Supply Chain Uncertainty and Diversification

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Abstract

How do firms adapt their sourcing strategies when faced with supply chain uncertainty? To answer this question, we develop a multi-country sourcing model, in which firms choose where to import from, accounting for the possibility of supply-chain disruptions. We show that uncertainty introduces a positive option value, that favors diversifying the set of suppliers, and a hedging motive, that favors having less suppliers and reshoring. We estimate the model on Chilean Customs data, and we study how the increase in trade risk that followed the Covid-19 pandemic affected firms' sourcing strategies. We find that uncertainty tended to induce Chilean firms to enter into importing and diversify their sourcing portfolio rather than concentrate it or reshore the supply of their inputs. This response is mostly explained by the option value effect and the general equilibrium competitive forces that are generated by it.

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This study was developed within the scope of the research agenda conducted by the CBC in economic and financial affairs of its competence. The CBC has access to anonymized information from various public and private entities, by virtue of collaboration agreements signed with these institutions. To secure the privacy of workers and firms, the CBC mandates that the development, extraction, and publication of the results should not allow the identification, directly or indirectly, of natural or legal persons. Officials of the CBC processed the disaggregated data. All the analysis was implemented by the authors and did not involve nor compromise Aduanas, the Administradora de Fondos de Cesantía, and the Servicio de Impuestos Internos (IRS, in English). The information contained in the databases of the Chilean IRS is of a tax nature, originating in self-declarations of taxpayers presented to the Service; therefore, the veracity of the data is not the responsibility of the service. The views expressed in this paper are those of the authors and do not necessarily represent the views of the Central Bank of Chile or its board members as well as those of Analysis Group, its affiliates, clients, or employees.
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1 Introduction

For most of the 21st century, trade disruptions were relatively infrequent. However, recent trade wars, the Covid-19 pandemic, and more frequent geopolitical conflicts have increased uncertainty about the reliability of supply chains. This higher risk has manifested itself in longer delivery times and higher shipping costs. For example, Alessandria et al. [2023] document that, from the start of the pandemic through February 2022, the costs of shipping goods from Asia to the United States by air nearly doubled. In this line, there is an ongoing discussion about whether firms will respond to this riskier environment by reshoring their sources of inputs to protect themselves from disruptions abroad, or by diversifying their supplier base to reduce overall sourcing risk, see Javorcik [2020], Bonadio et al. [2021], IMF [2022].

This paper studies the drivers of firms' sourcing decisions when faced with supply chain uncertainty. We develop a multi-country sourcing model based on Antràs, Fort, and Tintelnot [2017], in which heterogeneous firms choose where to import from accounting for international supply-chain uncertainty, which is represented as the variability in possible trade costs. Firms form expectations about supply-chain risk, after which they select their set of suppliers up to a fixed cost for every new firm-supplier relationship. Once the set is decided, trade shocks are realized, and firms decide how much to spend on the goods provided by each supplier within the set.

We decompose the effect on a firm's expected profits of adding a country to its sourcing set into five channels. The first is the gain in the firm's sourcing capability evaluated at expected trade costs — the marginal-cost reduction an additional source delivers absent any risk. The second is an *option-value* term: a riskier source raises sourcing capability and profit by granting an extra chance to draw a low trade cost, as firms reallocate imports once shocks are realized. These two cost-side channels are scaled by the third, the firm's expected market demand measuring the average competition from other firms. The fourth is a hedging channel, the covariance between sourcing capability and market demand: a source where disruptions co-move with the ones hitting the origins most other firms rely on lowers the firm's capability precisely when aggregate prices, and hence its residual demand, are high, contributing negatively to profit. The fifth is the fixed cost of forming the new trade relationship.

A numerical analysis delivers two findings. First, the level of firms' ex-ante profits is governed primarily by sourcing capability at expected costs: cheaper expected access to foreign inputs is what makes importing worthwhile, with the risk channels an order of magnitude smaller. Second, as the environment becomes riskier, aggregate ex-ante profits fall, a decline that nets out several offsetting forces. The option value rises, since a more dispersed cost distribution makes the favorable trade shocks more likely. In contrast, the expected-cost contribution deteriorates in general equilibrium: higher risk induces more firms to enter importing and diversifying their supplier origins, lowering their marginal costs and intensifying competition on incumbents, which erodes residual demand. Additionally, the hedging effect grows stronger, reducing profit, as firm's sourcing capability co-moves with the aggregate prices that govern its market demand, and fixed costs accumulate as firms source from more countries. On net, the gain in option value does not offset the weaker expected-cost contribution, the stronger hedging penalty, and the higher fixed costs, so aggregate ex-ante profits decline with risk — even though, at the margin, the option value dominates the hedging motive and firms diversify.

We quantitatively study the impact of changes in supply chain uncertainty on sourcing decisions. We estimate our model using Customs and tax firm-level data for Chile, spanning the 2012-2023 period. The estimation process is made in two steps. First, we use the structure of the model and data for average sales and imports to infer time series of supply-chain shocks. Second, after assuming complementarity in the sourcing decisions between countries and firms, we infer the values of the parameters of the model with Jia [2008]'s algorithm and the simulated method of moments.

Finally, we perform a counterfactual analysis in which we evaluate what would be the sourcing decisions of firms facing the supply chain uncertainty of the 2020-2023 period compared to the 2012-2019 period. We find that the change in the distribution of trade shocks after the COVID-19 pandemic had strong reallocation effects across countries. The decline in average costs from China and the rise in US costs made Chilean firms change their sourcing choices from the latter to the former, which reflects that cost minimization was the primary concern in firms' import choices. However, the increase in supply chain risk in 2020-2023 still motivated some supplier diversification. The option value effect was more potent than the hedging effect, so firms were indeed willing to tolerate higher uncertainty for the possibility of a beneficial trade shock. As a result, more firms self-selected into importing, which diversified Chilean trade supply chains.

Related Literature

We contribute to the literature on firms' sourcing decisions by embedding supply-chain uncertainty directly into a multi-country sourcing framework and by taking that framework to firm-level customs and tax data. The canonical backbone comes from models such as Antràs et al. [2017] and Antràs and Helpman [2004, 2006], where fixed relationship costs and firm-level productivity heterogeneity generate selection into importing and multi-sourcing, and where more productive firms optimally expand their supplier base across countries. Empirical work such as Blaum et al. [2018] quantifies the aggregate gains from input trade in these environments. Our model preserves these mechanisms while introducing stochastic trade costs so that ex-ante supplier choice reflects both expected costs and the distribution of disruptions. This approach is consistent with the Eaton and Kortum [2002] tradition and with recent dynamic extensions such as Gumpert et al. [2020], who show that sunk costs and time-varying productivity shape firms' transitions between exporting and multinational production, reinforcing the idea that sourcing decisions are forward-looking and sensitive to uncertainty.

A second strand of the literature studies supply-chain uncertainty, resilience, and the policy trade-offs that arise when firms face stochastic disruptions. Handley et al. [2020] develop a sourcing model with policy uncertainty in which firms weigh expected marginal costs against sunk entry costs, and they show that China's WTO accession—by reducing tariff uncertainty—expanded firms' import portfolios. Grossman et al. [2023a] analyze optimal policy in the presence of exogenous supply-disturbance risk and show that the welfare implications of diversification versus reshoring depend critically on demand structure and the externalities firms do not internalize. Grossman et al. [2023b] extend this logic to vertical production tiers and characterize first- and second-best resilience policies. Complementary theory by Gervais

[2018, 2021] and ambiguity-based analyses such as Kancs [2023] emphasize managerial risk aversion and ambiguity aversion as motives for sourcing from lower-variance suppliers or coordinating across the chain to improve robustness. Perelló [2026] shows that intermediaries help firms mitigate supply-chain risk by providing access to larger and more stable supplier networks, effectively allowing smaller firms to outsource resilience. Relatedly, Ferrari and Pesaresi [2026] show that excessive input specialization reduces resilience because firms cannot easily replace incompatible suppliers after disruptions, generating a network externality that pushes equilibrium specialization above the socially efficient level. Recent work on geoeconomic fragmentation adds a geopolitical dimension to these risks: Gopinath et al. [2025] document that trade, FDI, and portfolio flows have begun to fragment along geopolitical lines since the war in Ukraine, while Panon et al. [2026] show that European firms are highly exposed to disruptions in "foreign critical inputs," with a 50% reduction in imports from China-aligned countries reducing manufacturing value added by nearly 3%. These findings underscore the importance of modeling country-specific risk, a key feature of our framework.

A third strand emphasizes inventories, anticipatory behavior, and the short-run propagation of shocks. Alessandria et al. [2024], Carreras-Valle [2021], and related work show that trade-policy uncertainty induces stockpiling and alters shipment timing and entry incentives, generating short-run booms and busts around policy resolution. Novy and Taylor [2020] develop a trade model with supply-chain uncertainty and inventories and find that when uncertainty is high and fixed costs are large, firms may stop sourcing from foreign suppliers altogether. Ferrari [2026] provides causal evidence of the bullwhip effect in production networks, showing that demand shocks amplify as they propagate upstream and that inventories increase output elasticities by roughly 18%. While we abstract from explicit inventory decisions to isolate the pure effect of stochastic trade costs on ex-ante supplier choice, this literature informs our interpretation of short-run shipment patterns and motivates several of the moments we target in estimation.

Finally, a growing empirical and quantitative literature documents how firms reconfigure suppliers in response to risk and how diversification shapes general-equilibrium outcomes. Castro-Vincenzi et al. [2024] show that multi-sourcing is widespread, that safer suppliers command higher prices, and that diversification reduces wage volatility while sometimes lowering expected wages in equilibrium. Fan and Luo [2025] and Adamopoulos and Leibovici [2025] demonstrate that even rare, high-impact policy shocks can materially reshape sourcing patterns, as firms respond to tail risks rather than average conditions. Heise et al. [2025] and Ahn and Tan [2025] emphasize the role of procurement organization, relationship stickiness, and transition frictions: contractual rigidities and sticky buyer-seller links slow reallocation and make diversification more valuable than static cost comparisons would suggest. These micro-level frictions interact with the macro-level fragmentation documented by Gopinath et al. [2025] and the critical-input vulnerabilities highlighted by Panon et al. [2026], reinforcing the need for models like ours that can separate expected-cost effects from risk-driven diversification.

The rest of the paper is organized as follows. In Section 2, we present a series of stylized facts. In Section 3, we describe our trade model and the main mechanisms. In Section 4, we present our decomposition of the effect of adding an additional country to the supplier set. In Section 5, we estimate our model. In Section 6, we perform our counterfactual analysis. Finally, in Section 8, we conclude.

2 Sourcing after the Covid-19 pandemic

2.1 Data description

We utilize administrative data from the Chilean Customs office, which has product-origin-firm level information of all import transactions. The products are classified using the Harmonized System (HS) at the 6-digit level (HS6). In addition, we use VAT records from the Chilean Internal Revenue Service (SII, in Spanish), which provide information on sales and materials purchases. Finally, we have access to employer-employee data from the Unemployment Fund Administrator (AFC, in Spanish), institution that manages the contributions that every worker of the formal private sector must make to her own unemployment insurance fund. With this last database, we obtain information on the employment and wage bill of firms.

We cover the Mining, Manufacturing, and Trade sectors. These sectors represent approximately 80% of the total import value in Chile. Our sample spans the 2012-2023 period at a quarterly frequency. We drop firms with negative or zero sales or with less than 5 employees. Moreover, we create a category denoted as "rest of the world" (RoW), encompassing all countries with 100 or fewer firms engaged in importing from them. Our dataset includes approximately 50 countries each quarter, including Chile, and around 24% of firms are importers.

We also construct an auxiliary dataset on yearly country characteristics, spanning the years 2012 to 2019, that combines information from CEPII[1] and the World Bank's Worldwide Governance Indicators. This dataset provides information on origin country-specific attributes, such as distance, language, and corruption.

In Table 1 we show some descriptive statistics of our merged dataset. We define a product as a distinct HS6 code. In the 2012q1-2023q4 period, firms import approximately 9 distinct products from 2 countries on average. The median number of imported products is around 2, while the 95$^{\text{th}}$ percentile is around 33. The median number of countries from which firms import from is approximately 1, while the 95$^{\text{th}}$ percentile is around 6 countries.

Table 1: Descriptive statistics

Date	nb of firms	employment	wage bill	imports	inputs	sales	domestic	imp share
2012q1-2015q4	35,742	1,393	4,640	13,717	63,353	27,731	45,059	0.238
2016q1-2019q4	40,706	1,566	5,454	12,720	62,993	27,822	44,908	0.239
2020q1-2023q4	43,819	1,588	5,734	16,272	75,464	36,170	53,485	0.255

Notes: Table reports the unweighted average for the number of firms, the total number of employees in thousands, wage bill, value of imports, value of inputs, value of sales, value of domestic inputs, all in millions of USD, and the share of importers obtained using the number of firms that import over the total number of firms.

We can also observe that the number of firms in our data increases with time, starting with an average of 35,742 firms between 2012q1 and 2015q4, to an average of 43,819 firms between 2020q1 and 2023q4.

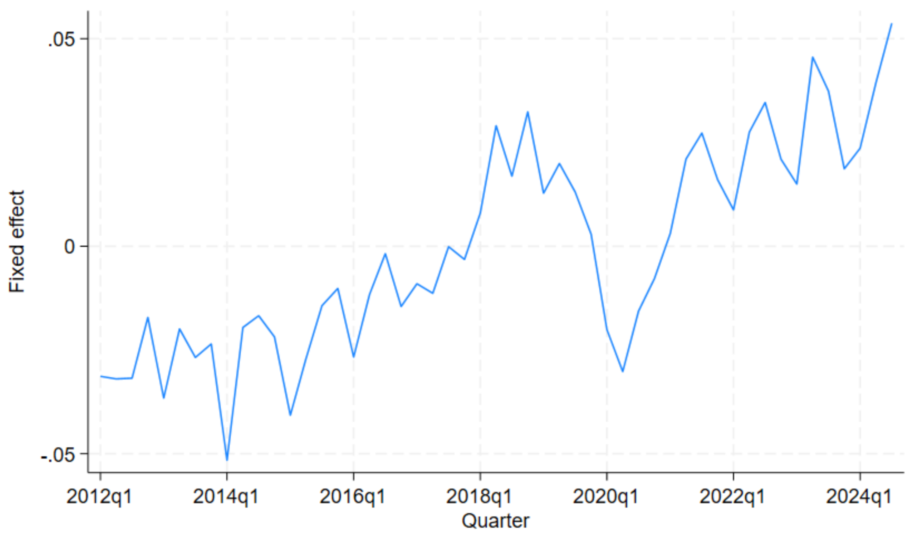
[1] *Centre d'Etudes Prospectives et d'Informations Internationales*, in French. It is a research center located in France that conducts analyses on international trade, migrations, macroeconomics, and finance.(`www.cepii.fr`)

This situation also holds for the number of employees, the value of imports, the value of inputs, the value of sales, and the value of domestic input purchases.

2.2 Supplier diversification

In Figure 1 we show how the number of sourcing origins per importing firm-product pair evolved on average over 2012-2024 in Chile. The number of sourcing origins was relatively stable until 2017, year in which Donald Trump's first administration began. Later, in the middle of the first U.S.-China trade war in 2018-2019, the number of sourcing origins increases, to then abruptly fall upon the impact of the Covid-19 pandemic. However, after the initial impact, the number of sourcing origins recovered quickly, to continue increasing up and above the levels observed during the trade war.

Figure 1: Evolution of the number of sourcing origins per firm-product pair



Note: The graph shows the time fixed effects from the following regression: $\log N_{fpt} = \alpha_{fp} + \delta_t + \epsilon_{fpt}$, where f is firm, p is HS6 product category, and t is quarter, N_{fpt} is number of sourcing regions, α_{fp} is a firm-product fixed effect, δ_t is the plotted time fixed effect, and ϵ_{fpt} is a random error.

2.3 Pecking order

We order countries according to the number of firms that import from them. Later we count the number of firms that import from the number one destination only, then the number of firms that import from the number one and number two destinations only, and we keep going until we have the ordering for the first top ten importing origins. We find that more than 12,000 firms, or 35.67% of importers who import from the top-10 countries, follow a pecking order. We then compare those results with those obtained from assuming that firms select their suppliers randomly. This is done by using the share of importers from origin country i as the probability that any firm will source from i. We find that only 4,855 firms follow a pecking order, or 14.42% of importers, which is less than the 35.67% we find in our data. This means that we find a stronger pecking order than the one that would be generated by assuming randomness in sourcing. As the percentage of the data following a pecking order is still around just one third, there might be firm-relationship-specific costs of sourcing, and not just relationship-specific.

Table 2: Pecking Order

String of countries	Data		Random Entry	
	Firms	% of Importers	Firms	% of Importers
CHN	7,970	23.68	1,865	5.54
CHN-USA	2,201	6.54	2,034	6.04
CHN-USA-RoW	348	1.03	664	1.97
CHN-USA-RoW-ESP	75	0.22	209	0.63
CHN-USA-RoW-ESP-DEU	58	0.17	60	0.18
CHN-USA-RoW-ESP-DEU-ITA	98	0.29	17	0.05
CHN-USA-RoW-ESP-DEU-ITA-BRA	102	3.03	5	0.01
CHN-USA-RoW-ESP-DEU-ITA-BRA-ARG	301	0.89	1	0.00
CHN-USA-RoW-ESP-DEU-ITA-BRA-ARG-HKG	133	0.40	0	0.00
CHN-USA-RoW-ESP-DEU-ITA-BRA-ARG-HKG-TWN	719	2.14	0	0.00
TOTAL Following Pecking Order	12,005	35.67	4,855	14.42

Notes: The string CHN means importing from China but no other among the top 10; CHN-USA means importing from China and the United States of America but no other; and so forth. % of Importers shows percent of each category relative to all firms that import from top 10 countries. RoW stands for rest of the world as defined in Section 2.1; ESP for Spain; DEU for Germany; ITA for Italy; BRA for Brazil; ARG for Argentina; HKG for Hong-Kong; and TWN for Taiwan.

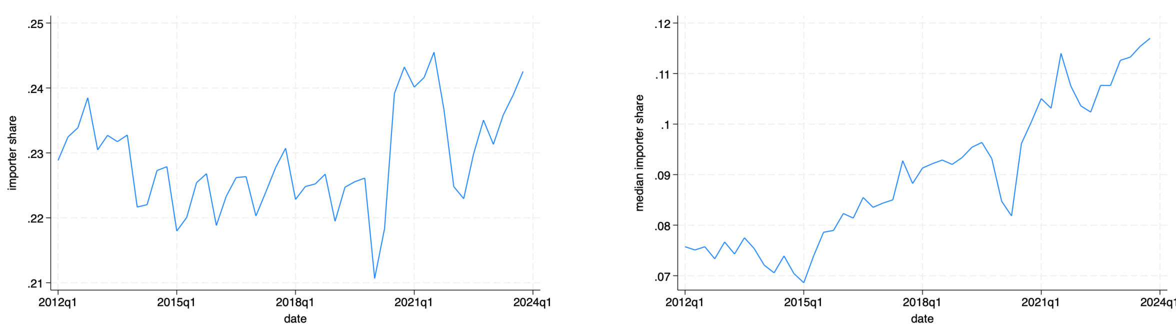
2.4 Entry into importing

We then obtain the share of importers among all firms and among firms with sales below the median, since we will use these for our empirical strategy. From Figure 2, we observe that the share of importers among all firms have been slowly trending downwards in time, but starts trending upwards after 2020. We also see an upward trend in the share of importers among firms sales below the median. In both cases, we observe that the share of importers is not constant over time. The average share of importers among all firms from 2012q1 to 2019q4 is 0.2264, while the average share of importers among firms with sales below the median is 0.0819.

Figure 2: Share of importers

(a) Share of importers for all firms

(b) Share of importers w/firm sales below median

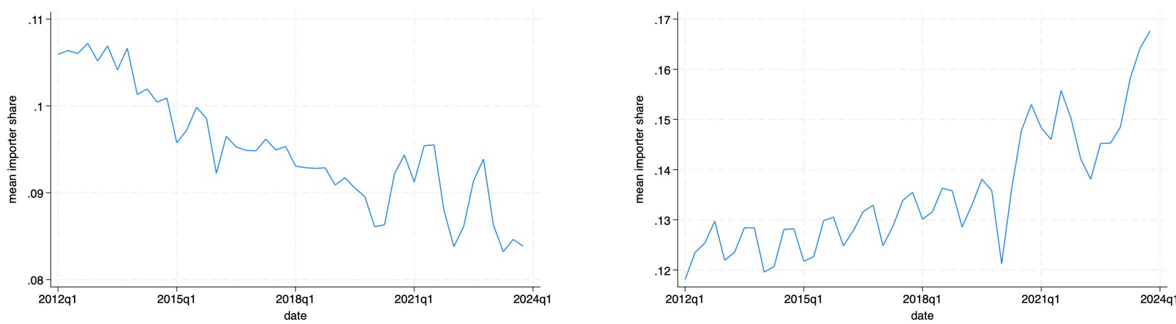


2.5 Substitution among origins

Finally, we plot the share of importers by country of origin. We show the U.S. and China because they are the top sourcing countries for Chile. From Figure 3 we learn that while the share of importers from the U.S. seem to be going downwards, the share of importers from China is trending upwards, which suggests that firms are replacing one country for the other. The average share of importers from the U.S. in the 2012q1-2023q4 period is 0.098, while for China is 0.128.

Figure 3: Share of importers by country of origin

(a) USA (b) China



3 Model of firm sourcing with supply chain uncertainty

We construct a multi-country sourcing model based on Antràs et al. [2017]. The world consists of I countries, with $i, j = 1, \ldots, I$ denoting the origin and destination countries respectively. In destination j, there is a measure 1 of households consuming goods and supplying labor L_j, and a measure N_j of final good firms purchasing input from intermediary firms in origin i. We incorporate supply chain uncertainty, γ_{ij}, which affects the cost of those intermediate inputs.

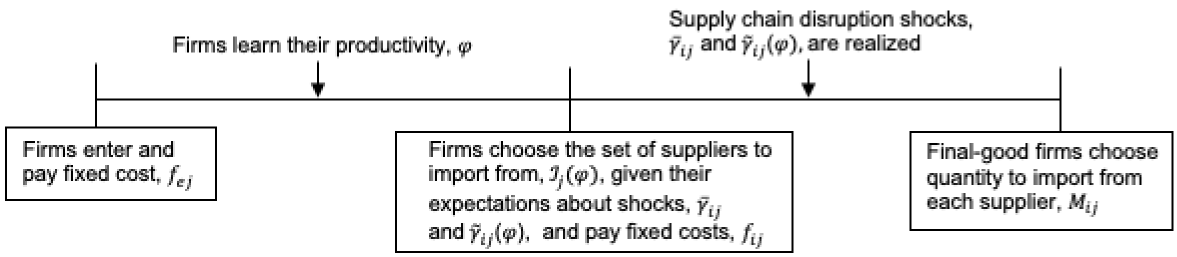
3.1 Preferences

Households consume a bundle of differentiated final good varieties as well as a homogeneous good produced in an outside sector, whose price serves as the numéraire. The utility function is Cobb-Douglas over those two types of goods $U(C_{0j}^{1-\eta} C_j^{\eta})$. Differentiated varieties, denoted by ω, are imperfect substitutes, with $\sigma > 1$ the elasticity of substitution: $C_j = \left(\int_\Omega q_j(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}$.

3.2 Technology and Market Structure

Final-good varieties in country j are produced by firms subject to monopolistic competition and free entry. Those firms make decisions over three stages, as illustrated in Figure 4. First, they commit to pay a fixed entry cost, f_{ej}, and enter the market prior to knowing their productivity, φ. Following entry, firms learn their productivity, drawn from distribution $dG_j(\varphi)$ with support $[\underline{\varphi}_j, \infty)$, and form expectations over supply chain cost shocks γ_{ij}. These firms then select a set of suppliers $\mathcal{I}_j(\varphi)$. To create any trade relationship with country i, firms must pay a relationship-specific fixed cost f_{ij}. Subsequently, shocks γ_{ij} are realized and firms choose the quantities to import from each previously established supplier $M_{ij}(\varphi, \gamma)$.

Figure 4: Timeline



Supply chain disruption shocks enter firms' expectations as a random variable γ_{ij} that is decomposed between a world shock $\bar{\gamma}_j$, a country-i level shock $\hat{\gamma}_{ij}$, and a firm-level (φ or idiosyncratic) shock $\tilde{\gamma}_{ij}(\varphi)$. We assume that $\bar{\gamma}_j \sim_{\text{iid}} \Psi_j(\bar{\gamma})$, $\hat{\gamma}_{ij} \sim_{\text{iid}} \Psi_{ij}(\hat{\gamma})$, and $\tilde{\gamma}_{ij}(\varphi) \sim_{\text{iid}} \Psi_{ij}(\tilde{\gamma})$. These shocks could represent national level quarantine, wars, natural disasters, disruptions due to input specificity, or any other risks that affect the production and delivery of the input to the country j.[2] We interpret these events as stochastic disturbances to iceberg trade costs, as they affect the price a country has to pay to import intermediates from the affected country. The presence of both a world shock $\bar{\gamma}_j$ and country level shocks $\hat{\gamma}_{ij}$ is meant to represent arbitrary levels of correlation – or common risk – between foreign producers for firms in destination j, as if could arise, for example, during the Covid-19 pandemic.

Note, we assume that the firm can not insure against these disruption shocks: in this sense, the financial markets are incomplete and the firm should self-insure against those risks by changing their portfolio of suppliers, diversifying or reshoring their input suppliers.

In addition to final good producers, in every country there are firms that produce varieties of intermediate goods. These firms operate a constant returns to scale technology using solely labor. The unit labor requirement, $a_i(\nu, \varphi)$, is specific to the intermediate good variety $\nu \in [0, 1]$, the productivity of the customer firm, φ, and the origin country $i \in I$. There is perfect competition on intermediate-good markets, so intermediate-good firms sell at marginal cost.

Thus, the price at which final-good firms in country j procure intermediate goods from country i encompasses the iceberg trade cost of shipping from country i to country j, τ_{ij}, the supply chain shocks, γ_{ij}, and the labor cost or wage, w_i. Moreover, the intermediate inputs imported are imperfectly substitutable across different varieties, with constant elasticity ρ, and perfectly substitutable across different origins.[3]

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[2] Note that these could also materialize a supply, cost, or productivity shock in origin i as long as it spills over the costs for the importing country j.

[3] This implies that the price $s(\nu, \varphi, \cdot)$ paid for intermediate input ν, and marginal cost $c_j(\varphi, \gamma)$ for firm φ in j are

We assume that the productivity – the inverse of the labor unit requirement to produce intermediates – $1/a_i(\nu,\varphi)$ follows a Fréchet distribution, with $T_i > 0$ and $\theta > 0$ the scale and shape parameters respectively, with $\mathbb{P}(a_i(\nu,\varphi) \geq a) = e^{-T_i a^{\theta}}$. A higher T_i means a better average technology in country i, while a higher θ implies a smaller dispersion of productivity and thus a lower comparative advantage across countries.

3.3 Firm sourcing strategy

First, firms in country j choose to enter and pay entry cost f_{ej}. Second, productivity φ is revealed and firms choose their sourcing choices $\mathcal{I}_j(\varphi)$ subject to fixed cost and expectations of future costs and profit. Third, supply chain shocks γ_{ij} are realized, and firms decide on their share of intermediate input purchases. We solve sequentially for firms decision using backward induction. From now on, we will denote final good firms by their productivity level φ.

3.3.1 Quantity choice conditional on sourcing strategy

Firm φ incurs fixed cost of entry f_{ej}, and country-specific fixed cost of sourcing f_{ij} associated with a given sourcing strategy $\mathcal{I}_j(\varphi)$. Afterward, they minimize the cost of intermediate goods for each specific variety ν by choosing the cheapest cost $w_i a_i(\nu,\varphi)\tau_{ij}\gamma_{ij}$ for each $i \in \mathcal{I}_j(\varphi)$. Leveraging properties of the Fréchet distribution, we derive the share of intermediate input purchases by firm φ in country j from country i. We obtain:

$$\mathcal{X}_{ij}(\varphi,\gamma) = \frac{T_i(\tau_{ij}\,\gamma_{ij}\,w_i)^{-\theta}}{\Theta_j(\varphi,\gamma)} \text{ if } i \in \mathcal{I}_j(\varphi) \tag{1}$$

and $\mathcal{X}_{ij}(\varphi,\gamma) = 0$ if $i \notin \mathcal{I}_j(\varphi)$, where

$$\Theta_j(\varphi,\gamma) \equiv \sum_{k\in\mathcal{I}_j(\varphi)} T_k(\tau_{kj}\gamma_{kj}w_k)^{-\theta} \tag{2}$$

Thanks to the Fréchet distributed $a_i(\nu,\varphi)$, we find that firms always buy a positive input expenditure from each country i in their sourcing strategy set $\mathcal{I}_j(\varphi)$. Following Antràs et al. [2017], we denote $\Theta_j(\varphi,\gamma) \equiv \sum_{k\in\mathcal{I}_j(\varphi)} T_k(\tau_{kj}\,\gamma_{kj}w_k)^{-\theta}$ as the *sourcing capability* of firm φ and the variable $\xi_i = T_i\,(\tau_{ij}\,\gamma_{ij}\,w_i)^{-\theta}$ as the *sourcing potential* of country i from the point of view of country j. The sourcing potential is increasing in technology T_i, and is decreasing in iceberg costs τ_{ij}, supply chain shocks γ_{ij} and wages w_i. Then, the sourcing capability $\Theta_j(\varphi,\gamma)$ sums those sourcing potentials of the countries within firm φ's sourcing strategy. We call this expenditure choice, *ex-post* Eaton and Kortum, within the firm.[4]

$s(\nu,\varphi,\gamma;\mathcal{I}_j(\varphi)) = \arg\min_{i\in\mathcal{I}_j(\varphi)} \left\{w_i a_i(\nu,\varphi)\tau_{ij}\gamma_{ij}\right\}$ and $c_j(\varphi,\gamma) = \frac{1}{\varphi}\left(\int_0^1 s(\nu,\varphi,\gamma;\mathcal{I}_j(\varphi))^{1-\rho}d\nu\right)^{1/(1-\rho)}$

[4] Note, that, as it is standard in the Eaton-Kortum framework, we cannot distinguish price from quantity decisions and only characterize expenditure share, which is what one observe from firm's data. As a result, a supply chain disruption γ_{ij} could be representing both a quantity disruption or an increase in costs.

Once final good firms φ choose their least costly supplier, as in Eaton and Kortum [2002] and Antràs et al. [2017], the overall marginal cost is written as:

$$c_j(\varphi, \gamma) = \frac{1}{\varphi} \left(\bar{\eta}\Theta_j(\varphi, \gamma)\right)^{-1/\theta} \tag{3}$$

with $\bar{\eta} = \left[\Gamma\left(\frac{\theta+1-\rho}{\theta}\right)\right]^{\frac{\theta}{1-\rho}}$ and Γ the Gamma function. The marginal cost faced by the firm is positively affected by supply chain uncertainty: larger (positive) cost shocks γ_{ij} increases marginal costs. To ensure that those quantity are well defined, as in Eaton and Kortum [2002], we need that $\theta > \rho - 1$. Since final-good firms are monopolistically competitive they charge a homogeneous markup over marginal cost, so the price charged by the final-good firm φ in country j is given by: $p_j(\varphi, \gamma) = \frac{\sigma}{\sigma-1} c_j(\varphi, \gamma)$

We also observe that having a higher sourcing capability reduces overall intermediate inputs costs. Therefore, incorporating an additional country into a firm's sourcing strategy, for given shocks, reduces the overall marginal cost and, consequently, lowers their prices. This outcome arises because adding a country gives the firm an extra chance to draw on a lower marginal cost, which increases competition and lowers the expected minimum price per intermediate good for all varieties ν and countries in the sourcing strategy. In the presence of uncertainty, it also provides the firm a chance to draw on supply chain shock γ_{ij} which can potentially lower marginal costs.

As a result, the ex-post profits of firm φ given the sourcing strategy $\mathcal{I}_j(\varphi)$ can be expressed as

$$\pi(\varphi, \gamma) = \varphi^{\sigma-1} \left(\eta\Theta_j(\varphi, \gamma)\right)^{\frac{\sigma-1}{\theta}} B_j(\gamma) - w_j \sum_{i \in \mathcal{I}_j(\varphi)} f_{ij} \tag{4}$$

where we define $B_j(\gamma)$ as a *market demand* term for country j:

$$B_j(\gamma) \equiv \frac{1}{\sigma} \left(\frac{\sigma}{\sigma - 1}\right)^{1-\sigma} E_j \, P_j(\gamma)^{\sigma-1} \tag{5}$$

From this equation we learn that, for a fixed market demand $B_j(\gamma)$, there is a trade-off between including a country in the sourcing set $\mathcal{I}_j(\varphi)$, thus increasing the sourcing capability $\Theta_j(\varphi, \gamma)$, and paying the fixed cost of starting the relationship with that country f_{ij}. For ex-post profits $\pi(\varphi, \gamma)$, we see that, the bigger the sourcing set, the less the profits are affected by specific shocks through the sourcing capability term. Then, there is an additional trade-off between adding more countries to be diversified against particular shocks γ_{ij} and paying the fixed cost of sourcing f_{ij}. When market demand term changes, there are also equilibrium effects on the price index when disruption are aggregate shocks to countries from where many firms source or to the whole world. To sum up, the ex-post profit depend on the realization of shocks, while the uncertainty affects the profit ex-ante expectation, to which we will turn next.

3.3.2 Choice of Optimal Sourcing Strategy

Firms φ use information on fixed costs f_{ij}, and expectation on sourcing potential and in particular supply chain costs to choose their optimal sourcing strategies $\mathcal{I}_j(\varphi) \subseteq I$, and maximize their ex-ante profits. The ex-ante problem of the firm is expressed as:

$$\max_{\mathbb{1}_{ij}\in\{0,1\}_{i=1}^{I}} \mathbb{E}\big(\pi_j(\varphi,\gamma)\big) = \max_{\mathbb{1}_{ij}\in\{0,1\}_{i=1}^{I}} \mathbb{E}\left(\varphi^{\sigma-1}\Big(\underbrace{\eta\sum_{i=1}^{I}\mathbb{1}_{ij}T_i\big(\tau_{ij}\,\gamma_{ij}\,w_i\big)^{-\theta}}_{\equiv\Theta_j(\varphi,\gamma)}\Big)^{\frac{\sigma-1}{\theta}}B_j(\gamma)\right) - w_j\sum_{i=1}^{I}\mathbb{1}_{ij}f_{ij}\ , \qquad (6)$$

with $\mathbb{1}_{ij}$ an indicator function if country i is included in the sourcing strategy of firm φ in country j.

For $(\sigma-1)/\theta > 1$, the firm faces a trade-off between the expected increase in revenues from adding a country to their sourcing strategy and the increase in costs due of country-specific fixed costs $w_j f_{ij}$. When γ_{ij} is an aggregate shock, either to the whole world $\bar{\gamma}_j$ or to country i, $\hat{\gamma}_{ij}$, the effect on profits is twofold: uncertainty affects both the sourcing capability $\Theta_j(\varphi,\gamma)$ and the market demand $B_j(\gamma)$, because total expenditure on imports and thus the ideal price index rise with this aggregate disruption shock.

This aggregate risk – both at world $\bar{\gamma}_j$ and country level $\hat{\gamma}_{ij}$ – creates an externality of firm's sourcing decisions: they affect each other's profit through the aggregate demand term $B(\gamma)$ – if more firms source from abroad, it creates systemic risk – and is not taken into account by the individual firm.

Examining equation 6, firms face a combinatorial discrete choice optimization problem in expectation, introducing complexity due to uncertainty and the inherent interdependence in sourcing decisions. The decision to incorporate a country in the sourcing strategy depends on the number and characteristics of the other countries in the set. If we just calculate the expected profits for each sourcing strategy, with an exhaustive enumeration, and choose the strategy that maximizes profit, one would have to compute 2^I expectations and choose the best combination. This is feasible for a small number of countries, but becomes quickly unfeasible for a larger number of sourcing destinations. To address this computational challenge, we show that our problem adheres to a pecking order in expectation. This distinctive property allows for the application of Jia [2008]'s algorithm, offering a more computationally tractable solution to the optimization problem, particularly in scenarios involving a substantial number of countries.

From Antràs et al. [2017], we know that, without risk, the profit function is supermodular in φ and $\Theta_j(\varphi,\gamma)$. In the presence of uncertainty $\gamma_{ij} \neq 1$, as expectations are weighted averages, we face a weighted average of supermodular functions, which is supermodular. Therefore, this proves that profit is also supermodular in (φ,Θ) in expectation.

Proposition 1: For random variable γ_{ij}, the optimal sourcing choice $\mathbb{1}_{ij}(\varphi) \in \{0,1\}_{i=1}^{I}$ is such that:

(a) $\mathbb{E}\big(\Theta_j(\varphi,\gamma)^{\frac{\sigma-1}{\theta}}B_j(\gamma)\big) = \mathbb{E}\big((\sum_{i=1}^{I}\mathbb{1}_{ij}(\varphi)T_i(\tau_{ij}\,w_i\,\gamma_{ij})^{-\theta})^{\frac{\sigma-1}{\theta}}\,B_j(\gamma)\big)$, i.e. the firm's expected sourcing capability times its market demand term is nondecreasing in φ

(b) if $(\sigma-1)/\theta \geq 1$, then $\mathcal{I}_j(\varphi_L) \subseteq \mathcal{I}_j(\varphi_H)$ for $\varphi_L \leq \varphi_H$, where $\mathcal{I}_j(\varphi) = \{i : \mathbb{1}_{ij}(\varphi) = 1\}$

Proof: See theoretical appendix.

From Proposition 1, part (a), more productive firms exhibit a larger expected sourcing capability times market demand – i.e. profit without counting fixed costs – compared to less productive firms. Firstly, they may source from a greater number of countries than their less productive counterparts, reducing the overall marginal cost thanks to improved competition across countries. Alternatively, high-productivity could source strategically from countries with high sourcing potential, due to: (i) high technology, (ii) low wages, (iii) low iceberg costs, (iv) low supply costs γ, or because (v) these shocks negatively correlate with market size $B(\gamma)$.

As explained, Proposition 1, part (a) leaves the specific mechanism undisclosed, while part (b) provides additional insights: under the condition $(\sigma-1)/\theta \geq 1$, it implies complementarity in sourcing decisions, and more productive firms source from more countries compared to less productive ones. This is explained by expected profits having increasing differences in $(\mathbb{1}_{ij}, \mathbb{1}_{kj})$ for $i, k \in \{1, \ldots, I\}$ and $j \neq k$. The marginal benefit of adding an additional country is weakly increasing in the set $\mathcal{I}_j(\varphi)$. Such complementarity occurs for a high σ and/or a low θ: Consumers are more price elastic with high σ, and thus more sensitive to lower prices. Low θ means that inputs have more heterogeneous costs, and comparative advantage is stronger. When either of these is true, lowering the price has higher benefits, so more productive firms would always add more countries to their sourcing strategy to reduce costs through such mechanism.

From Proposition 1 (b), there exists a "pecking" order in productivity, i.e. a strict hierarchical ranking for sourcing locations at the extensive margin. All firms importing from one country source from the same one (e.g. China), firms importing from two countries do so from the same specific ones too (e.g., China and the United States), and so on. However, it is crucial to note that this hierarchical order, under supply chain risk γ, is not necessarily identical to the case without uncertainty. The determination of the hierarchical order now encompasses not only countries' marginal and fixed costs but also the distribution of trade cost shocks and how they correlate with market demand. The pecking order is maintained in expectation when fixed costs f_{ij} that are country-i-specific but not country-firm (i, φ)-specific f^n_{ij} – setting we use in the extension of section 5.

Following Proposition 1, because of increasing differences, when $\sigma - 1 \geq \theta$, we can now write:

Proposition 2: For all $i \in \{1, \ldots, I\}$, define the mapping $V_{ij}(\varphi, \mathcal{I})$ to take the value of one whenever including country i in the sourcing strategy $\mathcal{I}$ raises firm-level expected profits $\mathbb{E}(\pi_j(\varphi, \gamma, \mathcal{I}))$, and zero otherwise. Then, whenever $(\sigma-1)/\theta \geq 1$, $V_{ij}(\varphi, \mathcal{I}') \geq V_{ij}(\varphi, \mathcal{I})$ for $\mathcal{I}' \supseteq \mathcal{I}$.

Proof: See theoretical appendix.

We exploit the insights of this proposition to employ the algorithm of Jia [2008], akin to Antràs et al. [2017]. This reduces the dimensionality of our problem by leveraging the expected hierarchical order of different countries as we will explain in the section 5.3 below. By adopting this approach, we circumvent the need to compute all potential sourcing strategies to address the firm's problem. This reduction in dimensionality enables the resolution of the problem for a larger number of countries. However, it is important to note that this method is applicable exclusively in the "complements" case, where $\sigma - 1 > \theta$ and is not suitable to the "substitute" case, which would necessitate additional assumptions, such as a common fixed cost for all foreign countries.

Finally, one can also obtain firm-level intermediate input purchases from country $i \in \mathcal{I}_j(\varphi)$. This ex-post decision is a fraction $(\sigma-1)\mathcal{X}_{ij}(\varphi,\gamma)$ of firm's ex-post profits $\pi_j(\varphi,\gamma)$:

$$M_{ij}(\varphi,\gamma)=(\sigma-1)\;\eta^{\frac{\sigma-1}{\theta}}\;\;\varphi^{\sigma-1}\;\left(\Theta_j(\varphi,\gamma)\right)^{\left(\frac{\sigma-1}{\theta}-1\right)}\;T_i(\tau_{ij}\gamma_{ij}\,w_i)^{-\theta}\;B_j(\gamma), \tag{7}$$

with $M_{ij}(\varphi,\gamma)=0$ if $i\notin\mathcal{I}_j(\varphi)$. This represents the gravity equation. For $(\sigma-1)\geq\theta$, and fixing market demand, $B_j(\gamma)$, firm-level import from $i\in\mathcal{I}_j(\varphi)$ are increasing in both the sourcing potential, $T_i(\tau_{ij}\gamma_{ij}\,w_i)^{-\theta}$, and the sourcing capability, $\Theta_j(\varphi,\gamma)$. Moreover, supply chain shocks γ_{ij} affect φ's firm intermediate import expenditure through both the sourcing capability and country i's sourcing potential. A negative cost shock (high γ_{ij}) divert trade M_{ij} away from i. However, when aggregate shocks hit, it also influences market demand $B_j(\gamma)$ and the price index. The impact on $M_{ij}(\varphi,\gamma)$ is dampened: The negative $\hat{\gamma}_{ij}$ shock increase aggregate prices which improves trade flow, offsetting the negative shock.

3.4 Equilibrium

We assumed that household spend $(1-\alpha)$ of their labor income on a perfectly competitive outside sector, which uses labor linearly and is large enough to pin down wages w_j elastically in each country j. With Cobb-Douglas preferences, consumers spend α-share of their income w_jL_j on the final good. Thus, we only need to determine $P_j(\gamma)$.

Following our timeline, firms decide to enter and pay the fixed cost f_{ej} before learning their productivity. Consequently, firms enter until expected profits from entry are zero, and the free-entry condition in the final good sector is expressed as:

$$\int_{\tilde{\varphi}_j}^{\infty}\int_{\gamma}\left[\varphi^{\sigma-1}(\eta\Theta_j(\varphi,\gamma))^{\frac{\sigma-1}{\theta}}B_j(\gamma)-w_j\sum_{i\in\mathcal{I}_j(\varphi)}f_{ij}\right]d\Psi_{ij}(\gamma)\,dG_j(\varphi)=w_jf_{ej}, \tag{8}$$

where $\tilde{\varphi}_j$ denotes the productivity of the least productive firm in country j, and $\Psi_{ij}(\gamma)$ the distribution over γ_{ij} the product of the three supply chain shocks, world level $\bar{\gamma}_j$, country-level $\hat{\gamma}_{ij}$ and firm-level $\tilde{\gamma}_{ij}$.

Finally, we obtain the number of active firms in equilibrium $N_j[1-G_j(\tilde{\varphi}_j)]$ by using equations above, the fact that E_j is a share α of labor income[5] as well as Fubini's theorem for swapping integrals. In our empirical strategy, we set the domestic fixed cost, f_{jj}, to zero[6] and all firms produce, since in our data we only observe firms that are producing.

Finally, the equilibrium price index is given by

$$\begin{aligned}P_j(\gamma)&=\left(\int_{\omega\in\Omega_j}\int_{\gamma}p_j(\omega,\gamma)^{1-\sigma}\,d\Psi_{ij}(\gamma)\,d\omega\right)^{\frac{1}{1-\sigma}}\\&=\left(\int_{\tilde{\varphi}_j}^{\infty}\int_{\gamma}\frac{\sigma}{(\sigma-1)}\,\frac{\eta^{\frac{\sigma-1}{\theta}}}{\varphi}\;\Theta_j\big(\varphi,\gamma\big)^{\frac{\sigma-1}{\theta}}\;d\Psi_{ij}(\gamma)\,dG_j(\varphi)\right)^{\frac{1}{1-\sigma}}\end{aligned} \tag{9}$$

[5] We find $N_j=\alpha L_j/\sigma\left(\int_{\tilde{\varphi}_j}^{\infty}\int_{\gamma}\sum_{i\in\mathcal{I}_j(\varphi)}f_{ij}d\Psi_{ij}(\gamma)dG_i(\varphi)+f_{ej}\right)$

[6] When the fixed cost of entry is non-zero, it results in a positive measure of firms choosing not to produce.

averaging over idiosyncratic, firm-level shocks $\tilde{\gamma}_{ij}$, while the price index does depend, ex-post to the aggregate country-level $\hat{\gamma}_{ij}$ and world level $\bar{\gamma}_j$ shocks.

3.5 Discussion of the assumptions

Convexity of the profit function. We assume that firms are risk neutral with constant return to scale production. As a result, and under the assumption that $(\sigma-1)/\theta \geq 1$ profit is convex in the sourcing capability $\Theta(\varphi,\gamma)$ and hence in cost shocks γ_{ij}. This results in a Hartman–Abel effect, where mean-preserving uncertainty about (import) prices increase investment and, here, sourcing from those risky locations. Here, adding an additional location allows for an extra chance of importing cheaper products, which drives a motive behind diversification.[7]

It goes against the more conventional mechanism where uncertainty reduces sourcing (and investment as a "wait-and-see" effect). This mechanism – where risky-imports would cause reshoring – is also present in our framework due to the correlation between costs $\Theta_j(\varphi,\gamma)$ and market demand $B_j(\gamma)$ as explained in section 4. However, this effect would be reinforced if firms' managers were risk-averse, as in Gervais [2021]. A CRRA utility over profits $U(C) \propto C^{1-\eta}$ yields an objective of the form $U(\pi(\gamma)) \sim (\Theta_j(\gamma))^{\frac{\sigma-1}{\theta}(1-\eta)}$. The profit would be concave and this risk-aversion effect would dominate the Hartman–Abel effect.

Timing assumption. In our setting, final good firms choose sourcing in two steps: first, their sourcing locations $\mathcal{I}_j(\varphi)$ and, second, their expenditure shares $\chi_{ij}(\varphi)$. Alternatively, we could assume that firms choose input quantities before shocks γ hit their costs and import prices, or that firms fix price contracts before the "delivery" quantity shocks are realized. Would these two alternative assumptions change our results and amplify the costs of supply chain disruptions? The answer is no. Those two different settings would still be isomorphic to our *"ex-post* Eaton-Kortum", as in equation 1.[8] Our setting only characterizes the expenditure shares – i.e. price times quantity. However, in appendix XXX we provide two alternative settings with CES demands for import sources, where quantity or price are determined ex-ante and separately, and the outcome is isomorphic to our shares in 1. These shares will be matched from firm-level data, thus identifying the shocks, as shown in section 5.2.

Market structure. Supply chain disruptions γ_{ij} are uninsurable for firms in country j. In this sense, financial markets are *incomplete* and firms need to self-insure against these shocks by changing their sourcing strategies as "Arrow-Debreu securities" do not exist to hedge against this risk.

Inefficiencies. This model is inefficient for two reasons: First, as in standard trade models with monopolistic competition, market power reduces final good quantities produced by firms. It hence reduces sourcing at the extensive margin: the thresholds for importing shift up the firm productivity (φ)

[7] In particular, when $(\sigma-1)/\theta \geq 1$, demand is elastic (high σ) and comparative advantages are stronger (more dispersion, low θ), the need for additional "cheap" sourcing countries is emphasized. In the presence of risk, this generates such Hartman–Abel effect where good shocks help more than the bad shocks hurt.

[8] More precisely, as long as one variable is adjusting ex-post, this isomorphism holds. Indeed, in a model where firms choose quantity ex-ante q_{ij}, costs shocks γ realized expost would pass through price p_{ij} and thus reflected in expost share $\chi_{ij} = \frac{q_{ij}p_{ij}}{\sum_k q_{kj}p_{kj}} = \frac{(w_i\tau_{ij}\gamma_{ij})^{-\theta}}{\sum_k (w_k\tau_{kj}\gamma_{kj})^{-\theta}}$, and in marginal costs exactly as in equation 2.

distribution. Second, due to market incompleteness, firms can not self-insure against supply chain disruptions. This also affects importing decisions as firms choose to diversify against those shocks to reduce their costs.

4 Theoretical investigation on the effects of uncertainty

To understand the influence of uncertainty on the sourcing decision, we study analytically and numerically how firms profit change with supply chain risk. Through a theoretical decomposition, we see that disruption uncertainty has ambiguous effects on firm sourcing.

4.1 Expected Profits' Decomposition

To study the influence of supply chain risk on firms' decisions, we use firms' profit from equation 6, and we decompose it theoretically into five key elements: (i) the sourcing capability for expected costs $\Theta_H(\varphi, \mathbb{E}[\gamma])$, (ii) the impact of uncertainty on sourcing capability, (iii) the expected market demand, (iv) the covariance between sourcing capability and market demand, and (v) the fixed costs of sourcing.

$$\mathbb{E}\big[\pi_H(\varphi,\gamma)\big] = \varphi^{\sigma-1}\Big(\underbrace{\Theta_H(\varphi,\mathbb{E}[\gamma])^{\frac{\sigma-1}{\theta}}}_{\substack{\text{Sourcing capability}\\ \text{for expected shock}}} + \underbrace{\mathbb{E}\big[\Theta_H(\varphi,\gamma)^{\frac{\sigma-1}{\theta}} - \Theta_H(\varphi,\mathbb{E}[\gamma])^{\frac{\sigma-1}{\theta}}\big]}_{\text{Effect of uncertainty on sourcing capability}}\Big) \times \underbrace{\mathbb{E}(B_H(\gamma))}_{\substack{\text{Expected}\\ \text{market demand}}} + \varphi^{\sigma-1}\underbrace{Cov(\Theta_H(\varphi,\gamma)^{\frac{\sigma-1}{\theta}}, B_H(\gamma))}_{\substack{\text{Covariance btw sourcing capability}\\ \text{\& market demand}}} - \underbrace{w_H \sum_{i\in\mathcal{I}(\varphi)} f_{iH}}_{\text{Fixed cost of sourcing}} \tag{10}$$

The first term, the sourcing capability for the expected cost $\Theta_H(\varphi, \mathbb{E}[\gamma])$, encapsulates the expected impact of incorporating an additional country into the set of sourcing options. Adding a country allows firms to draw an additional variety ν with potentially lower costs, as given by the Fréchet distribution of productivity. As observed in Antràs et al. [2017], reduces overall costs due to the pro-competitive effects of trade. Notably, this term is affected by the cost in expectation but remains unaffected by the disruption risk surrounding it. This expected change in profit is at the heart trade models without trade cost uncertainty.

The second term, the risk effect on the sourcing capability, introduces a first effect of uncertainty that we denote the "option value of trade risk". Given by the difference between the realized sourcing capability after a shock $\Theta_H(\varphi, \gamma)$ and the sourcing capability for the average cost $\Theta_H(\varphi, \mathbb{E}[\gamma])$, this term reflects the influence of the variance of trade cost shocks on the variance of the sourcing capability. Since a higher sourcing capability implies lower cost and higher revenues, it contributes to the overall expected profits. Indeed, firms prefer to add countries to their sourcing strategy when they have high trade cost risk for the chance to lower their costs $c_j(\varphi, \gamma)$ when one of those is positively shocked i.e. $\gamma < 1$. Because firms can adjust their intensive margin ex-post, they can increase the import share they buy from the countries positively shocked and then sell final goods at a lower price. Overall, firms have higher expected profits from higher mean-preserving variance in costs. Additionally, both the sourcing capability for the expected cost (i) term and the option value (ii) terms are then multiplied by the expected market demand $B_H(\gamma)$. This market demand is related to the aggregate price index $P(\gamma)$: for a given individual firm' price $p(\varphi, \gamma)$, a higher $P(\gamma)$ redirect the demand to the firm φ.

Third, another impact comes from the covariance between the sourcing capability $\Theta_H(\varphi, \gamma)$ and the market demand $B_H(\gamma)$, which we call the "hedging effect". Firms would want to hedge and source from countries that are negatively correlated with the countries most other firms source from. While the sourcing capability term is influenced by both aggregate $\bar{\gamma}$ and idiosyncratic uncertainty $\tilde{\gamma}$, the market demand is affected solely by aggregate uncertainty $B_H(\bar{\gamma})$. This term implies a negative impact on profit: if a firm φ sources from a country A from which all other firms source from, the firm's price correlates with aggregate prices $P(\bar{\gamma})$. This firm is thus not competitive against the rest of the market, which reduces its demand when the country it sources from has higher risk. When the covariance is negative, firms would like to hedge and capture a higher market share by diversifying, or sourcing for less "common" origins to offer lower prices than their competitors.

Lastly, expected profits decrease due to the fixed costs $w_j f_{ij}$ of adding a country i to their sourcing strategy. The presence of these fixed costs of sourcing is the reason why firms do not simply source from all countries. More productive firms, which have higher revenues/sales and profit, can source from more countries, which increase imports at the extensive margin.

4.2 Simple Experiment with three countries

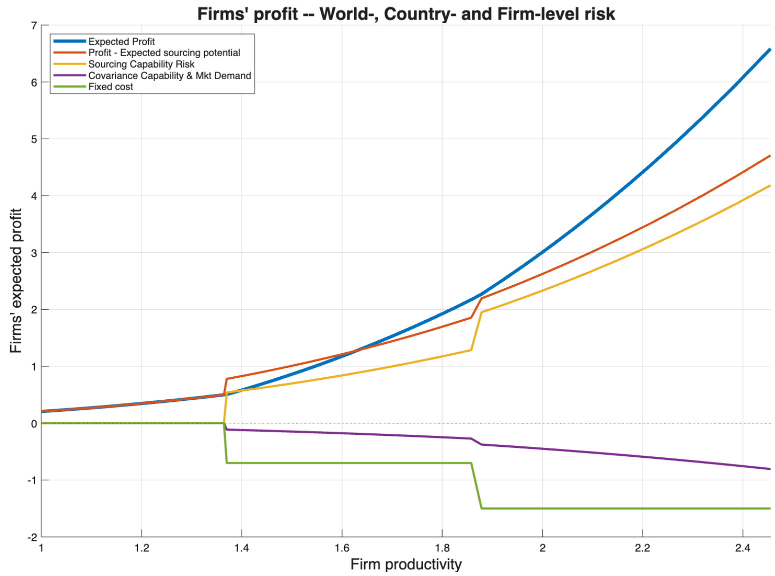
To understand the mechanisms at play in our model, we simulate an example with three countries: the domestic country and two foreign countries with different sourcing potential $\xi_0 = 1, \xi_1 = 0.8, \xi_2 = 0.3$. This toy example is inspired from our quantitative analysis with Chile and its two main trade partners, China and the United States, where the first has ≈ 3 times higher sourcing potential than the second. Following Antràs et al. [2017], we set the elasticity of substitution $\sigma = 3.8$ and the comparative advantage $\theta = 1.8$, which imply $(\sigma - 1)/\theta = 1.58 > 1$ and complementarity across sourcing locations. The fixed costs of sourcing from the United States and China are 0.8 and 0.7, respectively. We plot firms' expected profits against productivity levels φ and their sourcing strategies in Figure 5.

We consider a striking example. The world-shocks $\bar{\gamma}$, country-level shocks $\hat{\gamma}_{i\cdot}$, and firm level shocks $\tilde{\gamma}_{i\cdot}$ are all distributed Bernoulli with two values: either $\gamma = 1$ with probability 90%, or $\gamma = 5$, a fourfold increase in cost with 10% change.[9] The calibration can be found in Appendix B.

We can appreciate that the different components of expected profits show a staggered pattern. The staggering is a reflection of the cutoff productivity levels for different sourcing strategies. Thanks to our pecking order result, we observe that small firms below the first jump in the lines only source from Home, medium ones from Home and Foreign 1, and largest ones from all the three countries, allowing them to

[9]This implies a expected value for γ to be $\mathbb{E}[\gamma] = 1.3$ and a variance $\mathrm{Var}(\gamma) = 1$. This is an order of magnitude higher than the empirical estimates we will find in section 5.

Figure 5: Three countries - Profit decomposition



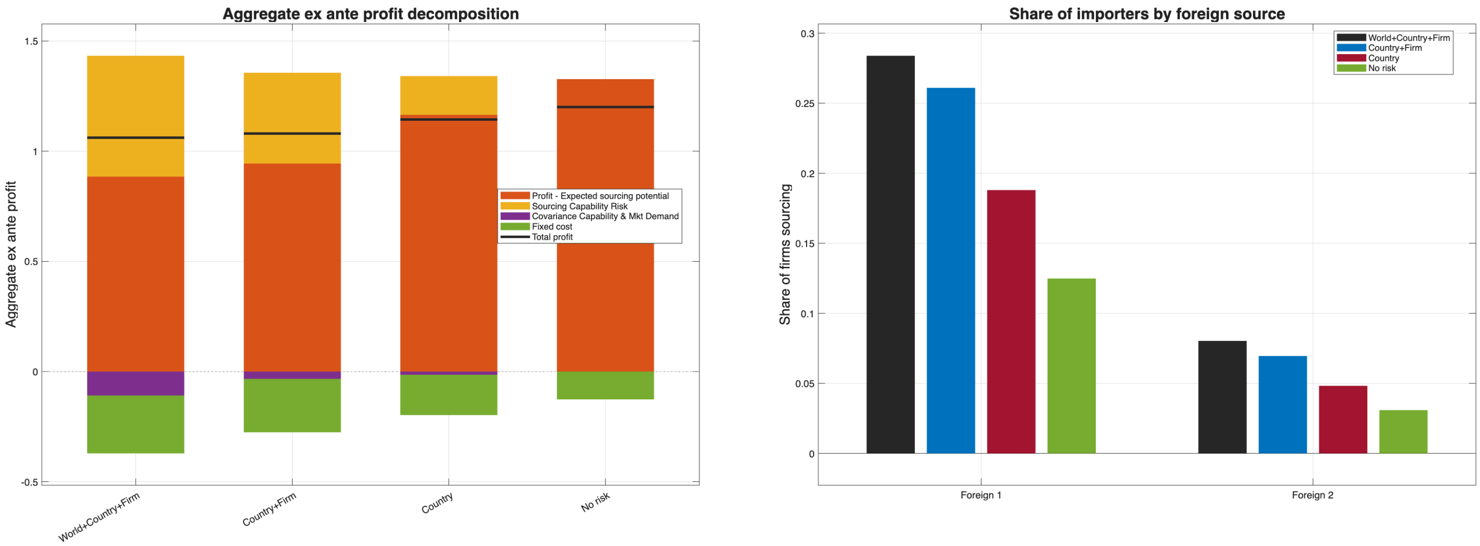
obtain a much higher profit.

First, the blue line displays firms' total expected profits and accounts for all the effects. Second, the red line indicates the effect of the sourcing capability for expected costs, emphasizing the desire to add more countries to the sourcing set to reduce costs. Third, the "option value" effect, in yellow, shows how risk provides the ex-post option for firms to source from cheaper countries if they experience positive shocks. Firms gain from starting a relationship with countries with higher cost variance as they can import more ex-post – at the intensive margin – thanks to lower costs. On the other hand, when there is a negative shock, the firm can reduce their exposure, or source from Home's input producers. Fourth, the purple line represents the covariance term between the sourcing capability and market demand, the "hedging effect". This is negative due to the fact that expected profits decrease if the firm gets hit with higher trade costs –and lower sourcing capability – when every other firms also set higher prices. Fifth, the green line illustrates the fixed cost of adding a country to the sourcing strategy, acting as a deterrent for adding more countries at the extensive margin as it reduces expected profits.

Figure 5 highlights that the primary driver of expected profits is the sourcing capability for expected shocks. Sourcing from more countries reduces overall costs through increased competition. Subsequently, uncertainty impacts through the risk effect on capability – or option value effect – and the covariance between the sourcing capability and market demand, or hedging effect. As these two effects pull in opposing directions, a trade-off emerges between incorporating countries with higher variance and those displaying a negative covariance with the shocks experienced by countries favored by most firms. However, quantitatively, the option value effect – driven by the variance in sourcing capability is more relevant for expected profits than the hedging effect. As a result, firms want to increase diversification. However, the impact of risk is small compared to the expected sourcing potential.

We compare different scenarios for risk: (i) this baseline with both firm-level $\tilde{\gamma}_{ij}$ and country-level

Figure 6: Firms' sourcing strategies and extensive margin



(a) Ex-ante profit decomposition

(b) Share of importers by source

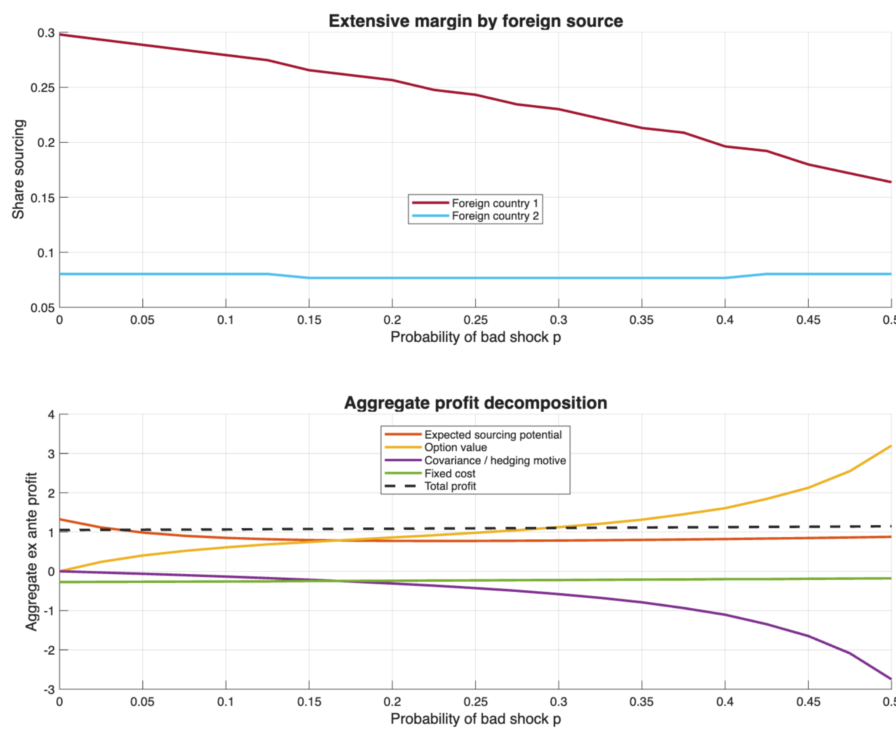
risk $\hat{\gamma}_{ij}$, and world risk $\bar{\gamma}_i$ (ii) a case with both firm-level $\tilde{\gamma}_{ij}$ and country-level risk $\hat{\gamma}_{ij}$, (iii) a case with only idiosyncratic risk $\tilde{\gamma}_{ij}$, (iv) a case with only country-risk $\hat{\gamma}_{ij}$, (v) a case with only-world risk, and finally (iv) a case without any risk keeping the expected cost constant $\gamma_{i\cdot} = \mathbb{E}[\gamma] = 1.3$. We study how risk affects the firm's extensive margin to import, diversify or reshore input production. In Figure 6, we decompose the aggregate ex-ante profit of firms and compare the share of firms sourcing from countries Foreign 1 (China) and Foreign 2 (United States).

We can see that, as more risk is added to the firms' environment, the aggregate ex-ante profits are reduced. This reduction masks opposing effects. On the one hand, profits grow due to a higher sourcing capability effect, which reflects that firms are expecting to gain more from a riskier environment as very good outcomes become more likely. On the other hand, the expected sourcing potential deteriorates, as more firms start sourcing from an additional country, which reduces their marginal costs and exert a competitive pressure on those firms that already imported from there. In addition to this negative effect, the covariance effect plays a more negative role, due to the role that a higher risk has on market demand, and fixed effects start to pile up, as more firms start to import from more countries. On net, the higher sourcing capability is not enough to compensate for the negative effects coming from the option value effect, the hedging effect, and the fixed costs, so aggregate ex-ante profits have a negative gradient with respect to risk.

Another way of looking at the sourcing strategies of firms is focusing on the share of importers by source. In our model, by construction, all firms source from Home as it does not have a fixed cost of sourcing. In all the scenarios, a large share of top firms source from Foreign 1, and only the most productive firms source from both Foreign 1 and Foreign 2, following the pecking-order logic discussed above. In the case without risk, this maps our model to the framework of Antràs et al. [2017], where firms only balance sourcing capability and fixed cost of sourcing. In all scenarios with uncertainty, more firms source from foreign countries than in the case without risk. Firms diversify to leverage the option-value of such trade cost risk. This is particularly the case in the baseline scenario, where the cost of each firm is subject to firm- $\tilde{\gamma}_{ij}$, country- $\hat{\gamma}_{ij}$, and world- $\bar{\gamma}_i$ level risk.

In the cases with country-risk or world-risk, both the positive "option-value" effect and the negative "hedging effect" coexist. If the option-value term matters more quantitatively, we see that in the case where there's is only country-risk $\hat{\gamma}_{ij}$ or world-shocks $\bar{\gamma}_j$, the covariance across firms is negative which lower ex-post sales and profits when the cost imports correlate negatively with the price index.

Figure 7: Extensive margin and aggregate profit decomposition



In Figure 7 we study how the extensive margin of importing and the aggregate profit decomposition vary when we change the probability p of the high-cost scenario for every type of trade cost shock (world, origin-specific, and firm-specific). A change in p changes both the mean and the variance of the composite trade cost shock. We find two things. First, as the probability of the bad scenario goes up, the share of firms importing from Foreign 1 declines monotonically. Given what we had seen in Figure 6, in which more risk induced more entry into importing, the fall in the share of importers from Foreign 1 is likely to be the consequence of the increase in the mean of the composite trade cost shock. Second, we observe that aggregate ex-ante profits are pretty much constant across the set of values considered for p, which points to offsetting forces. As expected, the expected sourcing potential is weakly decreasing in p, which is a consequence of higher expected trade costs. The option value effect is increasing in the probability of the bad shock, which is a direct outcome of the higher resulting variance of the composite trade cost shock. On the other hand, the hedging motive is ever decreasing in p. As the sourcing capability is negatively associated with the probability of the high trade cost shock, and the covariance of the sourcing capability with market demand is negative, this effect gets more negative as p grows. In addition to this, market demand goes up as p increases, due to the higher exit rates from importing from different sources of other firms, which leads to higher marginal costs, and a larger residual demand. Fixed costs are to a large extent constant. On net, sourcing capability and option value effects are almost perfectly offset by the hedging motive and the fixed cost.

5 Structural Model Estimation

We now consider a quantitative version of the structural model, estimated on the data from section 2. Leveraging firm-level panel data on import values by origin, we separately identify the model primitives: (i) persistent cross-country differences in sourcing potentials $\xi_i = T_i(\tau_{ij}w_i)^{-\theta}$; (ii) time variations in trade costs and supply chain disruptions γ_{ij}; and (iii) firm heterogeneity in exposure to such risk and their fixed costs of sourcing f_{ij}^n.

Following Antràs et al. [2017], we set the elasticity of substitution $\sigma = 3.85$ and the demand elasticity parameter $\theta = 1.789$, implying $(\sigma-1)/\theta = 1.583 > 1$. A value for $(\sigma-1)/\theta$ above unity means that there is complementarity across sourcing locations. In our model, it has two implications: (i) under such condition, large firms can source from multiple countries, while they only source for their best one under substitutability $(\sigma-1)/\theta < 1$, and (ii) complementarity guarantees a monotonicity property required to solve firms' combinatorial discrete choice problem using the algorithmic approach of Jia [2008], Antràs et al. [2017], and Arkolakis et al. [2023].

5.1 Average sourcing potentials across origins

Let $\mathcal{X}_{ij}^n$ denote firm n's expenditure share on intermediates sourced from origin i (relative to total intermediate expenditure), and let j denote the home country (Chile). The model implies that, conditional on a firm's sourcing set, relative expenditure shares isolate the origin component of sourcing efficiency. In particular, the origin-level term can be written as

$$\xi_i \equiv T_i \left(\tau_{ij}\bar{\gamma}_{ij}w_i\right)^{-\theta},$$

while firm-level deviations enter through $\left(\tilde{\gamma}_{ij}^n\right)^{-\theta}$.

We make use of this result by comparing each firm's import share from origin i to its domestic share and estimating the origin component through a fixed-effects specification:

$$\log \mathcal{X}_{ij}^n - \log \mathcal{X}_{jj}^n = \alpha_i + u_{in}, \tag{11}$$

where α_i is an origin-specific fixed effect that maps to $\log \xi_i$ up to a normalization, while u_{in} collects firm–origin deviations and measurement error. We normalize the domestic component so that $\xi_j = 1$, and impose $\bar{\gamma}_{jj} = 1$ and $\tilde{\gamma}^n_{jj} = 1$ (no domestic disruptions in the baseline) so that α_i is interpretable as the average sourcing efficiency relative to Chile.

We estimate the regression using firm-level data on import values by origin, domestic input expenditures, and wage bills to construct $\mathcal{X}^n_{ij}$ and $\mathcal{X}^n_{jj}$. We focus on the origins in the firm's observed sourcing set. To reduce the dimensionality of the estimation, we aggregate origins with fewer than 100 sourcing firms into a residual category (RoW), ending up with 50 origins.

Identification relies on the timing of information in the model: firms choose sourcing sets prior to learning about firm–origin disruptions so, conditional on the sourcing set, the residual u_{in} is orthogonal to the choice margin.

5.2 Supply-chain disruptions

We use the quarterly panel to characterize time variation in sourcing conditions. We treat changes in relative import shares as reflecting changes in effective sourcing costs and disruptions that affect the cost of importing. This reduced-form mapping accommodates various types of trade costs, such as freight, delivery delays, fuel prices, labor disruptions, etc.

Let ξ_{it} denote the time-varying world- and origin-specific components of import shares and let ϵ_{int} denote the firm–origin component:

$$\xi_{it} \equiv T_i \left(\tau_{ij}\bar{\gamma}_{j,t}\hat{\gamma}_{ij,t}w_i\right)^{-\theta}, \qquad \epsilon_{int} \equiv \left(\tilde{\gamma}^n_{ij,t}\right)^{-\theta}.$$

Using the model's implication for relative shares, we estimate year-over-year changes in this variable:

$$\Delta_4 \left[\log \mathcal{X}^n_{ij,t} - \log \mathcal{X}^n_{jj,t}\right] = \underbrace{-\theta \log(\bar{\gamma}_{j,t}/\bar{\gamma}_{j,t-4})}_{\bar{\lambda}_t} + \underbrace{-\theta \log(\hat{\gamma}_{ij,t}/\hat{\gamma}_{ij,t-4})}_{\hat{\lambda}_{it}} + \underbrace{-\theta \log(\tilde{\gamma}^n_{ij,t}/\tilde{\gamma}^n_{ij,t-4})}_{e^n_{it}},$$

where Δ_4 denotes a four-quarter difference, $\bar{\lambda}_t$ is a time fixed effect, $\hat{\lambda}_{it}$ is an origin-by-time fixed effect, and e_{int} captures firm–origin deviations. We estimate this specification via OLS with time and origin-by-time fixed effects.

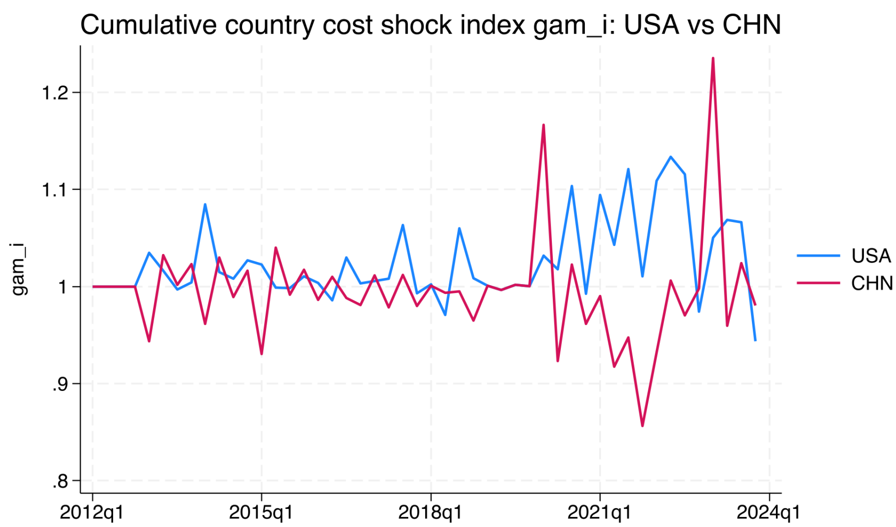
Recovering level processes from differences requires a normalization. We set $\bar{\gamma}_{j,t}$, $\hat{\gamma}_{ij,t}$, and $\tilde{\gamma}^n_{ij,t}$ to one in the first quarter each tuple is observed, and we assume that log shocks evolve as random walks. We then impose a parametric log-normal approximation to summarize the implied distributions (mean, variance, skewness, kurtosis) for both aggregate and firm-level components.[10] In Appendix C.2 we provide the distribution and the time series of the shocks to $\hat{\gamma}_{ij,t}$ that are obtained for each source country.

In Figure 8 we can observe what was obtained for the $\hat{\gamma}_{ij,t}$ components of the trade cost shocks in the case of the U.S. and China. The higher a $\hat{\gamma}_{ij,t}$ component is, the lower is the relative sourcing share of

[10] To address the issues of possible origin-specific trends in trade costs and seasonality we proceed as follows. We take the time-series of the relative shares of each origin and remove its 2012q1-2019q4 mean from them. Then we remove from the adjusted series its mean per quarter during the 2012q1-2019q4 period. The resulting series would be clean of trends and seasonal components.

the sourcing country in question. We can see that it was relatively harder to source from the U.S. and easier from China while the pandemic was on, which probably reflects the different virus circulation and mobility restrictions that both countries faced during 2020 and 2021. China was able to smash contagion with harsh control measures, which allowed them to have a more or less normal life during this period. The U.S, on the other hand, suffered the spread of the alpha, beta, and delta variants, which increased the death rate in the population and impaired production, although it allowed it to gain some herd immunity. As a consequence of these different paths, the virus spread in China later than in the West, once control measures were relaxed. At the same time, due to the vaccine roll-out, the West reopened, increasing production and demand for goods. This combination of more virus presence in China and more economic activity in the West resulted in a more difficult sourcing from China and an easier one from the U.S. at the end of the sample.

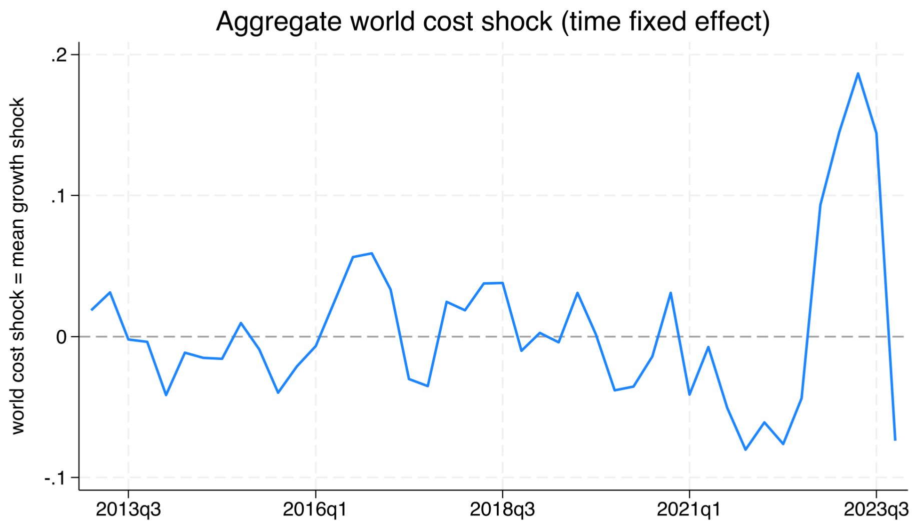
Figure 8: Cumulative source-specific cost shock: USA vs. China



Note: The graph shows the values of the $\hat{\gamma}_{it}$ components of the trade cost to source from the US and from China. USA = United States of America; CHN = China.

Globally, based on the results obtained from the $\bar{\gamma}_t$ component of the trade cost shocks, we can also see the impact of the pandemic on the easiness of sourcing from abroad. In particular, when the pandemic hit, trade did not plummet as it actually became easier to source from abroad. The expansion of working from home and the genereous support packages that governments granted to people in the Western world led to an increase in the demand for goods that expressed itself in more international trade. This process came to a halt when the increase in demand hit supply constraints in 2022, which were not easy to resolve in the short-term due to sanitary restrictions in the East and slow reallocation processes. On top of this, the Russia-Ukraine war imposed an additional layer of difficulty to source from certain origins close to the Mediterranean and the Middle East. By the end of the sample, most of these bottlenecks had started to be addressed and world demand for goods had cooled as central banks started raising interest rates to combat inflation.

Figure 9: Global cost shock



Note: The graph shows the value of the $\bar{\gamma}_t$ component of the trade cost shocks of sourcing from abroad.

5.3 Fixed costs of sourcing

We estimate fixed costs of forming and maintaining sourcing relationships using the simulated method of moments (SMM) for 13 countries, including Chile. Fixed costs vary across firms and origins and are allowed to depend on standard bilateral drivers:

$$\log f_{ij}^n = \beta_c^f + \beta_d^f \log \text{distance}_{ij} + \beta_l^f \text{language}_{ij} + \beta_C^f \text{corruption}_i + \nu_{ij}^n, \qquad \nu_{ij}^n \sim \mathcal{N}(0, (\beta_{\text{disp}}^f)^2).$$

We set $f_{jj}^n = 0$, since active firms necessarily source domestically, and for the residual RoW origin we use population-weighted averages of bilateral shifters.

To solve for firms' sourcing choices we leverage on the complementarity property implied by $(\sigma-1)/\theta > 1$, which allows us to compute firms' optimal sourcing sets with an efficient monotone algorithm. The details of the algorithm's implementation can be found in Appendix C.3. As sourcing decisions are made under uncertainty in our model, expected profits require integrating over the distributions of aggregate and idiosyncratic disruptions. We approximate these expectations using Quasi–Monte Carlo integration based on Sobol sequences.

The parameter vector $\delta = [E, \beta_c^f, \beta_d^f, \beta_l^f, \beta_C^f, \beta_{\text{disp}}^f]$ is chosen to match four sets of moments: (i) the overall importer share; (ii) the importer share among below-median sales firms; (iii) the vector of origin-specific importer shares; and (iv) the share of firms with below-median domestic input purchases. Let m collect the corresponding moments in the data and let $\hat{m}(\delta)$ be their simulated counterparts. We estimate $\hat{\delta}$ by minimizing a quadratic objective with equal weights across moments:

$$\hat{\delta} = \arg\min_{\delta} (m - \hat{m}(\delta))' (m - \hat{m}(\delta)) .$$

Appendix C.4 provides additional details on simulation design and numerical implementation.

5.4 Estimation and model fit

In Table 3, we show the average estimated values for the fixed cost for China, the US, and the Rest of the world region. These are in thousands of USDs, which means that the estimated average fixed cost for China is 27,720 USD, for the United States 12,760 USD, and for the rest of the world 5,510. The fixed costs of sourcing increase with a common language by around 3,000 USD (exponential of 1.12), increase with distance with an elasticity of 0.27, and decrease with corruption with an elasticity of 0.26.

Table 3: Estimated parameters

E	f_{CHN}	f_{USA}	f_{ROW}	β_c^f	β_d^f	β_l^f	β_C^f	β_{disp}^f
256.6	27.72	12.76	5.51	1.73	0.277	1.122	-0.259	0.625

Figure 10: Estimated sourcing potential and median fixed cost by country

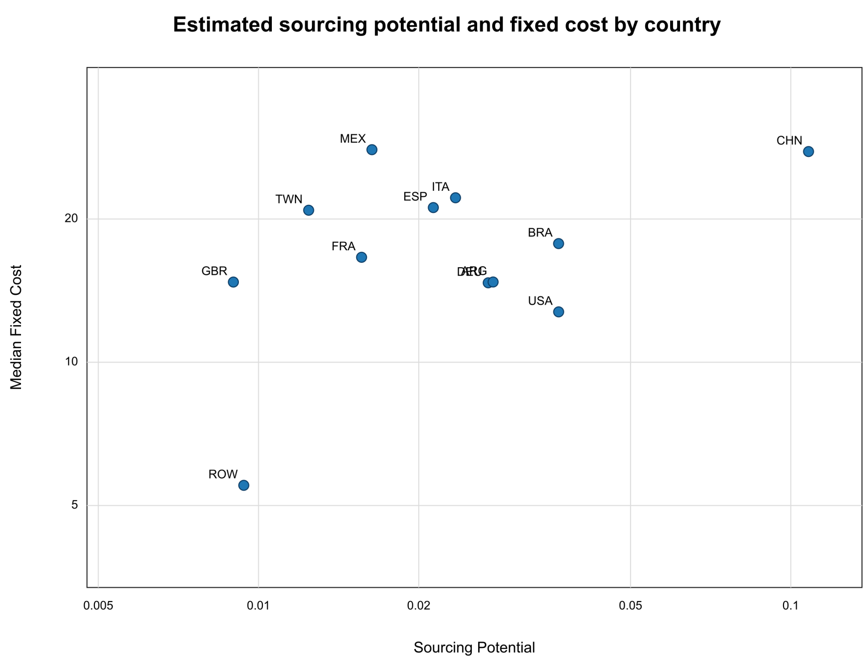


Figure 10 shows the estimated median fixed cost and sourcing potential. We observe that China has both one of the highest sourcing potentials as well as the highest fixed cost, while Mexico has a smaller sourcing potential but a median fixed cost as high as China's. Something similar arises with the United States, which has a high sourcing potential, and Italy, which has a smaller sourcing potential but a higher median fixed cost. These results are helpful in making sense of the difference found between countries' extensive and intensive margins. They also show that heterogeneous fixed costs across countries are relevant to matching the model to the data.

We now show how our model fits the data. From Table 4 we learn that for the overall share of importers, the model underestimates the data value in approximately 3 pp., while for the share of importers with sales below the median, the model fits the data reasonably well, as there is only a 0.28 pp. difference. In the case of the median firm's input purchases from Chile the gap between model and data is somewhat larger, although less than 12%. In Appendix C.5 we show the fit of the importers share by country.

Table 4: Fit of the model

Moments	Data	Model
Share of importers	0.226	0.1959
Share imp. w/sales below median	0.082	0.0848
Median input purchases	124.430	112.56

5.5 Supply chain disruptions shocks

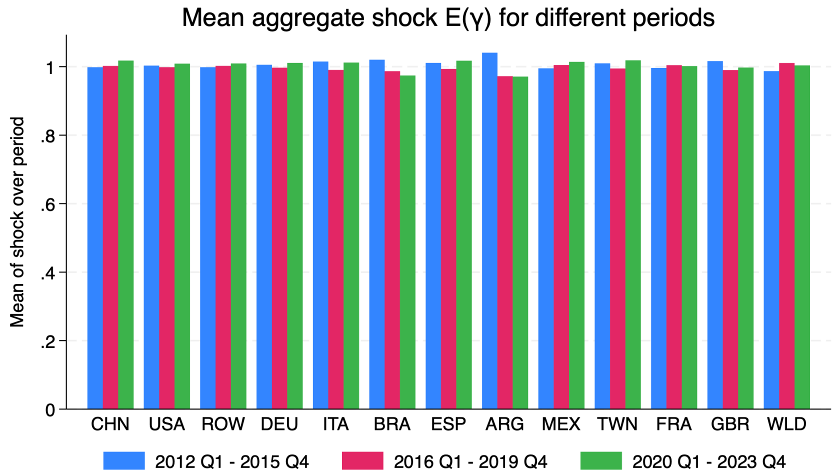
We split the sample into three periods and evaluate the mean and standard deviation of aggregate shocks in each one of them. The first period is 2012q1-2015q4, the second one is 2016q1-2019q4, and the third one is 2020q1 to 2023q4. We make this division to illustrate the evolution of the selected variables over three periods of equal length. In addition to this basic reason, the first period corresponds to a time in which trade relations were pretty much stable, the second period one in which the first Trump trade war occurred, and the third period to the pandemic and the Russia-Ukraine war.[11]

In Figure 11 we show the evolution of the mean of aggregate shocks, both country-specific and global (WLD). We can appreciate that the evolution of the mean is heterogeneous across sources. In general, the mean of trade cost shocks tends to go up from the first period to the last, such as in the cases of China (CHN), the US (USA), and the rest of the world (ROW). Some notable exceptions are sources that are closer to Chile, such as Brazil (BRA) and Argentina (ARG), which perhaps reflects some opening of these countries to international trade in the last decade. The world shock increases from the first period to the last, but the maximum value for the mean takes place in the 2016q1-2019q4, which emphasizes how disturbing was Trump's trade war for the sourcing decisions of Chilean firms.

In Figure 12 in turn we plot the dynamics of the standard deviation of aggregate shocks over the three periods named above. Here there is more heterogeneity across time and countries. In particular, there is a clear increase in the uncertainty surrounding trade shocks when sourcing from China or the world more generally. This increase is mirrored by most countries in the sample, although the change is less big in magnitude. The only origins in which uncertainty does not change much are Italy and Spain. The rise in risk is coherent with the narrative that supply chains became much more uncertain in the 2020q1-2023q4 period due to the pandemic, global bottlenecks and the Russia-Ukraine war.

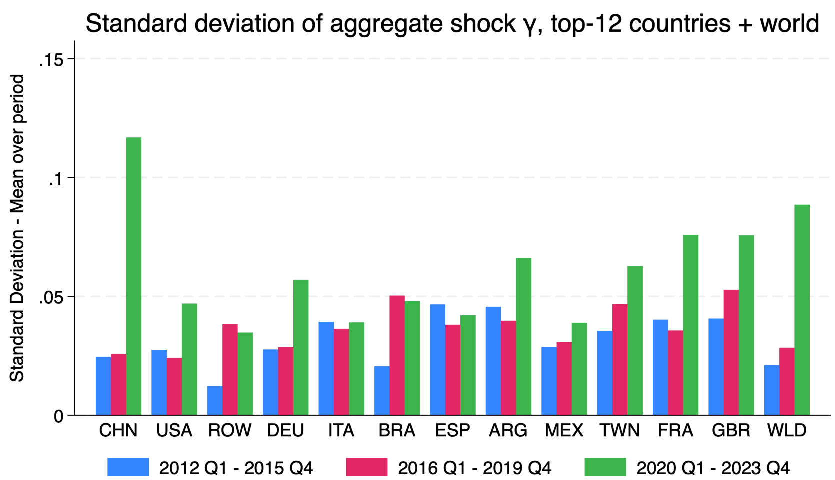
[11] The 2012q1-2015q4 is just used for expositional purposes. It is not independently used for model estimation or counterfactual analysis.

Figure 11: Mean aggregate shock



Note: The graph shows the value of either $\mathbb{E}[\bar{\gamma}_t]$ or $\mathbb{E}[\hat{\gamma}_{jt}]$ over the three periods and the countries considered.

Figure 12: Standard deviation aggregate shock



Note: The graph shows the value of the standard deviation of either the $\bar{\gamma}_t$ or $\hat{\gamma}_{jt}$ components of the trade cost shocks of sourcing from abroad across the time periods and countries considered.

6 Post-Covid-19 Supply Chain Uncertainty and Firms' reactions

We perform several counterfactual exercises to evaluate the incidence of uncertainty on the sourcing decisions of Chilean firms. We estimate the model with 2012q1-2019q4 Chilean Customs data. This estimation and the corresponding sourcing and entry into importing decisions will constitute our baseline values (State 1). We then calculate the mean and variance of trade cost shocks for the 2020q1-2023q4 period. The idea of the exercises is to quantitatively account for the impact that a major trade disrupting event, such as the pandemic, had on the sourcing decisions of firms over different margins.

The first counterfactual simulation is one in which we keep all 2012q1-2019q4 values but change the means of trade cost shocks $\mathbb{E}[\gamma_{ij}]$ to their values for period 2020q1 to 2023q4 (State 2). In Table 5, Panel A, we show the level of several variables of interest. We can appreciate that from State 1 to State 2, the share of importers among all firms goes down in 0.12 pp. However, the number of origins per firm increases and the HHI too, which points to some large firms enhancing their sourcing portfolio while most firms cut back on importing. This is reflected in the behavior of the China and U.S. shares of importers among all firms. They both decline, which talks of most firms dropping from importing from some regions. As it is more costly to produce, welfare falls relative to the baseline. In Panel B, we do a decomposition of these effects on ex-ante aggregate profits into the four channels described above. The contribution of the change in expected costs goes up, as intermediates are harder to source in State 2 relative to State 1, which reduces competitive pressures from other firms. The option value, on the other hand, decreases its contribution to profits, as it is less attractive to bet that the bad scenario will not unfold. Fixed costs, on the other hand, get less negative, as less firms source from abroad. In total, profits go up, due to the strength of the expected sourcing cost channel.

In the second counterfactual simulation (State 3), in addition to the changes in the mean trade costs $\mathbb{E}[\gamma_{ij}]$, we also change the variance of firm-specific (idiosyncratic) shocks $\tilde{\gamma}_{ij}$ to its 2020q1-2023q4 value. In this case, we can appreciate in Panel A that the importer share goes up both with respect to the baseline and State 2. There are less origins per firm, the HHI goes down, and the China share clearly goes up. All of this may suggest that more firms enter into importing and start sourcing exclusively from China. On the other hand, the U.S. share goes down, suggesting some insufficiency of the U.S. as an origin with which you can hedge broad market demand variations. All these movements have their counterparts in the Panel B effects. The contribution of the change in expected costs goes down relative to both the baseline and State 2, as the increase in risk reduces the expected sourcing capability, due to the lower marginal costs that firms offer when they start importing, which exerts a competitive pressure and lower other firms market demand. Nonetheless, the option value goes up more than a whole point with respect to State 2, reflecting a stronger force in favor of diversification, and the hedge covariance term contributes more negatively due to the inclusion of more sources. The contribution of fixed costs also gets more negative due to selection into importing. As the expected sourcing capability falls and the hedging motive effect gets stronger, due to the inclusion of more origins, ex-ante profits fall relatively to States 1 and 2.

Finally, in the last counterfactual exercise we add the change in aggregate risk – varying volatility of the country-level shocks $\sigma(\hat{\gamma})$ and the world shocks $\sigma(\bar{\gamma})$ to their 2020q1-2023q4 values, in addition to the other change in mean trade cost (stage 2) and the change in idiosyncratic risk (stage 3). In Panel A we can see that the importer share goes up again, suggesting the entry of of more firms into importing as risk is higher, although the number of origins per firm and the HHI fall, which again points to new firms entering into importing with just one foreign source. The China share goes up again, and the US share recovers some ground relative to State 3, although not enough to be below the baseline, which suggests that the option value effect is stronger in this scenario. In Panel B we see how the contribution of the expected cost falls again, while that of the option value increases. The hedging motive is reinforced in its negative contribution as more firms are sourcing from the same two countries (China and the US) which are becoming more risky and induce correlation across firms. Additionally, the incorporation of more sources by firms is also the reason of the more negative contribution of fixed costs. In total, profits ex-ante in aggregates are reduced again due to the competitive effects arising in equilibrium, as well as hedging motives and fixed costs paid by firms selecting into importing.

In **??** we provide a graphical representation of Panel B, in levels and in differences compared to the baseline ex-ante profit decomposition. In summary, our counterfactual exercises seem to highlight the importance of the expected cost and the option value effects in determining sourcing decisions and ex-ante profits. A competitive force coming from the change in other firms' marginal cost when changing sourcing decisions seems to be the main explanation for the result on the expected cost, while the gains from diversification rationalize the option value effect.

Table 5: Covid Decomposition and Ex-Ante Profit Components

	Panel A. Covid decomposition					
	Importer share	Origins per firm	HHI	China share	U.S. share	Welfare
State 1: Baseline	0.1968	2.9555	0.9453	0.1430	0.0999	0.9907
State 2: Mean shock	0.1956	2.9681	0.9459	0.1404	0.0990	0.9906
State 3: Idiosyncratic shock	0.2095	2.8324	0.9400	0.1665	0.0958	0.9907
State 4: Aggregate shock	0.2135	2.8149	0.9383	0.1717	0.0963	0.9907
$\Delta_{1\to2}$: mean	-0.0013	0.0126	0.0006	-0.0025	-0.0010	-0.000003
$\Delta_{2\to3}$: idiosyncratic	0.0139	-0.1358	-0.0059	0.0261	-0.0031	0.000030
$\Delta_{3\to4}$: aggregate	0.0040	-0.0174	-0.0016	0.0052	0.0005	0.000011
Total change, $\Delta_{1\to4}$	0.0167	-0.1406	-0.0070	0.0287	-0.0036	0.000039
Mean component, %	-7.64	-8.98	-8.81	-8.87	26.87	-6.88
Idiosyncratic component, %	83.50	96.58	85.20	90.76	87.07	77.95
Aggregate component, %	24.14	12.40	23.61	18.11	-13.94	28.93

	Panel B. Aggregate ex-ante profit decomposition				
	Expected cost	Option value	Hedging effect	Fixed cost	Total
State 1: Baseline	57.701	8.9534	-0.0081	-7.8151	58.831
State 2: Mean shock	57.758	8.8841	-0.0081	-7.7806	58.853
State 3: Idiosyncratic shock	56.697	9.9859	-0.0094	-8.1624	58.511
State 4: Aggregate shock	56.334	10.449	-0.1320	-8.2976	58.353
Δ from baseline: mean	0.0573	-0.0692	-0.000015	0.0345	0.0226
Δ from baseline: idiosyncratic	-1.0040	1.0325	-0.0013	-0.3473	-0.3200
Δ from baseline: aggregate	-1.3668	1.4956	-0.1239	-0.4825	-0.4776
Share of total profit: baseline	0.9808	0.1522	-0.00014	-0.1328	1.0000
Share of total profit: mean	0.9814	0.1510	-0.00014	-0.1322	1.0000
Share of total profit: idiosyncratic	0.9690	0.1707	-0.00016	-0.1395	1.0000
Share of total profit: aggregate	0.9654	0.1791	-0.00226	-0.1422	1.0000

Notes: Panel A reports levels across the four counterfactual states, incremental changes across transitions, the total change from the baseline to the final state, and the percentage attribution of the total change to each component. Panel B decomposes aggregate ex-ante profits into export-cost, option-value, hedge-covariance, and fixed-cost components. Profit shares are computed relative to total ex-ante profits in each state. Values are rounded for presentation.

7 Conclusion

In this paper, we study the international sourcing decisions by firms when faced with supply-chain uncertainty. The framework we use is inspired on Antràs et al. [2017], extended to include uncertainty in trade cost shocks. We show that uncertainty determines sourcing decisions through several channels that can go in opposite directions. The first one is a sourcing capability effect, that reflects how risk changes sourcing decisions of competitors and through them expected profits. The second one is an option value effect, which consists in that firms will try to diversify their source portfolio when there is more risk, as there is a higher chance of getting a very convenient trade cost draw, raising expected profits. The third one is a hedging motive, that comes from the change in residual market demand and sourcing capability. If sourcing capability goes up due to a change in uncertainty, residual demand goes down, so it decreases expected profits. Finally, there are fixed costs of adding sources to the source set.

We show in a numerical exercise that more risk tends to reduce expected profits, even though the option value effect dominates the hedging motive and more sources are added to the firms' source portfolio. In order to explore this result in a more realistic way, we use the model to estimate the change in the distribution of trade cost shocks before and after the pandemic. We find that even though the means of the shocks did not change very much, although they did increase for Chile's most important trading partners, the standard deviations of them went up almost across the board, and in a large magnitude for China and the world as a whole. We then quantitatively evaluate how Chilean firms changed their sourcing decisions in response to the increase in trade uncertainty that occurred since the pandemic, separating between mean and variance effects. Uncertainty did induce Chilean firms to diversify their sourcing set, driven for the most part by the option value effect, which operated both directly and through general equilibrium competition effects, although risk did reduce ex-ante profits in aggregate.

In sum, we have shown the relevance of risk for firms when they decide whether to self-select into importing and where to source from. In particular, we contribute to the literature by highlighting the option value and hedging motives for diversifying input sources, and have found that quantitatively the option value effect seems to the most quantitatively relevant channel. If our model is stylized and abstracts from other types of responses to uncertainty, such as spillovers, network effects, or cascades, that firms may have beyond input sourcing management. Some of these margins of adjustment are inventory management and the acquisition of financial instruments to transfer supply-chain risk to other specialized agents. We view inventory management as a complementary line of research to ours and the insurance acquisition response as something to explore in the future.

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A Theoretical Appendix

A.1 Proof of Proposition 1

(a) Two firms with productivity $\varphi_H > \varphi_L$. Denote $\mathcal{I}_j(\varphi_H) = \{i : \mathbb{1}_{ij}(\varphi_H) = 1\}$ and $\mathcal{I}_j(\varphi_L) = \{i : \mathbb{1}_{ij}(\varphi_L) = 1\}$, and $\mathcal{I}_j(\varphi_H) \neq \mathcal{I}_j(\varphi_L)$ (if $\mathcal{I}_j(\varphi_H) = \mathcal{I}_j(\varphi_L)$, it holds trivially). For firm φ_H to prefer $\mathcal{I}_j(\varphi_H)$ over $\mathcal{I}_j(\varphi_L)$:

$$\begin{aligned}
&\mathbb{E}(\varphi_H^{\sigma-1}(\eta\Theta_j(\mathcal{I}_j(\varphi_H, \gamma(\varphi_H))))^{\frac{\sigma-1}{\theta}} B_j(\gamma)) - w_j \sum_{i\in\mathcal{I}_j(\varphi_H)} f_{ij} \\
&> \mathbb{E}(\varphi_H^{\sigma-1}(\eta\Theta_j(\mathcal{I}_j(\varphi_L, \gamma(\varphi_L))))^{\frac{\sigma-1}{\theta}} B_j(\gamma)) - w_j \sum_{i\in\mathcal{I}_j(\varphi_L)} f_{ij}
\end{aligned}$$

and

$$\begin{aligned}
&\mathbb{E}(\varphi_L^{\sigma-1}(\eta\Theta_j(\mathcal{I}_j(\varphi_H, \gamma(\varphi_H))))^{\frac{\sigma-1}{\theta}} B_j(\gamma)) - w_j \sum_{i\in\mathcal{I}_j(\varphi_H)} f_{ij} \\
&< \mathbb{E}(\varphi_L^{\sigma-1}(\eta\Theta_j(\mathcal{I}_j(\varphi_L, \gamma(\varphi_L))))^{\frac{\sigma-1}{\theta}} B_j(\gamma)) - w_j \sum_{i\in\mathcal{I}_j(\varphi_L)} f_{ij}
\end{aligned}$$

Combining these two, we find

$$[\varphi_H^{\sigma-1} - \varphi_L^{\sigma-1}][\mathbb{E}(\Theta_j(\mathcal{I}_j(\varphi_H, \gamma(\varphi)))^{\frac{\sigma-1}{\theta}} B_j(\gamma)) - \mathbb{E}(\Theta_j(\mathcal{I}_j(\varphi_L, \gamma(\varphi)))^{\frac{\sigma-1}{\theta}} B_j(\gamma))]\eta^{\frac{\sigma-1}{\theta}} > 0$$

Given that $\varphi_H > \varphi_L$, $\eta > 0$, and the fact that γ's are the same and the expectations formed about these shocks are the same, and shocks are i.i.d, $\mathbb{E}(\Theta_j(\mathcal{I}_j(\varphi_H, \gamma(\varphi_H)))^{\frac{\sigma-1}{\theta}} B_j(\gamma)) > \mathbb{E}(\Theta_j(\mathcal{I}_j(\varphi_L, \gamma(\varphi_L)))^{\frac{\sigma-1}{\theta}} B_j(\gamma))$.

(b) When $(\sigma - 1)/\theta > 1$, the expected profit function features increasing differences in $\mathbb{1}_{ij}, \mathbb{1}_{kj}$ for $i, k \in \{1, \ldots, I\}$ with $i \neq k$. To prove this, we show it first for the case without risk and then we include uncertainty:

$$\begin{aligned}
(T_i(\tau_{ij}\gamma_{ij}(\varphi)w_i)^{-\theta} + T_k(\tau_{kj}\gamma_{kj}(\varphi)w_k)^{-\theta}))^{\frac{\sigma-1}{\theta}} - (T_k(\tau_{kj}\gamma_{kj}(\varphi)w_k)^{-\theta})^{\frac{\sigma-1}{\theta}} \geq T_i(\tau_{ij}\gamma_{ij}(\varphi)w_i)^{-\theta})^{\frac{\sigma-1}{\theta}} \\
(T_i(\tau_{ij}\gamma_{ij}(\varphi)w_i)^{-\theta} + T_k(\tau_{kj}\gamma_{kj}(\varphi)w_k)^{-\theta}))^{\frac{\sigma-1}{\theta}} \geq (T_i(\tau_{ij}\gamma_{ij}(\varphi)w_i)^{-\theta})^{\frac{\sigma-1}{\theta}} + (T_k(\tau_{kj}\gamma_{kj}(\varphi)w_k)^{-\theta})^{\frac{\sigma-1}{\theta}}
\end{aligned}$$

which is true for $(\sigma - 1)/\theta > 1$ since, for $\alpha > 1$:

$$\begin{aligned}
x^\alpha + y^\alpha &= (x+y)^\alpha \left[\left(\frac{x}{x+y}\right)^\alpha + \left(\frac{y}{x+y}\right)^\alpha\right] \\
&\leq (x+y)^\alpha \left[\left(\frac{x}{x+y}\right) + \left(\frac{y}{x+y}\right)\right] \\
&= (x+y)^\alpha
\end{aligned}$$

Where we take $\alpha = (\sigma - 1)/\theta$, $x = (T_i(\tau_{ij}\gamma_{ij}(\varphi)w_i)^{-\theta}$, and $y = T_k(\tau_{kj}\gamma_{kj}(\varphi)w_k)^{-\theta}$.

Now, because this is true almost surely, and since $\bar{\gamma}_{ij}, \tilde{\gamma}_{ij}(\varphi) > 0$, we can just take the expectation on both sides and this will still be valid.

Furthermore, it also features increasing differences in $(\mathbb{1}_{ij}, \varphi)$ for any $i \in I$, since

$$(\varphi_H^{\sigma-1} - \varphi_L^{\sigma-1})(T_i(\tau_{ij}\gamma_{ij}(\varphi)w_i)^{-\theta} + T_k(\tau_{kj}\gamma_{kj}(\varphi)w_k)^{-\theta})^{\frac{\sigma-1}{\theta}} \geq (\varphi_H^{\sigma-1} - \varphi_L^{\sigma-1})(T_k(\tau_{kj}\gamma_{kj}(\varphi)w_k)^{-\theta})^{\frac{\sigma-1}{\theta}}$$

Then, again, we can just take expectation and it is still true.

Finally, we use Topki's theorem, which states that if f is supermodular in (x, θ) and D is a lattice, then $x^*(\theta) = \text{argmax}_{x \in D} f(x, \theta)$ is non-decreasing in θ, we can then conclude that $\mathcal{I}_j(\varphi_L) \subseteq \mathcal{I}_j(\varphi_H)$ for $\varphi_H \geq \varphi_L$.

A.2 Proof of Proposition 2

Consider first the case, $i \neq \mathcal{I}_j(\varphi)$. The mapping defined in Proposition 2 is such that $V_{ij}(\varphi, \gamma, \mathcal{I}) = 1$ if

$$\varphi^{\sigma-1}\gamma^{\frac{\sigma-1}{\theta}}[\mathbb{E}(B_j(\gamma)\Theta_j(\mathcal{I} \cup i)^{\frac{\sigma-1}{\theta}}) - \mathbb{E}(B_j(\gamma)\Theta_j(\mathcal{I})^{\frac{\sigma-1}{\theta}})] > f_{ij}$$

and $V_{ij}(\varphi, \gamma, \mathcal{I}) = 0$ otherwise. Because of increasing differences, the term $\mathbb{E}(\Theta_j(\mathcal{I} \cup i)^{\frac{\sigma-1}{\theta}} B_j(\gamma)) - \mathbb{E}(\Theta_j(\mathcal{I})^{\frac{\sigma-1}{\theta}} B_j(\gamma))$ is increasing by the addition of elements to the set $\mathcal{I}$ (for $(\sigma - 1)/\theta > 1$). As a result, for $\mathcal{I} \subseteq \mathcal{I}'$, we cannot possibly have $V_{ij}(\varphi, \gamma, \mathcal{I}) = 1$ and $V_{ij}(\varphi, \gamma, \mathcal{I}') = 0$. Instead, we must have either $V_{ij}(\varphi, \gamma, \mathcal{I}) = V_{ij}(\varphi, \gamma, \mathcal{I}') = 0$, $V_{ij}(\varphi, \gamma, \mathcal{I}) = V_{ij}(\varphi, \gamma, \mathcal{I}') = 1$ or $V_{ij}(\varphi, \gamma, \mathcal{I}) = 0$ and $V_{ij}(\varphi, \gamma, \mathcal{I}') = 1$.

Second, consider the case $i \in \mathcal{I}$. The mapping $V_{ij}(\varphi, \gamma, \mathcal{I})$ defined in Proposition 2 is such that

$$\varphi^{\sigma-1}\gamma^{\frac{\sigma-1}{\theta}}[\mathbb{E}(B_j(\gamma)\Theta_j(\mathcal{I})^{\frac{\sigma-1}{\theta}}) - \mathbb{E}(B_j(\gamma)\Theta_j(\mathcal{I} \setminus i)^{\frac{\sigma-1}{\theta}})] > f_{ij}$$

and $V_{ij}(\varphi, \gamma, \mathcal{I}) = 0$ otherwise. Similarly to above, the term $\mathbb{E}(\Theta_j(\mathcal{I})^{\frac{\sigma-1}{\theta}}) - \mathbb{E}(\Theta_j(\mathcal{I} \setminus i)^{\frac{\sigma-1}{\theta}})$ is increased by the addition of elements to the set $\mathcal{I}$. As a result, for $\mathcal{I} \subseteq \mathcal{I}'$, we cannot possibly have $V_{ij}(\varphi, \gamma, \mathcal{I}) = 1$ and $V_{ij}(\varphi, \gamma, \mathcal{I}') = 0$. Instead, we must have either $V_{ij}(\varphi, \gamma, \mathcal{I}) = V_{ij}(\varphi, \gamma, \mathcal{I}') = 0$, $V_{ij}(\varphi, \gamma, \mathcal{I}) = V_{ij}(\varphi, \gamma, \mathcal{I}') = 1$ or $V_{ij}(\varphi, \gamma, \mathcal{I}) = 0$ and $V_{ij}(\varphi, \gamma, \mathcal{I}') = 1$.

Thus, we can conclude that $V_{ij}(\varphi, \gamma, \mathcal{I}') \geq V_{ij}(\varphi, \gamma, \mathcal{I}')$ for $\mathcal{I} \subseteq \mathcal{I}'$ as stated in the proposition.

A.3 Gravity Equation

As final goods are not traded, all transactions occur at the intermediate goods level. Then, to find the aggregate volume of bilateral trade, or gravity equation, we only need to aggregate the firm-level intermediate input purchases from origin country i across firms in destination country j. Given that trade in intermediate goods occurs ex-post, we formulate the gravity equation for a specific realization of the shocks $\bar{\gamma}_{ij}, \tilde{\gamma}_{ij}(\varphi)$. Substituting equation (14), we obtain:

$$
\begin{aligned}
M_{ij}(\bar{\gamma}) &= N_j \int_{\tilde{\varphi}_{ij}}^{\infty} \int_{\tilde{\gamma}(\varphi)} M_{ij}(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi)) d\tilde{\Psi}_i^{\varphi}(\gamma) dG_i(\varphi) \\
&= N_j (\sigma - 1) \eta^{\frac{\sigma-1}{\theta}} T_i (\tau_{ij} \bar{\gamma}_{ij} w_i)^{-\theta} B_j(\bar{\gamma}) \times \\
&\quad \int_{\tilde{\varphi}_{ij}}^{\infty} \int_{\tilde{\gamma}(\varphi)} \mathbb{1}_{ij}(\varphi) \varphi^{\sigma-1} (\Theta_j(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi)))^{\left(\frac{\sigma-1}{\theta} - 1\right)} (\tilde{\gamma}_{ij}(\varphi))^{-\theta} d\tilde{\Psi}_i^{\varphi}(\gamma) dG_i(\varphi),
\end{aligned}
\tag{12}
$$

so,

$$
M_{ij}(\bar{\gamma}) = N_j (\sigma - 1) \eta^{\frac{\sigma-1}{\theta}} T_i (\tau_{ij} \bar{\gamma}_{ij} w_i)^{-\theta} B_j(\bar{\gamma}) \Lambda_{ij}(\bar{\gamma}), \tag{13}
$$

with,

$$
\Lambda_{ij}(\bar{\gamma}) \equiv \int_{\tilde{\varphi}_{ij}}^{\infty} \int_{\tilde{\gamma}(\varphi)} \mathbb{1}_{ij}(\varphi) \varphi^{\sigma-1} (\Theta_j(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi)))^{\left(\frac{\sigma-1}{\theta} - 1\right)} (\tilde{\gamma}_{ij}(\varphi))^{-\theta} d\tilde{\Psi}_i^{\varphi}(\gamma) dG_i(\varphi), \tag{14}
$$

where, again, $\tilde{\varphi}_{ij}$ represents the productivity of the least productive firm in country j importing from country i. Notably, $B_j(\bar{\gamma})$ will not be a part of the definition of $\Lambda_{ij}(\bar{\gamma})$, since idiosyncratic shocks do not affect the price index. Using the definition of $B_j(\bar{\gamma})$ and $Q_i = \sum_k M_{ik}$ the total production of intermediate inputs in country j, for general shocks, we get,

$$
M_{ij}(\bar{\gamma}) = \frac{E_j}{P_j(\bar{\gamma})/N_j} \times \frac{Q_i}{\sum_k \frac{E_k}{P_k(\bar{\gamma})/N_k} (\tau_{ik} \bar{\gamma}_{ik})^{-\theta} \Lambda_{ik}(\bar{\gamma})} \times (\tau_{ij} \bar{\gamma}_{ij})^{-\theta} \times \Lambda_{ij}(\bar{\gamma}), \tag{15}
$$

with,

$$
P_j(\bar{\gamma}) = \left(N_j \int_{\tilde{\varphi}_{ij}}^{\infty} \int_{\tilde{\gamma}(\varphi)} p_i(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi))^{1-\sigma} d\Psi_{ij}^{\varphi}(\tilde{\gamma}) dG_j(\varphi) \right)^{\frac{1}{1-\sigma}},
$$

the ideal price index and E_j the expenditure in our sector, which is fixed as a proportion α of labor income.

This equation implies a relationship between bilateral trade flows and exporter fixed effects, importer fixed effects, and iceberg costs. However, it also includes the term $\Lambda_{ij}(\bar{\gamma})$, which varies for both i and j, unless all firms import from all countries. As shown in Antràs et al. [2017], this could happen if $f_{ij} = 0$ for all i, resulting in $\Lambda_{ij}(\bar{\gamma}) = \Lambda_j(\bar{\gamma})$. In this case, shocks shouldn't matter in terms of sourcing strategies, since firms are already importing from all countries, so after the shocks are realized they can just buy from the countries that were positively or least negatively affected. The parameter θ provides the elasticity of trade flows with respect to changes in these bilateral trade frictions and the aggregate elasticity coincides with the firm-level elasticity, which is not the case whenever $f_{ij} > 0$. As shown in their paper, in this case, the elasticity of trade flows with respect to changes in the bilateral trade frictions is higher than θ.

To control for the extended gravity forces, we again follow Antràs et al. [2017] and define an importer-specific term: $\Xi_j(\bar{\gamma}) \equiv K_j(\bar{\gamma}) T_j (\tau_{jj} \bar{\gamma}_{jj} w_j)^{-\theta} N_j B_j(\bar{\gamma})$, with $K_j(\bar{\gamma}) = (\sigma - 1)\eta^{(\sigma-1)/\theta} N_j B_j(\bar{\gamma})$ so we can write,

$$\Lambda_{ij}(\bar{\gamma}) = \frac{K(\bar{\gamma})}{\Xi_j(\bar{\gamma})}\int_{\tilde{\varphi}_{ij}}^{\infty}\int_{\tilde{\gamma}_{ij}(\varphi)} \mathbb{1}_{ij}(\varphi)\varphi^{\sigma-1}(\Theta_j(\varphi,\bar{\gamma},\tilde{\gamma}(\varphi))^{\frac{\sigma-1}{\theta}-1}T_j(\tau_{jj}\tilde{\gamma}_{jj}(\varphi)w_j)^{-\theta}d\tilde{\Psi}^{\varphi}_{ij}(\varphi)dG_j(\varphi), \tag{16}$$

where the second term on the right-hand side corresponds to the *domestic input purchases* aggregated over all firms based in j that import inputs from i, so now the elasticity of trade θ is closer to the firm-level estimates. We obtain this expression in the following way.

Using equation (19), $\sigma - 1 = \theta$ (entry decisions are independent), and the formula for the Pareto distribution, $G_j(\varphi) = 1 - (\underline{\varphi}_j/\varphi)^\kappa$, to solve for the integral in equation (20) and plug it back in equation (19):

$$M_{ij}(\bar{\gamma}) = (\sigma-1)\eta^{\frac{\sigma-1}{\theta}}N_jB_j(\bar{\gamma})T_i(\tau_{ij}w_i\gamma_{ij}(\varphi))^{-\theta}\kappa\underline{\varphi}_j^{\kappa}\frac{(\tilde{\varphi}_{ij})^{\sigma-1-\kappa}}{\kappa-\sigma+1}$$

With $\sigma - 1 = \theta$, we have that the threshold is now given by

$$\tilde{\varphi}_{ij}^{\sigma-1} = \frac{w_jf_{ij}}{\eta\mathbb{E}(B_j(\bar{\gamma})T_i(\tau_{ij}w_i\gamma_{ij}(\varphi))^{-\theta})}$$

Then, we plug this back in our equation for $M_{ij}(\bar{\gamma})$ with $\sigma - 1 = \theta$ and after some manipulation, we find:

$$M_{ij}(\bar{\gamma}) = \frac{N_jB_j(\bar{\gamma})^{\frac{\kappa}{\sigma-1}}(\tau_{ij})^{-\kappa}(w_i\tilde{\gamma}_{ij}(\varphi)\bar{\gamma}_{ij})^{1-\frac{\kappa}{\sigma-1}}(\underline{\varphi_j})^{\kappa}Q_i}{\sum_k N_kB_k(\bar{\gamma})^{\frac{\kappa}{\sigma-1}}(\tilde{\varphi}_k)^{\kappa}(w_k\tilde{\gamma}_{ik}(\varphi)\bar{\gamma}_{ik}f_{ik})^{1-\frac{\kappa}{\sigma-1}}}$$

Using the definition of $B_j(\bar{\gamma})$ and using the resulting N_j of equilibrium obtained for the Pareto case with shape parameter κ, and defining

$$\Phi_j = \frac{f_{ej}}{L_j}\underline{\varphi_j}^{-\kappa}P_j(\bar{\gamma})^{-\kappa}w_j^{\frac{\kappa}{\sigma-1}-1} \tag{17}$$

we obtain equation (21).

A.4 Herfindahl-Hirschman Index (HHI)

As we aim to understand both the sourcing strategy (extensive margin) and the decision on how much to purchase from each available source (intensive margin), we are also concerned with the impact of supply chain risk on intermediate input purchases and market concentration. In our introduction, we used publicly available data at the product-origin level for Chile, classified using the harmonized-system (HS) at the 8-digit level, which is a standardized method of classifying traded products using numerical digits. We obtained Figure **??**, which shows the unweighted average of the yearly country-level HHI from 2017 to May 2023. Notably, there is a substantial increase in market concentration post-2020, coinciding with the heightened supply chain uncertainty due to Covid-19. The concentration subsequently exhibits a gradual decrease. This suggests that following Covid-19, the concentration of foreign suppliers increased. This phenomenon may arise from either a reduction in the set of countries Chile imports from or firms adjusting the intensive margin by subsequently purchasing from a smaller set of countries less, or positively, affected by the shock.

We would like to be able to match this with our model and understand the mechanism in action. To do that, we need to obtain the model-implied HHI. Using equation (19), aggregating over all sources of import to obtain the total imports for country j, which gives us the market share, then squaring that and summing over all sources, we get the HHI for country j, which is:

$$\begin{aligned} HHI_j &= \sum_{i=1}^{I} (ms_{ij})^2 \\ &= \sum_{i=1}^{I} \left(\frac{M_{ij}(\bar{\gamma})}{\sum_{k=1}^{I} M_{kj}(\bar{\gamma})} \right)^2 \\ &= \sum_{i=1}^{I} \left(\frac{T_i(\tau_{ij}\bar{\gamma}_{ij}w_i)^{-\theta}\Lambda_{ij}(\bar{\gamma})}{\sum_{k=1}^{I} T_k(\tau_{kj}\bar{\gamma}_{kj}w_k)^{-\theta}\Lambda_{kj}(\bar{\gamma})} \right)^2 \end{aligned} \tag{18}$$

We are summing over all countries and not just the set of suppliers since we know that the value will be zero if no firm buys from that country. The term $\Lambda_{ij}(\bar{\gamma})$ is defined as detailed in section 3.4. We can subsequently leverage our findings from the structural estimation process to obtain the model-implied HHI and assess the fit of our model.

A.5 Different timing assumption

In the main text, we developed a model where the firm' decision occurs in three steps: (i) firm decide to enter and then learn their productivity, (ii) they choose (ex-ante) the set of suppliers, (iii) supply chain cost shocks are realized and firm choose their quantities imported and used in production. This restriction is imposed by the structure of the Eaton-Kortum style of model – which allow to match (realized) expenditure shares $\chi_{ij}(\varphi, \gamma)$ to their data counterpart. Note that this class of model does not allow us to distinguish quantities decisions from expenditure decisions.

In this section, we compare our model to an alternative model where firms choose quantity ex-ante, before the realization of the trade cost shock. To show that, we leverage the isomorphism between a CES-based Armington model and the Eaton-Kortum model. In this alternative model, final-good firms now have a CES demand (and love for varieties) for imports from different countries, subject to supply chain risks on trade costs γ_{ij}. We draw this comparison conditional on an ex-ante sourcing strategy $_j(\varphi)$.

To recall this isomorphism between the two models, let us compare the marginal cost of a final good firm of productivity φ and cost shock γ. First, in the Eaton-Kortum / Antras-Fort-Tintelnot model we have:

$$c_j(\varphi, \gamma) = \frac{1}{\varphi}\eta^{-1/\theta}\Big(\sum_{i\in\mathcal{I}_j(\varphi)} T_i(\tau_{ij}\gamma_{ij}w_j)^{-\theta}\Big)^{-1/\theta}$$

Second, in the CES-demand Armington model, we have the marginal cost:

$$c_j(\varphi,\gamma) = \frac{1}{\varphi}\eta^{\frac{1}{1-\varsigma}}\Big(\sum_{i\in\mathcal{I}_j(\varphi)} \alpha_{ij}(\tau_{ij}\gamma_{ij}w_j)^{1-\varsigma}\Big)^{\frac{1}{1-\varsigma}}$$

where α_{ij} are the demand shifters and $\varsigma = \theta+1$ is the Constant Elasticity of Substitution across importing countries.[12]

In the following, we derive a model where firms choose quantities before costs shocks are realized, and we will show that such setting yield expenditure shares $\chi_{ij}(\varphi,\gamma)$ that are less tractable compared to the model developed in the main text.

Let us consider the optimization problem of the firm, choosing the import quantity ex-ante, i.e. in expectation before the γ_{ij} shocks are realized. Since the final-good firms are monopolistically competitive (with CES σ), the final (ex-post) demand for that variety is simply $q_j(\varphi,\gamma) = EP_j^{\sigma-1}p_j(\varphi,\gamma)^{-\sigma}$, we have the monopoly pricing $p_j(\varphi,\gamma) = \frac{\sigma}{\sigma-1}c_j(\varphi,\gamma)$ and expost profit writes as $\pi_j = \mathbb{E}\big[B_j(\gamma)c_j(\varphi,\gamma)^{1-\sigma}\big]$ where $B_j(\gamma) = \frac{1}{\sigma}\Big(\frac{\sigma}{\sigma-1}\Big)^{1-\sigma}E_jP_j(\gamma)$ as in the main text. As a result, since profits are increasing in final quantity,[13] this implies that maximizing profits is equivalent to maximizing output q_j subject to constraint $\sum_i q_{ij}\tau_{ij}\gamma_{ij}w_i = c_jq_j$. This yields the following firms quantity choice maximization:

$$\max_{q_{ij}} \mathbb{E}\Big[\varphi\Big(\sum_{i\in\mathcal{I}_j(\varphi)} \alpha_{ij}^{\frac{1}{\varsigma}}(q_{ij})^{\frac{\varsigma-1}{\varsigma}}\Big)^{\frac{\varsigma}{\varsigma-1}}\Big] \qquad s.t. \qquad \sum_i q_{ij}\tau_{ij}\gamma_{ij}w_i = c_jq_j \quad [\lambda_j(\gamma)\Psi_j(\gamma)]$$

where $\lambda_j(\gamma)\Psi_j(\gamma)$ is the multiplier of the "budget constraint", scaled by the probability of the shocks $\Psi_j(\gamma)$, when the firm sets its marginal cost c_j as function of the input prices $\tau_{ij}\gamma_{ij}w_i$.

Deriving the First-Order Conditions and manipulating the terms, we obtain:

$$\frac{q_{ij}}{q_j} = \varphi^{\varsigma-1}\alpha_{ij}\,\mathbb{E}\big[\lambda_j(\gamma)\,(\tau_{ij}\gamma_{ij}w_i)\big]^{-\varsigma}$$

We see that, because the quantities are chosen ex-ante, they include typical "covariance term" between the goods' cost γ_{ij} and the shadow value of the budget constraint in a particular state of the world λ_j, which represents the "risk premium" that penalizes the import of a particular country i if it correlates with states of the world where production is low and marginal value λ_j high. Rearranging, we obtain an implicit function for the final cost:

$$c_j(\varphi,\gamma) = \frac{1}{\varphi}\Big(\sum_{i\in\mathcal{I}_j(\varphi)} \alpha_{ij}(\tau_{ij}\gamma_{ij}w_i)\,\mathbb{E}\big[\lambda_j(\gamma)\,(\tau_{ij}\gamma_{ij}w_i)\big]^{1-\varsigma}\Big)^{\frac{1}{1-\varsigma}}$$

[12] In the following, we renormalize the firm productivity φ to be equal $\tilde{\varphi} = \varphi\,\eta^{\frac{1}{\varsigma-1}}$ without loss of generality.

[13] Since we have $\pi = (p_j - c_j)q_j = \frac{1}{\sigma}p_jq_j$, we can also rewrite $\pi_j = \mathbb{E}\big[\frac{1}{\sigma}E^{\frac{1}{\sigma}}P_j(\gamma)^{1-\frac{1}{\sigma}}q_j^{1-1\sigma}$

which depends non-linearly on $\lambda_j(\gamma)$, which itself is defined implicitely as a function of p_i

$$\Big(\sum_{i\in\mathcal{I}_j(\varphi)}\alpha_{ij}\mathbb{E}\big[\lambda_j(\gamma)\,(\tau_{ij}\gamma_{ij}w_i)\big]^{1-\varsigma}\Big)^{\frac{1}{1-\varsigma}} = 1$$

which is stochastic and varies with the supply chain shock γ. As a result, the expost expenditure shares are therefore:

$$\chi_{ij}(\varphi,\gamma) = \frac{q_{ij}\tau_{ij}\gamma_{ij}w_i}{c_j q_j} = \frac{\alpha_{ij}\varphi^{\varsigma}(\tau_{ij}\gamma_{ij}w_i)^{-\varsigma}\mathbb{E}\big[\lambda_j(\gamma)\,(\tau_{ij}\gamma_{ij}w_i)\big]^{-\varsigma}}{\Big(\sum_{k\in\mathcal{I}_j(\varphi)}\alpha_{kj}(\tau_{kj}\gamma_{kj}w_i)\,\mathbb{E}\big[\lambda_j(\gamma)\,(\tau_{kj}\gamma_{kj}w_k)\big]^{1-\varsigma}\Big)^{\frac{1}{1-\varsigma}}}$$

If one were compare to the original Eaton-Kortum type of formula, we could not seperate the shocks from the rest, as

$$\log\chi_{ij}^{n}(\varphi,\gamma)-\log\chi_{jj}^{n}(\varphi,\gamma) = \log(\alpha_{ij}/\alpha_{jj}) - \varsigma\log(\tau_{ij}\gamma_{ij}w_i)\ -\varsigma\Big(\log\mathbb{E}\big[\lambda_j(\gamma)\,(\tau_{ij}\gamma_{ij}w_i)\big]-\log\mathbb{E}\big[\lambda_j(\gamma)\big]\Big)$$

Hence, we see that a country i fixed effect – as we do in the estimation section – would not be able to recover the shock γ_{ij} as the direct effect and the precautionary anticipatory effects are mixed and can not be disentangled without additional expectation data.

As a result, this timing assumption is less tractable for estimation and we keep the distinction (i) ex-ante choice of sourcing relationship $\mathcal{I}_j(\varphi)$ and (ii) expost expenditure shares, in the main analysis of the paper.

A.6 Planner's problem and inefficiencies

In this section, we consider a Social Planner in country j that would choose the allocation on behalf of the firms and households. They would choose all the decisions, such as :

$$\mathbf{X} = \{C_{0j}, C_j, q_j(\varphi,\gamma), q_{ij}(\varphi,\nu,\gamma), L_{0j}, \ell_{ij}(\varphi,\nu,\gamma), \ell_{ij}^{f}(\varphi), \ell_j^{e}\}$$

where C_{0j}, L_{0j} are the output and labor for the outside sector, $q_{ij}(\varphi,\nu), \ell_{ij}(\varphi,\nu)$ the quantity and labor for the import from i by firm φ in variety ν, and $\ell_{ij}^{f}, \ell_j^{e}$ are the labor used to pay for the fixed costs of relationship and entry. We omit the index j on every variable to alleviate notations. The Lagrangian, with expectations drawn on the shocks $\psi(\gamma)$

$$
\begin{aligned}
\mathcal{L}(\mathbf{X},\lambda) = {} & \mathbb{E}\Big[U(C_{0j}^{1-\eta}C_j^{\eta})\Big] + \mu_0(C_0\bar{w} - L_0) + \int_\gamma \mu_C(\gamma)\Big(\Big(\int q(\varphi,\gamma)^{\frac{\sigma-1}{\sigma}}dG(\varphi)\Big)^{\frac{\sigma}{\sigma-1}} - C_j\Big)d\Psi(\gamma) \\
& + \int_\gamma\int_\varphi \mu(\varphi,\gamma)\Big[\varphi\Big(\int_\nu q_{i(\nu)}(\nu,\varphi,\gamma)^{\frac{\rho-1}{\rho}}d\nu\Big)^{\frac{\rho}{\rho-1}} - q(\varphi,\gamma)\Big]dG(\varphi)d\Psi(\varphi) \\
& + \int_\gamma\int_\varphi\int_\nu \mu(\nu,\varphi,\gamma)\Big[\max_{i(\nu)}\big[\ell_{i(\nu)}(\varphi,\nu,\gamma) - \tau_{ij}\gamma_{ij}a_j(\nu,\varphi,\gamma)q_j(\nu,\varphi,\gamma)\big]\Big]d\nu\, dG(\varphi)\, d\psi(\gamma) \\
& + \lambda_j\Big(L_j - L_0 - \int_\gamma\int_\varphi\int_\nu \ell_j(\varphi,\nu,\gamma)d\nu\, dG(\varphi)\, d\psi(\gamma) - \sum_{i\in\mathcal{I}}\int \ell_{ij}^f(\varphi)dG(\varphi) - \ell_j^e\Big) \\
& + \sum_{i\neq j}\lambda_i\Big(L_j - L_0 - \int_\gamma\int_\varphi\int_\nu \ell_j(\varphi,\nu,\gamma)d\nu\, dG(\varphi)\, d\psi(\gamma)\Big)
\end{aligned}
$$

Note that, due to the presence of the outside sector pinning down wages, we get $\mu_0 = 1$ and $\lambda_j = \bar{w}$ the "shadow wage", and similarly for other countries. We can derive all the First-Order Conditions to find the optimal planner's decisions subject to these resource constraint. We would find many similar optimality conditions as in the competitive equilibrium, where the prices are replaced by the Lagrange multipliers.

$$
\begin{aligned}
\mu_C(\gamma) &= \Big(\int_\varphi \mu(\varphi,\gamma)^{1-\sigma}dG(\varphi)\Big)^{\frac{1}{1-\sigma}} \\
\mu(\varphi,\gamma) &= \frac{1}{\varphi}\bar{\eta}\Big(\sum_{i\in\mathcal{I}_j(\varphi)} T_i(\tau_{ij}\gamma_{ij}\lambda_i)^{-\theta}\Big)^{-1/\theta}
\end{aligned}
$$

exactly the identical counterparts to the price index $P_j(\gamma)$ and the firms' marginal cost $c_i(\varphi,\gamma)$.

Due to the Cobb-Douglas preference, and the manufacturing good representing a fraction η of (labor) income (here normalized to $\bar{w}_jL_j$, the aim of the Social Planner is to minimize the price index $\mu_C(\gamma)$, or shadow value of the final good aggregate. Using CRRA utility $U(C) = C^{1-\vartheta}/(1-\vartheta)$ we see that the objective becomes:

$$
\mathbb{E}\big[U(C_{0j}^{1-\eta}C_j^{\eta})\big] = \mathbb{E}\big[\tilde{E}\,\mu_C(\gamma)^{-\eta(1-\vartheta)})\big]
$$

with the constant $\tilde{E} = \eta^\eta(1-\eta)^{1-\eta}\bar{w}_jL_j/(1-\vartheta)$, and $U(\cdot)$ a concave utility function. Using the formula for $\mu_C(\gamma)$ and $\mu(\varphi,\gamma)$, we get that the objective becomes:

$$
\mathcal{W} = \max_{\{\mathcal{I}_j(\varphi)\}_\varphi} \mathbb{E}\Big[\tilde{E}\Big(\int_\varphi \varphi^{\sigma-1}\bar{\eta}\Big(\sum_{i\in\mathcal{I}_j(\varphi)} T_i(\tau_{ij}\gamma_{ij}\lambda_i)^{-\theta}\Big)^{\frac{\sigma-1}{\theta}}dG(\varphi)\Big)^{-\frac{\eta(1-\vartheta)}{1-\sigma}}\Big] - \int_\varphi \sum_{i\in\mathcal{I}_j(\varphi)} \lambda_j f_{ij}
$$

As a result, the Social Planner internalizes the full vector of firms' sourcing decision $\{\mathcal{I}_j(\varphi)\}\ \forall\varphi$ and its effect on the price index, and household consumption.

If one were to make a perturbation of the objective function, in the shock γ_{ij}, one would find the first and second order effects on welfare to be:

$$\frac{d\mathcal{W}}{d\gamma_{ij}} \propto -\eta$$
$$\frac{d^2\mathcal{W}}{d\gamma_{ij}^2} \propto \frac{\eta}{2}[\eta(1-\vartheta)-\theta]$$

showing a declining and concave welfare effect since $\vartheta > 1$.

Additionally, there are two differences between the Social planner allocation and the competitive equilibrium: First, there is firm' market power, as final good firms are internalizing monopolistic competition and charge markups $\frac{\sigma}{\sigma-1}$ over marginal costs. That affects the firm φ's sourcing decisions, selection into importing as well as the aggregate price. Second, there is market incompleteness as firms' can not hedge against supply chain disruption risk γ_{ij}, and use their sourcing decision to self-insure against those shocks, which also change the choices $\{\mathcal{I}_j(\varphi)\}\forall\varphi$ – as the Social Planner care about the price index and the integral over all firms. Those two inefficiencies interact, changing the thresholds of selection into importing – the extensive margin, which then also affect the total expenditure shares and intensive margin as a consequence of those supply chain disruptions.

$$\mathcal{W} = \max_{\{\mathbb{1}_i(\varphi)\}_\varphi} \int_\gamma \Big(\int_\varphi \varphi^{\sigma-1} \Big(\sum_{i=1}^{n} \mathbb{1}_i(\varphi) T_i (\tau_{ij}\gamma_{ij}\lambda_i)^{-\theta} \Big)^{\frac{\sigma-1}{\theta}} dG(\varphi) \Big)^{-\frac{\eta(1-\vartheta)}{1-\sigma}} d\Psi_{ij} - \int_\varphi \sum_{i=1}^{n} f_{ij}\mathbb{1}_i(\varphi)$$

B Numerical Experiment Appendix

Table 6 presents the parameter values used in our toy model to generate figures that will allow us to understand the mechanisms of our model. The numerical specifications used for our experiments are as follows:

Table 6: Numerical Experiment Values

Variable	Definition	Value
SD(γ)	Standard deviation of shock	0.25
ρ	Substitutability accross intermediates varieties	2.00
I	Number of countries	3.00
$T_D(\tau_D w_D)^{-\theta}$	Domestic sourcing potential	1.00
$T_{F1}(\tau_{F1} w_{F1})^{-\theta}$	Sourcing potential Foreign 1	0.10
$T_{F2}(\tau_{F2} w_{F2})^{-\theta}$	Sourcing potential Foreign 2	0.03
N	Number of domestic firms	150
f_D	Fixed cost of sourcing Domestic	0.00
f_{F_1}	Fixed cost of sourcing Foreign 1	0.22
f_{F_2}	Fixed cost of sourcing Foreign 2	0.12
Calibration for high complementarity $(\sigma-1)/\theta = 1.58$ following Antràs et al. [2017]		
σ	Elasticity of final demand	3.85
θ	Productivity Fréchet distribution shape	1.789

C Data and Estimation

C.1 Sourcing potential

Figure 13: Country Sourcing Potential and Extensive Margin

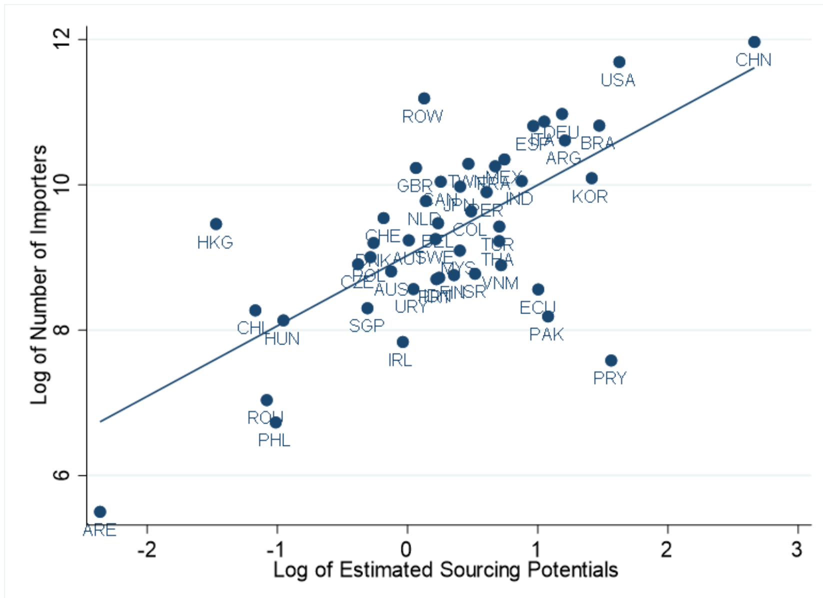
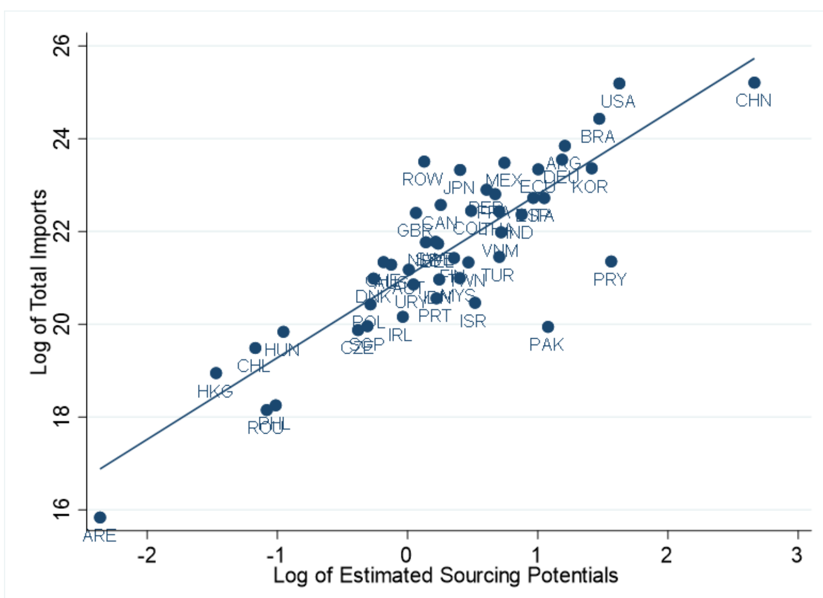
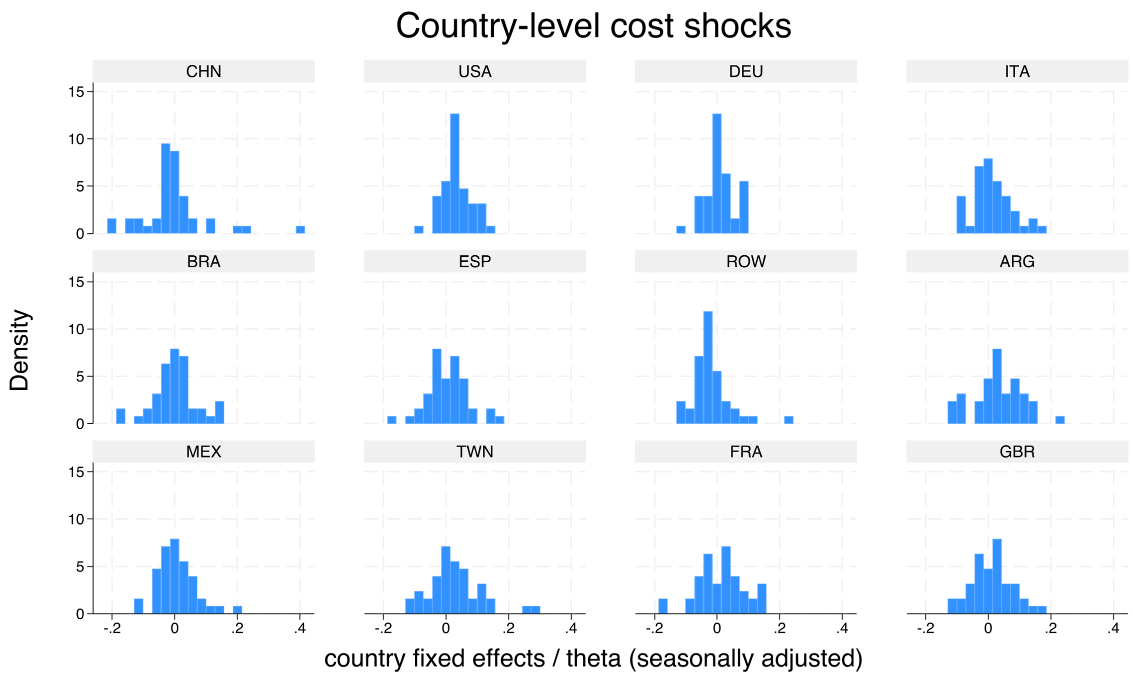


Figure 14: Country Sourcing Potential and Intensive Margin



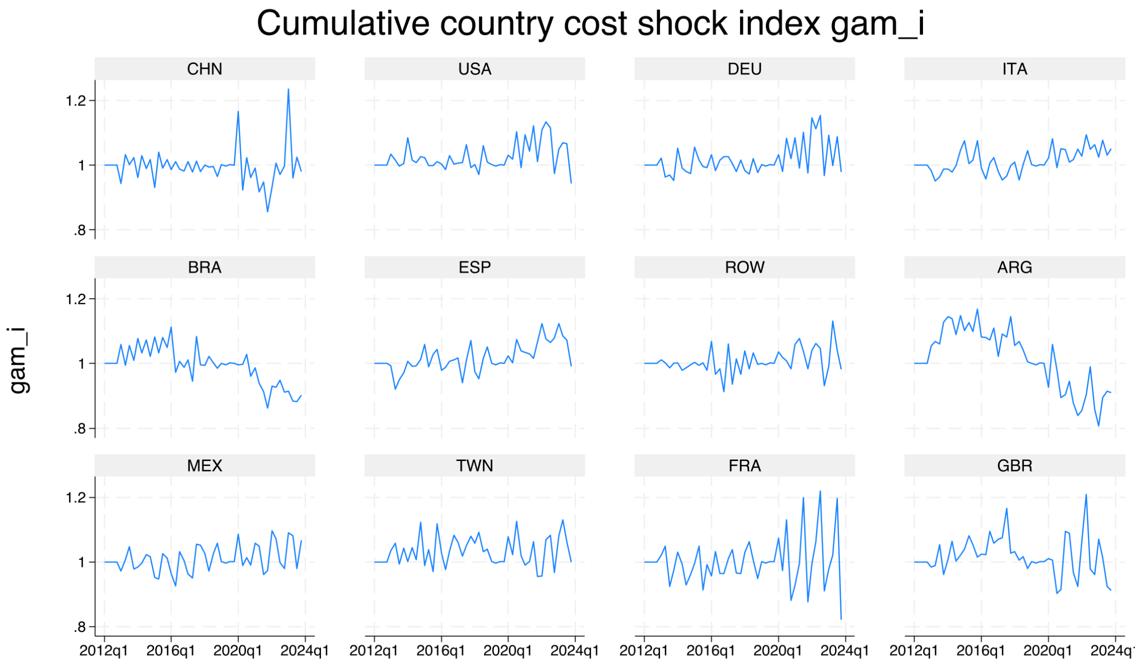
C.2 Trade cost shocks

Figure 15: Distribution of origin-specific shocks



Note: The graph shows the histograms of the log variations in the $\hat{\gamma}_{it}$ component of trade costs for each of the origins considered. CHN = China; USA = United States; DEU = Germany; ITA = Italy; BRA = Brazil; ESP = Spain; ROW = Rest of the World; ARG = Argentina; MEX = Mexico; TWN = Taiwan; FRA = France; GBR = Great Britain.

Figure 16: Evolution of origin-specific shocks



Note: The graph shows the evolution of the $\hat{\gamma}_{it}$ component of trade costs for each of the origins considered. $\hat{\gamma}_{it} = 1$ for all countries at 2012q1. CHN = China; USA = United States; DEU = Germany; ITA = Italy; BRA = Brazil; ESP = Spain; ROW = Rest of the World; ARG = Argentina; MEX = Mexico; TWN = Taiwan; FRA = France; GBR = Great Britain.

C.3 Model's solution algorithm

Given a core productivity φ, a guess $\mathcal{I}$ for the firm n's sourcing strategy, $\mathcal{I}^n$, and distributions of the supply chain shocks, we define the expected marginal benefit of including country i in the sourcing strategy $\mathcal{I}$ as

$$\begin{cases} \varphi^{\sigma-1}\ \eta^{(\sigma-1)/\theta}\ [\mathbb{E}(B_j(\bar{\gamma})\Theta_j(\mathcal{I}\cup\{i\},\bar{\gamma},\tilde{\gamma}(\varphi))) - \mathbb{E}(B_j(\bar{\gamma})\Theta_j(\mathcal{I},\bar{\gamma},\tilde{\gamma}(\varphi)))] - f_{ij}^n, & \text{if } i \notin \mathcal{I} \\ \varphi^{\sigma-1}\ \eta^{(\sigma-1)/\theta}\ [\mathbb{E}(B_j(\bar{\gamma})\Theta_j(\mathcal{I},\bar{\gamma},\tilde{\gamma}(\varphi))) - \mathbb{E}(B_j(\bar{\gamma})\Theta_j(\mathcal{I}\backslash\{j\},\bar{\gamma},\tilde{\gamma}(\varphi)))] - f_{ij}^n, & \text{if } i \in \mathcal{I}\ . \end{cases}$$

As in Proposition 2, we introduce a mapping, $V_i^n(\mathcal{I})$ equal to 1 if the expected marginal benefit is positive and zero if not. We showed that for $(\sigma-1)/\theta > 1$, this is an increasing function of $\mathcal{I}$. When we start from the set that contains no countries, $\underline{\mathcal{I}}$, and iterate the V-operator by adding each country one-by-one to the set it gives us the lower bound of the firm's sourcing strategy. Alternatively, if we start from the set that contains all countries, $\bar{\mathcal{I}}$, and again iterate the V-operator by taking each country one-by-one out of the set, this provides us with the upper bound of the set. If these sets are not exactly the same, then we only need to evaluate the expected profits from all the possibilities in the upper bound set.

However, adding uncertainty to this procedure is computationally intensive. Indeed, computing the model equilibrium at every step of the Simulated Method of Moments requires (i) drawing a large number of I-dimensional shocks $\bar{\gamma}$ and $\tilde{\gamma}(\varphi)$ to compute expectation of sales and profits using Quasi Monte Carlo methods, (ii) simulating a large number of fixed-cost draws f_{ij}^n also using Quasi Monte Carlo methods, (iii) solving the firms' sourcing decisions using combinatorial discrete choice algorithm following Jia [2008], and (iv) solving for the fixed-point equilibrium for $B(\bar{\gamma})$, since the price index aggregates the individual pricing decisions:

$$P_j(\bar{\gamma}) = \left(N_j \int_{\varphi}\int_{\tilde{\gamma}(\varphi)} p_j(\varphi,\bar{\gamma},\tilde{\gamma}(\varphi))^{1-\sigma} d\tilde{\Psi}_j^{\varphi}(\tilde{\gamma})dG(\varphi)\right)^{\frac{1}{1-\sigma}}$$

and finally (v) repeat these four steps for every iteration of the parameters β.

C.4 Model estimation

To estimate the structural model, we adopt distributional assumptions for the model parameters. Following the approach of Antràs et al. [2017] and Melitz and Redding [2015], we assume that the productivity φ follows a Pareto distribution with a shape parameter $\kappa = 4.25$. For the estimation of the remaining parameters $\delta = [E, \beta_{c,f}^n, \beta_{d,f}^n, \beta_{l,f}^n, \beta_{C,f}^n, \beta_{\text{disp},f}^n]$, we simulate a large number of firms. We draw φ from a uniform distribution and invert it to obtain the Pareto distribution given κ. Additionally, we draw aggregate and idiosyncratic shocks from their specified distributions and obtain an I-dimensional vector of fixed costs from a standardized normal distribution. The parameter vector δ is then estimated through a guess-and-verify process, iteratively adjusting the values to match the log-normal firm-origin specific fixed costs obtained from the simulation. Therefore, we consider a continuum of final-good firms, each characterized by different combinations of productivity levels φ^n, fixed costs f_{ij}^n, aggregate and idiosyncratic supply chain shocks $\bar{\gamma}_{ij}, \tilde{\gamma}^n_{ij}$.

We simulate firms to generate four sets of moments that compare with the actual data. These moments are crucial to estimate the structural model's parameters. The four sets of moments are as follows:

i. The first moment is the share of importers for all firms. This is a scalar. We denote the data counterpart as m_1 and simulated moment as $\hat{m}_1(\delta)$.

ii. The second one is the share of importers with firm sales below the median. This is also a scalar, denoted m_2 for the actual data and $\hat{m}_2(\delta)$ for the simulated data.

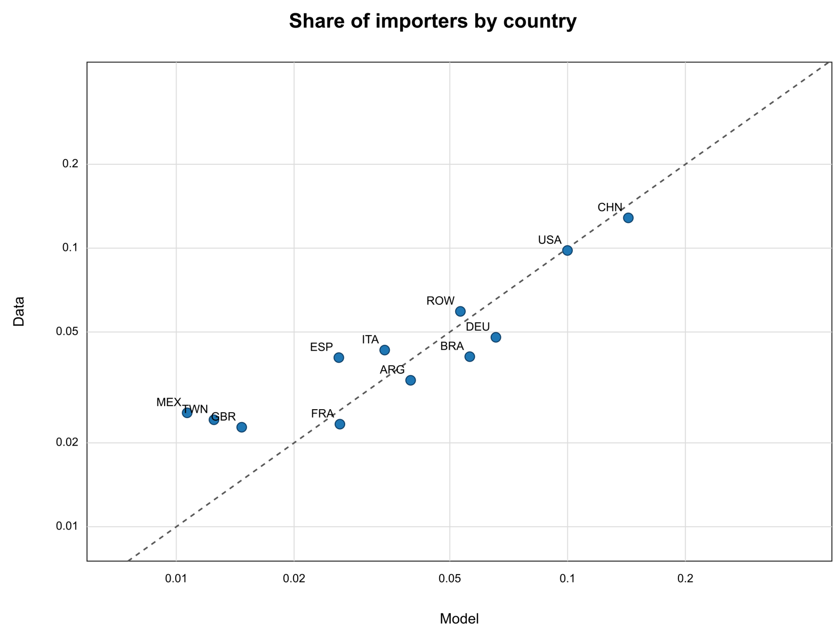
iii. The third set of moments includes the shares of firms that import from each country. This is an $(I-1)$ vector, and the actual data is denoted as m_3 and the simulated data as $\hat{m}_3(\delta)$.

iv. The fourth moment is the share of firms whose input purchases from Chile are less than the median input purchases from Chile in the data, which is a scalar, denoted m_4 in the data and $\hat{m}_4(\delta)$ in the simulated model.

The first three sets of moments inform us about the magnitude of the fixed costs of sourcing, and how they vary with distance, language, and control of corruption. The share of importing firms from the most popular country relative to the total share of importers serves as an indicator of the fixed cost dispersion parameter. In the absence of dispersion in fixed costs across firms, the total share of importers would match the share of importers from the most popular sourcing country. Similarly, the share of importers among firms with sales below the median firm provides insight into the dispersion parameter. The fourth moment helps determine the level of input purchases as it determines the scale parameter E.

C.5 Model fit

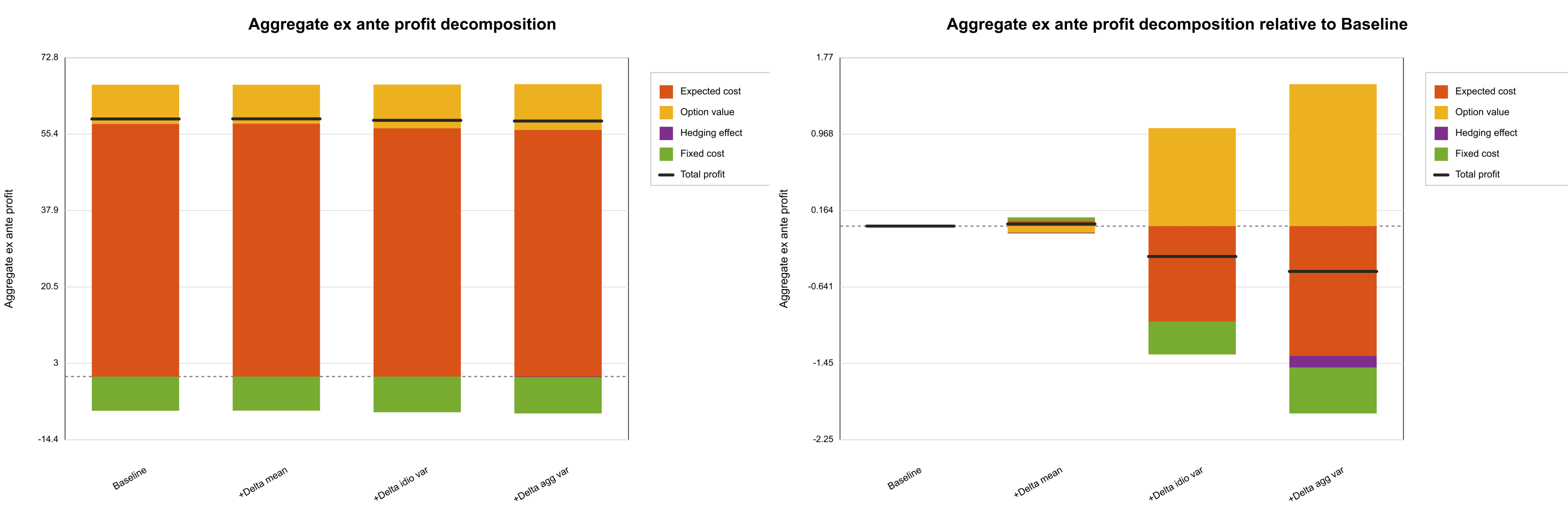
Figure 17: Model fit: share of importers by country



C.6 Counterfactual analysis and decomposition

These figures are graphical representation of the panel B of the table 5

Figure 18: Firms' sourcing strategies and extensive margin



(a) Profit decomposition of 2020-23 Uncertainty

(b) Different relative to baseline 2012-19