships are associated with lower import prices and greater resilience to supply chain disruptions. Figure 5 illustrates that firms engaged in longer-term trading relationships tend to pay lower import prices. The top panel shows the distribution of experience across exporters, importers, and trading relationships. The median duration of these relationships spans 2-3 years, suggesting persistent firm-to-firm engagement. The bottom panels further reveal that both exporters and importers with higher experience levels—categorized as "High"—are associated with significantly lower import prices compared to those with "Low" experience. This pattern indicates that relationship-specific investments such as trust-building, coordination, and information-sharing reduce transaction costs and improve supply chain efficiency. These relationships likely serve as a buffer against price volatility and disruptions, highlighting the role of relational capital in stabilizing agricultural trade.

Figure 5: Import Prices and Relationship Experience



Notes: The left panel shows the distribution of trading relationship tenure (years) between importers and exporters in agricultural firm-to-firm trade data. The right panel displays average import prices grouped by relationship experience. Longer-tenured relationships are associated with lower import prices, suggesting that relationship-specific investments help mitigate the impact of supply chain disruptions. Data are aggregated for agricultural products (HS codes 04, 07, 08, 10, 11, 12, 15, 19, and 21).

Table 3: Prices and Bilateral Concentration

	(1)	(2)	(3)	(4)	(5)	(6)
Exporter Share	1.348***	1.280***	1.276***	0.398***	0.680***	0.682***
	(0.004)	(0.010)	(0.010)	(0.008)	(0.006)	(0.006)
Importer Share	0.113***	-0.190***	-0.189***	-0.464***	-0.808***	-0.823***
	(0.005)	(0.010)	(0.010)	(0.009)	(0.007)	(0.006)
Controls	No	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	Yes	Yes	Yes	No
HS-6 Digit FE	No	No	No	Yes	Yes	No
Exporter–Importer FE	No	No	No	No	Yes	Yes
HS $\times$ Year FE	No	No	No	No	No	Yes
Observations	6,557,003	1,601,911	1,601,911	1,424,742	1,413,592	1,412,507
R^2	0.029	0.025	0.026	0.430	0.818	0.824

Notes: This table reports the results from regressions of log prices on exporter and importer concentration shares. **Exporter Share** is the share of exporter i in importer j's imports of product g at time t; **Importer Share** is the share of importer j in exporter i's exports of product g at time t. All regressions include varying sets of controls and fixed effects as indicated. Standard errors are clustered at the exporter-importer-product level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3 Empirical Evidence for the Ukraine-Russia War

The Ukraine-Russia war, which began in February 2022, has had profound impacts on global agricultural supply chains. Ukraine and Russia are major exporters of key agricultural commodities such as wheat, corn, sunflower oil, and fertilizers. Figure A.4a illustrates the critical role of Ukraine and Russia in global food exports and production. Both countries are among the world's leading producers and exporters of grains, oilseeds, and fertilizers. The onset of the Ukraine-Russia war has led to significant disruptions in their agricultural output, with estimates indicating a decline in production by as much as 38%. These disruptions have had far-reaching consequences for global food supply chains, contributing to increased price volatility and increased food security in countries in the Middle East and North Africa (MENA) region, which were heavily reliant on imports from this region.

We leverage the Russian invasion of Ukraine as an exogenous supply shock upstream of global agri-food value chains to estimate how diversification of supply networks buffered operations of downstream firms in the US.

3.1 Effects of the Ukraine-Russia War

First, we assess the impact of the Ukraine-Russia war on import prices and conduct a monthly event study using firm-to-firm shipment data. Specifically, we examine whether relative import prices paid by Ukrainian importers diverged from those paid by similar importers in other countries following the onset of the conflict. Our empirical specification is as follows:

$$\log Y_{ijhtm} = \alpha + \sum_{k=-K}^{K} \beta_k \cdot \text{UkraineBuyer}_j \cdot \mathbb{I}\{\text{Month} = k\} + \gamma_{ijh} + \delta_t + \epsilon_{ijhtm}, \tag{3}$$

where Y_{ijhtm} denotes the price, quantity and value of product h imported by importer j from exporter i in year t and month m. UkraineBuyer_j is an indicator for Ukrainian importers, and $\mathbb{I}\{\text{Month} = k\}$ is an event-time dummy for k months relative to the war onset. γ_{ijh} are exporter-importer-product fixed effects, and δ_t are year fixed effects. This specification allows us to trace the dynamic evolution of import prices for Ukrainian buyers relative to the control group.

Table 4 presents the results from the event study regression examining the impact of the Ukraine-Russia war on import prices. Standard errors are clustered at the importer level, and all regressions include importer and product-year fixed effects. The estimates indicate that agricultural import prices for Ukrainian buyers rose disproportionately following the onset of the war, consistent with heightened supply chain disruptions, higher insurance premiums, and war-related increased transport cost,s as well as increased uncertainty overall.

Second, we estimate a continuous difference-in-differences model where the post-shock effect varies with a firm's pre-war exposure to Ukraine as a sourcing country. Let j index importing firms (consignees), i exporting suppliers (shippers), h HS-2 product, and t month. The outcome y_{jiht} is ln price, ln quantity, or ln value at the firm–supplier–product–month level. Our baseline

Table 4: Effect of the Ukraine War on Import Outcomes: Baseline and Continuous DiD

	Ukraine Suppliers			*PostShare*		
	(1) Log Price	(2) Log Quantity	(3) Log Value	(4) Log Price	(5) Log Quantity	(6) Log Value
DID	0.331***	-0.195***	0.136***	0.660**	-0.203*	0.458***
	(0.067)	(0.066)	(0.053)	(0.331)	(0.120)	(0.151)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm–Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,236,404	6,236,789	6,236,404	6,236,404	6,236,789	6,236,404
R^2 adj. (Baseline)	0.762	0.722	0.656	0.753	0.722	0.643

Notes: This table reports regression results from two specifications estimating the effect of the Ukraine war on agricultural import outcomes. Columns 2–4 report the baseline specification using a Ukraine supplier dummy, while columns 5–7 report the continuous DiD specification using *PostShare*. The dependent variables are the log of unit price, quantity, and value. All regressions include firm–product and month fixed effects. Standard errors, clustered at the importer level, are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

specification is:

$$y_{jiht} = \beta \left(\text{Post}_{\ t} \times share_j^{\text{UKR}} \right) + \gamma_{jih} + \tau_t + \varepsilon_{jiht}, \tag{4}$$

where $\text{Post}_{\ t} = 1\{t \geq \text{Feb 2022}\}$, γ_{jih} are firm-supplier-product fixed effects (implemented in practice as firm-pair $\times$ HS2 fixed effects), and τ_t are month fixed effects. Standard errors are clustered at the firm (j) level.

The coefficient of interest, β, captures how the post–Feb 2022 effect scales with the firm's pre-war exposure to sourcing from Ukraine. Define the firm's Ukraine exposure share as the pre-war value share of imports sourced from Ukraine:

$$share_j^{\text{UKR}} = \frac{\sum_{t \in \mathcal{T}_0} \sum_h \sum_i 1\left\{\text{origin}_{\ i} = \text{UKR}'\right\} \ \text{Value}_{\ jiht}}{\sum_{t \in \mathcal{T}_0} \sum_h \sum_i \ \text{Value}_{\ jiht}}. \tag{5}$$

By construction, $share_j^{\text{UKR}} \in [0, 1]$ and is time-invariant within the estimation window. In implementations with fine product detail, one may equivalently compute s_j^{UKR} as a value-weighted average of product-level Ukraine shares.

3.2 Importers' Strategies and Responses to the Ukraine-Russia War

We investigate whether U.S. importers with more diversified supplier bases are better able to scale up imports during supply chain shocks. To estimate the effect of the Russia-Ukraine war on the diversification strategies of firms, we employ a triple differences (DDD) specification. The outcome variables include total revenue, exports, imports, total suppliers, and total customers of firms sourcing from Ukraine and Russia.

The DDD model tests whether supplier diversification mitigates the effect of the war on firm outcomes $y_{jiht} \in \{\ln \text{price}, \ln \text{quantity}, \ln \text{value}\}$:

$$
\begin{aligned}
y_{jiht} =& \beta_1 \left[\mathbb{1}(t > \text{Feb2022})_t \times \text{Treat}_j\right] + \beta_2 \left[\mathbb{1}(t > \text{Feb2022})_t \times Diversification_j\right] + \\
& \beta_3 \left[\mathbb{1}(t > \text{Feb2022})_t \times \text{Treat}_j \times Diversification_j\right] + \gamma_j + \tau_t + \mathbf{X}_{jiht}\zeta + \epsilon_{jiht},
\end{aligned} \tag{6}
$$

where Treat_j is a firm-level treatment indicator (equal to 1 if the firm has positive pre-war exposure to Ukraine), $\mathbb{1}(t > \text{Feb2022})_t$ is an indicator for months $t \geq$ February 2022, and $Diversification_j$ is the firm-level diversification index. The diversification index is calculated using the six months immediately before the war (August 2021 to January 2022) and is defined as the weighted value of supplier diversification across products/countries. We include firm–product fixed effects γ_{jh} (firm-pair $\times$ HS-6) and month fixed effects τ_t. $\mathbf{X}_{jiht}$ is a vector of control variables, including total revenue and employment of importers. Standard errors are clustered at the importer firm level.

Diversification Index. To measure firm-level diversification, we employ multiple metrics that capture the characteristics of a firm's supplier network. These metrics reflect the number of distinct suppliers, the distribution of purchases across suppliers, and the geographic and product-level diversification of sourcing.

First, we construct a firm-level diversification index that captures the average number of suppliers weighted by the importance of each product in the firm's total imports, following Elliott, Golub and Leduc (2022). For each firm j and product h, the diversification index is then defined as:

$$
\text{Div}_j = \sum_h Share_{jh} \times NumSuppliers_{jh}, \tag{7}
$$

where we define $Share_{jh} = Value_{jh} / \sum_{h'} Value_{jh'}$. $Value_{jh}$ is the total import value of product h by firm j over a baseline period, which we use 6 months before the Ukraine war. This index reflects the value-weighted average number of suppliers across the firm's input mix. A higher Div_j indicates broader supplier options across products. For interpretability, we standardize Div_j in the pre-war period.

Second, we compute the HHI for each product h following Khanna, Morales and Pandalai-Nayar (2022) to capture the concentration of a firm's purchases among its suppliers

$$
\text{HHI}_{jh} = \sum_i \left(\frac{\text{Value}_{ijh}}{\text{Value}_{jh}} \right)^2, \tag{8}
$$

where Value_{ijh} is the value of imports from supplier i for product h, and Value_{jh} is the total value of imports for product h. A higher HHI_{jh} indicates greater concentration of purchases among a small number of suppliers. At the firm level, we compute the average HHI across all products: $\text{HHI}_j = (1/H_j) \sum_h \text{HHI}_{jh}$, and H_j is the number of products imported by firm j.

Third, we calculate the number of suppliers per product for each firm to assess diversifi-

cation at the product level, $NumSuppliers_{jh} = \#\{\text{distinct suppliers } i \text{ serving } (j,h)\}$. A higher $NumSuppliers_{jh}$ indicates that the firm sources a given product from multiple suppliers, which may facilitate adjustments in response to supply chain shocks.

Fourth, we measure the geographic diversification through the origin countries. We compute the HHI of supplier countries for each product to capture the geographic concentration of a firm's suppliers, $CountryHHI_{jh} = \sum_c \left(\text{Value}_{jhc}/\text{Value}_{jh}\right)^2$, and Value_{jhc} is the value of imports of product h from country c, and $Value_{jh}$ is the total value of imports of product h. At the firm level, we compute the average *Country HHI* across all products: $CountryHHI_j = (1/H_j)\sum_h \text{CountryHHI}_{jh}$. A lower $CountryHHI_j$ indicates greater geographic diversification of suppliers.

Finally, we measure the *potential* diversification access through the availability of alternative suppliers in the market for each product the firm imports. For each product h, we calculate the total number of suppliers available in the dataset. At the firm level, we compute a value-weighted average of market-level supplier availability (MA): $MA_j = \sum_h Share_{jh} \times MarketSuppliers_h$. A higher MA_j suggests that the firm has more potential suppliers available for its inputs, which may enhance resilience to supply chain disruptions.

Table 5 reports difference-in-difference-in-differences (DDD) estimates of the effect of the Ukraine–Russia war on firm-to-firm trade outcomes, with treatment defined by a firm's exposure to the conflict through its trading partners, and heterogeneity captured by various measures of supplier diversification. Across specifications, the triple interaction term (*Treat* × *Post* × *Diversification*) is generally statistically significant, indicating that the war's impact varies systematically with pre-war diversification levels. For instance, in Panel A, firms with a greater value-weighted supplier count experienced smaller post-war price increases and quantity declines, suggesting that broader supplier bases helped mitigate the shock. Similarly, Panels B and C show that higher diversification, measured via the negative HHI or average supplier count, attenuated adverse effects on trade volumes and values. However, Panel D indicates that country-level diversification (HHI Countries) is associated with higher post-war prices and values, possibly reflecting shifts toward costlier alternative sources. In Panel E, greater market availability appears to have modestly reduced the war's negative quantity effects. Overall, the findings show that supplier diversification could play a key role in protecting firm-to-firm trade from large geopolitical shocks.

3.3 A Crude Summary of Reduced-form Evidence

Based on the empirical evidence and data, we ask several "what-if" questions about building more resilient agricultural supply chains. First, what if we subsidize diversification among U.S. agri-food firms to encourage more varied sourcing? Second, what if we increase competition among upstream firms instead of allowing a few major exporters to control supply chains? Third, what role does risk aversion play in mitigating risks through risk-sharing? To answer these questions, we develop a firm-to-firm trade model that incorporates these elements.

Table 5: Effect of Diversification on Firm-to-Firm Trade

	(1) Log Price	(2) Log Quantity	(3) Log Value
Panel A: Val-Wtd Supplier Count			
Treat × Post × Val-Wtd Supplier Count	−0.00801***	0.00560***	−0.00240***
	(0.000566)	(0.000388)	(0.000429)
Treat × Post	0.164***	−0.0772**	0.0871**
	(0.0496)	(0.0351)	(0.0341)
Post × Div1	0.00679***	−0.00518***	0.00161***
	(0.000409)	(0.000288)	(0.000329)
Panel B: Negative HHI Suppliers			
Treat × Post × (-HHI Suppliers)	−0.179**	0.1000**	−0.0783*
	(0.0709)	(0.0455)	(0.0412)
Treat × Post	0.302***	−0.167**	0.135*
	(0.116)	(0.0738)	(0.0748)
Post × Div2	0.0399	−0.0489*	−0.00892
	(0.0392)	(0.0272)	(0.0154)
Panel C: Avg Supplier Count			
Treat × Post × Avg Supplier Count	−0.0123***	0.00905***	−0.00323***
	(0.00180)	(0.000900)	(0.00118)
Treat × Post	0.179***	−0.0900**	0.0887**
	(0.0509)	(0.0361)	(0.0350)
Post × Div3	0.0103***	−0.00835***	0.00194*
	(0.00165)	(0.000797)	(0.00106)
Panel D: Negative HHI Countries			
Treat × Post × (-HHI Countries)	0.0922***	−0.0360	0.0558***
	(0.0333)	(0.0231)	(0.0216)
Treat × Post	0.144**	−0.0680	0.0762*
	(0.0611)	(0.0431)	(0.0396)
Post × Div4	−0.00227	0.00384	0.00157
	(0.00392)	(0.00269)	(0.00189)
Panel E: Market Availability			
Treat × Post × Market Availability	−0.0151*	0.0113**	−0.00385
	(0.00807)	(0.00569)	(0.00293)
Treat × Post	0.156***	−0.0736**	0.0820**
	(0.0497)	(0.0349)	(0.0348)
Post × Div5	0.0124	−0.0103*	0.00214
	(0.00797)	(0.00567)	(0.00283)

Notes: Standard errors are reported in parentheses. All regressions include firm-product and month fixed effects. Standard errors are clustered at the firm level. The baseline period is August 2021 to January 2022. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We use five methods to define supplier diversification: (1) Value-Weighted Supplier Count, (2) Negative Herfindahl–Hirschman Index (HHI) of Suppliers, (3) Average Supplier Count, (4) Negative HHI of Countries, and (5) Market Availability.

4 Model

In this section, we model firms' sourcing strategies along the agricultural supply chain under the risk aversion assumption. Our model rationalizes the empirical findings in the following ways. First, it is necessary to account for firms' risk aversion. Second, the market structure is an oligopoly and varies for each product. In general, the production network in the agricultural value chain is characterized by one-to-one matching. Third, the endogenous firm-to-firm trade network exhibits two-sided market power and non-negligible matching costs. However, sourcing models are not as straightforward or tractable as many standard trade models that capture firm export behavior.[4] We consider *two-sided heterogeneity* in firms' productivity and risk aversion, and the endogenous firm-to-firm trade network.

4.1 Setup

The importing country is denoted by $i \in \mathcal{J}$, and the source (exporting) country is denoted by $j \in \mathcal{J}$. Input sectors are indexed by $k \in \mathcal{K}$, and suppliers are indexed by $s \in \mathcal{S}_{jk}$, representing potential upstream firms in sector k located in country j. A buyer $\varphi \in \mathcal{I}_i$ is located in country i and has a productivity parameter $\varphi > 0$, where a higher φ corresponds to lower marginal costs.[5] Trade costs are modeled using iceberg trade costs $\tau_{ijk} \geq 1$, consistent with standard trade theory. Downstream firms source inputs from foreign suppliers and exhibit absolute risk aversion, denoted by $\beta \geq 0$. To activate sourcing from a given country-sector pair, firms incur matching costs and pay a fixed cost for each active supplier, with S representing the number of active suppliers.[6]

4.2 Preferences

The final goods market in country i has a representative consumer who allocates expenditure between an outside manufacturing good C_{i0} and an agricultural composite C_{iA} according to a log-linear utility function:

$$U_i \;=\; (1-\alpha_i)\,\ln C_{i0} \;+\; \alpha_i\,\ln C_{iA}, \qquad \alpha_i \in (0,1). \tag{9}$$

Let total nominal expenditure be Y_i.Then we obtain the constant expenditure shares:

[4] Esposito (2020) extends the Melitz model to incorporate portfolio choice and risk aversion, addressing demand uncertainty. Heise et al. (2024) demonstrates how changes in trade policy uncertainty influence firms' sourcing strategies.

[5] The use of the symbol φ for both the buyer and the buyer's productivity parameter follows the standard convention in the Melitz framework.

[6] There are inconsistencies in terms of notations between the empirical and model sections. In the empirical section, we denote the importer as firm j and the exporter as firm i. In the model, we add detail by indexing both countries and firms: I is the importing country and J is the exporting country. We use φ for importer productivity, and s to represent suppliers. We use this notation in the model to follow the convention in the literature, e.g. in Eaton and Kortum (2002).

$$E_{i0} = (1 - \alpha_i) Y_i, \qquad E_{iA} = \alpha_i Y_i, \tag{10}$$

where E_{iA} is the *aggregate final-demand shifter* for agriculture that enters the firm's revenue equations. We normalize the outside manufacturing good price to one ($p_{i0} \equiv 1$) without loss of generality. Agricultural consumption is a CES aggregator over products $\omega \in \Omega_A$ with elasticity of substitution $\sigma > 1$:

$$C_{iA} = \left[\int_{\omega \in \Omega_A} q_i(\omega)^{\frac{\sigma-1}{\sigma}} \, d\omega \right]^{\frac{\sigma}{\sigma-1}}, \qquad P_{iA} = \left[\int_{\omega \in \Omega_A} p_i(\omega)^{1-\sigma} \, d\omega \right]^{\frac{1}{1-\sigma}}. \tag{11}$$

Conditional on (E_{iA}, P_{iA}), demand for variety within food is Dixit–Stiglitz:

$$q_i(\omega) = E_{iA} \, P_{iA}^{\sigma-1} \, p_i(\omega)^{-\sigma}, \tag{12}$$

where σ is the elasticity across varieties within the food and agriculture sector, the top tier fixes the food budget share (and embeds macro demand via E_{iA}), while the lower tier governs substitution across agricultural products through substitution elasticity.

4.3 Technology

We model the production technology of downstream and upstream firms, deriving their cost structures and pricing rules following Antras, Fort and Tintelnot (2017). We incorporate the implications for firm-to-firm trade relationships under a market structure that is consistent with the empirical facts.

Downstream firms. We assume that U.S. importers operate in a monopolistic market structure. The goal of these importers is to maximize profits, which is the difference between their revenue and costs. The profit maximization problem is given by:

$$\max_{p_i(\omega)} \left(p_i(\omega) - c_i(\omega) \right) q_i(\omega), \quad \text{s.t.} \quad q_i(\omega) = E_{iA} P_{iA}^{\sigma-1} p_i(\omega)^{-\sigma}, \tag{13}$$

where $p_i(\omega)$ is the price set by the importer for product ω, $c_i(\omega)$ is the marginal cost, and $q_i(\omega)$ is the quantity demanded. The demand function shows that the quantity demanded decreases as the price increases, with the elasticity of substitution between varieties denoted by σ.

The optimal price that the importer sets is a markup over marginal cost:

$$p_i(\omega) = \frac{\sigma}{\sigma - 1} c_i(\omega) \tag{14}$$

The marginal cost $c_i(\varphi)$ for a firm with productivity φ is determined by the firm's sourcing decisions. Specifically, the firm minimizes its costs by choosing the optimal mix of inputs from

different countries and sectors. The marginal cost is given by:

$$c_i(\varphi) = \frac{1}{\varphi}\left(\sum_{j=1}^{J}\sum_{k=1}^{K} I_{ijk}(\varphi)c_{ijk}(\varphi)^{1-\eta}\right)^{\frac{1}{1-\eta}} \tag{15}$$

Here, $I_{ijk}(\varphi)$ is an indicator variable that equals 1 if the firm sources inputs from country j and sector k. The parameter η governs the elasticity of substitution across inputs from different countries and sectors.

The composite cost $c_{ijk}(\varphi)$ for inputs from a specific country-sector pair is determined by aggregating the costs of individual suppliers:

$$c_{ijk}(\varphi) = \left(\int_0^1 z_{ijk}(\varphi, v)^{1-\lambda} dv\right)^{\frac{1}{1-\lambda}}, \tag{16}$$

where λ represents the elasticity of substitution across suppliers within the same country-sector pair.

Finally, the sourcing cost $z_{ijk}(\varphi, v)$ reflects the minimum cost of obtaining inputs from a set of suppliers:

$$z_{ijk}(\varphi, v) = \min_{s \in \mathcal{S}_{ijk}(\varphi)} \left\{\tau_{ijk} \cdot p_{ijks}(\varphi) \cdot \xi_{ijks}(\varphi, v)\right\} \tag{17}$$

This cost depends on the trade cost τ_{ijk}, the price $p_{ijks}(\varphi)$ set by supplier s, and a random matching shock $\xi_{ijks}(\varphi, v)$. The matching shock follows a log-normal distribution, which captures the idea that some suppliers are inherently more efficient or better matched to the buyer's needs.

Upstream firms. Suppliers operate in an oligopolistic market, maximizing:

$$\max_{p_{ijks}(\varphi)} \pi^{UI}_{ijks}(\varphi) = Q_{ijks}(\varphi)\left(p_{ijks}(\varphi) - c_{jks}\right) \tag{18}$$

where $Q_{ijks}(\varphi) = Q_{ijk}(\varphi)\chi_{ijks}(\varphi)$, and:

$$\chi_{ijks}(\varphi) = \frac{p_{ijks}(\varphi)^{-\theta}}{\sum_{s'=1}^{S_{ijk}(\varphi)} p_{ijks'}(\varphi)^{-\theta}} \tag{19}$$

The total demand $Q_{ijk}(\varphi)$ for inputs from country j and sector k is given by:

$$Q_{ijk}(\varphi) = \left(\frac{\sigma - 1}{\sigma}\right)^{\sigma} E_{iA} P_{iA}^{\sigma-1} \varphi^{\eta-1} c_i(\varphi)^{\eta-\sigma} c_{ijk}(\varphi)^{-\eta}. \tag{20}$$

where $\omega_{ijk}(\varphi)$ is the expenditure share on inputs from country j and sector k, η is the elasticity of substitution across inputs, and σ is the elasticity of substitution for final goods.

Thus, we can obtain the price of the supplier to the buyer:

$$p_{ijks}(\varphi) = \frac{\varepsilon_{ijks}(\varphi)}{\varepsilon_{ijks}(\varphi) - 1} c_{jks}, \tag{21}$$

where $\varepsilon_{ijks}(\varphi) = \left[\sigma\lambda_{ijk}(\varphi) + \eta\left(1 - \lambda_{ijk}(\varphi)\right)\right]\chi_{ijks}(\varphi) + \theta\left[1 - \chi_{ijks}(\varphi)\right]$ is the elasticity of substitution between suppliers s and s' in sector k for firm i sourcing from country j. pi_{ijk} is the trade share of country i sourcing from country j in sector k. The price reflects pricing to the firm, compared to the traditional pricing to market.

Proof. See proof in Appendix D.1. □

4.4 Endogenous Network

For a downstream firm φ in country i, it chooses its set of country-product and suppliers to maximize total profits,

$$\max_{\substack{I_{ijk}(\varphi)\in\{0,1\}_{j=1,k=1}^{J,K} \\ S_{ijk}(\varphi)\in\left\{0,1,2,\ldots,S_{ijk}\right\}_{j=1,k=1}^{J,K}}} \pi_i^D(\varphi) = B_i c_i(\varphi)^{1-\sigma} - \sum_{j=1}^{J} I_{ijk}(\varphi) w_i f_{ijk}^D\left(S_{ijk}(\varphi)\right). \tag{22}$$

where I is the indicator that equals one if firm φ is firm i's supplier. B_i is demand, S_{ij} represents the suppliers' fixed cost.

$$c_i(\varphi) = \frac{\gamma}{\varphi}\Theta_i(\varphi)^{\frac{1}{1-\eta}}, \quad \Theta_i(\varphi) \equiv \sum_{j=1}^{J} I_{ijk}(\varphi)\tau_{ijk}^{1-\eta}\left[\sum_{s=1}^{S_{ijk}(\varphi)} p_{ijks}(\varphi)^{-\theta}\right]^{-\frac{1-\eta}{\theta}}, \tag{23}$$

where $\Theta_i(\varphi)$ is the sourcing capability, and firms' sourcing marginal cost decreases with their sourcing capability.

5 Sourcing Under Uncertainty

Next, we extend the framework to sourcing under uncertainty. For buyer φ, country j, sector k, and supplier $s = 1, \ldots, S_{ijk}$, define the delivered unit cost

$$d_{ijks} \equiv \tau_{ijk} p_{ijks} \xi_{ijks}, \qquad \xi_{ijks} > 0, \tag{24}$$

where p_{ijks} is the upstream price (which may include oligopolistic markups derived earlier) and $\tau_{ijk} \geq 1$ are iceberg trade costs.

Correlation structure of shocks. We introduce trade shocks with correlation following Lind and Ramondo (2023). Let $\varepsilon_{ijks} \equiv \ln \xi_{ijks}$ with

$$\mathbb{E}[\varepsilon_{ijks}] = -\tfrac{1}{2}\sigma_\xi^2, \qquad \text{Var}(\varepsilon_{ijks}) = \sigma_\xi^2, \tag{25}$$

We assume a parsimonious correlation structure:

$$\text{Corr}(\varepsilon_{ijks}, \varepsilon_{ijks'}) = \rho \in [-1, 1] \qquad \text{for } s \neq s' \text{ within the same country } j, \tag{26}$$

$$\text{Corr}(\varepsilon_{ijks}, \varepsilon_{ij'k's'}) = \delta \in [-1, 1] \qquad \text{for } j \neq j'. \tag{27}$$

Correlated matching costs. Activating country j entails a convex matching cost

$$f_{ij}(S_{ij}) \equiv f_{ij0}\, m_{ij} + \kappa_{ij} S_{ij}^{\psi}, \qquad S_{ij} \equiv \sum_k S_{ijk}, \quad \psi > 1. \tag{28}$$

where $m_{ij} > 0$ is a multiplicative shifter representing uncertain relationship costs. Let $\mu_{ij} \equiv \ln m_{ij}$ satisfy

$$\mathbb{E}[\mu_{ij}] = -\tfrac{1}{2}\sigma_m^2, \quad \text{Var}(\mu_{ij}) = \sigma_m^2, \quad \mathbb{E}[m_{ij}] = 1, \quad \text{Corr}(\mu_{ij}, \mu_{ij'}) = \chi \in [-1, 1]. \tag{29}$$

When m_{ij} is realized after sourcing choices, it contributes to the variance of profits; when realized before, it shifts expected costs only.

5.1 Mean-variance Profits Maximization

With the final demand we obtained in the prior section, revenue for a given buyer is $R_i(\varphi) = B_i\, c_i(\varphi)^{1-\sigma}$ with $\sigma > 1$ and $B_i \equiv (\sigma/(\sigma-1))^{1-\sigma}\, E_{iA}\, P_{iA}^{\sigma-1}$. Profits are

$$\pi_i^D(\varphi) \equiv R_i(\phi) - \sum_j I_{ij}\, w_i\, f_{ij}(S_{ij}). \tag{30}$$

A risk-averse buyer ($\beta \geq 0$) maximizes a local quadratic approximation to expected utility:

$$\max_{\{I_{ijk}, S_{ijk}\}} \underbrace{\mathbb{E}[R_i]}_{\text{mean revenue}} - \frac{\beta}{2} \underbrace{\text{Var}(R_i)}_{\text{revenue risk}} - \underbrace{\sum_j I_{ij} w_i\, \mathbb{E}[f_{ij}(S_{ij})]}_{\text{expected matching cost}} - \frac{\beta}{2} \underbrace{w_i^2\, \text{Var}\Big(\sum_j I_{ij} f_{ij}(S_{ij})\Big)}_{\text{matching-cost risk}}. \tag{31}$$

Using $\mathbb{E}[m_{ij}] = 1$, we have $\mathbb{E}[f_{ij}(S_{ij})] = f_{ij0} + \kappa_{ij} S_{ij}^{\psi}$. Writing $f_{\cdot 0} \equiv \sum_j I_{ij} f_{ij0}$ and $\omega_{ij} \equiv f_{ij0}/f_{\cdot 0}$,

$$\text{Var}\Big(\sum_j I_{ij} f_{ij}\Big) = f_{\cdot 0}^2\, \sigma_m^2 \left(\sum_j I_{ij}\, \omega_{ij}^2 \;+\; \chi \sum_{j \neq j'} I_{ij} I_{ij'}\, \omega_{ij} \omega_{ij'}\right). \tag{32}$$

5.2 Risks in Agricultural Supply Chains

We define the supplier-tier and country–sector weights

$$w^S_{ijks} \equiv \frac{d'^{1-\lambda}_{ijks}}{\sum_{s'} d'^{1-\lambda}_{ijks'}}, \qquad w^C_{ijk} \equiv \frac{c'^{1-\eta}_{ijk}}{\sum_{j',k'} I_{ij'k'} c'^{1-\eta}_{ij'k'}}, \qquad W_{ijks} \equiv w^C_{ijk} w^S_{ijks}. \tag{33}$$

Lemma 1. *For small multiplicative shocks $\varepsilon_{ijks} = \ln \xi_{ijks}$ and holding τ_{ijk}, p_{ijks} fixed,*

$$d \ln c_i = \sum_{j,k} \sum_{s=1}^{S_{ijk}} W_{ijks}\, d\varepsilon_{ijks}. \tag{34}$$

Proof. $d \ln c_{ijk} = \sum_s w^S_{ijks}\, d \ln d_{ijks}$. Differentiate the outer CES: $d \ln c_i = \sum_{j,k} w^C_{ijk}\, d \ln c_{ijk}$. Compose and use $d \ln d_{ijks} = d \ln \xi_{ijks} = d\varepsilon_{ijks}$. □

Lemma 2. *With $\mathrm{Var}(\varepsilon_{ijks}) = \sigma^2_\xi$ and correlations in (26)–(27),*

$$\mathrm{Var}(\ln c_i) = \sigma^2_\xi \left[(1-\rho) \sum_{j,k,s} W^2_{ijks} + \rho \sum_j \Big(\sum_{k,s} W_{ijks} \Big)^2 + (\delta - \rho) \sum_{j \neq j'} \Big(\sum_{k,s} W_{ijks} \Big) \Big(\sum_{k',s'} W_{ij'k's'} \Big) \right]. \tag{35}$$

Equivalently, using $\pi_{ij} \equiv \sum_{k,s} W_{ijks}$ the trade share and within-country concentration $H_{ij} \equiv \sum_{k,s} (W_{ijks}/\lambda ij)^2 \in [1/S_{ij}, 1]$, we get

$$\mathrm{Var}(\ln c_i) = \sigma^2_\xi \left[(1-\rho) \sum_j \pi^2_{ij} H_{ij} + \delta + (\rho - \delta) \sum_j \pi^2_{ij} \right]. \tag{36}$$

Proof. From Lemma 1, $\ln c_i$ is a weighted sum of jointly correlated shocks. The variance equals the quadratic form in the weights with covariances σ^2_ξ (own), $\rho\sigma^2_\xi$ (same j across different s), and $\delta\sigma^2_\xi$ (across $j \neq j'$). Group terms to obtain (35). Using $\sum_{k,s} W^2_{ijks} = \pi^2_{ij} H_{ij}$ and $\sum_{j \neq j'} \pi_{ij} \lambda_{ij'} = 1 - \sum_j \lambda ij^2$ yields (36). □

Since $R_i = B_i\, c_i^{1-\sigma}$, a first-order delta method gives

$$\mathrm{Var}(R_i) \approx B_i^2 (1-\sigma)^2\, \bar{c}_i^{\,2(1-\sigma)}\, \mathrm{Var}(\ln c_i), \tag{37}$$

with $\bar{c}_i$ the baseline cost.

5.3 Implications for Diversification and Supplier Choice

Define the optimization over I_{ijk}, S_{ijk} using (31), with risk terms given by (36) and (37), and matching-cost risk by (32).

Proposition 1 (Diversification lowers risk when cross-country comovement is weaker)**.** *If $\delta < \rho$, then (i) any reallocation of trade shares π_{ij} that reduces $\sum_j \pi^2_{ij}$ strictly reduces $\mathrm{Var}(\ln c_i)$; and (ii) for fixed π_{ij}, any reduction of within-country concentration H_{ij} reduces $\mathrm{Var}(\ln c_i)$ whenever $\rho < 1$.*

Proof. In (36), the coefficient on $\sum_j \pi_{ij}^2$ is $(\rho - \delta) > 0$ when $\delta < \rho$, hence the function is Schur-convex in λ. Thus, spreading mass (lower $\sum_j \pi_{ij}^2$) lowers variance. For fixed λ, the term $(1 - \rho) \sum_j \pi_{ij}^2 H_{ij}$ is weakly decreasing in each H_{ij} since $(1 - \rho) \geq 0$. □

Proposition 2 (Optimal number of suppliers within a country)**.** *Fix a country j. Suppose $W_{ijks} = \lambda ij / S_{ij}$ symmetrically across S_{ij} suppliers, so $H_{ij} = 1/S_{ij}$. Let $f_{ij}(S) = f_{ij0} + \kappa_{ij} S^{\psi}$ with $\psi > 1$. Ignoring the fixed part f_{ij0}, the optimal supplier count solves*

$$S_{ij}^{\star} = \left(\frac{\beta B_i^2 (1 - \sigma)^2 \bar{c}_i^{2(1-\sigma)} \sigma_{\xi}^2 (1 - \rho) \lambda ij^2 w_i}{\kappa_{ij} \psi} \right)^{\frac{1}{\psi + 1}}. \tag{38}$$

Proof. Under symmetry, country j contributes $\sigma_{\xi}^2 (1 - \rho) \lambda ij^2 / S_{ij}$ to $\mathrm{Var}(\ln c_i)$ by (36). The associated revenue variance term in (31) is $\frac{\beta}{2} B_i^2 (1 - \sigma)^2 \bar{c}_i^{2(1-\sigma)}, \sigma_{\xi}^2 (1 - \rho) \lambda ij^2 / S_{ij}$. The marginal cost of suppliers is $w_i \kappa_{ij} \psi S_{ij}^{\psi - 1}$. Setting the derivative of the objective w.r.t. S_{ij} to zero yields $\kappa_{ij} \psi S_{ij}^{\psi - 1} = \frac{\beta}{2} B_i^2 (1 - \sigma)^2 \bar{c}_i^{2(1-\sigma)}, \sigma_{\xi}^2 (1 - \rho) \pi_{ij}^2, S_{ij}^{-2}, w_i$, which rearranges to (38). □

Proposition 3 (Country activation under correlated revenue and matching-cost risk)**.** *Consider adding an inactive country j with a small portfolio weight $\pi_{ij} = \epsilon > 0$ (maintaining $\sum_j \pi_{ij} = 1$) and symmetric suppliers within the country. A necessary condition for activation, the first-order deterministic cost benefit dominates the quadratic risk penalty and the expected matching costs:*

$$\Delta U_j \approx -\frac{\beta}{2} B_i^2 (1 - \sigma)^2 \bar{c}_i^{2(1-\sigma)} \sigma_{\xi}^2 \left[\delta - (\rho - \delta) \sum_{j'} \alpha_{ij'}^2 \right] \epsilon^2 - w_i f_{ij0} - w_i \kappa_{ij} S_{ij}^{\psi}. \tag{39}$$

Positive χ raises the matching-cost risk penalty and discourages multi-country activation.

Proof. From (36), the curvature of $\mathrm{Var}(\ln c_i)$ along the simplex at an inactive corner is quadratic with coefficient $\delta - (\rho - \delta) \sum_{j'} \lambda ij'^2$. Multiplying by the delta-method factor in (37) and the risk weight $\beta/2$ gives the revenue-risk term. Expected matching costs add $w_i (f_{ij0} + \kappa_{ij} S_{ij}^{\psi})$. If m_{ij} is realized after choices, the variance of $\sum_j I_{ij} f_{ij}$ in (32) contributes the last linearly homogeneous term, increasing with χ. The deterministic benefit depends on τ_{ijk}, p_{ijks} via the reduction in $\bar{c}_i$ and is first order in ϵ. □

Proposition 4 (intensive margin)**.** *Suppose $\{\lambda ij\}$ are chosen continuously to minimize the risk component in equation (36) (treating $\{H_{ij}\}$ and $\bar{c}_i$ as locally fixed), subject to $\sum_j \lambda ij = 1$. Then*

$$\pi_{ij}^{\star} \propto \left[(1 - \rho) H_{ij} + (\rho - \delta) \right]^{-1}, \tag{40}$$

so $\partial \pi_{ij}^{\star} / \partial \rho < 0$ when $H_{ij} > 1/S_{ij}$ and $\partial \pi_{ij}^{\star} / \partial \delta > 0$ (toward concentration).

Proof. Minimize $F(\lambda) = (1 - \rho) \sum_j \lambda_j^2 H_j + (\rho - \delta) \sum_j \lambda_j^2$ subject to $\sum_j \lambda_j = 1$. The first order condition is $2[(1 - \rho) H_j + (\rho - \delta)] \lambda_j = \lambda$, yielding equation (40). □

Proposition 5 (market power). *If upstream prices are $p_{ijks} = \mu_{ijks} c_{jks}$ with markups $\mu_{ijks} = \varepsilon_{ijks}/(\varepsilon_{ijks} - 1)$ from oligopoly pricing, then Propositions 1–4 remain valid. Markups change baseline weights W_{ijks} and $\bar{c}_i$, but the comparative statics follow from equation (36) and are unchanged in sign.*

Proof. Lemmas 1–2 depend only on multiplicative shocks and CES structure, not on the deterministic level of d_{ijks}. Oligopoly affects the levels of W_{ijks} and $\bar{c}_i$. □

5.4 Market Clearing

Let M_i be the mass of active downstream firms in country i and M_{jk} the mass of active upstream suppliers in (j,k). For each (j,k), input-market clearing requires

$$\sum_i \int X_{ijk}(\phi)\, dM_i(\phi) \;=\; Q_{jk}, \tag{41}$$

where $X_{ijk}(\phi)$ denotes buyer i's expenditure on the (j,k) input (endogenous via sourcing choices), and Q_{jk} is aggregate output in (j,k). On the final good side, the agricultural price index and expenditure satisfy

$$P_{iA} = \left[\int_{\omega\in\Omega_A} p_i(\omega)^{1-\sigma}\, d\omega\right]^{\frac{1}{1-\sigma}}, \qquad E_{iA} = \alpha_i Y_i, \qquad Y_i = w_i L_i + \Pi_i, \tag{42}$$

with Π_i total profits distributed to households. All goods markets clear given these aggregations.

5.5 General Equilibrium

A *general equilibrium* is a collection

$$\Big\{p_i(\omega),\ c_i(\phi),\ I_{ijk}(\phi),\ S_{ijk}(\phi),\ P_{iA},\ E_{iA},\ Y_i,\ M_i,\ M_{jk},\ \bar{\phi}_i,\ \bar{s}_{jk}\Big\}$$

(and implied prices p_{ijks}, shares W_{ijks}) such that:

1. **Households:** Given prices, E_{iA} and P_{iA} satisfy equation (42), with the outside good normalized and budget Y_i.
2. **Downstream buyers:** For each i and ϕ, $\{I_{ijk}, S_{ijk}\}$ solve equation (31) with risk terms given by equation (36), (37), and (32). Pricing to the final market follows the Dixit–Stiglitz rule.
3. **Upstream suppliers:** Pricing (markups) satisfy the oligopoly structure derived earlier, and entry satisfies equation (68) for marginal types $\bar{s}_{jk}$.
4. **Entry:** Downstream free entry holds by equation (66), determining $\bar{\varphi}_i$ and M_i.
5. **Market clearing:** Input markets clear via equation (41); the final-good sector clears by construction of E_{iA} and P_{iA}.

6. **Consistency:** Shocks (ε, μ) follow equation (25)–(29); all shares W_{ijks} are computed at equilibrium $\{p, \tau\}$ and sourcing sets.

Increases in ρ or δ raise measured risk via (36), which (i) elevate the downstream entry cutoff (Lemma 3); (ii) reduce supplier counts within countries (Proposition 2); (iii) reallocate country weights as in (40); and (iv) depress upstream entry (Proposition 6). Positive matching-cost correlation χ further discourages multi-country activation (Proposition 3).

6 Estimation and Calibration

In this section, we use the firm-to-firm transaction-level data of US importers in conjunction with country-level data to estimate the key parameters of the model. We distinguish firm sourcing potential from the fixed cost, trade costs, and matching costs. The parameter estimates obtained here are used in the following section to perform the counterfactual analysis.

We estimate the key parameters in the following steps. First, we estimate the demand elasticity from the share and pass-through equations. Second, we recover trade costs from gravity and posted-price instruments. Third, we back out the country-sector scales T_{jk} and the common shifter γ from average effective costs. Fourth, we estimate correlation components (v_j, v_G) that imply (ρ, δ) using covariance restrictions. Finally, we estimate risk aversion β and matching-cost parameters of $f^D_{i\varphi jk}(S)$ by simulated moments that match market share volatility; (6) calibrate remaining fixed costs to hit entry/extensive margins.[7]

6.1 Elasticities

We start from equation (19) to (21) to estimate the elasticities in the final goods demand, and the Frechét parameter in the matching function,

$$\begin{aligned} \ln p_{ijks} &= \underbrace{\beta_{jks}}_{\ln c_{jks}} + m\left(\varepsilon_{ijks}(\eta,\theta)\right) + u_{ijks}, \quad m(x) \equiv \ln\left(\frac{x}{x-1}\right), \\ \varepsilon_{ijks}(\eta,\theta) &= \left[\sigma\delta_{ijk} + \eta\left(1-\delta_{ijk}\right)\right]\chi_{ijks} + \theta\left(1-\chi_{ijks}\right), \end{aligned} \tag{43}$$

Variation in χ_{ijks} at given λ_{ijk} identifies θ through the slope on $(1-\chi)$ and variation in λ_{ijk} at given χ_{ijks} identifies η through the slope on $\chi(1-\lambda)$. The markup map $m(x)$ is strictly increasing on $x > 1$ with derivative $m'(x) = 1/[x(x-1)]$, so elasticities that raise ε increase $\ln p$ conditional on costs. A useful diagnostic is the monotonicity condition $\rho_{ijk} \equiv \theta - \eta + (\eta - \sigma)\lambda_{ijk} > 0$.

We use Nonlinear Least Square (NLS) to estimate (η, θ) by concentrating out $\{\alpha_{jks}\}$ and minimizing:

[7] We draw 20% random samples of downstream US buyers and marginal costs, and their supplier firms and their productivity for estimation.

$$\min_{\eta>0,\theta>0} \sum_{i,j,k,s} \left[\ln p_{ijks} - \widehat{\beta}_{jks}(\eta,\theta) - m\left(\varepsilon_{ijks}(\eta,\theta)\right) \right]^2, \tag{44}$$

subject to $\varepsilon_{ijks}(\eta,\theta) > 1$ (finite markups). For any trial (η,θ), $\widehat{\beta}_{jks}(\eta,\theta) = \ln p_{ijks} - m\left(\varepsilon_{ijks}(\eta,\theta)\right)$. so the objective becomes a sum of squared residuals r_{ijks}.

We take $\widehat{\sigma} = 5$ following Gaubert and Itskhoki (2021). Given $\widehat{\sigma}$ and the estimated importer $\times$ time fixed effects $\widehat{\phi}_{it}$, the revenue scale entering the buyer problem, $B_{it} = (\sigma/(\sigma-1))^{1-\sigma} E_{iA,t} P_{iA,t}^{\sigma-1}$ is recovered as $\widehat{B}_{it} = (\widehat{\sigma}/(\widehat{\sigma}-1))^{1-\widehat{\sigma}} \exp\{\widehat{\varphi}_{it}\}$ and normalized to have mean 1 in a base period. We present the estimation results in Table 6. Our estimation of equation 44 shows low substitutability across country–sector ($\widehat{\eta} = 0.780$) and R^2 is small (0.049), which also shows gravity is weak but not zero in agricultural firm-to-firm supply chains.

6.2 Cost Distribution and Sourcing Potential

Our baseline identification of (σ,η,θ) and (ρ,δ) does not impose a parametric form on the cross-supplier distribution of costs. For counterfactuals that alter trade frictions and supplier entry (or when the observed set of transacting suppliers is sparse), it is convenient to summarize the origin-specific heterogeneity in marginal costs with a parsimonious distribution. Because we only observe suppliers whose costs are sufficiently low to be selected, we fit an upper-truncated Pareto to the supplier $\times$ HS-6 cost proxies recovered from the pricing equation.

For each origin j (or country–sector jk where sample size permits), assume supplier marginal costs follow a truncated Pareto: $G_j(c) = \Pr(c_{jks} \le c) = (c/c_{Mj})^{k_j}, \quad c \in (0, c_{Mj}]$ with shape $k_j > 0$ and upper bound c_{Mj}. Let $c_{q,j}$ denote the qth percentile of the distribution $\{\widehat{c}_{jks}\}_s$ from the pricing step. Using $(c_{1,j}/c_{Mj})^{k_j} = 1/100, \quad (c_{10,j}/c_{Mj})^{k_j} = 1/10$, we identify $\widehat{k}_j = \ln 10 \,/\, (\ln c_{10,j} - \ln c_{1,j}), \quad \widehat{c}_{Mj} = 100^{1/\widehat{k}_j}\, c_{1,j}$.

We use MLE to estimate the cost of the firms. For observations $c_r \in (0, c_{Mj}]$, $\ell_j\left(k_j, c_{Mj}\right) = n_j \ln k_j - n_j k_j \ln c_{Mj} + \left(k_j - 1\right) \sum_{r=1}^{n_j} \ln c_r$ follow Gaubert and Itskhoki (2021). The MLE satisfies $\hat{c}_{Mj} = \max_r c_r, \widehat{k}_j = n_j / \left(n_j \ln \hat{c}_{Mj} - \sum_r \ln c_r\right)$. To reduce sensitivity to the sample maximum, we trim the top 1% and treat that quantile as the bound when optimizing k_j. We report bootstrapped SEs.

Following Antras, Fort and Tintelnot (2017), we parameterize the fixed cost of sourcing as a function of exogenous shipping, communication, and contracting costs. We estimate a gravity PPML for flows X_{ijkt} with importer $\times$ time, origin $\times$ time, and HS-6 fixed effects, and observables (log CEPII distance, tariffs). We map fitted coefficients into a multiplicative iceberg proxy $\widehat{\tau}_{\text{ijkt}}$ used in sourcing-potential inversion and counterfactuals.

6.3 Risk and Matching Cost

We now estimate the parameters governing risk and the matching cost. The buyer's mean-variance objective implies that sourcing choices load on (i) how the supplier network maps into

revenue risk, and (ii) the level and dispersion of activation/matching costs across origins.

We estimate the vector of 6 parameters $\Theta_{\text{RM}} = \left(\beta, \kappa_0, \psi, \zeta_{\text{dist}}, \chi, \sigma_m^2\right)$, with simulated moments of method (SMM), with an initial variance-components step to recover shock correlations.

$$Q(\Theta) = \left[m^{\text{data}} - m^{\text{sim}}(\Theta)\right]^{\top} W \left[m^{\text{data}} - m^{\text{sim}}(\Theta)\right], \tag{45}$$

where W is a positive-definite weighting matrix. In our baseline, W is the identity matrix while in robustness checks, we use the inverse of the variance-covariance matrix of the empirical moments. β is the buyer's coefficient of absolute risk aversion; $\kappa_{ij} = \kappa_0 \exp\{\zeta_{\text{dist}} \ln \text{dist}_{ij}\}$ scales the convex matching cost $f_{ij}(S) = f_{ij0} + \kappa_{ij} S^{\psi}$ with curvature $\psi > 1$; and (χ, σ_m^2) parameterize the correlation and scale of country-activation shocks. Identification relies on a simulated method of moments (SMM) that targets both intensive- and extensive-margin evidence.

First, on the intensive margin, we match how often and how broadly buyers source across countries. The moments are: (i) the slope b_S from the fixed-effects regression $\ln S_{ijt} = b_S \ln \text{VarR}_{it} + \gamma_{\text{dist}} \ln \text{dist}_{ij} + \mu_i + \varepsilon_{ijt}$, (ii) the distance slope γ_{dist} from the same regression, (iii)–(vi) four activation rates by distance quartile (share of $I_{ijt} = 1$ in each bin of $\ln \text{dist}_{ij}$), (vii) the mean of S_{ijt} on the active set ($S_{ijt} > 0$); (viii) the median of S_{ijt} on the active set, (ix) the average off-diagonal correlation of activations I_{ijt} across countries within a buyer–year, and (x) the variance of the number of countries sourcing from per buyer–year ($J_{it} = \sum_j I_{ijt}$). Together, these moments discipline how risk and distance shape the decision to be active and how many links a buyer keeps.

Second, on the extensive margin, we match how sourcing intensity shifts once a buyer is active with a country. The moments are: (i) the slope b_H from $H_{ijt} = b_H \ln \text{VarR}_{it} + \mu_i + \mu_t + u_{ijt}$, which ties within-country concentration to buyer risk; and (ii) the allocation elasticity b_α from $\ln S_{ijt} = b_\pi \ln \pi ijt + \tilde{b} \ln \text{VarR}_{it} + \mu_i + e_{ijt}$, which measures how breadth responds to the buyer's spending share on that country.

We estimate the model in two steps. First, we pre-estimate the pricing block to obtain the pass-through elasticities $(\widehat{\eta}, \widehat{\theta})$, a buyer–year demand shifter $\widehat{B}_{it}$, and two variance components that summarize common and aggregate cost shocks $(\widehat{\rho}, \widehat{\delta})$. Using these objects, we construct the predicted revenue variance $\widehat{\text{Var}}(R_{it})$ from the portfolio formula implied by the pricing parameters and the observed sourcing weights. We treat $\widehat{\text{Var}}(R_{it})$ as an input to the SMM stage to avoid a fixed-point between risk and the choice of suppliers. Because the risk scale depends on θ through the idiosyncratic-cost variance σ_ξ^2, we anchor $\widehat{\theta}$ in the pricing step and treat σ_ξ^2 as given in SMM to prevent collinearity with the matching-cost level κ_0. All moment regressions include importer and year fixed effects and are implemented with within (demeaning) transforms. The SMM objective is a weighted quadratic in the gap between simulated and empirical moments, the weighting matrix is the inverse of a buyer-level bootstrap covariance of the empirical moments, and we report standard errors based on the same bootstrap and a ridge-stabilized numerical Hessian. Our estimates of $\widehat{\zeta_{\text{dist}}} = 0.021$.

Identification follows a simple mean–variance trade-off. Buyers expand the number of suppliers until the marginal reduction in revenue risk equals the marginal matching cost. In the data,

a higher predicted $\widehat{\text{Var}}(R_{it})$ is associated with broader sourcing networks, which identifies the utility weight on risk (β). Geography shifts matching costs. We model $\kappa_{ij} = \kappa_0 \exp(\zeta_{\text{dist}} \ln \text{dist}_{ij})$, so longer distances compress the supplier count at a given risk and pin down ζ_{dist} (and, jointly with levels, κ_0). The curvature $\psi > 1$ governs how fast marginal cost rises with additional suppliers, and is informed by the elasticity of $\ln S_{ijt}$ with respect to risk and to the buyer's spending share on the country, $\ln \alpha_{ijt}$. On the extensive margin, a larger σ_m^2 generates more dispersion in the number of active origins per buyer–year, while a higher χ induces co-movement in activation across origins. To guard against flat regions of the criterion when moments are weak, we impose economically sensible bounds ($\psi > 1$, $\kappa_0 > 0$, $|\chi| < 1$), use multiple starting values, and scale moments to similar magnitudes before weighting.

6.4 Model Fit

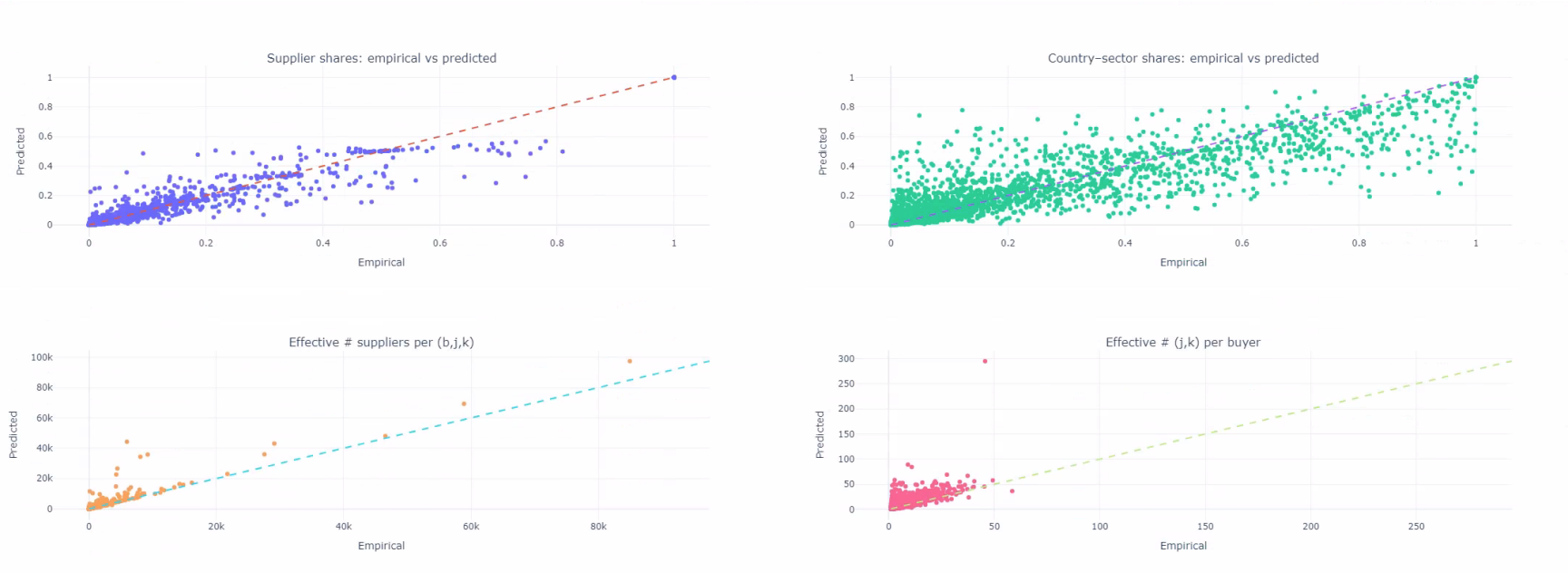
We evaluate the quantitative performance of the risk-matching block by confronting its predictions with micro evidence on supplier counts and activation patterns. Given the estimated primitives, we reconstruct the buyer-specific revenue variance $\widehat{Var}(R_{it})$ using the portfolio aggregator and the demand scale $\widehat{B}_{it}$. We then feed the parameter vector $\widehat{\Theta}_{\text{RM}} = (\widehat{\beta}, \widehat{\kappa}_0, \widehat{\psi}, \widehat{\zeta}_{\text{dist}}, \widehat{\chi}, \widehat{\sigma}_m^2)$ into the intensive-margin formula for the predicted network size and simulate the extensive margin via a single-factor probit for country activation. The fit is summarized along two dimensions.

Table 6: Key Parameters, Values, and Methods

Symbol	Meaning	Value	Methods
σ	Final-good elasticity across varieties	5.00	Gaubert and Itskhoki (2021)
η	Elasticity across country-sector composites	0.78	Estimate by equation (43)
λ	Elasticity across suppliers within (j,k)	0.75	Estimate by equation (43)
ψ	Search-cost curvature parameter	1.20	SMM
β	Absolute risk aversion	0.05	SMM
ρ	Within-country shock correlation	0.69	Estimate
δ	Cross-country shock correlation	0.21	Estimate by equation (43)
χ	Matching-cost correlation across countries	0.20	SMM
σ_ξ^2	Variance of supplier log-shock	1.39	SMM
σ_m^2	Variance of log matching-cost shifter	0.10	SMM
τ_{ijk}	Iceberg trade costs	/	Calibrate
f_{ij0}	Country specific fixed cost	/	Estimate
κ_{ij}	Convex supplier cost parameters	0.50	SMM
π_{ij}	Trade shares	Figure 6	Construct from data

Notes: σ can be disciplined by price–cost margins or pass-through; (η, λ) by cross- and within-country input shares; (ρ, δ) via co-movement in buyer-level supplier costs or values; β from the sensitivity of $\{\lambda ij, S_{ij}\}$ to volatility and correlations.

Figure 6: Model Fit



Notes: This figure compares the model's predicted values with the observed data to assess the overall fit. The horizontal axis represents the observed values, while the vertical axis represents the predicted values from the model.

7 Counterfactuals

We run two counterfactual exercises to assess the effects of supply chain disruptions and policy interventions: (1) the Ukraine–Russia war, and (2) subsidized diversification of U.S. firms' sourcing. We compare the results under different levels of risk aversion and market structure, showing that both the market power of upstream firms and the risk preferences of downstream importers play a key role in diversification strategies. In the first exercise, an existing supply chain is disrupted by the war, which raises manufacturing costs and causes buyers to lose suppliers in the affected regions. The second exercise simulates the impact of subsidies for diversification on supplier linkages.

7.1 Effects of the Ukraine-Russia War

Using the calibrated model, we first back out the matching cost by $\kappa_{ij} = \kappa_0 \exp\left\{\zeta_{\text{dist}} \ln \text{dist}_{ij}\right\}$. We focus on three main outcomes: expected number of suppliers, number of origin countries sourcing from, and total imports and prices.

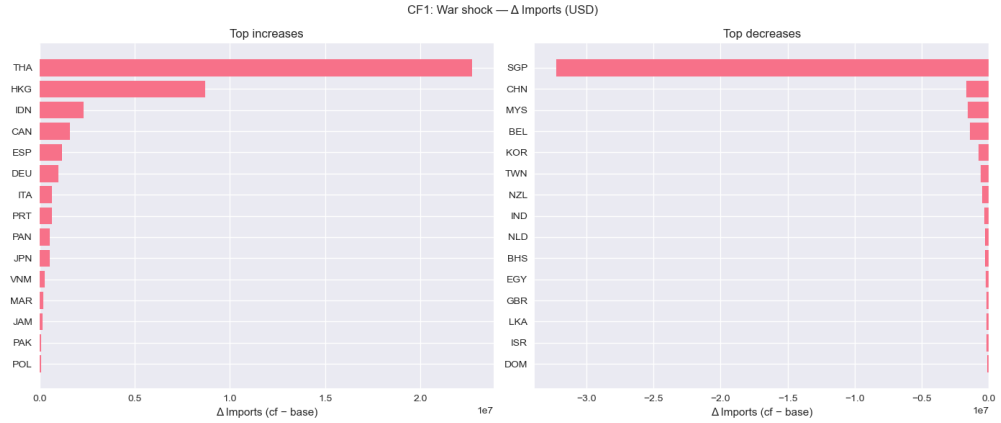
We simulate the impact of the Ukraine-Russia war by introducing a shock to the availability and prices of agricultural inputs from these countries. We model the conflict as (i) removal of relationships with war origins and (ii) higher effective cost and correlation for remaining exposure to those origins. Specifically, we increase ρ (within-country correlation) and δ (cross-country correlation) for suppliers in Ukraine and Russia. Figure 7 shows the results of the outcome changes.

Figure 7 illustrates the heterogeneous effects of the Ukraine-Russia war across countries. Panel (a) shows that the number of suppliers per importer decreased significantly for countries with high pre-war reliance on Ukrainian and Russian suppliers, reflecting the disruption in supply chains. Panel (b) highlights a reallocation of trade shares, with importers shifting sourcing to alternative countries, particularly those with lower trade costs and higher supplier availability. Panel (c) demonstrates that import prices increased more sharply for countries with limited diversification, showing the importance of supplier network resilience in mitigating the impact of geopolitical shocks. US. will increase their imports from Thailand, Hongkong and India. And US sourcing suppliers have a structural change from China, the Dominican Republic, and New Zealand, to Portugal and Germany.

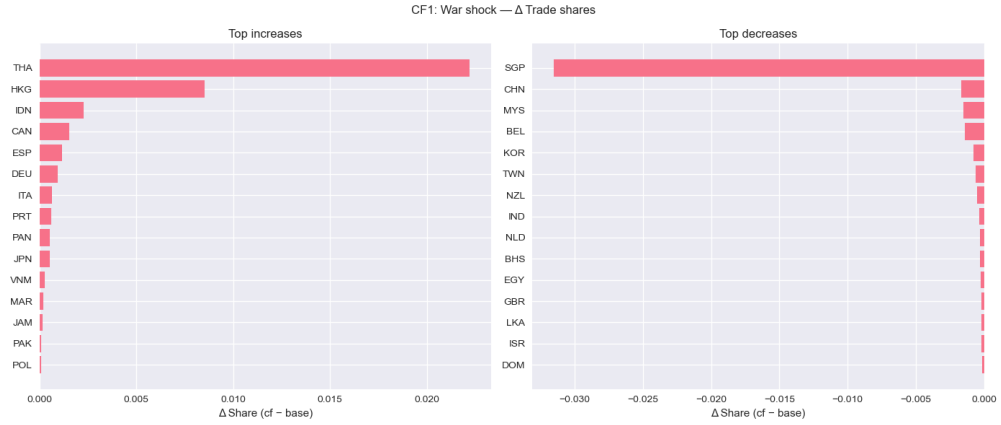
7.2 Subsidized Diversification

We evaluate the effects of a policy that subsidizes the fixed costs of establishing new supplier relationships. Specifically, the subsidy targets potential suppliers in the same sector producing the same HS-6 products. The policy supports U.S. firms that source from suppliers located outside the top exporting countries.

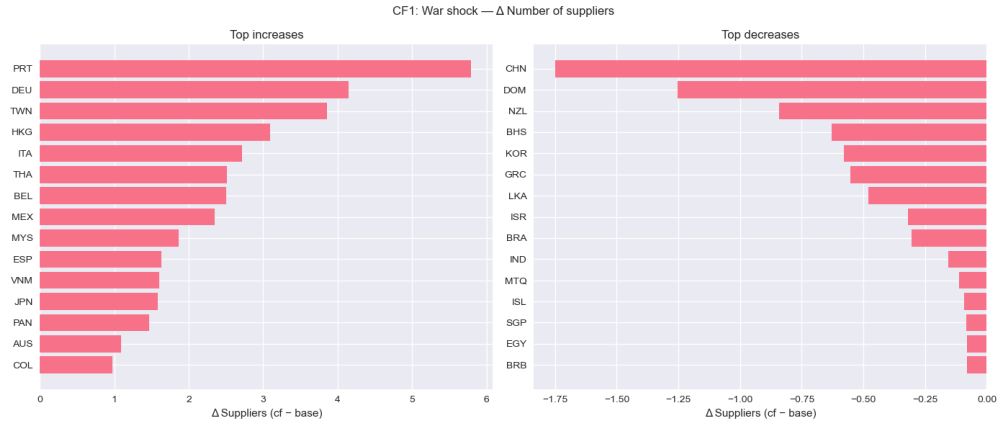
Figure 7: Counterfactual 1: Impact of Ukraine-Russia War on Supplier Networks



(a) Change in Total Imports



(b) Change in Trade Shares



(c) Change in Number of Suppliers

Notes: Panel (a) shows the change in the number of suppliers per importer due to the Ukraine-Russia war. Panel (b) illustrates the change in total trade shares of U.S. firms across different countries. Panel (c) depicts the change in average import prices, reflecting the impact of disrupted supply chains and increased trade costs.

Subsidized Diversification Policies. We consider two counterfactual policies that reduce buyers' matching costs and thereby promote supply-chain diversification. First, a *uniform diversification subsidy* lowers the matching cost κ_{ij} for *all* importer–country pairs by a common factor, easing the formation and maintenance of relationships across the board without favoring particular suppliers. Second, a *targeted non-top supplier subsidy* applies the cost reduction only to "fringe" suppliers—those outside the top-2 (ranked by value share) within each importer–country pair—so that the incentive specifically encourages expansion beyond dominant partners. The uniform policy provides broad-based incentives to diversify, while the targeted policy concentrates support where the marginal diversification margin is largest, potentially increasing the number of active relationships and reducing concentration without disproportionately subsidizing incumbents.

Table 7 summarizes the variance changes across scenarios. The base scenario reflects the original model parameters, while the counterfactual scenarios show how variance changes under the two subsidy policies. The uniform subsidy significantly reduces variance, indicating a broad diversification effect, while the non-top supplier subsidy has a smaller but still notable impact.

Table 7: Variance changes across scenarios $(thound\ dollars)^2$

Scenario	Variance	Δ Variance	Δ Variance (%)
base	95507090	0	0.000000
CF2_uniform	26612390	-68894690	-72.135686
CF2_nontop	88514130	-6992958	-7.321925

Figure 8 illustrates the effects of subsidized diversification policies on U.S. firms' sourcing strategies. Panel (a) shows that total imports increased under both uniform and non-top supplier subsidies, with the uniform subsidy having a larger impact. Panel (b) highlights that the number of suppliers per importer also rose, reflecting enhanced diversification. These results demonstrate that reducing matching costs can significantly improve supply chain resilience and reduce concentration in global agricultural supply chains.

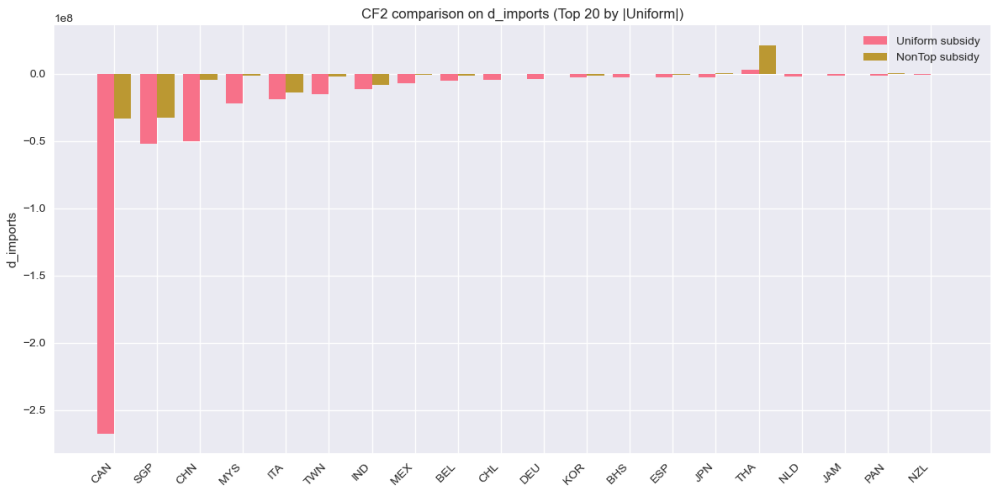
7.3 Sensitivity Analysis and Additional Results

Finally, we test the robustness of the model's counterfactual predictions across several dimensions. First, we examine how sourcing strategies change under different market structures. Second, we present results under alternative assumptions about firms' risk attitudes—comparing risk aversion with risk neutrality.

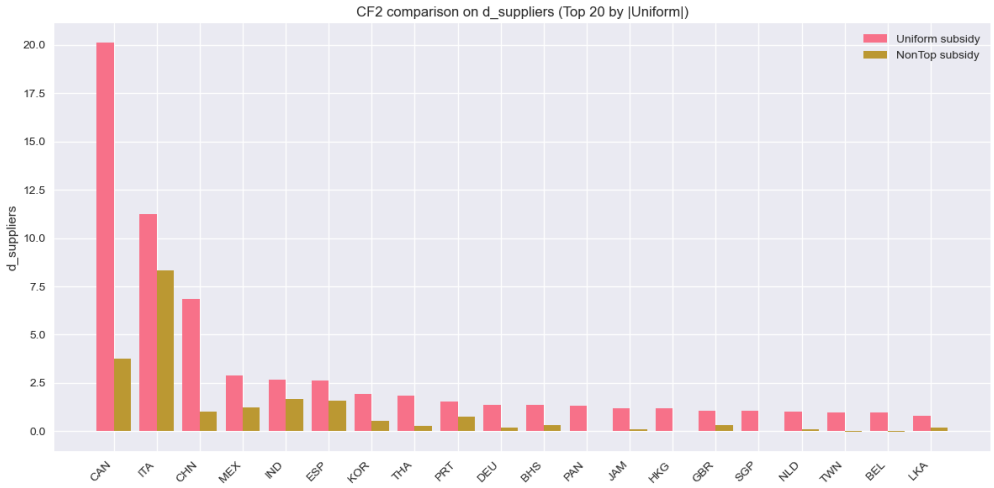
To further explore the robustness of our counterfactual results, we conduct a two-dimensional sensitivity analysis by varying two key parameters simultaneously: the degree of upstream market power and the downstream firms' risk attitudes. We summarize the effects in a three-dimensional response surface, allowing us to visualize how these two forces jointly influence key outcomes such as the number of suppliers, import values, and average import prices.

We parameterize upstream market structure using a concentration index parameter, μ, where

Figure 8: Counterfactual 2: Subsidized Diversification Effects



(a) Change in Total Imports



(b) Change in Number of Suppliers

Notes: Panel (a) shows the change in total imports due to subsidized diversification policies. Panel (b) illustrates the change in the number of suppliers per importer under the same policies. Data are aggregated across firms and sectors.

higher values correspond to greater market power (e.g., fewer, larger exporters with higher markups), and lower values correspond to more competitive conditions. Risk attitude is captured by the coefficient of relative risk aversion, β, where $\beta = 0$ corresponds to risk neutrality and a higher β reflects a stronger aversion to variance in revenues from supplier relationships.

For each (μ, β) combination in a predefined grid, we solve the model and recover the endogenous sourcing patterns, prices, and trade flows. This generates a smooth mapping from the (μ, β) parameter space to the outcomes of interest. By plotting these mappings in three dimensions, we can assess the complementarity or substitutability between market power and risk aversion in shaping trade patterns. For example, increases in β tend to shift sourcing toward lower-risk suppliers, but the magnitude of this effect is amplified when μ is high, as buyers face fewer competitive pricing options.[8]

The resulting surfaces illustrate non-linearities and interaction effects that would be obscured in a one-parameter-at-a-time analysis. In particular, the slope of the import-price surface with respect to β becomes markedly steeper when μ is large, highlighting how market power magnifies the role of risk aversion in determining equilibrium prices. This suggests that policy interventions aimed at either reducing concentration or mitigating risk exposure may have stronger effects when the other force is also present.

8 Conclusions

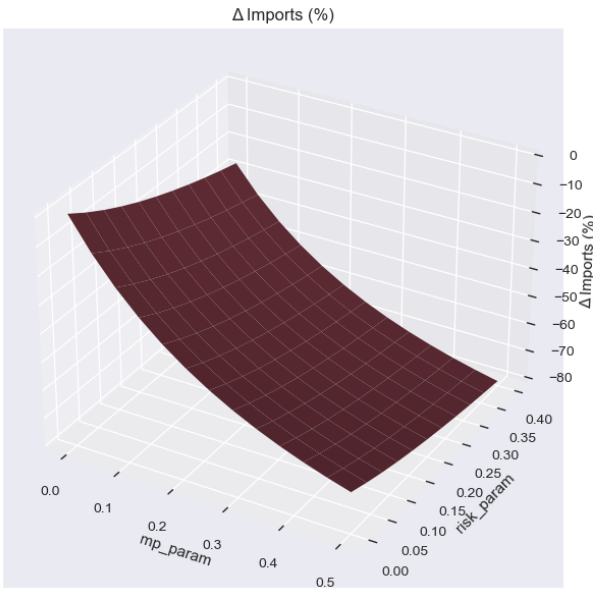
This paper examines the structure and resilience of global agricultural supply chains, addressing how uncertainty and diversification influence firms' sourcing strategies and market outcomes. Motivated by the high volatility and concentration in agricultural trade, we leverage detailed firm-to-firm trade data to document key empirical facts. We find that agricultural supply chains are highly concentrated, with a small number of exporters and importers dominating trade flows. Larger firms tend to diversify their supplier networks more extensively, while long-term trading relationships are associated with lower prices and greater resilience to shocks.

Our empirical analysis highlights the role of market power in shaping transaction prices, with both supplier and buyer concentration affecting price formation. Using the Ukraine-Russia war as a natural experiment, we show that geopolitical shocks significantly disrupt trade flows, with firms exposed to riskier suppliers experiencing greater price volatility and relationship breakdowns. Diversification emerges as a key strategy for mitigating these risks, particularly when cross-country shock correlation is low.

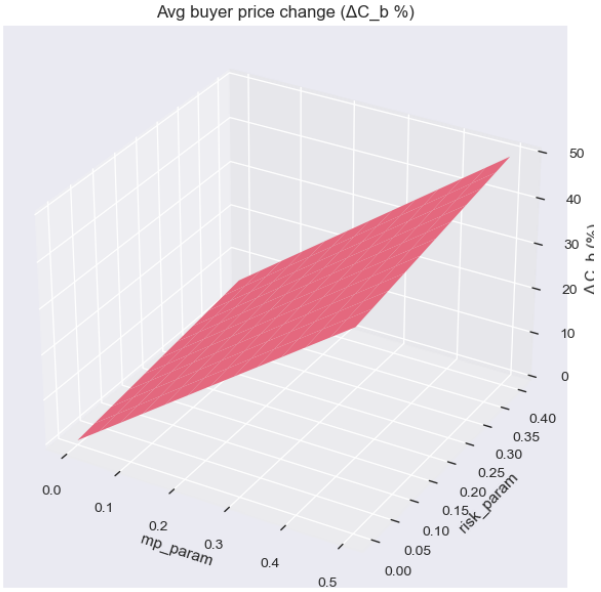
To rationalize these findings, we develop a theoretical model of firm-level sourcing under uncertainty, incorporating risk aversion, matching frictions, and endogenous network formation. The model predicts that firms balance the cost savings from concentrated sourcing against the risks of supply disruptions, with higher within-country shock correlation incentiviz-

[8] Appendix C present reduced-form evidence on how market power affect prices. Buyers are willing to pay a price premium for a larger exporter in global agricultural supply chains.

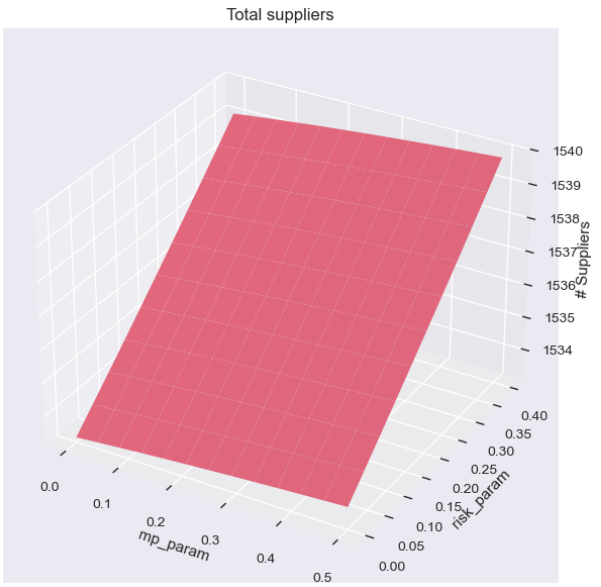
Figure 9: Impact of Upstream Market Power and Risk Aversion on Key Variables



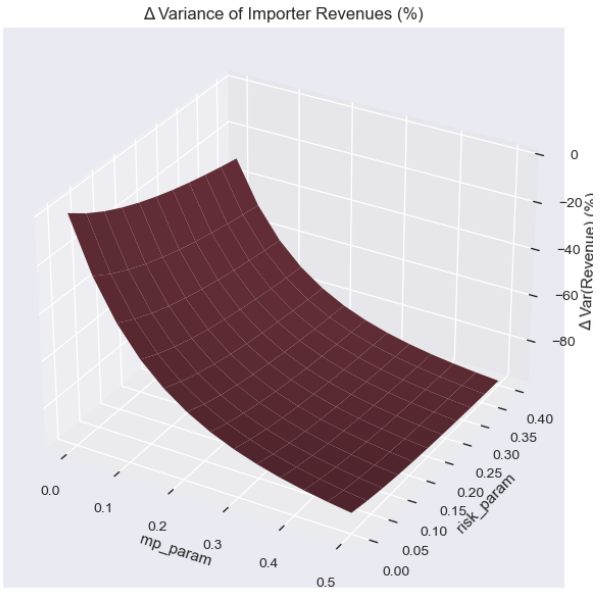
(a) Average Imports



(b) Average Buyer Price Change



(c) Total Suppliers



(d) Variance of US Importers

Notes: Panel (a) illustrates the relationship between risk aversion (β) and the average number of suppliers (S_{ijk}). Panel (b) shows how average imports (X_{ijk}) vary with risk aversion. Panels (c) and (d) provide 3D visualizations of average imports and the number of suppliers as functions of both market power (μ) and risk aversion (β). Data are aggregated across firms and sectors.

ing cross-country diversification. Our counterfactual simulations demonstrate that policies reducing matching frictions and promoting supplier entry can enhance supply chain resilience by lowering trade concentration and price volatility.

Overall, our findings underscore the importance of diversification and relationship-specific investments in stabilizing agricultural supply chains. Policy interventions aimed at reducing barriers to supplier diversification and fostering competition in upstream markets can play a critical role in mitigating the risks associated with concentrated trade networks. Future research should explore the dynamic adjustments of supply chains to shocks, the differing role of market powers across agricultural products and trading partners, the nature of relational contracts in agricultural value chains especially those involving multinational firms, and the long-term implications of policy measures on global food security.

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Online Appendix

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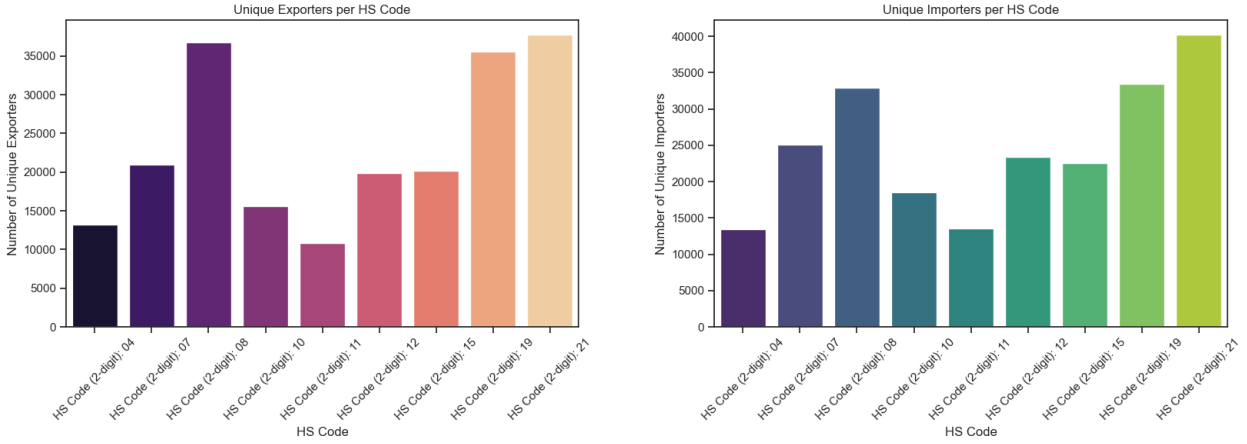
Risky Global Agricultural Supply Chains: Evidence from Firm-to-Firm Trade

Appendix Contents

1. Additional Figures and Tables A2
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A Additional Figures and Tables

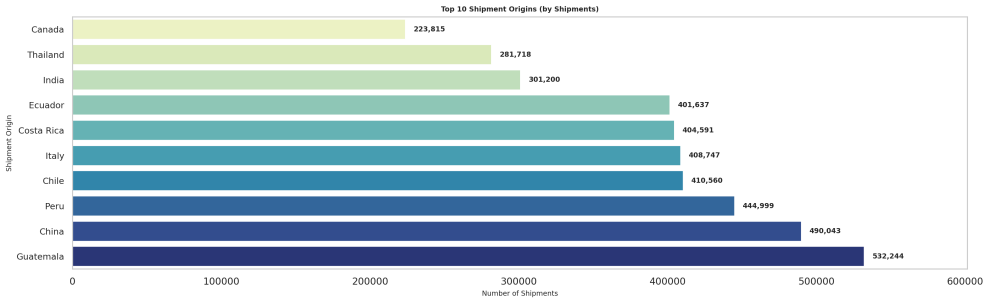
Figure A.1: Number of unique exporters and importers in firm-to-firm agricultural trade data.



(a) Unique Exporters (b) Unique Importers

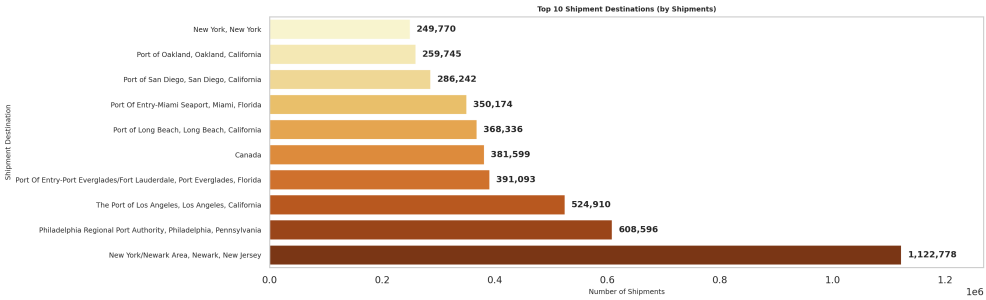
Notes: Panel (a) shows unique exporters; Panel (b) shows unique importers. The left panel shows the number of unique exporters in the dataset; the right panel shows the number of unique importers. Both figures are based on firm-to-firm trade data for agricultural products (HS codes 04, 07, 08, 10, 11, 12, 15, 19, and 21). Data are aggregated at the annual level.

Figure A.2: Top 10 Shipment Origin Countries



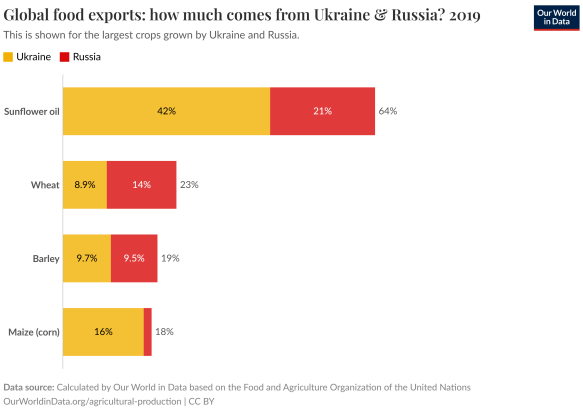
Notes: This figure shows the top 10 countries of origin for shipments in the firm-to-firm trade dataset (2015–2025). Data are aggregated by shipment counts.

Figure A.3: Top 10 Shipment Destination States

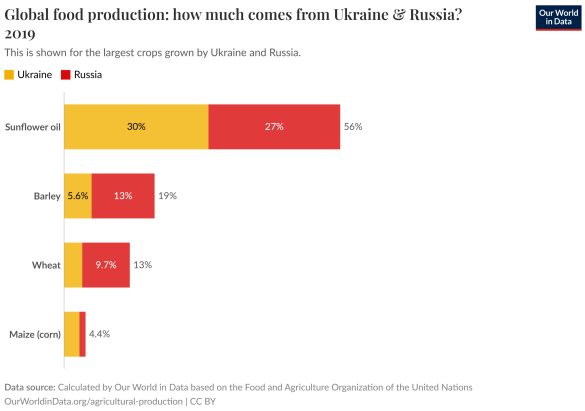


Notes: This figure shows the top 10 U.S. destination states for shipments in the firm-to-firm trade dataset (2015–2025). Data are aggregated by shipment counts.

Figure A.4: Global food exports and production



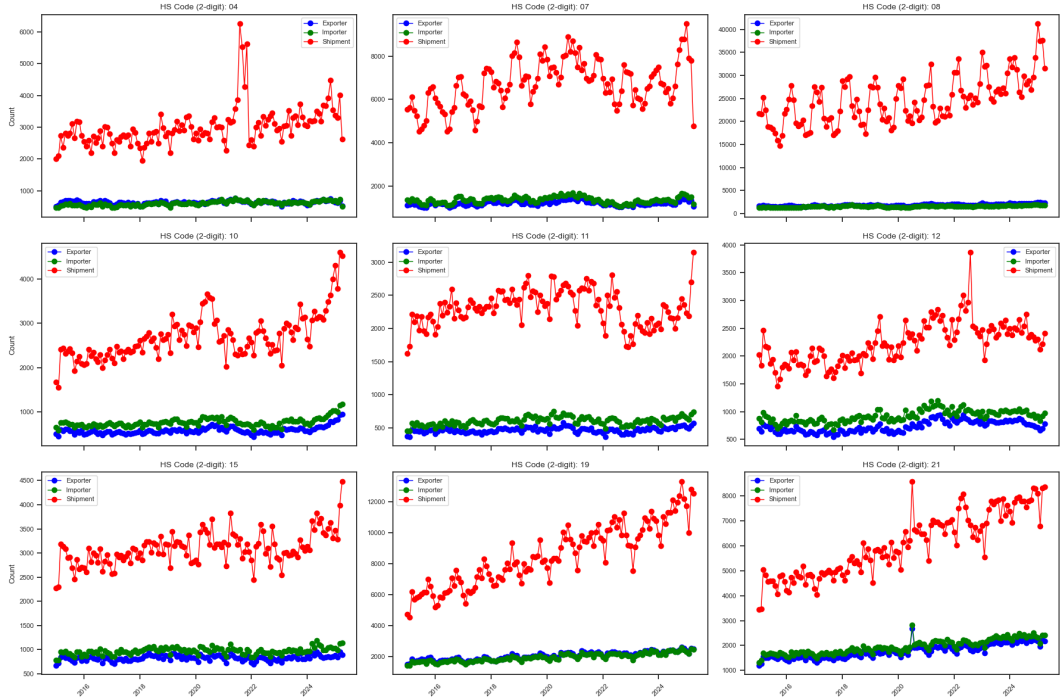
(a) Share of global food exports



(b) Share in global food production

Notes: Panel (a) shows the share of global food exports from Ukraine and Russia; Panel (b) shows their share in global food production. Data sources: Our World in Data.

Figure A.5: Summary of Firm-to-Firm Linkages by HS Code



Notes: This figure summarizes the structure of firm-to-firm trade linkages across different HS codes for agricultural products. It shows the distribution and concentration of supplier-buyer relationships in the dataset, highlighting patterns of diversification and concentration at the product level.

Figure A.6: Bilateral Concentration by HS Code and Year



Notes: This figure shows the evolution of bilateral concentration in agricultural firm-to-firm trade, disaggregated by HS code and year. Concentration is measured as the average share of top exporters and importers for each product-year combination.

B Data Appendix

Table B.1: Key Variables in Bill of Lading Database

Variable	Description
panjivarecordid	Unique shipment ID
arrivaldate	Day of arrival
conname	Consignee name
shpname	Shipper name
volumeteu	Volume of shipment in TEUs
conpanjivaid	Consignee ID
shppanjivaid	Shipper ID
hscode	6-digit HS code
companyid	Capital IQ company ID
constateregion	Location (state) of consignee
weightt	Weight of shipment in metric tons
portoflading	Port where shipment was loaded
portofunlading	U.S. port where cleared customs
vessel	Name of vessel
valueofgoodsUSD	Value of shipments in U.S. dollars
shpcountry	Shipper's country

Notes: This table lists the main variables from the Bill of Lading database used in the analysis. TEU stands for twenty-foot equivalent unit. HS code refers to the Harmonized System classification at the 6-digit level. Company identifiers allow linkage to firm-level financial information from Capital IQ and Orbis.

Table B.2: Missing Values in Shipper Variables in the Firm-to-Firm Trade Dataset, 2015–2025

Year	Shipper Name	Shipper ID	Shipper Revenue	Shipper Employees	Shipper Ultimate Parent
2015	14.29	45.02	51.89	42.45	45.16
2016	18.77	48.59	55.25	46.79	48.61
2017	22.06	50.61	58.27	49.24	50.67
2018	21.78	50.27	58.46	48.93	50.36
2019	20.35	48.69	57.09	46.75	48.70
2020	19.93	50.09	57.76	47.44	50.10
2021	22.04	52.42	61.47	50.42	52.43
2022	20.25	51.50	62.93	51.51	51.50
2023	19.73	51.75	65.65	53.07	51.86
2024	22.36	54.95	68.72	55.93	55.26
2025	22.33	55.66	70.59	57.11	56.26

Notes: This table reports the percentage of missing values for key shipper variables in the firm-to-firm trade dataset from 2015 to 2025. All values are percentages. "Shipper ID" refers to the S&P Capital IQ identifier. "Revenue" and "Employees" represent firm-level financial characteristics. "Ultimate Parent" indicates missingness in linking the shipper to its parent company.

Table B.3: Missing Values in Consignee Variables in the Firm-to-Firm Trade Dataset, 2015–2025

Year	Consignee Name	Cons. ID	Cons. Employees	Cons. Revenue	Cons. Ultimate Parent
2015	9.23	27.49	22.65	38.71	27.70
2016	9.13	27.91	23.59	38.57	27.92
2017	10.47	29.50	25.75	39.64	29.56
2018	8.95	28.64	24.70	38.60	28.71
2019	9.27	29.73	24.15	38.88	29.75
2020	9.82	31.22	25.62	40.36	31.22
2021	10.09	32.45	26.56	40.28	32.46
2022	10.55	32.08	28.65	45.44	32.09
2023	10.20	33.48	31.12	48.68	33.57
2024	11.93	35.92	34.69	51.45	36.08
2025	12.17	35.00	35.44	53.60	35.23

Notes: This table reports the percentage of missing values for key consignee variables in the firm-to-firm trade dataset from 2015 to 2025. All values represent percentages. "Consignee ID" refers to the S&P Capital IQ identifier. "Revenue" and "Employees" are firm-level financial characteristics. "Ultimate Parent" indicates missingness in linking the consignee to its parent company.

Table B.4: Missing Values in Shipment and Transaction Variables, 2015–2025

Year	HS Code	Volume (TEU)	Value of Goods (USD)	Shipment Origin	Shipment Destination	Port of Unlading	Port of Lading
2015	0.0	4.361	0.012	0.003	0.000	0.000	0.000
2016	0.0	4.012	0.015	0.005	0.000	0.000	0.001
2017	0.0	3.182	0.011	0.004	0.000	0.000	0.001
2018	0.0	3.012	0.010	0.038	0.000	0.000	0.000
2019	0.0	2.636	0.008	0.146	0.001	0.002	0.000
2020	0.0	1.784	0.089	0.045	0.001	0.001	0.001
2021	0.0	1.619	0.086	0.036	0.004	0.004	0.002
2022	0.0	2.098	0.008	0.038	0.003	0.004	0.001
2023	0.0	1.765	0.029	0.006	0.000	0.000	0.002
2024	0.0	1.315	0.098	0.003	0.002	0.003	0.003
2025	0.0	2.143	0.254	0.010	0.001	0.001	0.004

Notes: This table reports the percentage of missing values for key shipment and transaction variables in the firm-to-firm trade dataset from 2015 to 2025. HS Code refers to the 6-digit Harmonized System classification. Volume is measured in twenty-foot equivalent units (TEUs). Value of Goods is the reported shipment value in U.S. dollars. Origin and Destination refer to the shipment's country of origin and U.S. state of destination. Port of Lading and Port of Unlading refer to the foreign and U.S. ports, respectively.

C Additional Results

We also examine the causal effect on import prices when a U.S. importer becomes a customer of an ABCD firm. The identification strategy compares importers who start sourcing from ABCDs (treatment group) to similar importers who do not source from ABCDs during the sample period (control group).

We estimate the following regression specification:

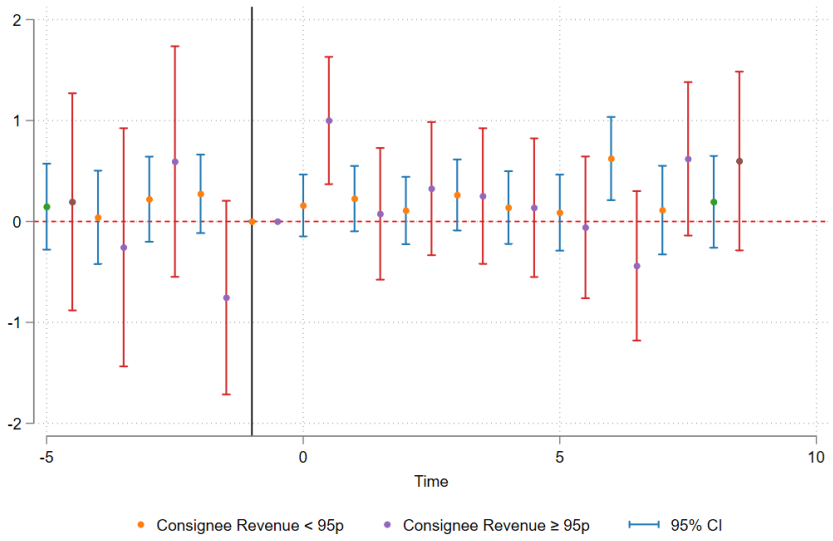
$$\log P_{ijht} = \alpha + \beta \cdot \text{ABCD}_{jt} + \gamma_j + \delta_{ht} + \epsilon_{ijht}$$

where P_{ijht} is the price of product h imported by importer j from exporter i at year t, ABCD_{jt} is an indicator for whether importer j is a customer of an ABCD firm in year t, γ_j are importer fixed effects, and δ_{ht} are product-year fixed effects.

A positive and significant β would indicate that importers pay higher prices when sourcing from ABCD firms, consistent with the notion that buyers are willing to pay a premium for lower risk and greater reliability. This premium may reflect the value placed on supply chain stability, quality assurance, and the ability of ABCDs to deliver during periods of heightened uncertainty or market disruption.

Figure C.1 illustrates the difference in import prices between ABCD and non-ABCD suppliers. The evidence suggests that importers sourcing from ABCD firms tend to pay higher prices, supporting the hypothesis that risk mitigation and supplier reputation command a premium in global agricultural supply chains.

Figure C.1: Importer Diversification: ABCD vs. Non-ABCD Firms



D Proofs

D.1 Proofs in Section 4

We assume oligopolistic competition when firms sell to domestic final demand and monopolistic competition when firms export. When firm i sells to domestic households, the firm's maximization problem,

$$\begin{aligned} &\max_{p_{iH}} \left(p_{iH} - c_i\right) q_{iH} \\ &\text{subj. to: } q_{iH} = \beta_{iH}^{\sigma} p_{iH}^{-\sigma} P^{\sigma-1} E. \end{aligned} \tag{46}$$

Solving the above yields the following optimal markup with the price being the markup μ_{iH} over the marginal cost c_i, $p_{iH} = \mu_{iH} c_i$:

$$\mu_{iH} = \frac{\varepsilon_{iH}}{\varepsilon_{iH} - 1}, \tag{47}$$

$$\varepsilon_{iH} = \left(1 - s_{iH}\right)\sigma + s_{iH}. \tag{48}$$

where the term s_{iH} represents the share firm i has in domestic final demand, $s_{iH} = \beta_{iH}^{\sigma} p_{iH}^{1-\sigma} / P^{1-\sigma}$. Equations (47) and (48) imply that as firm i has a larger share in the market, s_{iH} the higher markup it charges.

Proof. The key difference is that here the relevant shares and markups are defined for each buyer-supplier pair. we assume that the supplier takes as given the buyer's unit cost and output, while all aggregations in the production functions are made with finite sums. This is consistent with the assumption of **Bertrand competition** with n firms.

$$\left(p_i - c_i\right) \beta_i^{\sigma} p_i^{-\sigma} \left(\sum_j \beta_j^{\sigma} p_j^{1-\sigma}\right)^{-1} E \tag{49}$$

So, the F.O.C:

$$\begin{aligned} &\frac{1}{p_i} s_i + \frac{1}{p_i^2}\left(p_i - C_i\right)(-\sigma) s_i + \left(p_i - C_i\right) S_i \frac{1}{p_i}(\sigma - 1)\frac{1}{p_i} s_i = 0 \\ &\frac{p_i}{p_i - c_i} = s_{-}(1 - \sigma) + \sigma \\ &p_i = \frac{\left(1 - s_i\right)\sigma + s_i}{\left(1 - s_i\right)\sigma + s_i - 1} \end{aligned} \tag{50}$$

That is

$$\mu_{iH} = \frac{\varepsilon_{iH}}{\varepsilon_{iH} - 1}, \tag{51}$$

□

When firms export, **monopolistic competition** implies that they charge a constant markup

over marginal cost, with the price being the product of the two, $p_{iF} = \mu_{iF} c_i$

$$\mu_{iF} = \frac{\sigma}{\sigma - 1} \tag{52}$$

In sum, when selling to firm i, firm j sets price p_{ji} that maximizes variable profits by taking as given prices of all other firms, including those of i's other suppliers. The firm's problem is as follows:

$$\begin{aligned} &\max_{p_{ji}} \left(p_{ji} - c_j\right) q_{ji} \\ &\text{subj. to: } q_{ji} = \alpha_{ji}^{\sigma_{v(j)}} \alpha_{v(j)}^{\rho} p_{ji}^{-\sigma_{v(j)}} \left(p_{v(j)i}^{m}\right)^{\sigma_{v(j)}-1} \left(p_{v(j)i}^{m}\right)^{1-\rho} p_{mi}^{\rho} q_{mi} \\ &\qquad\qquad q_{mi} = \omega_m^{\eta} p_{mi}^{-\eta} \varphi_i^{\eta-1} c_i^{\eta} q_i. \end{aligned} \tag{53}$$

with the price being the markup over firm j 's marginal cost $p_{ji} = \mu_{ji} c_j$

$$\mu_{ji} = \frac{\varepsilon_{ji}}{\varepsilon_{ji} - 1}, \tag{54}$$

$$\varepsilon_{ji} = \sigma_{v(j)} \left(1 - s_{ji}^{v(j)}\right) + \rho s_{ji}^{v(j)} \left(1 - s_{v(j)i}^{m}\right) + \eta s_{ji}^{v(j)} s_{v(j)i}^{m}. \tag{55}$$

Equations (54) and (55) imply that the markup firm j charges on firm i depends on the input share that j's goods have in i's intermediate goods, $s_{ji}^{v(j)}$ and $s_{v(j)}^{m}$.

D.2 Gravity

Define the within-country χ-weighted average log cost

$$\mu_{jkt} := \sum_r \chi_{i\phi jkrt} \ln(\tau_{ijkt} p_{ijkrt}). \tag{56}$$

Micro elasticities. Let $\omega := \omega_{i\phi jkt}$ and $\chi := \chi_{i\phi jkst}$. Then:

$$\frac{\partial \ln X_{i\phi \to jkst}}{\partial \ln E_{i\phi kt}} = 1, \tag{57}$$

$$\frac{\partial \ln X_{i\phi \to jkst}}{\partial \ln(\tau_{ijkt} p_{ijkst})} = -\theta\left(1 - \chi\right) + \left(1 - \eta\right)\chi\left(1 - \omega\right), \tag{58}$$

$$\frac{\partial \ln X_{i\phi \to jkst}}{\partial \ln \tau_{ijkt}} = \left(1 - \eta\right)\left(1 - \omega\right), \tag{59}$$

$$\frac{\partial \ln X_{i\phi \to jkst}}{\partial \ln T_{jk}} = \frac{\partial \ln X_{i\phi \to jkst}}{\partial \ln \Psi_{ijt}} = \frac{\partial \ln X_{i\phi \to jkst}}{\partial \ln G_t} = -\frac{1 - \eta}{\theta}\left(1 - \omega\right), \tag{60}$$

$$\frac{\partial \ln X_{i\phi \to jkst}}{\partial \eta} = \sum_m \omega_{i\phi mkt} \ln c_{i\phi mkt} - \ln c_{i\phi jkt}, \tag{61}$$

and, writing $\psi(\cdot)$ for the digamma function,

$$\begin{aligned}\frac{\partial \ln \kappa_\theta}{\partial \theta} &= -\frac{1}{\theta^2}\psi\left(1+\frac{1}{\theta}\right), \quad \frac{\partial \ln \chi_{i\phi jkst}}{\partial \theta} = -\ln\left(\tau_{ijkt}p_{ijkst}\right) + \mu_{jkt}, \\ \frac{\partial \ln c_{i\phi jkt}}{\partial \theta} &= -\frac{1}{\theta^2}\psi\left(1+\frac{1}{\theta}\right) + \frac{1}{\theta^2}\left[\ln T_{jk} + \ln \Psi_{ijt} + \ln G_t + \ln S_{jkt}\right] + \frac{\mu_{jkt}}{\theta}.\end{aligned} \tag{62}$$

Then,

$$\frac{\partial \ln X_{i\phi\to jkst}}{\partial \theta} = (1-\eta)(1-\omega)\frac{\partial \ln c_{i\phi jkt}}{\partial \theta} + \frac{\partial \ln \chi_{i\phi jkst}}{\partial \theta} \tag{63}$$

Aggregate derivatives. 1. U.S. absorption

$$\frac{\partial \ln X_{jkt}^{\text{US}}}{\partial \ln E_{kt}^{\text{US}}} = 1.$$

2. Country-level symmetric trade cost for exporter j

$$\frac{\partial \ln X_{jkt}^{\text{US}}}{\partial \ln \tau_{ijkt}} = (1-\eta)\left(1-\omega_{jkt}\right).$$

3. Technology/scale

$$\frac{\partial \ln X_{jkt}^{\text{US}}}{\partial \ln T_{jk}} = \frac{\partial \ln X_{jkt}^{\text{US}}}{\partial \ln \Psi_{ijt}} = \frac{\partial \ln X_{jkt}^{\text{US}}}{\partial \ln G_t} = -\frac{1-\eta}{\theta}\left(1-\omega_{jkt}\right).$$

4. Fréchet tail θ

$$\frac{\partial \ln X_{jkt}^{\text{US}}}{\partial \theta} = (1-\eta)\left[\frac{\partial \ln c_{jkt}}{\partial \theta} - \sum_m \omega_{mkt}\frac{\partial \ln c_{mkt}}{\partial \theta}\right],$$

where

$$\frac{\partial \ln c_{jkt}}{\partial \theta} = -\frac{1}{\theta^2}\psi\left(1+\frac{1}{\theta}\right) + \frac{1}{\theta^2}\left[\ln T_{jk} + \ln \Psi_{ijt} + \ln G_t + \ln S_{jkt}\right] + \frac{\mu_{jkt}}{\theta}, \quad \mu_{jkt} := \sum_r \chi_{jkrt}\ln\left(\tau_{ijkt}p_{ijkrt}\right) \tag{64}$$

E Theoretical Analysis

We collect equilibrium conditions for downstream entry, upstream entry, market clearing, and define a general equilibrium.

E.1 Downstream Buyer Entry

Let $G_i(\varphi)$ denote the cdf of buyer productivities in country i. Given optimal sourcing choices $\{I_{ijk}(\phi), S_{ijk}(\varphi)\}$, define the (mean–variance) value of entry for type ϕ as

$$V_i(\varphi) \equiv \mathbb{E}[R_i(\varphi)] - \frac{\beta}{2}\operatorname{Var}(R_i(\varphi)) - \sum_j I_{ij}(\varphi) w_i \,\mathbb{E}[f_{ij}(S_{ij}(\varphi))] - \frac{\beta}{2} w_i^2 \operatorname{Var}\Big(\sum_j I_{ij}(\varphi) f_{ij}(S_{ij}(\varphi))\Big). \tag{65}$$

Let f_i^E be the entry cost (in units of labor). The free-entry condition pins down the cutoff $\bar{\phi}_i$ such that

$$\int_{\bar{\varphi}_i}^{\infty} V_i(\varphi)\, dG_i(\varphi) \;=\; w_i f_i^E, \qquad V_i(\bar{\varphi}_i) = 0. \tag{66}$$

Lemma 3 (Risk raises the entry cutoff)**.** *If ρ rises or δ rises (holding other objects fixed), then $\operatorname{Var}(R_i(\varphi))$ increases by (37)–(36); consequently, $V_i(\varphi)$ falls pointwise and the entry cutoff $\bar{\varphi}_i$ weakly increases.*

Proof. Immediate from (36) and the mean–variance objective (65) since $\partial V_i / \partial \operatorname{Var}(R_i) = -\beta/2 < 0$. □

E.2 Upstream Supplier Entry

Consider a potential supplier in (j,k) with marginal cost c_{jks} and markup rule derived earlier. For a given buyer i and sourcing profile, quantity sold is $Q_{ijks} = Q_{ijk}\,\chi_{ijks}$, where Q_{ijk} is the composite demand and χ_{ijks} is the within-composite share (from the CES structure and/or oligopoly). The supplier's (risk-neutral) expected profit is

$$\mathbb{E}[\pi^U_{ijks}] = \mathbb{E}\big[(p_{ijks} - c_{jks}) Q_{ijks}\big]. \tag{67}$$

Let f^U_{jk} be the (per-supplier) entry cost in units of labor at wage w_j. A free-entry or zero-profit condition for a marginal supplier type $\bar{s}$ in (j,k) is

$$\mathbb{E}[\pi^U_{ijk\bar{s}}] \;=\; w_j f^U_{jk}. \tag{68}$$

Proposition 6 (Risk reduces upstream entry via buyer-side diversification)**.** *If ρ rises or δ rises, then (i) by Propositions 2 and 4, buyers reduce S_{ij} and shift portfolio weights α_{ij} away from high-H_{ij} countries; (ii) consequently, Q_{ijk} and/or χ_{ijks} fall for marginal suppliers, reducing $\mathbb{E}[\pi^U_{ijk\bar{s}}]$ and raising the set of (j,k) pairs failing (68).*

Proof. From (38), $S_{ij}^{\star}$ is decreasing in ρ. From (40), $\alpha_{ij}^{\star}$ shifts away from countries with high H_{ij} as ρ rises and toward concentration as δ rises. Both reduce the mass of demand faced by marginal suppliers in affected (j,k), lowering $\mathbb{E}[\pi_{ijks}^{U}]$ and tightening (68). □

E.3 Gravity Equation: Firm-to-Firm Trade

For destination country i (U.S.), buyer ϕ (also its productivity), exporter j, HS6 product k, supplier s, year t:

$$\omega_{i\phi jkt} = \frac{I_{i\phi jkt}\, c_{i\phi jkt}^{1-\eta}}{\Phi_{i\phi kt}}, \qquad \Phi_{i\phi kt} := \sum_{m} I_{i\phi mkt}\, c_{i\phi mkt}^{1-\eta}, \tag{69}$$

$$\chi_{i\phi jkst} = \frac{(\tau_{ijkt} p_{ijkst})^{-\theta}}{\sum_{r} (\tau_{ijkt} p_{ijkrt})^{-\theta}} = \frac{z_{ijkst}}{S_{jkt}}, \quad z_{ijkst} := (\tau_{ijkt} p_{ijkst})^{-\theta}, \quad S_{jkt} := \sum_{r} z_{ijkrt}, \tag{70}$$

$$c_{i\phi jkt} = \kappa_{\theta}\, (T_{jk} \Psi_{ijt} G_t)^{-\frac{1}{\theta}}\, S_{jkt}^{-\frac{1}{\theta}}, \qquad \kappa_{\theta} := \Gamma\Big(1 + \tfrac{1}{\theta}\Big). \tag{71}$$

Let $E_{i\phi kt}$ be buyer ϕ's total expenditure on HS6 k in year t. The *firm-to-firm (link) flow* is

$$X_{i\phi \to jkst} = E_{i\phi kt}\, \omega_{i\phi jkt}\, \chi_{i\phi jkst} = \frac{E_{i\phi kt}\, I_{i\phi jkt}\, \kappa_{\theta}^{1-\eta}\, (T_{jk} \Psi_{ijt} G_t)^{-\frac{1-\eta}{\theta}}\, z_{ijkst}}{\Phi_{i\phi kt}\, S_{jkt}^{1+\frac{1-\eta}{\theta}}} \tag{72}$$

Aggregate Industry gravity. Let total U.S. imports for HS-6 k be $E_{kt}^{\mathrm{US}} := \sum_{\phi} \sum_{j,s} X_{i\phi \to jkst}$. Aggregating over buyers and suppliers and using $\sum_s \chi = 1$:

$$X_{jkt}^{\mathrm{US}} = \sum_{\phi} \sum_{s} X_{i\phi \to jkst} = \Big(\sum_{\phi} E_{i\phi kt} \Big)\, \omega_{jkt} = E_{kt}^{\mathrm{US}}\, \omega_{jkt}, \tag{73}$$

$$\omega_{jkt} = \frac{c_{jkt}^{1-\eta}}{\sum_{m} c_{mkt}^{1-\eta}}, \qquad c_{jkt} = \kappa_{\theta}\, (T_{jk} \Psi_{ijt} G_t)^{-\frac{1}{\theta}}\, S_{jkt}^{-\frac{1}{\theta}}. \tag{74}$$

Log form:

$$\ln X_{jkt}^{\mathrm{US}} = \ln E_{kt}^{\mathrm{US}} + (1-\eta) \ln c_{jkt} - \ln\Big(\sum_{m} c_{mkt}^{1-\eta} \Big). \tag{75}$$

F Estimation

F.1 Elasticity Estimation

Setup. For supplier s in origin j, sector k, selling product ω to buyer i at time t, the oligopoly markup rule implies

$$p_{ijkst} = \mu_{ijkst}\, c_{jks}, \qquad \mu_{ijkst} = \frac{\varepsilon_{ijkst}}{\varepsilon_{ijkst} - 1},$$

with residual demand elasticity

$$\varepsilon_{ijkst} = \big[\sigma\, \delta_{ijkt} + \eta(1 - \delta_{ijkt})\big]\chi_{ijkst} + \theta\big(1 - \chi_{ijkst}\big),$$

where χ_{ijkst} is the within-(i, j, k, t) supplier share and δ_{ijkt} is the buyer's share of the (j, k) composite in total inputs (both observable from values). Taking logs and absorbing c_{jks} with supplier$\times$product fixed effects (FE):

$$\ln p_{ijkst} = \underbrace{\alpha_{jks}}_{\ln c_{jks}} + \underbrace{\ln\!\Big(\tfrac{\varepsilon_{ijkst}}{\varepsilon_{ijkst}-1}\Big)}_{\text{markup}(\sigma,\eta,\theta;\chi,\delta)} + \nu_{ijkst}. \tag{76}$$

Estimate (η, θ) (and optionally σ) by minimizing

$$\min_{\eta,\theta\,(,\sigma)} \sum_{(i,j,k,s,t)} w_{ijkst} \left[\ln p_{ijkst} - \widehat{\alpha}_{jks} - \ln\!\Big(\tfrac{\varepsilon_{ijkst}(\eta,\theta\,(,\sigma))}{\varepsilon_{ijkst}(\eta,\theta\,(,\sigma))-1}\Big)\right]^2, \tag{77}$$

where $\widehat{\alpha}_{jks}$ are FE and w_{ijkst} are observation weights (e.g., inverse estimated variance of $\ln p$). If you prefer IV, instrument the markup term with supplier input cost indices, exchange-rate shocks, freight/fuel, and tariffs, and solve by 2SLS/GMM with cluster-robust standard errors at (j, k, s) or supplier level.

The FE $\widehat{\alpha}_{jks}$ are proxies for $\ln c_{jks}$. By origin (or origin–sector with enough s), fit a truncated Pareto $G_j(c) = (c/c_{Mj})^{k_j}$ via percentile identities:

$$\widehat{k}_j = \frac{\ln 10}{\ln c_{10,j} - \ln c_{1,j}}, \qquad \widehat{c}_{Mj} = 100^{1/\widehat{k}_j}\, c_{1,j},$$

where $c_{q,j}$ are empirical qth percentiles of $\{\exp(\widehat{\alpha}_{jks})\}_s$.