Supply Chain Uncertainty and Diversification

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This version: September 25, 2024

Abstract

Supply chain disruptions have become increasingly frequent, generating substantial uncertainty for companies that rely on sourcing inputs for production. We investigate how firms facing supply chain uncertainty adapt their sourcing strategies, by diversifying foreign suppliers, re-shoring, or selecting suppliers based on cost and risk considerations. To answer these questions, we develop a multi-country sourcing model in which firms choose where to import from, accounting for international supply-chain disruptions. Our findings reveal that mean-preserving uncertainty introduces a positive option value associated with diversifying the set of suppliers. However, country-specific aggregate risk also features hedging motives, yielding ambiguous predictions on firms' sourcing decisions. Leveraging firm-level data from Chile, we use this structural model to estimate supply chain risk over time for major trade partners as well as fixed costs of sourcing. We assess the impact of the recent surge in trade risk following the Covid-19 pandemic, and we perform counterfactual exercises to evaluate how this affected firms' sourcing strategies. Our results indicate that the observed change in sourcing patterns correspond more to changes in expected costs rather than solely to increases in risk.

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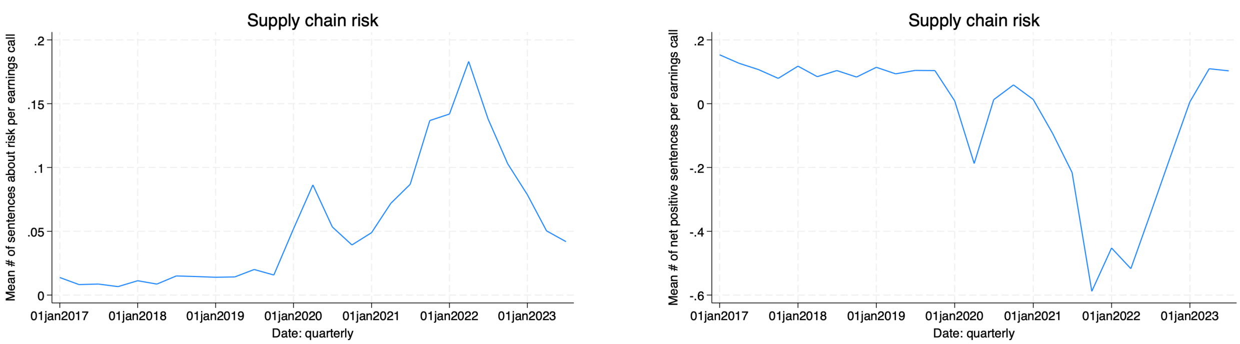
We are extremely grateful to Felix Tintelnot, Rodrigo Adao, and Mike Golosov for their guidance and helpful comments. We would like to thank Sebastián Andalaft, who provided outstanding research assistance. We would also like to thank Milena Almagro, Olivia Bordeu, Agustín Gutierrez, Tom Hierons, Nadia Lucas, Sebastián Poblete, Tanya Rajan, Jordan Rosenthal-Kay, Marcos Sorá, Jeanne Sorin and all the participants at the Macro and Trade Seminar at UChicago, as well as the Central Bank of Chile's internal seminar series, and the 5th Alumni Workshop at Pontifical Catholic University of Chile, for very helpful comments and insights. 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. All errors remain our own.

1 Introduction

Until recently, trade disruptions were relatively infrequent, allowing companies to reduce costs through externalization and just-in-time strategies, without considering the diversification of their suppliers for risk mitigation. Recent events such as Covid-19, the Russia-Ukraine war, as well as rapidly deteriorating climate change, have brought higher uncertainty to supply chains. As stated in Baldwin and Freeman [2021], the Business Continuity Institute (BCI) Supply Chain Resilience Report found that over a 25% of the surveyed firms experienced ten or more disruptions in 2020, while the number in 2019 was under 5%.

The recent adverse supply chain risk have increased delivery times as well as shipping costs. For example, Alessandria et al. [2023] shows 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 line with this, LaBelle and Santacreu [2022] find that exposure to supply chain disruptions through global value chains greatly influenced the transmission of supply chain shocks to U.S. prices. These effects all impacted how firms evaluated their expected profits.

Figure 1: Quarterly average of supply chain risk and supply chain disruption sentiment



(a) Quarterly average of risk

(b) Quarterly average of sentiment

Notes: Own creation using Hassan et al. [2023]'s data where they obtain firms' exposure to the shock by using text-based measures and finding the proportion of firms' earning calls dedicated to the event of interest. Sentiment and risk are, in our case, supply chain disruption's overall perceived impact on the mean and variance of the firm's economic outlook, respectively.

Firms all over the world are evidently concerned about supply chain uncertainty, as illustrated in Figure 1. We observe how "supply-chain risk" appears in the firms' earning calls – associated to deteriorated sentiments in the recent years – using text-based measure from Hassan et al. [2023]. This uncertainty has worsened the expected average economic outlook and increased the predicted variance of their profits. However, there is an ongoing debate regarding the appropriate response of firms to this heightened uncertainty. Some argue in favor of re-shoring operations, while others advocate for diversifying their portfolio of suppliers. This diversification includes both domestic and foreign suppliers, aiming to reduce exposure to the uncertainties of specific countries (Javorcik [2020], Bonadio et al. [2021], IMF [2022]).

Consistent with this perspective, research by Dhyne et al. [2021] and Caselli et al. [2020] suggests that diversifying suppliers can decrease aggregate volatility and enhance resilience against sectoral shocks. The relevance of this theoretical discussion is reflected in actual sourcing decisions, where companies are actively considering the best strategies to manage supply chain risks, as depicted in Figure 1. For instance, a news article from the Financial Times on December 26, 2022, emphasizes this ongoing consideration of supply chain uncertainty by companies.

> *However, carmakers are also aiming to be more rigorous over their choice of suppliers as they* ***focus on the resilience of the supply chain as well as costs****, to make sure it does not break down. "It is no longer an era where cost is the major driving factor," said Masahiro Moro, senior managing executive officer at Mazda. "Right now,* ***robustness*** *of our supply chain* ***also needs to be considered*** *to ensure the stable procurement of parts."*

This implies that managers are not solely focused on cost reduction when making sourcing decisions; they are also prioritizing resilience and robustness. They fully take into consideration supply chain risk in their decision-making process, to ensure the resilience of production and mitigate price swings during disruptions. With that in mind, we are interested in understanding the effect of supply chain uncertainty on firms' sourcing decisions.

In this context, the objective of this paper is to understand the effect of supply chain uncertainty on the sourcing decision of firms. Do firms adapt their sourcing strategy in face of uncertainty, by diversifying their foreign suppliers, engaging in re-shoring, or selecting suppliers based on cost or risk considerations.

To answer these question, we develop a multi-country sourcing model where heterogeneous firms choose where to import from, accounting for international supply-chain disruptions. Risk on trade cost affect both firm-specific relationships and country-wide aggregate shocks from trade partners. Firms decide their sourcing strategy by selecting the set of suppliers and pay a fixed cost of initiating a relationship with an additional country. Given heterogeneity in productivity level, firms form expectations regarding supply-chain risk, and choose where to source to maximize expected profits. Upon the realization of the trade shocks, firms choose intermediate input expenditure from their available set of suppliers.

This model introduces risk in the framework of Antràs et al. [2017], and matches the empirical patterns observed in the literature and in our data. We focus on trade in intermediate goods as it constitutes a large portion of global trade flows, approximately two-thirds of trade volumes (Feenstra [1998], Hummels et al. [2001], Johnson and Noguera [2017]). Given the contemporary relevance of vertical specialization across countries (Hummels et al. [2001], Hanson et al. [2005]), understanding how firms navigate sourcing decisions amid supply chain uncertainty becomes crucial. For the case of the US, Antràs et al. [2017], and Bernard et al. [2007] find that importers are larger and more productive than non-importers, which implies heterogeneity on the firm's productivity. Antràs et al. [2017] find that firm size increases in the number of countries they import from, giving rise to country level fixed costs. However, Alessandria et al. [2023] and LaBelle and Santacreu [2022] find that supply chain disruptions increases final good prices and inflation. This implies that supply chain uncertainty has adverse consequences on consumers.

Using our model, we dissect the impacts of the decrease in marginal cost, supply chain shocks, market demand, and fixed costs on the expected profit of final good firms. Theoretical analysis reveals that uncertainty influences firms' profits and sourcing decisions through three margins: (i) sourcing potential, (ii) sourcing capability, and (iii) market demand. When decomposing firms' expected profits, we find five different effects: (i) the sourcing capability for expected shock, which is the term that increases when adding countries to the sourcing strategy through adding an extra cost draw which increases competition and lowers the overall cost. (ii) Risk effect on capability, which is an option value since firms gain from adding riskier countries by being able to sell cheap if countries in their sourcing strategy are hit with a positive shock. (iii) The covariance between sourcing capability and market demand, which is the effect of hedging by adding countries that negatively covaries with the countries that most firms add to their sourcing strategies. (iv) The market demand term, which is affected by the prices of all firms and only by aggregate, and not idiosyncratic, uncertainty. And (v) the fixed cost of sourcing, which negatively affects expected profits disincentivizing firms from adding all countries to their sourcing strategies. We then utilize a numerical example to elucidate how these terms influence expected profits and we find that the predominant driver of firms' ex-ante sourcing decisions is the sourcing capability for expected shocks term, while the risk effect on capability is positive but small and the covariance effect is negative but smaller. This suggests that the impact of uncertainty on firms' ex-ante sourcing decisions is marginal compared to the effect of decrease in expected marginal cost from adding more countries.

Finally, we explore these dynamics for Chile, aligning our model with empirical observations. We will estimate this model using quarterly data at the firm-level from the Chilean customs and IRS obtained through the Central Bank of Chile. We have data from the first quarter of 2012 to the fourth quarter of 2023, which we leverage to obtain the distribution of the shocks. For the estimation of the structural model, we measure the fixed cost of sourcing from each country, using the average sales and expenditure from 2012q1 to 2019q4. We do this to retrieve the firm-level fixed cost of sourcing, avoiding the period 2020q1-2023q4, since there is high supply chain uncertainty due to Covid-19 and wars. Because sourcing decisions interact between countries, the dimensionality of our problem is very high, however, assuming complementarity on these decisions, we leverage Jia [2008]'s algorithm to reduce the complexity of our problem. Finally, we perform a counterfactual analysis in which we compare the extensive and intensive margins for the cases of the average uncertainty from 2012q1-2019q4 to 2020q1-2023q4. We find an increase in the number of firms that import from countries whose uncertainty increased, and a decrease for those whose uncertainty decreased. The same occurs with the intensive margin, finding a positive correlation between the amount imported from countries and their supply chain uncertainty. From this, we learn that in our model, the option value effect is higher than the covariance effect, which implies that firms' want higher risk for the possibility of a positive shock.

Related literature

Our paper contributes to five literatures. We contribute to the literature on firms' sourcing decisions. Antràs et al. [2017] write a multi-country sourcing model with firm and fixed cost heterogeneity that accounts for the fact that more productive firms are heavier importers than less productive firms. They follow both Melitz [2003] and Eaton and Kortum [2002] and find that, under certain conditions, the interdependencies in the decision of firms on who to source from are very relevant. Blaum et al. [2018] also write a multi-country sourcing model to understand the aggregate effect of input trade when firms are heterogeneous. Using French data, they find that trade of inputs decreased manufacturing prices by around 27%. Antràs and Helpman [2004] write a model in which firms have to decide weather to produce intermediate goods or to import them, and from where. They then add contractual frictions in Antràs and Helpman [2006]. Finally, Bernard and Moxnes [2018] reviews the literature on networks in trade. The closest work to ours is Antràs et al. [2017], however, we contribute by adding both aggregate and idiosyncratic supply chain uncertainty to an international sourcing model. We are able to understand how this new channel affects both the decisions of who to source from (extensive margin) as well as how much to source from each of the importers they initiated a relationship with (intensive margin). To the best of our knowledge we are the first ones to add supply chain uncertainty to a sourcing model and calibrate it. We also contribute by calibrating our model for a small open economy, like Chile, which might provide a new insight as well as by recovering the moments of the supply chain uncertainty during the period 2012-2023.

Our work is also related to the theoretical literature on supply chain uncertainty and sourcing decisions. Grossman et al. [2023a] study's the effect of supply chain disruption uncertainty in the sourcing decision of firms. The authors focus on the efficiency of sourcing decisions for different utility functions when there are variable markups. They find that for the CES case, the government should subsidize diversification. Grossman et al. [2023b] writes a model for supply chain uncertainty resilience with vertical production tiers and study the first- and second-best policies. Gervais [2018] writes a theoretical model in which there is supply chain uncertainty and managers are risk-averse use diversification of suppliers to make their profits less variable. He finds that, in this case, firms tend to import from suppliers with less variance. Gervais [2021] writes a theoretical model to study if risk diversification can be motive enough by itself to produce multi-country sourcing when firms are risk averse. Our work expands on the previous papers by having a multi-country model that allows for a non-linear production function, sourcing interdependencies, and to separate effect of cost and aggregate and idiosyncratic uncertainty. We also have a model that can speak to features of the data, like the fact that most productive firms are the ones that import and they import from more countries, which is relevant to understand how different types of firms would react to uncertainty and how that would affect the aggregate economy. This will allow us to understand how much of the sourcing decision is being driven by the effect of uncertainty and how much comes from cost reduction and degree of complementarity between sourcing decisions as well as evaluate counterfactual scenarios.

Another literature we relate to is the literature on tariff policy uncertainty. Handley et al. [2020] write a sourcing model in which there is policy uncertainty. Firms have to decide who to buy from considering the expected marginal cost and the sunk cost they have to pay. They are able to separate between a substitution and complementarity effect between inputs and find that the accession of China to the WTO, which reduces tariff uncertainty, increased firms' imports. Handley and Limão [2017] also study the effects of reduced policy uncertainty from the accession of China to the WTO on trade, prices, and real income. Charoenwong et al. [2023] study the relationship between trade and foreign economic policy uncertainty and the supply chain networks of American firms, and find that firms that require more specific inputs, produce more differentiated products, have higher market shares, or those located in a more central position in the production network are more sensitive to policy uncertainty. Our model is very similar in spirit to Handley et al. [2020], since they add uncertainty to a multi-country sourcing model, but our shocks are supply chain shocks and we have a static model, whereas they have a dynamic one. We contribute to this literature by having a general framework for policy, supply-chain risk, and trade shocks.

We also contribute to the literature on trade disruption shocks. A way firms can deal with the uncertainty in supply chains is by holding inventories, as stated by Alessandria et al. [2023], Carreras-Valle [2021], firms have a trade-off between importing from the cheapest foreign supplier and uncertainty in the delivery time in a world with an idiosyncratic demand risk. Carreras-Valle [2021] finds that the decrease in delivery times explains more than half of the decline in inventory holding in the US. Novy and Taylor [2020] write a trade model with uncertainty in the supply chain and inventories which they take to the data and find that when there are uncertainty on supply chains, firms usually stop supplying from foreign countries because of the high fixed cost. Our work contributes to this literature by adding supply chain risk to a sourcing model that explains importing patterns and understand how uncertainty affects this. Another way to deal with uncertainty in supply and demand is by having a diversified set of suppliers. In this paper we focus on this counterpart of risk management, i.e., supply chain restructuring and we contribute by analyzing uncertainty and firm's sourcing choice using a structural model. In reality, we expect both options to be working along side, but we abstract from the inventory holding decision to focus on the specific effect of uncertainty in sourcing decisions.

Empirically, there seems to be contradictory evidence on the relationship between sourcing and uncertainty. Lafrogne-Joussier et al. [2022], study how firms in GVC react to input shortages and find that diversification doesn't help mitigate the effect of shocks since it seems like firms were willing to pay the sunk cost to import from other countries. LaBelle et al. [2021] investigate the role of global value chains in the declines of manufacturing employment and output in the U.S. during COVID-19 and find a modest impact of diversifying or re-nationalizing GVCs in mitigating the economy's exposure to foreign shocks, and Khanna et al. [2022] characterize what features make supply chains more resilient. D'Aguanno et al. [2021] find that re-shoring increases aggregate volatility, while diversifying can lower it by decreasing the exposure to a single country. Chung [2017] finds multi-sourcing seems to be more likely when the biggest supplier is more risky. Finally, Ersahin et al. [2023] use textual analysis of earnings conference calls to proxy for supply chain risk and find that firms that experience an increase in supply chain risk increase investment and establish relationships with closer and domestic suppliers and with suppliers that are industry leaders. Our paper contributes to this strand of the literature by providing a multi-country allows us to quantify how much of the sourcing decision comes from uncertainty because of supply chain disruptions.

The remainder of our paper is organized as follows. In Section 2 we present our trade model with exogenous supply chain disruptions and the main mechanisms for the competitive equilibrium. Then, in Section 3 we solve for the equilibrium. In section 4 we introduce our data and provide descriptive evidence. In Section 5 we estimate our structural model. In Section 6 we perform our counterfactual analysis. Finally, in Section 7 we conclude.

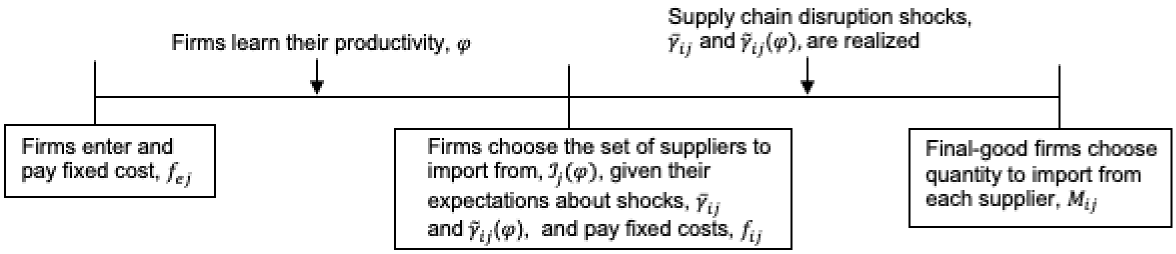
2 Model

In this segment, we construct a quantifiable multi-country sourcing model rooted in the framework proposed by Antràs et al. [2017]. The model incorporates supply chain uncertainty, which directly impacts the pricing for intermediate inputs acquired by final-good firms. The decision-making process for firms involves a decision to enter and pay the fixed cost of entry, without prior knowledge of their productivity levels. Once their productivity is realized, they decide to produce and choose the set of suppliers to source from by drawing expectations on the supply chain shocks and pay the relationship-specific fixed costs. Following the revelation of supply chain shock realizations, firms can adjust and make informed decisions regarding the quantity of imports they want from each available supplier they previously started a relationship with.

2.1 Setup

The world consists of I countries, with $i = 1, \dots, I$ denoting the origin country and $j = 1, \dots, I$ representing the destination country. Our proposed static model delineates a three-stage decision-making process for final-good firms. As illustrated in Figure 2, firms in country j commit to paying the fixed entry cost, f_{ej} and enter the market prior to know their productivity, denoted by φ. Following entry, firms learn their productivity, and draw expectations for both aggregate ($\bar{\gamma}_{ij}$) and idiosyncratic ($\tilde{\gamma}_{ij}(\varphi)$) supply chain shocks. Incorporating these expectations, firms select a set of suppliers, $\mathcal{I}_j(\varphi)$, and incur relationship-specific fixed costs, f_{ij}, for each country they decide to start a relationship with. Subsequently, the shocks $\bar{\gamma}_{ij}$ and $\tilde{\gamma}_{ij}(\varphi)$ are realized, but the ex-ante sourcing strategy dictates that firms cannot source from countries with which they lack established relationships. However, ex-post, firms retain the flexibility to determine the quantity of imports they want to get from each previously established supplier.

Figure 2: Timeline



2.2 Preferences

In each destination country j, there are L_j homogeneous individuals who value consumption of our designated sector of interest. This sector, as explored in our empirical analysis, encompasses a synthesis of mining, manufacturing, and business activities. Additionally, individuals also derive utility from goods originating in an outside sector in a Cobb-Douglas manner, given by

$$U_j(C_{oj}, C_{sj}) = C_{oj}^{1-\alpha} C_{sj}^{\alpha} \tag{1}$$

with C_{oj} denoting the consumption of the outside sector and C_{sj} the consumption of the sector of interest. This expenditure allocation is characterized by a parameter α, signifying the proportion of income dedicated to the consumption of goods from the sector of interest, while $1-\alpha$ corresponds to the spending on goods from the outside sector. Notably, within the sector of interest, individuals place value on the consumption of differentiated varieties, denoted as ω, with a constant elasticity of substitution. The elasticity of substitution for these varieties is characterized by $\sigma > 1$.

$$C_{sj} = \left(\int_{\omega \in \Omega_j} y_j(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}} \tag{2}$$

with Ω_j representing the set encompassing all available varieties accessible to individuals within country $j \in I$ under the prevailing state of the world. From these preferences, which we assume homogeneous for all individuals around the world, the resulting demand function for the variety ω in country j is as follows:

$$y_j(\omega, \bar{\gamma}, \tilde{\gamma}(\varphi)) = C_{sj} \left(\frac{p_j(\omega, \bar{\gamma}, \tilde{\gamma}(\varphi))}{P_j(\bar{\gamma})} \right)^{-\sigma} = E_j P_j(\bar{\gamma})^{\sigma-1} p_j(\omega, \bar{\gamma}, \tilde{\gamma}(\varphi))^{-\sigma} \tag{3}$$

where $p_j(\omega, \bar{\gamma}, \tilde{\gamma}(\varphi))$ is the price of variety ω in country j, for given aggregate and idiosyncratic shocks, $\bar{\gamma}$, and $\tilde{\gamma}(\varphi)$, respectively, E_j is the total expenditure in our sector of interest in country j, which we will take as fixed, and $P_j(\bar{\gamma})$ is the ideal price index, given. To simplify the notation from now on, we will define a market size term for country j as

$$B_j(\bar{\gamma}) \equiv \frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} E_j P_j(\bar{\gamma})^{\sigma-1} \tag{4}$$

where everything is independent of idiosyncratic shocks but the price index is dependent on aggregate shocks. The outside sector in this economy, denoted C_{oj}, which serves as a numeraire in our model, is homogeneous and freely tradable and big enough to pin down wages, w_j, in the economy in terms of the outside sector's output. This establishes the price of labor, the exclusive factor of production in our capital-free economy. Aggregate income in country j is expressed as $Y_j = w_j L_j$. Finally, equilibrium only necessitates the determination of the aggregate price index, $P_j(\bar{\gamma})$.

2.3 Technology and Market Structure

There exists a measure N_j of final-good firms in each country $j \in I$, owned by risk-neutral managers. Ex-post profits are entirely redistributed to these global managers that are outside our economy. Each of these firms specializes in producing a uniquely differentiated variety, since they each own a unique blueprint. There is free entry in the market and, to produce their specific variety, final-good firms use a unit measure of intermediate goods, and operate in a monopolistically competitive environment.

Drawing from the framework established by Melitz [2003], final-good firms face a sequential decision-making process. Initially, they decide to enter and pay the fixed cost of entry, f_{ej}, in units of labor specific to country j, before knowing the realization of their productivity, φ. Subsequently, after paying the fixed cost of entry and having learned their productivity, firms, indexed by their productivity level φ, decide to engage in production.

Firms anticipate the realization of supply chain shocks, shaping their decisions regarding their sourcing strategy, which is made before the realization of the shocks. The set of countries firms choose to start an importing relationship with is denoted as $\mathcal{I}_j(\varphi)$. Firms select this set of countries by maximizing their expected profits, and paying the fixed cost for each established sourcing relationship, f_{ij}, also in units of labor specific to country j.

Upon the realization of shocks, both aggregate ($\bar{\gamma}_{ij}$) and idiosyncratic ($\tilde{\gamma}_{ij}(\varphi)$), final-good firms must determine the quantity to procure from each supplier with whom a relationship has been initiated, denoted as $M_{ij}(\varphi, \gamma)$. The productivity parameter φ, which associates a final-good with a specific bundle of inputs, is drawn from a country-specific distribution $g_j(\varphi)$ characterized by a support in $[\underline{\varphi}_j, \infty)$, and an associated continuous cumulative distribution $G_j(\varphi)$. The supply chain disruptions are captured by $\gamma_{ij}(\varphi) = \bar{\gamma}_{ij} \times \tilde{\gamma}_{ij}(\varphi)$, where $\bar{\gamma}_{ij}$ represents common relationship-specific aggregate shocks, and $\tilde{\gamma}_{ij}(\varphi)$ accounts for firm-relationship-specific idiosyncratic shocks. We have that $\bar{\gamma}_{ij} \sim_{\text{iid}} \Psi_{ij}(\bar{\gamma})$, and $\tilde{\gamma}_{ij}(\varphi) \sim_{\text{iid}} \Psi^{\varphi}_{ij}(\tilde{\gamma})$, and idiosyncratic and aggregate shock are uncorrelated. Examples of these shocks can be found in cases like a national level quarantine, a war, a natural disaster, the Evergreen boat stuck in the Suez canal, a problem with output specificity, or weather problems. We interpret these as shocks to the iceberg cost because these events will affect the price a country has to pay to import intermediates from the affected country. We will take this shock to be mean-preserving and change the variance as to evaluate the effect of the uncertainty even though, as seen in Figure 1b, uncertainty is expected to affect both the mean and the variance.

Our model posits that final-good firms procure a unit measure of firm-specific intermediate inputs, characterized by imperfect substitutability within a firm and perfect substitutability across different firms, irrespective of their country of origin. The degree of substitution is captured by a constant elasticity parameter denoted as ρ. Notably, the specific value of the elasticity of substitution between intermediate inputs does not drive the results in our model, as it leverages a within-firm framework inspired by Eaton and Kortum [2002], similar to the approach taken by Antràs et al. [2017].

Intermediate-good firms in our model operate under a constant-returns-to-scale technology for the production of their varieties, utilizing labor as the primary input. The unit labor requirement associated with the production of firm φ's intermediate input $\nu \in [0,1]$ in country $i \in I$ is denoted as $a_i(\nu, \varphi)$, where the specificity of the firm is accounted for to avoid including innocuous fixed costs. There is perfect competition on the intermediate-good market, so intermediate-good firms sell at marginal cost. Then, in our world, the price at which final-good firms procure intermediate goods from country i encompasses the iceberg trade cost of shipping from country i to country j, τ_{ij}, as well as the potential different cost in case of supply chain shocks, $\bar{\gamma}_{ij} \times \tilde{\gamma}_{ij}(\varphi)$, as well as the cost of labor. Then, the cost of an input is given by $\tau_{ij}\bar{\gamma}_{ij}\tilde{\gamma}_{ij}(\varphi)a_i(\nu, \varphi)w_i$. This implies that the price paid by firm φ in country j for its input ν is given by:

$$s_i(\nu, \varphi, \gamma(\varphi); \mathcal{I}_j(\varphi)) = \arg \min_{i \in \mathcal{I}_j(\varphi)} \left\{ w_i a_i(\nu, \varphi) \tau_{ij} \bar{\gamma}_{ij} \tilde{\gamma}_{ij}(\varphi) \right\} \tag{5}$$

As the production of a final-good variety by final-good firms entails utilizing a unit measure of inputs, the marginal cost for firm φ situated in country j can be expressed as:

$$c_j(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi)) = \frac{1}{\varphi} \left(\int_0^1 s_i(\nu, \varphi, \bar{\gamma}, \tilde{\gamma}(\varphi); \mathcal{I}_j(\varphi))^{1-\rho} d\nu \right)^{1/(1-\rho)} \tag{6}$$

Following Antràs et al. [2017] and Eaton and Kortum [2002], we will allow the productivity parameter, $1/a_i(\nu, \varphi)$ to follow a Fréchet distribution, such that:

$$\mathbb{P}(a_i(\nu, \varphi) \geq a) = e^{-T_i a^\theta}, \text{ with } T_i > 0 \tag{7}$$

where T_i is the state of technology in country i, so better technology implies more productivity, while θ determines the variability of productivity draws across inputs. A low θ implies more comparative advantage within intermediates across countries.

2.4 Discussion of assumptions

Before closing down the model and finding the equilibrium, we discuss the reason behind several model assumptions, and how relevant they are to our results. First, in defining the timing of our model, we specify that firms determine their sourcing decisions before the occurrence of supply chain disruptions. Subsequently, once the shocks materialize, firms possess the flexibility to adjust through their intensive margin, dictating the quantity sourced from each pre-established supplier. We justify this timing assumption for several reasons. The first reason is our reliance on ex-post data; we typically observe the actual purchase made by firms after the realization of the state of the world, rather than having access to data on potential sourcing decisions for every conceivable state. The second reason is that this assumption serves as a simplifying heuristic, streamlining the analysis and enabling a focused examination of the distinct impacts of uncertainty on the sourcing decision, or extensive margin, apart from its influence on the intensive margin. This division facilitates a more nuanced understanding of the specific dynamics at play and contributes to the clarity of our analytical framework. This assumption is relevant in explaining why the effect of uncertainty is not as strong for ex-ante sourcing strategies, and why firms can risk sourcing from countries with high uncertainty. We will discuss this in more detail later in the paper.

The second assumption is about the ownership structure of final-good firms, which are owned by risk-neutral managers. Ex-post profits are entirely redistributed to these global managers outside our small open economy. To assess the sensitivity of our results to this assumption, in our numerical experiment appendix we introduce an alternative scenario where firms take households' preferences into account through the inclusion of a stochastic discount factor (SDF) in the profit function. Relying on finance and option pricing theory, changing the SDF is analogous to a change in the probability distribution of the shock, implying a larger weight on high-marginal utility events. From this, we find that our risk-neutral managers' assumption is not crucial for our results. Alternatively, the firm could be owned by risk-averse managers, like in Gervais [2021] and Gervais [2018]. While these alternative approaches in ownership and decision-making frameworks offer valuable insights, our focus remains on the trade literature's prevailing models concerning sourcing decisions. Our choice to maintain risk-neutral firms aligns with the majority of literature in this domain. By adhering to this standard, we aim to isolate and comprehend the distinct impact of uncertainty on firms' sourcing decisions within well-established frameworks. Comparisons with other motives for trade, such as comparative advantage, could be explored in future extensions to enrich the understanding of risk-neutral firms' importing decisions in the presence of uncertainty.

The third assumption in our modeling framework pertains to the specification of final-good firms' production functions as constant-elasticity-of-substitution (CES) across input varieties. Moreover, following Eaton and Kortum [2002], we use a Fréchet distribution for each intermediate-variety firms' productivities. Because of extreme values, there always exists a set of variety for which each country serves as the most cost-effective producer, exporting to the rest of the world. Notably, our assumption implies that the elasticity of substitution between inputs, ρ, does not influence the sourcing strategy decision across countries. As we previously discussed, this could potentially be an important assumption because Boehm et al. [2019] find that the elasticity of substitution between domestic factors and imported intermediates is close to zero, which means that the production function should be modeled closer to a Leontief production function. Despite this potential sensitivity, we adhere to the standard assumption in the trade literature, allowing for tractability in our analytical approach. Although it would be an interesting avenue to explore the impact of relaxing this assumption and setting the elasticity close to Leontief, we investigate how much this influences our results but going beyond that lies outside the scope of our current study. Our modeling framework remains aligned with Eaton and Kortum [2002] and Antràs et al. [2017] to facilitate a more direct comparison and integration into the existing literature.

The fourth assumption in our model involves the allocation of risk, designating final-good firms as the entities bearing all the risk. This decision arises from the consideration that intermediate-good firms operate in a perfectly competitive environment, selling their products at marginal cost. Consequently, any increase in prices is absorbed by final-good firms. This simplifying assumption is adopted to streamline the focus on the decision-making processes of final-good firms. This assumption is inherited from Antràs et al. [2017], where final-good firms operate in monopolistic competition while intermediate-good firms are perfectly competitive. We follow this assumption for the sake of analytical tractability and practical considerations, since this would introduce extra complexities into our structural estimation process.

Our fifth assumption involves the separation of supply chain shocks from iceberg costs. This decision is made primarily for exposition purposes, allowing for a more targeted examination of the specific effects of uncertainty and to be able to separately estimate them in our structural analysis. Alternatively, it could be conceivable to model iceberg costs as stochastic, which would be equivalent from a modeling perspective. Nonetheless, we wanted to be able to separate them to understand the specific effects of uncertainty on top of the usual iceberg cost motive. This assumption does not affect our results in any relevant manner.

Finally, we carry some of the same assumptions as Antràs et al. [2017], which are the fact that (i) labor requirements are specific to the final-good firm, introducing a motive for the existence of non-trivial fixed costs. However, the model remains unchanged if labor requirements are not firm-specific. (ii) Final goods are deemed too costly to be traded internationally. Consequently, individuals exclusively procure final goods from their own country, denoted as j. We assume this because it underscores the localized nature of the final goods market and allows us to focus on the intermediate-goods' imports, which accounts for 2/3 of international trade. (iii) Different market structures are used between intermediate and final good firms, where intermediate firms have perfect competition and final good firms monopolistic competition. We do this so that firms can cover the fixed cost of entry and of starting a relationship and to focus on the final-good firms. (iv) All final good producers combine a measure one of inputs in production, simplifying the structural estimation process. Finally, (v) wages are pinned down by this big outside sector, which provides tractability.

3 Sourcing Strategy and Equilibrium

The equilibrium of the competitive model is derived through a sequential backward induction process. First, we assume firms in country j already payed all the fixed costs, f_{ej} and f_{ij}, associated with a predetermined sourcing strategy, $\mathcal{I}_j(\varphi)$. With knowledge of the realization of φ, $\bar{\gamma}_{ij}$, and $\tilde{\gamma}_{ij}(\varphi)$, firms have to choose the optimal share of intermediate inputs to buy from their available sources. Second, we assume that firms have not yet payed the country-specific fixed cost of sourcing, f_{ij}, do not know the realization of the supply chain shocks, $\bar{\gamma}_{ij}$ and $\tilde{\gamma}_{ij}(\varphi)$, yet and have to form expectations about these shocks to choose their sourcing strategy, $\mathcal{I}_j(\varphi)$. Finally, after firms have solved for both the share of intermediate input purchase and their sourcing strategy, we aggregate and use the free-entry condition and the outside sector which pins down wages to solve for the number of firms that enter in equilibrium. From now on, we will denote firms in country j by their distinct productivity level, φ.

3.1 Final-Good Firm Behavior Conditional on Sourcing Strategy, $\mathcal{I}_j(\varphi)$

Consider a firm φ in country j that has already incurred the fixed cost of entry, f_{ej}, and all the country-specific fixed cost of sourcing, f_{ij}, associated with a given sourcing strategy, $\mathcal{I}_j(\varphi)$. Each firm wants to minimize the cost at which they get their intermediate goods for each specific variety, ν. As previously stated, final-good firms make decisions regarding the country from which to source each variety, by minimizing $w_i a_i(\nu,\varphi)\tau_{ij}\bar{\gamma}_{ij}\tilde{\gamma}_{ij}(\varphi)$ for each $i \in \mathcal{I}_j(\varphi)$. Now, leveraging the properties of the Fréchet distribution, we proceed to derive the expression for the share of intermediate input purchases by firm φ in country j from country i. We get

$$\mathcal{X}_{ij}(\varphi,\gamma) = \frac{T_i(\tau_{ij}\bar{\gamma}_{ij}\tilde{\gamma}_{ij}(\varphi)w_i)^{-\theta}}{\Theta_j(\varphi,\gamma)} \text{ if } i \in \mathcal{I}_j(\varphi) \tag{8}$$

and $\mathcal{X}_{ij}(\varphi,\gamma) = 0$ otherwise, where

$$\Theta_j(\varphi,\gamma) \equiv \sum_{k\in\mathcal{I}_j(\varphi)} T_k(\tau_{kj}\bar{\gamma}_{kj}\tilde{\gamma}_{kj}(\varphi)w_k)^{-\theta} \tag{9}$$

From the use of the Fréchet distribution, we get that firms always buy a positive amount of input from each country in their sourcing strategy set. Following Antràs et al. [2017], we will denote $\Theta_j(\varphi,\gamma) \equiv \sum_{k\in\mathcal{I}_j(\varphi)} T_k(\tau_{kj}\bar{\gamma}_{ij}\tilde{\gamma}_{kj}(\varphi)w_k)^{-\theta}$ as the *sourcing capability* of firm φ in country j and $T_i \times (\tau_{ij}\bar{\gamma}_{ij}\tilde{\gamma}_{ij}(\varphi)w_i)^{-\theta}$ as the *sourcing potential* of country i from the point of view of firm φ in country j. The sourcing potential of country i from the point of view of firms in country j is increasing in the technology parameter and decreasing in iceberg costs, supply chain shocks and wages. This is country i's contribution to the sourcing capability of firm φ in country j. Then, the sourcing capability of firm φ in country j also depends on these parameters, extending beyond a single country i to encompass all countries within firm φ's sourcing strategy. We will call this *ex-post* Eaton and Kortum, within the firm.

Once firm φ in country j chooses their least costly supplier for each variety ν, as obtained in Eaton and Kortum [2002], the overall marginal cost faced by firm φ from j can be written as

$$c_j(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi)) = \frac{1}{\varphi} \left(\eta \Theta_j(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi))\right)^{-1/\theta} \tag{10}$$

with $\eta = \left[\Gamma\left(\frac{\theta+1-\rho}{\theta}\right)\right]^{\frac{\theta}{1-\rho}}$ and Γ the Gamma function. From equation (10) we learn that the overall marginal cost faced by the firm is positively affected by both aggregate and idiosyncratic supply chain shocks, which means that a shock higher than 1 increases costs, while a shock lower than 1 decreases them. To ensure that this is 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

$$p_j(\varphi, \bar{\gamma}, \tilde{\gamma}) = \left(\frac{\sigma}{\sigma - 1}\right) c_j(\varphi, \bar{\gamma}, \tilde{\gamma}) \tag{11}$$

Analyzing the overall marginal cost for firm φ in country j, we observe that having a higher sourcing capability reduces the overall cost of intermediate inputs for the firm. Then, 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 context of uncertainty, it also gives the firm a chance to draw on an extra marginal cost of a country that was positively affected by supply chain uncertainty. Examining a fixed sourcing strategy reveals that negative (positive) supply chain shocks will increase (decrease) the overall marginal cost, and hence increase (decrease) final-good prices if the shocked countries are part of the firm's sourcing strategy.

Then, the ex-post profits of firm φ in country j given the sourcing strategy $\mathcal{I}_j(\varphi)$ can be written as

$$\pi(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi)) = \varphi^{\sigma-1} \left(\eta \Theta_j(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi))\right)^{\frac{\sigma-1}{\theta}} B_j(\bar{\gamma}) - w_j \sum_{i \in \mathcal{I}_j(\varphi)} f_{ij} \tag{12}$$

From this equation we learn that, for a fixed market demand, $B_j(\bar{\gamma})$, there is a trade-off between including a country in the sourcing set, thus increasing the sourcing capability, and paying the fixed cost of starting the relationship with that country. For the ex-post profits 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 extra trade-off between adding more countries to be less influenced by particular shocks and paying the fixed cost of sourcing. For a non-fixed market demand term, there is also an equilibrium effect of aggregate shocks on the price index, which directly impacts the market demand term. However, idiosyncratic shocks are washed away and do not affect the price index. Since this equation is ex-post, only actual shocks affect it, and not uncertainty, which affects ex-ante profits.

3.2 Choice of Optimal Sourcing Strategy, $\mathcal{I}_j(\varphi)$

We now assume that firms do not know the realization of the supply chain shocks. Then, firm φ in country j forms expectations of the supply chain shocks and chooses the optimal sourcing strategy, $\mathcal{I}_j(\varphi) \subseteq I$, that maximizes their ex-ante profits. With $\mathbb{1}_{ij}$ an indicator function that takes the value 1 if country i is included in the sourcing strategy of firm φ in country j and 0 if not, we can write the ex-ante problem of the firm as

$$\max_{\mathbb{1}_{ij}\in\{0,1\}_{i=1}^{I}} \mathbb{E}(\pi_j(\varphi,\bar{\gamma},\tilde{\gamma}(\varphi))) = \mathbb{E}\left(\varphi^{\sigma-1}\underbrace{\left(\eta\sum_{i=1}^{I}\mathbb{1}_{ij}T_i\big(\tau_{ij}\bar{\gamma}_{ij}\tilde{\gamma}_{ij}(\varphi)w_i\big)^{-\theta}\right)}_{\equiv\Theta_j(\varphi,\bar{\gamma},\tilde{\gamma}(\varphi))}{}^{\frac{\sigma-1}{\theta}}B_j(\bar{\gamma})\right) - w_j\sum_{i=1}^{I}\mathbb{1}_{ij}f_{ij} \tag{13}$$

From the above equation we observe that, given the market demand term $B_j(\bar{\gamma})$, 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 because of the country-specific fixed cost of starting a relationship, $w_j f_{ij}$. The effect of shocks on profits is twofold for the aggregate case; supply chain uncertainty affects both the sourcing capability of firms as well as the market demand in country j. To see the effect of aggregate supply chain disruption uncertainty on the market demand term for country j, remember that it is positively affected by the total expenditure in our sector and the ideal price index, where aggregate shocks affect the market demand through its effect on the price index. This can be thought of as an externality to the firm, since the decision of all other firms of where to source from affects firm φ's expected profits, but this is not taken into account by the firms when they are making their decisions. However, idiosyncratic uncertainty only affects expected profits through its effect on the sourcing capability and does not affect the market size. In the last subsections of section 3 we will dive deeper into the effect of aggregate uncertainty on the price index, and hence on the market demand, and how that affects firm's decisions on where to source from.

Examining equation (13), we observe that it is a combinatorial optimization problem in expectation, introducing complexity due to the 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 different sourcing strategies and we choose the one that maximizes the equation above, we would have to compute 2^I expectations and choose the highest one. This is feasible for a small number of countries, approximately 12, but it becomes quickly unfeasible for a larger number of countries. To address this computational challenge, we establish 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 the problem of the firm, we can see that there is a relationship between productivity, φ, and sourcing capability, $\Theta_j(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi))$. From Antràs et al. [2017] we know that, for the case under no uncertainty, the profit function is supermodular in φ and $\Theta_j(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi))$. In the case under uncertainty, we have that, by definition, $\bar{\gamma}_{ij},\ \bar{\gamma}_{ij}(\varphi) > 0$ and the expectation is a weighted average, so we have a weighted average of supermodular functions, which is supermodular. We will prove that the profit function is also supermodular in expectation.

Proposition 1: For $\bar{\gamma}_{ij},\ \tilde{\gamma}_{ij}(\varphi) > 0$ and i.i.d, the solution $\mathbb{1}_{ij}(\varphi) \in \{0,1\}_{i=1}^{I}$ to the optimal sourcing problem is such that

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

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

Proof: See theoretical appendix.

Proposition 1, part (a), reveals that more productive firms exhibit a larger expected sourcing capability times market demand compared to less productive firms. This outcome may arise from multiple factors. Firstly, more productive firms may engage in sourcing from a greater number of countries than their less productive counterparts. Alternatively, it could stem from their strategic sourcing from countries characterized by high sourcing potential, i.e., high $T_{ij}(\tau_{ij}\bar{\gamma}_{ij}\tilde{\gamma}_{ij}(\varphi)w_i)^{-\theta}$, attributed to factors such as (i) high technology, (ii) low wages, (iii) low iceberg costs, (iv) small/"positive" shocks, or because (v) their shocks negatively correlate with the shocks that affect the market size. It could happen that high productivity firms have a larger expected sourcing capability times market demand because they buy from one foreign country that has lower wages, or better technology, or has higher uncertainty, which could ex-post imply a smaller price, or that the shock covaries negatively with shocks from the countries that most firms source from. On the opposite side, low productivity firms could be buying from two countries with lower fixed cost of sourcing than the country from which the high productivity firm sources from, but have a higher marginal cost, because of worse technology, higher wages, or less uncertainty, for example. It could happen instead that high productivity firms are sourcing from more countries than low productivity firms thus reducing the overall marginal cost for the firm by giving an extra cost draw and increasing competition between countries.

As explained, Proposition 1, part (a), leaves the specific mechanism undisclosed, while part (b) provides insight that, under the condition $(\sigma-1)/\theta \geq 1$, implying complementarity in the sourcing decisions, more productive firms source from a greater number of countries compared to less productive firms. This is because the expected profit function has increasing differences in $(\mathbb{1}_{ij}, \mathbb{1}_{kj})$ for $i, k \in \{1, \ldots, I\}$ and $j \neq k$, implying that the marginal benefit of adding an extra country is not reduced by adding other countries to the set $\mathcal{I}_j(\varphi)$. We understand complementarity as the fact that the marginal benefit of adding an extra country increases with the number of countries, since there's an extra draw to lower the cost and that creates competition between countries which lowers the overall cost. This is the case when $(\sigma-1)/\theta \geq 1$

because it means that σ is high, and/or, θ is low. A high σ implies that consumers are price elastic, so they are more sensitive to lower prices, and a low θ means that inputs are more heterogeneous. When either of these is true, lowering the price has higher benefits, so more productive firms will always want to add countries to their sourcing strategy to reduce the cost through this mechanism.

From Proposition 1 (b), there exists a "pecking" order, which means that there is a strict hierarchical order in the extensive margin of offshoring. This implies a distinct hierarchical arrangement wherein all firms importing from one country source from the same one (e.g., China), and correspondingly, firms importing from two countries do so from the same specific countries (e.g., China and the United States). However, it is crucial to note that this hierarchical order, under uncertainty, 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 their expectations of shocks and how these shocks correlate with market demand, so the pecking order is maintained in expectation. This is the case if we have fixed costs that are relationship specific but not relationship-firm specific.

As we show in Proposition 1, because of increasing differences in the profit function, when $\sigma - 1 \geq \theta$, we can now write:

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

Proof: See theoretical appendix.

Building on Proposition 1, akin to Antràs et al. [2017], we exploit this proposition's insights to employ Jia [2008]'s algorithm. This allows us to reduce the dimensionality of our problem. Leveraging the expected hierarchical order, we initiate the process from the set comprising all countries, denoted as $\bar{\mathcal{I}}$. Subsequently, we iteratively eliminate countries until we identify the point where $V_{ij}(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi)) = 0$. This outcome provides the upper bound for the sourcing strategy. Conversely, starting with the set that encompasses no countries, denoted as $\underline{\mathcal{I}}$, we systematically incorporate countries until the point where $V_{ij}(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi)) = 1$ is reached. This procedure yields the lower bound for the sourcing strategy. 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's important to note that this method is applicable exclusively in the "complements" case, where $\sigma - 1 > \theta$. It is not suitable for the "substitutes" case, which would necessitate additional assumptions, such as a common fixed cost for all foreign countries.

Finally, we obtain the firm-level intermediate input purchases from any country $i \in \mathcal{I}_j(\varphi)$. This is an ex-post decision for firms so, for $i \in \mathcal{I}_j(\varphi)$, this will be a fraction $(\sigma - 1)\mathcal{X}_{ij}(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi))$ of firm's ex-post profits, which gives us

$$M_{ij}(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi)) = (\sigma - 1)\ \eta^{\frac{\sigma-1}{\theta}}\ \varphi^{\sigma-1}\ (\Theta_j(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi)))^{\left(\frac{\sigma-1}{\theta}-1\right)}\ T_i(\tau_{ij}\bar{\gamma}_{ij}\tilde{\gamma}_{ij}(\varphi)w_i)^{-\theta}\ B_j(\bar{\gamma}), \tag{14}$$

with $M_{ij}(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi)) = 0$ if $i \notin \mathcal{I}_j(\varphi)$.

From equation (14), we observe that, for $(\sigma - 1) \geq \theta$, i.e., when there are complementarities in the sourcing decisions, and with a fixed market demand, $B_j(\bar{\gamma})$, firm-level intermediate input purchases from any country $i \in \mathcal{I}_j(\varphi)$ are increasing in both the sourcing potential, $T_i(\tau_{ij}\bar{\gamma}_{ij}\tilde{\gamma}_{ij}(\varphi)w_i)^{-\theta}$, and the sourcing capability, $\Theta_j(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi)) = \sum_{k\in\mathcal{I}_j(\varphi)} T_k(\tau_{kj}\bar{\gamma}_{kj}\tilde{\gamma}_{kj}(\varphi)w_k)^{-\theta}$. This implies that, not only does the sourcing potential of country i contribute to firm-level intermediate input purchases, but also the sourcing potential from all other countries in the firm's sourcing strategy, $k \in \mathcal{I}_j(\varphi)$. In cases where $B_j(\bar{\gamma})$ is not fixed, the market demand is not directly affected by idiosyncratic shocks, which solely impact the sourcing potential and capability. Consequently, both aggregate and idiosyncratic shocks for all countries affect the firm-level intermediate input purchase decision of firm φ in country j's through the sourcing capability and country i's shock through the sourcing potential too. However, the realized aggregate shocks for all countries in any firm's sourcing strategy influence the market demand too, resulting in the sourcing decision of all other firms also affecting firm φ's intermediate input purchases.

In the absence of a constant market demand term, $B_j(\bar{\gamma})$, the impact of an aggregate shock $\bar{\gamma}_{ij}$ on $M_{ij}(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi))$ becomes nuanced. Consider a scenario where only country $i \in \mathcal{I}_j(\varphi)$ experiences a negative shock. This would lead to a reduction in both the sourcing potential of country i and the sourcing capability from the point of view of a firm φ in country j. However, the equilibrium-determined market demand will be affected through the change in the price index. A negative aggregate shock, i.e., $\bar{\gamma}_{ij} > 1$ implies an increase in the price index, and so an increase in the market demand. It could even happen that the increase in market demand is big enough to even offset the negative effect of the shock if i is the country where most firms are sourcing from and it is very negatively shocked. Conversely, if only country $k \in \mathcal{I}_j(\varphi)$ is negatively shocked, the sourcing potential of country i from the viewpoint of country j remains unaffected, but the sourcing capability diminishes, while the market demand rises. In this situation, it is plausible that the increase in market demand, triggered by the higher price of the alternative country k, could counterbalance the reduction in demand for intermediate inputs from country i due to the complementarities in sourcing capability. The outcome hinges on how big the shock is and the distribution of firms sourcing from each origin.

Consider now an idiosyncratic shock occurring for firm φ importing from country $k \neq i$, with $k \in \mathcal{I}_j(\varphi)$, such that $B_j(\bar{\gamma})$ remains unaffected by this shock. This shock will diminish the sourcing capability of firm φ in country j. Under the condition $(\sigma - 1)/\theta > 1$, this reduction will propagate to decrease firm-level intermediate input purchases from all countries, not limited to country k. In the case of a shock to country i, instead of k, the reduction to the intermediate input purchases from country i for firm φ will be even more pronounced due to the decrease in the sourcing potential of country i.

Nonetheless, except for the case of idiosyncratic shocks, the price index will adjust in equilibrium, which will affect the market demand. In the event of a shock to country k, the market demand term will rise, which could counterbalance the decrease of the sourcing capability or even increase the firm-level intermediate input purchases from country $i \neq k$. In section 4, we will take a closer look at the effect of uncertainty in the expected profits of final-good firms.

3.3 Equilibrium

To solve for the equilibrium, we assume that there is a perfectly competitive outside sector in which consumers spend $(1-\alpha)$ of their labor income on. This implies that they allocate α of their labor income to our relevant sector. The outside good, which is homogeneous and freely tradable across countries uses labor linearly and serves as our numeraire. We assume that the share $(1-\alpha)$ is large enough that the labor productivity of this sector pins down the wage rate w_j in each country j. As previously noted, we only need to determine $P_j(\bar{\gamma})$, since wages are exogenous.

Because of our assumed timeline, firms make the decision to enter and pay the fixed cost of entry before learning their productivities. Consequently, firms will continue to enter until the expected profits from entry become zero. Therefore, the free-entry condition in our sector of interest is expressed as:

$$\int_{\tilde{\varphi}_j}^{\infty}\int_{\bar{\gamma}}\int_{\tilde{\gamma}(\varphi)}\left[\varphi^{\sigma-1}(\eta\Theta_j(\varphi,\bar{\gamma},\tilde{\gamma}(\varphi)))^{\frac{\sigma-1}{\theta}}B_j(\bar{\gamma}) - w_j\sum_{i\in\mathcal{I}_j(\varphi)} f_{ij}\right]d\tilde{\Psi}^{\varphi}_{ij}(\tilde{\gamma})d\bar{\Psi}_{ij}(\bar{\gamma})dG_j(\varphi) = w_j f_{ej}, \tag{15}$$

where $\tilde{\varphi}_j$ denotes the productivity of the least productive firm in country j.

Finally, we want to obtain the number of active firms in equilibrium so, using equations (15), (4), (10), and (11), as well as Fubini's theorem, and the fact that E_j is a share α of labor income, we find[1]

$$N_j = \frac{\alpha L_j}{\sigma\left(\int_{\tilde{\varphi}_j}^{\infty}\int_{\tilde{\gamma}(\varphi)}\sum_{i\in\mathcal{I}_j(\varphi)} f_{ij}d\Psi^{\varphi}_{ij}(\tilde{\gamma})dG_i(\varphi) + f_{ej}\right)} \tag{16}$$

This leads to the equilibrium number of active firms denoted as $N_j[1-G_j(\tilde{\varphi}_j)]$. This is obtained when the fixed cost of sourcing from domestic is non-zero, resulting in a positive measure of firms choosing not to produce. For our empirical strategy, we set the domestic fixed cost, f_{jj}, to be zero, so all firms will produce, since in our data we only observe firms that are producing.

[1] Fubini's theorem states that if the integral of the absolute value is finite, then the order of integration does not matter, so we can interchange the order of the integrals.

Finally, the equilibrium price index is given by

$$P_j(\bar{\gamma}) = \left(\int_{\omega \in \Omega_j} \int_{\tilde{\gamma}(\omega)} p_j(\omega, \bar{\gamma}, \tilde{\gamma}(\omega))^{1-\sigma} d\tilde{\Psi}_j^{\omega}(\tilde{\gamma}) d\omega \right)^{\frac{1}{1-\sigma}} \tag{17}$$

where we see that idiosyncratic shocks do not affect the price index, but aggregate shocks do.

4 Theoretical investigation – effects of uncertainty

To understand the influence of uncertainty of the sourcing decision, we study both analytically and numerically how firms profit change with both aggregate and idiosyncratic supply chain risk. Through a theoretical decomposition, we see that mean-preserving spread shock have ambiguous effects on firm sourcing. Providing a simple example with three countries, we

4.1 Expected Profits' Decomposition

As firms choose sourcing to maximize profits, it becomes crucial to assess the relative the influence of different factors affecting these decisions. To achieve this, we decompose the components that contribute to firms' expected profits into five key elements: (i) sourcing capability for expected shocks, (ii) the impact of uncertainty on sourcing capability, (iii) expected market demand, (iv) covariance between sourcing capability and market demand, and (v) the fixed costs of sourcing. We first write the theoretical decomposition and then we explore the quantitative importance of each component through a numerical exercise.

$$\mathbb{E}\big[\pi(\varphi,\gamma)\big] = \varphi^{\sigma-1}\Big(\underbrace{\Theta_H(\varphi,\mathbb{E}[\gamma])^{\frac{\sigma-1}{\theta}}}_{\substack{\text{Sourcing capability}\\ \text{for expected shock}}} + \underbrace{\mathbb{E}\big[\Theta_H(\varphi,\gamma)^{\frac{\sigma-1}{\theta}} - \Theta_H(\varphi,\mathbb{E}[\gamma])^{\frac{\sigma-1}{\theta}}\big]}_{\text{Effect of uncertainty on sourcing capability}} \Big) \times \underbrace{\mathbb{E}(B_H(\bar{\gamma}))}_{\substack{\text{Expected}\\ \text{market demand}}} \tag{18}$$

$$+ \varphi^{\sigma-1} \underbrace{Cov(\Theta_H(\varphi,\gamma)^{\frac{\sigma-1}{\theta}}, B_H(\bar{\gamma}))}_{\substack{\text{Covariance btw sourcing capability}\\ \text{\& market demand}}} - \underbrace{w_j \sum_{i \in \mathcal{I}(\varphi)} f_{ij}}_{\text{Fixed cost of sourcing}}$$

The first term, the sourcing capability for the expected shock $\Theta_H(\varphi, \mathbb{E}[\gamma])$, encapsulates the expected impact of incorporating an additional country into the set of sourcing options. Adding a country allows the firms to draw an additional variety that can have lower costs, given the fat-tail of the Fréchet distribution of productivity across varieties. This heightens the competition between countries and thereby reduces overall costs, as observed in Antràs et al. [2017]. Notably, this term is affected by the shock itself but remains unaffected by the uncertainty surrounding it, given its dependence on the average rather than the variance. This expected change in profit is at the heart of deterministic models of trade.

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 shock $\Theta_H(\varphi, \mathbb{E}[\gamma])$, this term reflects the influence of the variance of the trade cost shocks on the variance of the sourcing capability. Since a higher sourcing capability implies a lower cost and higher revenues, it contributes to the overall expected profits. Indeed, firms prefer countries with high risk because they would get a chance to sell cheap if one of the countries in their sourcing strategy is positively shocked, i.e., $\gamma < 1$. Because firms can ex-post adjust their intensive margin, they can increase the share they buy from the country that is positively shocked and then sell at a lower cost, even if the other countries are negatively shocked. Both the sourcing capability for the expected shock term and the option value term are then multiplied by the expected market demand $B_H(\bar{\gamma})$. Overall, firms have higher expected profits from higher variance of shocks, i.e., higher uncertainty.

Another impact that uncertainty has on the firms sourcing comes from the covariance between the sourcing capability and the market demand, that we call "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 exhibits a negative impact on profit: if a firm sources from a country that all the other firm else also have in their sourcing sets, the firm price correlates with the average price $P(\bar{\gamma})$. As a result, it reduces the demand for that particular firm if this country has a higher uncertainty. In this case, a negative covariance suggests that a firm would like to hedge and capture a higher market share by being able to offer a lower price compared to other firms.

Lastly, the expected profits decrease due to the fixed cost of adding a country to the sourcing strategy, $w_j f_{ij}$ per country i in the sourcing strategy. The existence of these fixed cost of sourcing is the reason why firms do not just source from all countries. More productive firms, who have higher earnings, can source from more countries at the extensive margin.

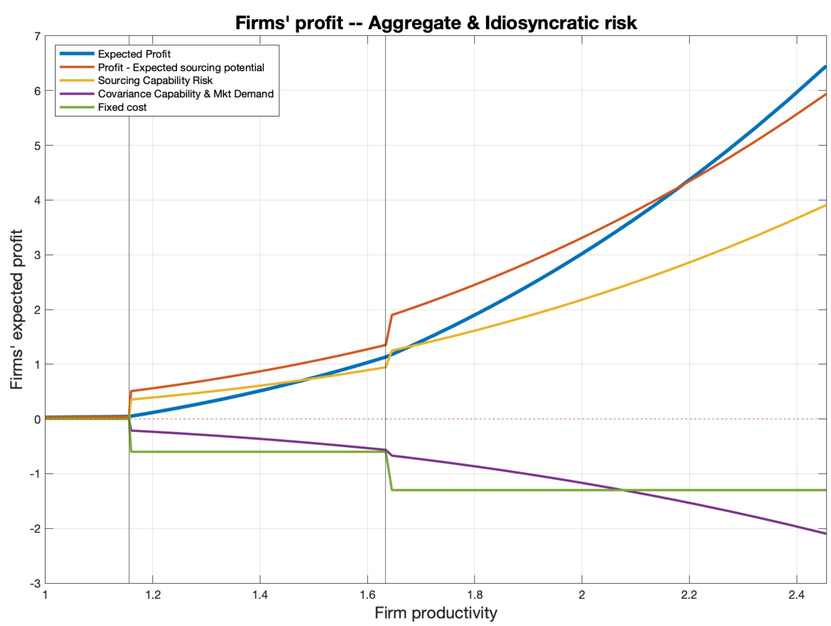
4.2 Numerical Experiment with three countries

To understand the mechanisms at play in our model, and the effect of uncertainty, we simulate an example with three countries: the domestic country, and two foreign countries with different sourcing potentials. We plot the expected profits of firms across various productivity levels φ and sourcing strategies. The numerical values are in appendix B. We then decompose the contribution of each component of the decomposition above to the overall expected profits, discerning variations across different sourcing strategies. We plot in figure 3, the expected profits of firms and we focus the differences between firms deciding to source only from the domestic country versus buying from Home and Foreign 1, versus Home, Foreign 1, and Foreign 2.

Each term from the decomposition of expected profits is displayed with the respective distinct colors representing each term. The x-axis illustrates firms' productivity levels φ, while the y-axis denotes firms' expected profits $\mathbb{E}\big(\pi(\varphi, \bar{\gamma}, \tilde{\gamma})\big)$. The vertical lines show the cutoff productivity level for the different sourcing strategies for the case where there is both aggregate and idiosyncratic uncertainty. Firms to the left of the first vertical line source inputs solely from Home, while those between the first and second vertical lines have sourcing relationships with both Home and Foreign 1, and those to the right-hand side of the second vertical line include Home, Foreign 1, and Foreign 2 in their sourcing strategy.

First, the blue line displays firms' expected profits, which accounts for all the different effects. Second, the red line indicates the effect on expected profits stemming from the sourcing capability for the expected shock, emphasizing the desire to add more countries to the sourcing strategy to reduce costs. The "option value" effect, shown with the yellow line, shows how risk provides the ex-post option to source from cheaper countries if they experience positive shocks. This means that firms gain from buying from countries that have a higher variance because of the option of getting a lower cost. Firms are willing to start a relationship with countries that have a higher variance because they can ex-post buy more from the countries that were positively affected by the shocks, and have the option to sell at a lower price. Instead, if countries are negatively affected, firms can ex-post change their inputs purchase.

Figure 3: Three countries - Profit decomposition



Third, the purple line represents the covariance term between the sourcing capability and market demand, or "hedging effect", which is negative due to the fact that expected profits decrease if the firm gets hit when every other firm gets hit too. However, a negative covariance, i.e., the firm being positively shocked while most other firms experience negative shocks increases expected profits. Then, fourth, the green line illustrates the fixed cost of adding a country to the sourcing strategy, acting as a deterrent for adding more countries, and reducing expected profits.

Looking at Figure 3 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's impact manifests 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, in terms of levels, the option value effect is more relevant for the expected profits then the hedging effect. This is driven by the uncertainty on sourcing capability, which makes firms to want to increase diversification. However, the impact of risk is small compared to the expected sourcing potential.

We compare the results for different types of uncertainty: (i) the baseline with both idiosyncratic and aggregate risk, (ii) a case with only aggregate risk, (iii) a case only with idiosyncratic risk and (iv) a case without any risk. From the decomposition, we see how all the cases differ in their understanding of supply chain uncertainty. The second case with only aggregate risk features both the "option-value" effect – positive on profit – and the "hedging effect" which is negative. However, the option-value term changes quantitatively, being subject to one channel of risk, instead of two. The third case, with only idiosyncratic risk, only features the "option-value" effect due to firm-specific uncertainty, while the hedging term disappears. The case without risk maps our model to the framework of Antràs et al. [2017], balancing the cost margin on sourcing capability and the fixed cost of sourcing.

We now study how the risk affect the extensive margin on the firms decision to import, diversify or reshore input production. In the figure 4, we compare the share of firms sourcing from countries Foreign 1 and Foreign 2. By definition, all firms source from the Domestic country which is not subject to fixed cost of sourcing. First, in the baseline case, 35% of firms source from Foreign 1, and 12% from both Foreign 1 and Foreign 2. This follows from the pecking-order logic discussed above.

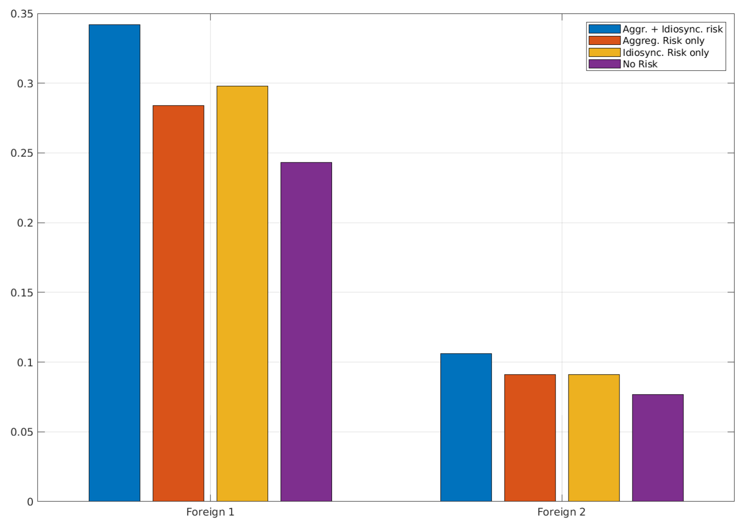
In the second case, with only aggregate risk, the option-value effect on sourcing capability is lower, but the hedging term is still negative. This reduction in profit from a lower uncertainty makes most firm reduce import: very productive firms switch from two country to one country, while smaller firms reshore production instead of importing from Foreign 1. This second channel is stronger added to the fact that the hedging motive is still present lowering profit for firms importing from Foreign 1. As a result, there is a larger drop in the extensive margin for Foreign 1, reducing the number from 35% to 28%, while the number of firms sourcing from Foreign 2 only went from 11% to 9%.

In the third case, with only idiosyncratic risk, the hedging term disappears, making the Foreign country 1 more profitable. Indeed, without aggregate risk, the market demand and aggregate price are not stochastic. This makes the sourcing capability of Foreign 1 uncorrelated with the aggregate price level, resulting in its increased profitability. More firms source from Foreign 1 than in the -aggregate risk only-case, 30%

compared to 28%, while the number of firms sourcing from country 1 is the same.

Finally, without risk, only the marginal cost vs. fixed-cost trade-off is at play. There is no more option value of risk, and many less firm source from foreign countries – 25% for Foreign 1, and 7.5% for Foreign 1 + Foreign 2.

Figure 4: Firms' sourcing strategies and extensive margin



We also run comparative statics to understand how the expected profits and sourcing strategies for different types of uncertainty are affected by different levels of complementarity – the ratio $(\sigma - 1)/\theta$. We find that the lower the level of complementarity, the higher the effect of uncertainty. Moreover, complementarity creates a motive for diversification, reinforcing the willingness of firms to source from Foreign 1.

We also compare models with different level of risk. Leveraging the ex-ante profits equation we show that, everything else equal, firms get higher expected profits from higher idiosyncratic uncertainty. It increases the option value effect, giving a higher chance of reducing costs. However, the numerical experiments also demonstrates that firms with varying levels of productivity respond distinctively to different types of uncertainty. We observe that, ceteris paribus, higher productivity firms gain more from adding countries with higher idiosyncratic uncertainty to their sourcing strategy than less productive firms, This occurs because higher productivity firms gain more from "better" countries, for a given number of countries in their sourcing strategy, than low productivity firms. This is the case because revenues are multiplied by the productivity of the firm $\varphi^{\sigma-1}$.

Finally, for the case of aggregate uncertainty, or both aggregate and idiosyncratic uncertainty together, the results are ambiguous. A higher aggregate shocks variance increases expected profits through the option value effect, i.e., the option of having a lower cost because of a positive aggregate shock. However, adding countries that every other firm sources from reduces expected profits through the hedging effect, since this increases the market demand for goods that are positively shocked when other firms are negatively shocked. These effects occur to both high and low productivity firms, but lower productivity firms are more affected by the hedging effect, while higher productivity firms sourcing decisions are more affected by the option value effect. However, if the option value effect is bigger than the hedging effect, then the effect is similar to the idiosyncratic case. If not, then the overall effect is uncertain.

5 Data

In the previous section we showed our theoretical model for firms' sourcing decision under supply chain uncertainty. This model provides a way for us to estimate aggregate and idiosyncratic supply chain uncertainty and analyze the effects of a counterfactual scenario using firm-level data from Chile. We will next describe the database we use in the paper and show descriptive evidence that supports the use of our model.

5.1 Data Description

We utilize confidential customs data from Chile, which has product-origin-firm level data encompassing all import transactions that enter Chile. The products are classified using the Harmonized System (HS) at the 6-digit level (HS-6), which is a globally recognized product classification system. Additionally, we leverage confidential tax forms that offer firm-to-firm level insights into sales based on VAT records from the Servicio de Impuestos Internos (SII) in Spanish, equivalent to the IRS in English, acquired through the Central Bank of Chile. Furthermore, access to the unemployment insurance fund at the firm level allows us to extract information regarding employment and wage bills based on contributions, covering only the formal private sector, from which one can back out monthly earnings. Our dataset primarily focuses on the Mining, Manufacturing, and Trade sectors, including Restaurants and Hotels. We chose this compilation of sectors because it covers approximately 80% of the total import value in Chile and spans the period from 2012 to 2023 on a quarterly basis[2]. We drop firm's with negative or zero sales and those 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, but for our structural analysis we use 13 countries. In our data, around 24% of our firms are importers, which is consistent with the pattern found in the literature for other countries, and the 13 countries we use for the structural analysis encompass 67.34% of the total value of imports.

[2]We take quarterly data because the time frame is long enough to avoid lumpiness but short enough that it is credible that firms are not changing their suppliers. This is based on Carvalho et al. [2021] who find that firms weren't able to quickly adjust their suppliers in the aftermath of the Japan earthquake

To capture the dynamics predicted by the model, we construct a dataset on yearly country characteristics spanning the years 2012 to 2019. This dataset is instrumental in determining firm-country-level fixed costs and sourcing potential. Country attributes, such as distance and language variables, are sourced from CEPII. Additionally, data on the control of corruption is extracted from the World Bank's Worldwide Governance Indicators. This comprehensive dataset enables us to incorporate critical country-specific factors into our analysis, aligning with the model's emphasis on the role of these characteristics in shaping fixed costs and sourcing potential.

5.2 Descriptive Evidence

We use the data from the first quarter of 2012 to the fourth quarter of 2023 to identify the aggregate and idiosyncratic uncertainty, while we use the average data from the first quarter of 2012 to the fourth quarter of 2019 to obtain the value for the firm-countrylevel fixed costs.

Since in our model we assume that firms source multiple products from multiple countries, we show that this is the case for our dataset too. To do that, we define a distinct product as a distinct Harmonized System six-digit code. In our data, we find that, for the period from 2012 quarter 1 to 2023 quarter 4, firms import approximately 9 distinct products from 2 countries on average. The median number of imported products is around 2, while the 95^{th} percentile is around 33. The median number of countries from which firms import from are approximately 1, while the 95^{th} percentile is around 6 countries. In the data appendix, Table 7, we also show that, as assumed in our model, the extensive and intensive margin differ in our dataset for the average from 2012 to 2023. For example, Spain is 4^{th} in terms of the number of firms that import from them but 12^{th} in terms of the value of imports.

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.

From Table 2 we learn that the number of firms in our data increases with time, starting with an average of 35,742 firms between the first quarter of 2012 and the last quarter of 2015, to an average of 43,819 firms between the first quarter of 2020 and the fourth quarter of 2023. We observe that all other variables, number of employees in hundreds, value of imports, value of inputs, value of sales, value of domestic input purchases, all in millions of USD, and the share of importing firms, they all experience an increase with time in our data.

Following Antràs et al. [2017] and Eaton et al. [2011], we now check if our dataset follows a pecking order by counting the number of firms that import from the number one destination only (in our case, China), and then the number of firms that import from the number one and number two destinations only, and not others (in our case, China and the United States), 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 proceed to compare that with what the number of firms and percentage of importers would have been if the firms selected randomly by using the share of importers from country i as the probability that any firm will source from i, independently. Doing this, 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 pecking order above the randomly generated one, even if not perfect, which supports our assumption.

This is similar to what Antràs et al. [2017] and Eaton et al. [2011] find for American and French firms, respectively. This implies that our data follows a pecking order over what would be randomly generated. However, because the percentage of the data following a pecking order is still around just one third, this implies that there might be firm-relationship-specific fixed costs of sourcing, and not just relationship-specific. We will take this into consideration for our empirical analysis when we estimate the fixed costs of sourcing.

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.

We then obtain the share of importer for all firms and for firms with sales below the median, since we will use these for our empirical strategy. From Figure 5, we observe that the share of importers for 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 with firm sales below the median. In both cases, we observe that the share of importers is not constant over time. The average share of importers for all firm from 2012 quarter 1 to 2019 quarter 4 is then 0.2264 and the average share of importers with firm sales below the median is 0.0819.

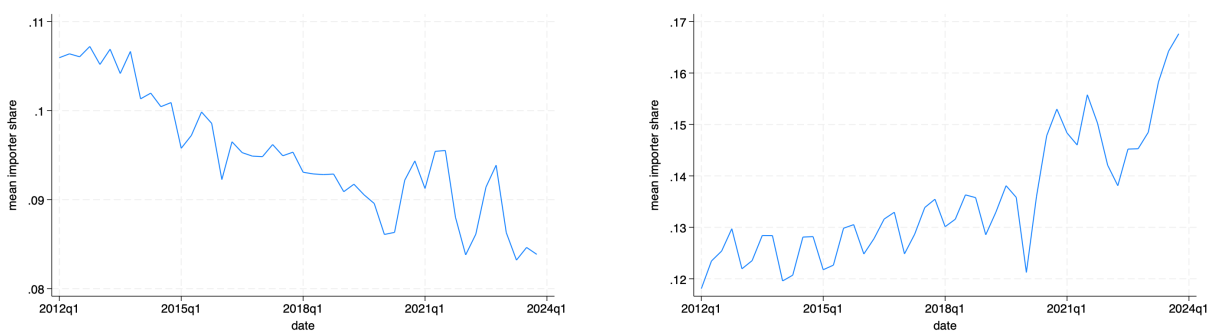
Figure 5: Share of importers

(a) Share of importers for all firms (b) Share of importers w/firm sales below median

Finally, we plot the share of importers by country of origin. We show the case for the United States of America and China because they have opposite trends. We learn from Figure 6 that while the share of importers in the USA seem to be going downwards, and less firms are importing from them, the share of importers from China is trending upwards, which could indicate that firms are replacing one country for the other. We also obtain the average share of importers from the United States, from 2012 quarter 1 to 2023 quarter 4, which is 0.098, and for China, it is equal to 0.128.

Figure 6: Share of importers by country of origin

(a) USA (b) China



These figures motivate our structural analysis, where we leverage the time difference in import shares between countries, as well as total countries, to identify both aggregate and idiosyncratic shock moments in our model and the averages to obtain our firm-relationship-specific fixed costs of sourcing.

6 Structural Analysis

Given the static nature of our model, we opt to utilize the panel data available to us by leveraging averages over specific periods. For step 3 of our structural estimation, we focus on the years spanning from the first quarter of 2012 to the fourth quarter of 2019. This time frame, prior to the onset of the supply chain uncertainty induced by Covid-19 and wars serves as our basis for analysis. However, the panel structure of our data also allows us to estimate both idiosyncratic and aggregate supply chain uncertainty. The Covid-19 pandemic stands out as a crucial event that introduced substantial uncertainty into global supply chains, so for that case we utilize all the available data, from the first quarter of 2012 to the third quarter of 2023. This approach facilitates a comprehensive understanding of supply chain dynamics by encompassing the pre-, and post-Covid-19 periods, during which significant supply chain uncertainty was prevalent.

Our estimation procedure involves three main steps, focusing on data at the firm level, denoted as n, to estimate the parameters $[\bar{\gamma}_{ij}, \tilde{\gamma}^n_{ij}, f^n_{ij}]$ in our model. We do not estimate the parameters for the demand elasticity, θ, and for the dispersion of productivities in input production, σ. Instead, we take their values from the literature. Following Antràs et al. [2017], we set σ to be equal to 3.85 and θ to be equal to 1.789. This implies a value of 1.583 for $(\sigma - 1)/\theta$, which is higher than 1, indicating the presence of complementarity between countries in our model, which allows us to use Jia [2008]'s algorithm.

6.1 Step 1. Estimate Average Country's Sourcing Potential

To estimate the sourcing potential of country i from the perspective of country j (in our case, Chile), we leverage firm-level sourcing strategies as given and exploit differences in the shares of sourcing between the two countries. The sourcing potential of country i concerning country j is given by $T_i(\tau_{ij}\bar{\gamma}_{ij}\tilde{\gamma}^n_{ij}w_i)^{-\theta}$, which can be decomposed into an origin-specific term, $T_i(\tau_{ij}\bar{\gamma}_{ij}w_i)^{-\theta}$, and an origin-firm-specific term, $(\tilde{\gamma}^n_{ij})^{-\theta}$. Given the ex-post nature of the firm's sourcing decisions in our model, the sourcing strategy is fixed for firms, and shocks have already been realized. To find the average sourcing potential of country i from the point of view of country j, we normalize equation (8) by the domestic sourcing strategy, canceling out the sourcing capability term. Taking the logarithm of this normalized equation yields the difference between the log sourcing potentials of country i and country j. Since we are normalizing by the domestic sourcing potential but are interested in the sourcing potential of country i for country j, we set the domestic sourcing potential equal to one, i.e. $T_j(\tau_{jj}\bar{\gamma}_{jj}\tilde{\gamma}^n_{jj}w_j)^{-\theta} = 1$, and assume no domestic aggregate and idiosyncratic supply chain uncertainty. This approach allows us to estimate the sourcing potential by comparing the share of intermediates sourced from each country relative to the domestic sourcing strategy. Since in our case we only have one domestic country, which is Chile, we can get rid of j on the right-hand side of the equation because the origin i will change but the destination j will be fixed. Then, we write

$$\log \mathcal{X}^n_{ij} - \log \mathcal{X}^n_{jj} = \log \bar{\xi}_i + \log \epsilon^n_i \tag{19}$$

where ϵ^n_i is a firm-country-specific shock. To measure the difference between a firm's share of inputs bought from country i and the firm's share of inputs sourced domestically, we leverage our dataset on the total value of imports from each of the countries from which firms' in Chile source their inputs from, wage bill, and the inputs each of these firms use. Our analysis is restricted to countries included in the firm's sourcing strategy, namely those from which the firm actively sources inputs from. Since the third step of the estimation is very computationally intensive, to reduce the dimensionality of the problem we created a country called rest of the world, or RoW, that includes all the countries from which 100 firms or less source from, which reduces the number of countries to 50.

This specification allows us to identify a country's average sourcing potential, $\bar{\xi}_i$. For this to be consistent, we need that there is no selection based on the errors, ϵ_i^n. Because we take the difference between the share of intermediate input purchases from country i and country j, the sourcing capability term, which is affected by the ex-ante decision on the sourcing strategy, is not relevant in out regression. Then, because our model timeline states that firms learn their firm-country-specific shocks after they choose their sourcing strategy, there is no selection of firms based on the errors. Alternatively, we could also treat ϵ_i^n as a measurement error, in which case we assume that we accurately observe the set of countries from which firms source from and they have positive imports for all the countries in their sourcing strategy.

To estimate Equation (31), we will employ Ordinary Least Squares (OLS) with fixed effects at the country level. The coefficients associated with these fixed effects, along with the residual term, will provide insights into the average origin-country-specific component of the estimated sourcing potential for each country, which we will later use for our structural analysis.

In the estimation appendix, Figure 17, we see that China has the highest sourcing potential for firms in Chile, and then the United States followed by Brazil and Paraguay. This shows that the fixed cost of sourcing might differ between countries, since, as we learn also from Table 7 in the estimation appendix, more firms are sourcing from the rest of the world than Brazil and more firms are sourcing from Spain than Paraguay, even though their average sourcing strategies are higher. This implies that the cost of sourcing from Spain might be lower than the cost of sourcing from Paraguay, for example.

6.2 Step 2. Estimate Aggregate and Idiosyncratic Uncertainty

We now utilize our panel data structure to estimate the moments for our aggregate and idiosyncratic shocks. To estimate this, we need to take a stance on what is time varying and what is not. We assume that any change in time is produce by supply chain shocks. This is a strong assumption, however, we are not making assumptions on what are the mechanisms behind this supply chain uncertainty. As seen in recent events, supply chain uncertainty can occur because of labor supply issues, which affects wages, as well as changes in the prices of fuels, which affects iceberg costs, or could even be caused by natural disasters, like the Japanese Earthquake, which was a shock to productivity. The only difference here is that we need to be careful with the interpretation we give to the parameters in each of these different scenarios since, for example, technology is not affected by the heterogeneity of inputs, i.e., the parameter θ. Considering this, we can write

$$\mathcal{X}_{ij,t}(\varphi, \gamma) = \frac{T_i(\tau_{ij}\bar{\gamma}_{ij,t}\tilde{\gamma}_{ij,t}(\varphi)w_i)^{-\theta}}{\Theta_{j,t}(\varphi, \gamma)} \text{ if } i \in \mathcal{I}_j(\varphi)$$

Then, we can decompose the time-dependent sourcing potential of country i into $\xi_{it} = T_i(\tau_{ij}\bar{\gamma}_{ij,t}w_i)^{-\theta}$ and $\epsilon^n_{i,t} = (\gamma^n_{ij,t})^{-\theta}$.

Utilizing the panel structure of our quarterly data to find the moments for our aggregate and idiosyncratic uncertainty, we can express the following first-difference equation:

$$(\log \mathcal{X}^n_{ij,t} - \log \mathcal{X}^n_{jj,t}) - (\log \mathcal{X}^n_{ij,t-4} - \log \mathcal{X}^n_{jj,t-4}) = \log \xi_{i,t-(t-4)} + \log \epsilon^n_{i,t-(t-4)} \tag{20}$$

where, using our model implied relationship and our assumption that only the shocks change in time, we have that $\log \xi_{i,t-(t-4)} = -\theta \log(\bar{\gamma}_{i,t}/\bar{\gamma}_{i,t-4})$ and $\log \epsilon_{i,t-(t-4)} = -\theta \log(\tilde{\gamma}^n_{i,t}/\tilde{\gamma}^n_{i,t-4})$. We take the difference between t and $t-4$ because we compare the same quarter in different years to control for seasonality. This helps us take care of time unobservables.

Subsequently, we perform an OLS estimation for the specified model using origin-country-time fixed effects and panel data on firm's total input usage, wage bill, and total imports from each country from which the firm imports from.

To obtain the time difference aggregate and idiosyncratic shocks from this regression, we make the assumption that technology, iceberg costs, and wages are not changing yearly. This can be seen as a strong assumption, nonetheless we are modeling supply chain shocks as anything that affects the cost of importing. It will be irrelevant for us if this occurs because of a change in TFP, iceberg costs, or wages. The only case that affects our interpretation slightly is the case of TFP shock, since this is the only term not affected by θ, which governs the heterogeneity of inputs. This needs to be taken into account when interpreting the results.

For this strategy to be consistent, we need, again, that there is no selection based on the errors, $\epsilon^n_{i,t-(t-4)}$. For this to be the case, we also exploit the timeline of our model which states that idiosyncratic supply chain shocks are learn by the firms after their sourcing strategies have been decided. We also assume that shocks are multiplicative and exponential and independent in time and with respect to home. These assumptions allow us that there is independence between the independent variables and the errors.

This regression allows us to obtain the average value of $-\theta \log(\widehat{\bar{\gamma}_{ij,t}/\bar{\gamma}_{ij,t-4}})$, as well as $-\theta \log(\widehat{\tilde{\gamma}^n_{ij,t}/\tilde{\gamma}^n_{ij,t-4}})$. However, we are not interested in this specific value, but on the moments for both aggregate and idiosyncratic shocks. Because want to recover the distribution of $\hat{\bar{\gamma}}_{ij,t}$ and $\hat{\tilde{\gamma}}^n_{ij,t}$, we first need to divide our results from the estimation by $-\theta$ and take the exponential of that. This means we now have the estimated value of $\widehat{\bar{\gamma}_{ij,t}/\bar{\gamma}_{ij,t-4}}$ and $\widehat{\tilde{\gamma}^n_{ij,t}/\tilde{\gamma}^n_{ij,t-4}}$, so we need to make some assumptions on the trend and initial values to be able to recover the aggregate and idiosyncratic shocks from this, and then make a parametric assumption to recover the distribution of shocks.

To recover the aggregate and idiosyncratic shocks, we assume that the shocks follow a linear trend process, i.e., a random walk, such that $\gamma_{ij,t} = \gamma_{ij,t-4} \times (\gamma_{ij,t}/\gamma_{ij,t-4})$. In order to estimate the values of the shocks, we set initial values, assuming that for every quarter, the initial value for a firm-, or country-, level shock is 1, indicating no shock in the first quarter in which we observe a value for that firm-country pair. Additionally, we make a parametric assumption, specifying that the shocks follow a log-normal distribution. Utilizing these assumptions, we can then recover the mean, variance, skewness, and kurtosis for both aggregate and idiosyncratic uncertainty.

6.3 Step 3. Estimate firm-level fixed costs of sourcing for each country pair

Following the approach from Antràs et al. [2017], we estimate the fixed costs of sourcing using the simulated method of moments (SMM). The estimation process involves simulating production and sourcing decisions of firms based in our model. We generate simulated data and use it to derive endogenous values, from which we obtain moments. These moments are then averaged across all simulations. By comparing the simulated moments with the real data, we determine the parameter values that minimize the difference between the two sets of moments. In our estimation, we allow the fixed cost of sourcing from a country to depend on gravity variables such as distance and language, as well as on a measure of the source country's control of corruption.

To address the discrepancy between the number of importing firms and the number of firms that source from the most popular country, we relax the assumption of country-specific fixed costs. Instead, we introduce firm-country-specific fixed costs of sourcing, denoted as f^n_{ij}. We assume these fixed costs follow a log-normal distribution with scale parameters $\log \beta^f_c + \beta^f_d \log \text{distance}_{ij} + \log \beta^f_l \text{language}_{ij} + \beta^f_C \text{control of corruption}_i$ and a dispersion parameter β^f_{disp}. As active firms must use domestic inputs, we set the fixed cost of sourcing from home to be zero, so $f^n_{jj} = 0$. For the rest of the world, we take the average values using population weight.

Due to the computational challenges associated with solving the firm's problem for a large number of countries, we implement Jia [2008]'s algorithm to reduce the dimensionality of the problem. In our timeline, the sourcing strategy decision is made before the realization of supply chain disruptions is known. Consequently, the decision is based on maximizing expected profits, requiring a Quasi-Monte Carlo simulation of the shocks, which uses a Sobol sequence of low-discrepancy quasi-random numbers for this simulation. While the firm's problem is manageable for up to 10 countries, the complexity increases significantly beyond that, as there are 2^I possible sourcing strategies for I countries from which the firm can source. To reduce the dimensionality of the firm's problem, we rely on our Proposition 2 and adopt Jia [2008]'s algorithm.

Next, following Jia [2008] and Antràs et al. [2017], we explain the ideal algorithm for our case. Given a core productivity φ, a guess $\mathcal{I}$ for the firm'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

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

As in Proposition 2, we introduce a mapping, $V^n_i(\mathcal{I})$ 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 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^n_{ij} 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:

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

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

Since steps (i) and (iii) are particularly slow, we simulate the problem with certainty-equivalence, computing the profit of expected shocks $\mathbb{E}[\bar{\gamma}]$ and $\mathbb{E}[\tilde{\gamma}(\varphi)]$. We then check that our results are not far from the expected case. This causes an upward bias in the estimation of the fixed-costs. However, our estimation with risk does not imply sourcing shares that are significantly different from the data.

Continuing with the structural estimation, we adopt the distributional assumptions for the model parameters. Following the approach of Antràs et al. [2017] and Melitz and Redding [2015], we assume that the productivity parameter φ follows a Pareto distribution with a shape parameter $\kappa = 4.25$, consistent with the value used in Melitz and Redding [2015]'s study. For the estimation of the remaining parameters $\delta = [E, \beta^n_{c,f}, \beta^n_{d,f}, \beta^n_{l,f}, \beta^n_{C,f}, \beta^n_{\text{disp},f}]$, we simulate a large number of firms. This involves drawing φ from a uniform distribution and inverting 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-check process, iteratively adjusting the values to match the log-normal firm-country specific fixed cost levels obtained from the simulation. In the model, we consider a continuum of final-good firms, each characterized by different combinations of productivity levels, fixed costs, aggregate and idiosyncratic supply chain shocks, and country-specific efficiency shocks. The distributional features of these parameters are assessed through the simulated firms, providing insights into the distributions of the model's key variables.

In the structural estimation process, we utilize simulated firms to generate four sets of moments for comparison with the actual data. These moments are crucial for the calibration of the model's parameters. The three sets of moments are as follows:

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

ii. The second set of moments includes the share of importers with firm sales below the median. This is also a scalar. We denote the second set of moments in the actual data as m_2 and in the simulated data as $\hat{m}_2(\delta)$.

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

iv. The fourth set of moments includes 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. We denote the third set of moments in the actual data as m_4 and in the simulated data as $\hat{m}_4(\delta)$.

The first three sets of moments inform us about the magnitude of fixed costs of sourcing, as well as on how they vary with distance, language, and control of corruption. Furthermore, 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 insights into the dispersion parameter. The fourth moment helps determine the scale parameter E, as E determines the level of input purchases.

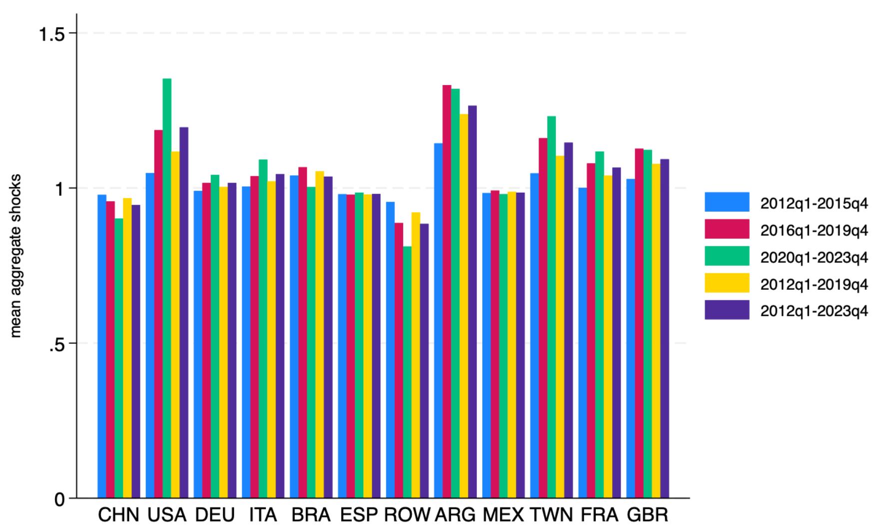
In section 5.4. we will show the parameter estimates obtained from the application of SMM. To do this, we estimate the average for China, the United States, and the rest of the world separately, as to improve the fit of the model, and use the SMM to obtain the scale and dispersion parameters for the rest of the countries.

6.4 Results

Next, we show the results obtained from our structural analysis. In the estimation appendix, Figure 17 and 18 we plot the country sourcing potential, obtained from step 1 of our structural analysis, against the extensive and intensive margins. We find that China, USA, Brazil, Paraguay, and Korea have the highest sourcing potentials for Chile. However, not many firms import from Paraguay, compared to Germany, Spain, or Argentina. This, again, suggests that fixed costs probably differ across countries, which supports the assumption we make in our model.

Next, we will plot our results for the average aggregate shock and standard deviation, and the idiosyncratic standard deviation. We plot these for 12 countries, which is equivalent to 67.34% of the total value of imports. We do this, because our model is very computationally intensive, so we obtain the firm-origin-level fixed costs by using 12 countries, from which we estimate the average for China, the United States and the rest of the world separately to improve the fit of the model. We then use these 12 countries to obtain our counterfactual. In the estimation appendix we plot the average aggregate shock and uncertainty, as well as the average idiosyncratic standard deviation for all our available countries.

Figure 7: Average aggregate shock for different time periods

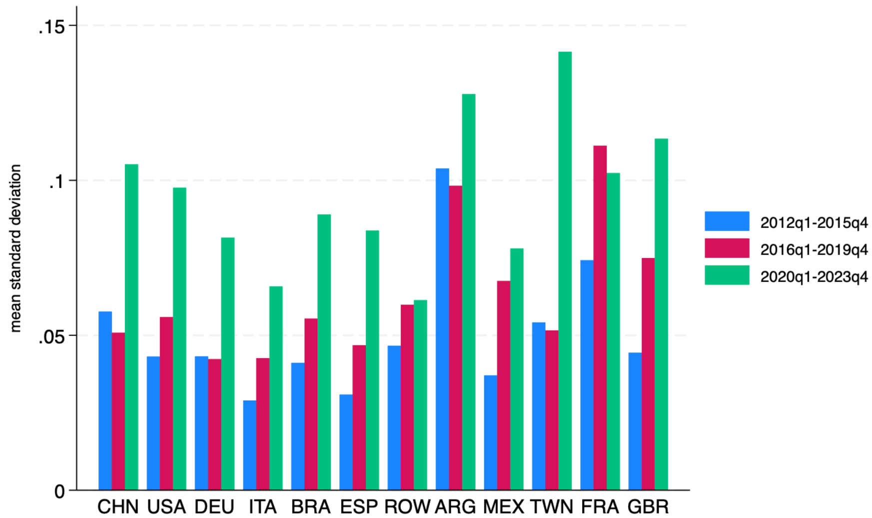


Notes: Figure constructed using the fixed effects obtained from equation (32), dividing by $-\theta$, taking exponential, using a linear assumption, and setting 1 as the initial value, to obtain the aggregate shocks by country. We show the top-12 countries sorted by their importing share.

In Figure 7, we plot the average aggregate shock for the top-12 importing countries, for different time periods, and sort it by their importing share. We observe that most countries had a lower average aggregate shock for the period of 2012q1-2015q4, which has increased for the period 2016q1-2019q4 and 2020q1-2023q4. Notable exceptions are China, Brazil, who's shocks decreased for the 2020q1-2023q4 period, and Mexico, who's average aggregate shocks seem to have been relatively constant over different period. We also observe that Argentina, Taiwan, and the US have the highest average aggregate shock compared to other countries and the difference increases even more during Covid-19. Surprisingly, we find a very low aggregate, i.e., positive. shock for China, which is even lower compared to the other countries during Covid, while the US has the highest proportional increase in negative shocks during 2020 to 2023.

In our sample, around 4-5 countries have positive average aggregate shocks for most periods, i.e., $\gamma < 1$, while all other countries experienced negative shocks during most periods.

Figure 8: Average standard deviation for aggregate shocks, top-12 countries

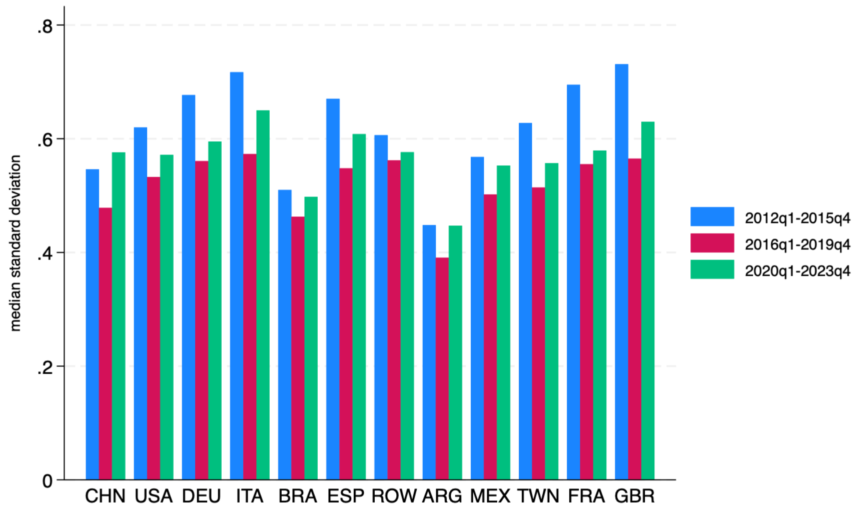


Notes: Figure constructed using the fixed effects obtained from equation (32), dividing by $-\theta$, taking exponential, using a linear assumption, and 1 as initial value. We then get the standard deviation over time for these shocks. We sort the top-12 countries by their importing share.

In Figure 8, we plot the average standard deviation of aggregate shocks for the top-12 importing countries, i.e the mean-preserving aggregate uncertainty. We observe that, in general, most countries have a lower level of uncertainty for the period 2012q1-2015q4 and 2016q1-2019q4 compared to 2020q1-2023q4. The average variance of aggregate shocks goes from around 3% for the period of lowest uncertainty for countries like Italy or Spain, to up to almost 15% for the periods of high uncertainty for countries like Taiwan, USA, and Argentina. Again, Taiwan and Argentina have the highest average standard deviation for aggregate shocks. The United States, instead, has a relatively small standard deviation of aggregate shocks initially but it increases strongly when considering the period 2020q1-2023q4. China's aggregate uncertainty is surprisingly low, however it has a big increase during the 2020q1-2023q4 period. From both Figure 7 and Figure 8 we learn that, even though for some countries the average aggregate shocks are very constant across time periods, the standard deviation is not. In fact, for all countries, the standard deviation changes a lot across periods of time.

In Figure 9, we show the standard deviation across time from 2012 to 2023 for each firm-origin idiosyncratic shock for the top-12 countries. Since we compute the idiosyncratic risk for every firm and every country, we show the median – over firm – standard deviation of that shock. We can see that, overall the idiosyncratic average is 0.6, which is roughly one order of magnitude higher than aggregate uncertainty – which is around $0.05 - 0.1$, which means that there is greater volatility at the firm level than at the origin level. Moreover, we see that there is trend over time of that idiosyncratic risk, which indicates

Figure 9: Average standard deviation for idiosyncratic shock



Notes: Figure constructed using the value of the residuals obtained from equation (32), dividing by $-\theta$, taking exponential, using a linear assumption, and setting 1 as the initial value. We then take the standard deviation across time for each firm-origin and then we average over all firms that import from that origin. We sort the top-12 countries by their importing share.

that the post-2020 supply chain disruptions are driven mainly by changes in aggregate conditions and not firms-specific relationship with importers. For that reason, we set the idiosyncratic risk to be constant at the average level 2012-2023 in the counterfactual analysis. For disclosure purposes, this is the lowest level of aggregation that we are able to show for the idiosyncratic shocks. In future work, we perform comparative statics with the level of idiosyncratic risk.

Using the simulated method of moments to obtain our firm-level fixed costs, but estimating specific fixed costs separately for China, USA, and RoW, we obtain the parameter estimates without uncertainty for 13 countries total, including Chile. We show the estimated parameters to obtain the mean and standard deviation of our log-normal distribution as well as the separate average fixed costs for China, USA, and RoW. We need these estimates because we are assuming that the firm-level fixed costs follow a log-normal($\log \beta_c^f + \beta_d^f \log \text{distance}_{ij} + \log \beta_l^f \text{language}_{ij} + \beta_C^f \text{control of corruption}_i, \beta_{\text{disp}}^f$).

Table 3: Estimated parameters

E	fc_{CHN}	fc_{USA}	fc_{ROW}	β_c^f	β_d^f	β_l^f	β_C^f	β_{disp}^f
222.42	19.258	7.635	2.624	1.272	0.255	1.093	-0.368	0.691

In Table 3 we show the average estimated values for the fixed cost for China, the US, and the rest of the world. These are in thousand of USDs, which means that the estimated average fixed cost for China is 19,258 USD, while for the United States it is 7,635 USD, and for the rest of the world it is 2,624 USD. We also learn that the fixed costs of sourcing increase with a common language by around 8.9 percent, increases with distance with an elasticity of 0.255, and decreases with corruption with an elasticity of

0.368 percent.

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

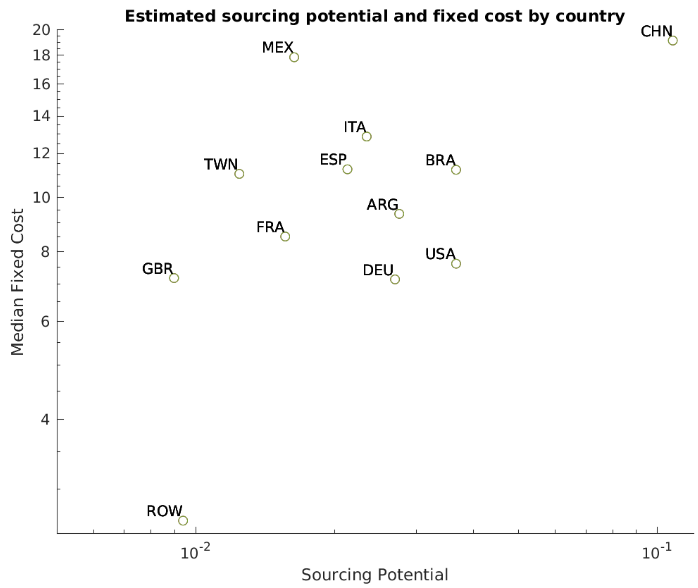


Figure 10 shows the estimated median fixed cost and sourcing potential. We observe that China has both one of the highest sourcing potentials as well as median fixed cost, while Mexico has a smaller sourcing potential but a median fixed cost almost as high as China's. We observe something similar with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

6.5 Fit of the model

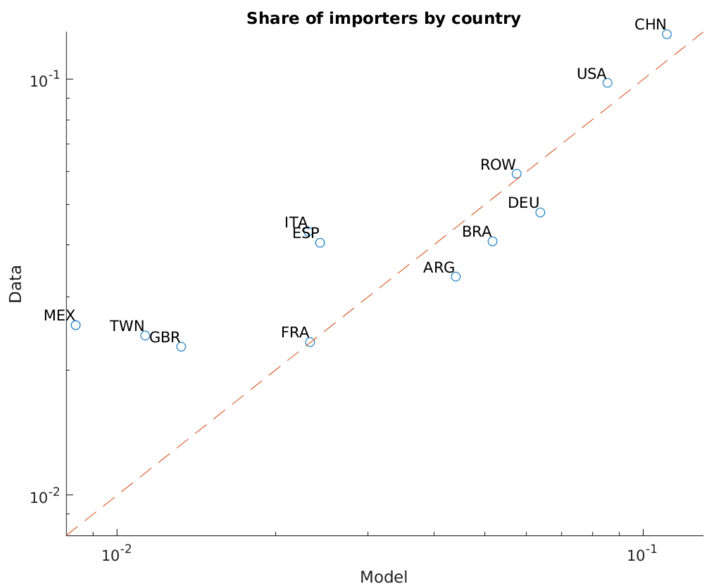
We now show how our model fits the data. From Table 4 we learn that for the case of the second moment, i.e., the share of importers with sales below the median, the model fits the data reasonably well. There is only a 3% difference between the data and the model. Something similar occurs for the case of the fourth moment, which is the median firm's input purchases from Chile, where the difference is bigger than for the second moment, but it is less than 10%. However, the model could do a better job at matching the first moment, i.e., the share of importers. For the third moment, we plot the difference between the data and the model implied share of importers 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

From Figure 11, we observe that some countries' share of importers, like the case of China, the United States, France, Argentina, Brazil, Germany, and the rest of the world, are well fitted with our model. However, for some other countries, like Mexico, Taiwan, the United kingdom, Italy, and Spain, we could improve the fit. However, overall, the fit of the model is reasonable for the number of countries we are evaluating.

Figure 11: Model fit: share of importers by country



7 Counterfactual – Covid-19 Supply Chain Uncertainty

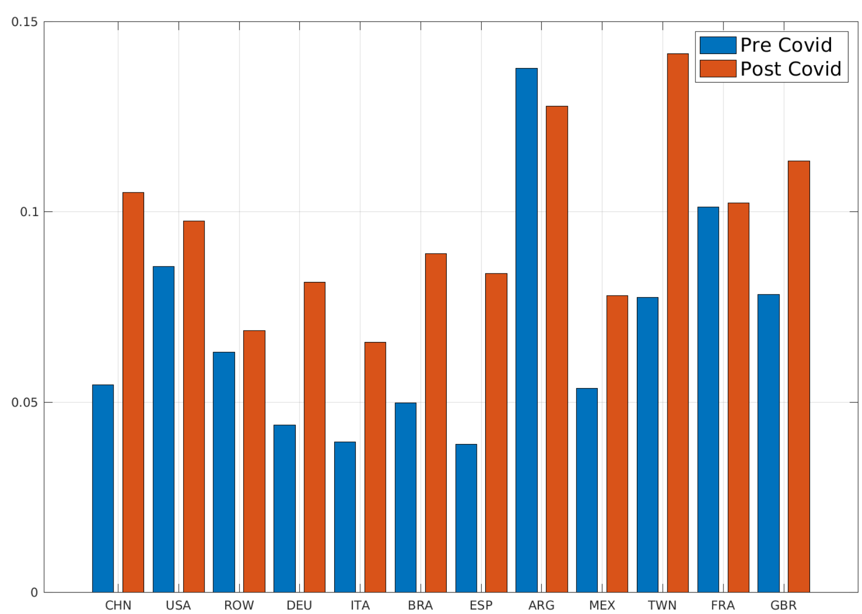
We now proceed to use the parameter values that we obtained in section 5 to evaluate the effect of a change in uncertainty for all countries in the extensive and intensive margin, i.e. we want to understand how a change in aggregate uncertainty can affect firms' decisions of who and how much to source from other countries. We focus on the variation in uncertainty that happened during the Covid-19 period compared to the average uncertainty levels from 2012 to 2019. Our focus is on the Covid-19 period, 2020-2023, because, as shown in Figure 8, it provides a big shock to supply chain uncertainty in the data that allows us to understand and compare the predictions of our model. These shocks also behave very differently between countries, which gives us some country variation in our counterfactual and helps us understand the effects of both increases and decreases in aggregate uncertainty. Our focus is on the counterfactual effect of mean-preserving change in aggregate uncertainty because this encompasses both mechanisms in which uncertainty affects expected profits, i.e., the option value and the hedging effect, so we maintain the average idiosyncratic uncertainty from 2012 to 2023 constant.

Our baseline specification uses the estimated parameters obtained with the average values for the first quarter of 2012 to the fourth quarter of 2019. To obtain our counterfactual, we apply our model to estimate the average variance of aggregate shocks for the period 2012-2019 and idiosyncratic shocks for the period 2012-2023, and then we proceed to do the same using the aggregate uncertainty for the period 2020-2023 instead. We hold all exogenous variables constant, but solve again for the price index and allow the mass of firms to adjust, while we increase the variance of aggregate shocks using the estimates for the period 2020-2023. For our counterfactual, we do not take a stance on what is producing the change in aggregate uncertainty for each country, and just focus on the effect of this change in variance of the shocks.

We first show the change in each country's uncertainty between the periods 2012-2019 and 2020-2023 to understand which countries increased their aggregate uncertainty during the 2020-2023 period and which ones decreased their uncertainty. We need to understand this first to be able to comprehend the mechanisms that are at work in our model and how that explains the results we get from our desired counterfactuals.

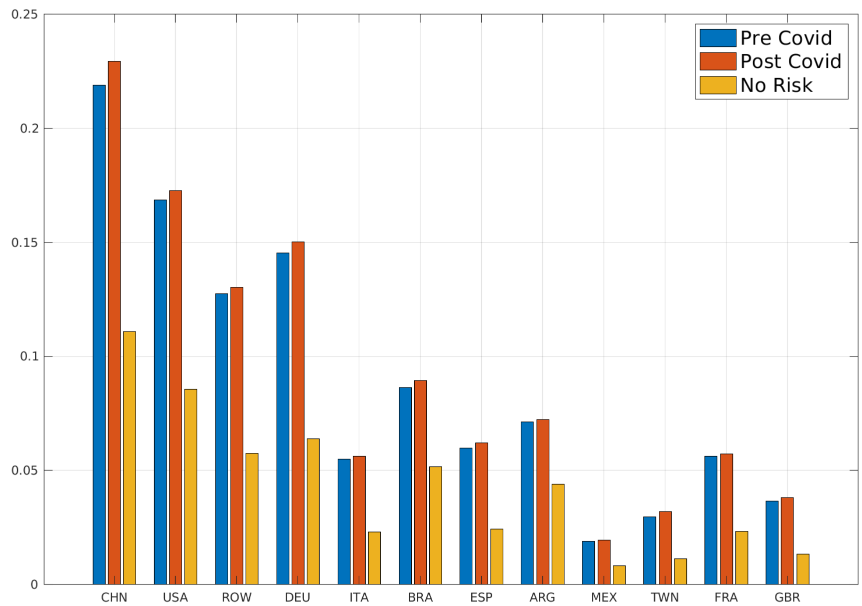
As we observe in Figure 12, uncertainty increases for all countries except Argentina for the 2020-2023, or "Post Covid", period. However, there is a lot of heterogeneity in the change of uncertainty for the period of 2020-2023 compared to 2012-2019. While countries like China, Germany, Italy, Spain, Mexico, and the Great Britain highly increased their aggregate uncertainty, countries like the United States, the rest of the world, and France, did not had a significant increase in aggregate uncertainty. Finally, even though Argentina decreased its aggregate uncertainty, the decrease is not as proportionally big as some of the increases.

Figure 12: Change in standard deviation of aggregate shock



We now proceed to simulate our model economy for the case without aggregate uncertainty, the case of the average value of aggregate uncertainty from 2012 to 2019's, and the average value of aggregate uncertainty from 2020 to 2023. The value of idiosyncratic uncertainty from 2012 to 2023 remains unchanged. We are interested in understanding how firms' extensive and intensive margin decisions were affected by the fact that there was aggregate uncertainty in the period 2012-2019 by comparing that to what would have happened if there wouldn't have been any aggregate uncertainty instead. We are also interested in understanding the effect on the intensive and extensive margin that comes from the change in aggregate uncertainty from the average from 2020 to 2023 compared to the average from 2012 to 2019.

Figure 13: Share of importing firms by country



In the figure 13, we plot the share of firms that are importing from each country pre- and post-Covid-19 average change in aggregate uncertainty. We denote this share of importers by the variable λ_{ij}, the share of firms in j that import from origin i:

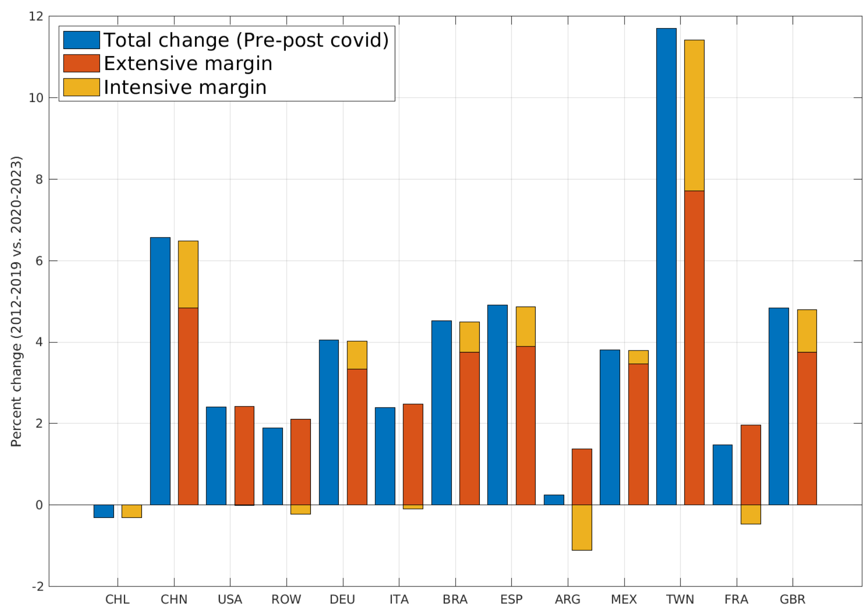
$$\lambda_{ij} = \int_{\varphi} \mathbb{1}_{ij}(\varphi) dG(\varphi) = \int_{\varphi} \mathbb{1}\{i \in \mathcal{I}_j(\varphi)\}\ dG(\varphi)$$

From the figure above, we learn that the share of importing firms by country increased with the increase in uncertainty. The biggest effect is for China where 23% of firms source from there, compared to slightly lower than 22 before the Covid-19 crisis. This increase in absolute number of firms is almost negligible for the countries where very few Chilean firms import from, such as Mexico, Taiwan or the UK. This is driven by the option value effect, where firms prefer to source for more countries, in presence of risk, to benefit from potentially lower costs in good state-of-the-world.
We compare this to the case without aggregate uncertainty. We see that now the share of firms – solely determined by average sourcing potential and fixed cost – is much lower. Indeed, the combination of

large idiosyncratic risk and the additional aggregate risk compounds and firms find it profitable to source from more countries and diversify their sourcing set.

Figure 28 in the estimation appendix plots the change in the share of value of imports by importing firms for each country in the case of no risk and in the case of the average pre- and post-Covid-19 aggregate uncertainty. From the figure, we learn that the effect on the change in the share of value of imports by importing firms has the same direction as the case of the share of importing firms by country, where we find a, mostly positive, correlation. However, as we will see next, these effects are small in levels albeit not as small in percentages, as observed in Figure 14.

Figure 14: Percentage change extensive v/s intensive margin



In Figure 14, we plot the percentage change of the two forces we plotted in levels before: the percentage change in the number of firms sourcing from a country, or extensive margin, and the percentage change in the total value that firms are buying from each country controlling for the number of firms, or intensive margin. We also plot the total change from these two forces from the change in uncertainty.

$$\bar{\chi}_{ij} := \mathbb{E}^{\gamma}\left[\int_{\varphi} \chi_{ij}(\varphi,\gamma)\ dG_j(\varphi)\right] = \underbrace{\lambda_{ij}}_{\substack{\text{extensive}\\ \text{margin}}} \times \underbrace{\frac{\bar{\chi}_{ij}}{\lambda_{ij}}}_{\substack{\text{intensive}\\ \text{margin}}}$$

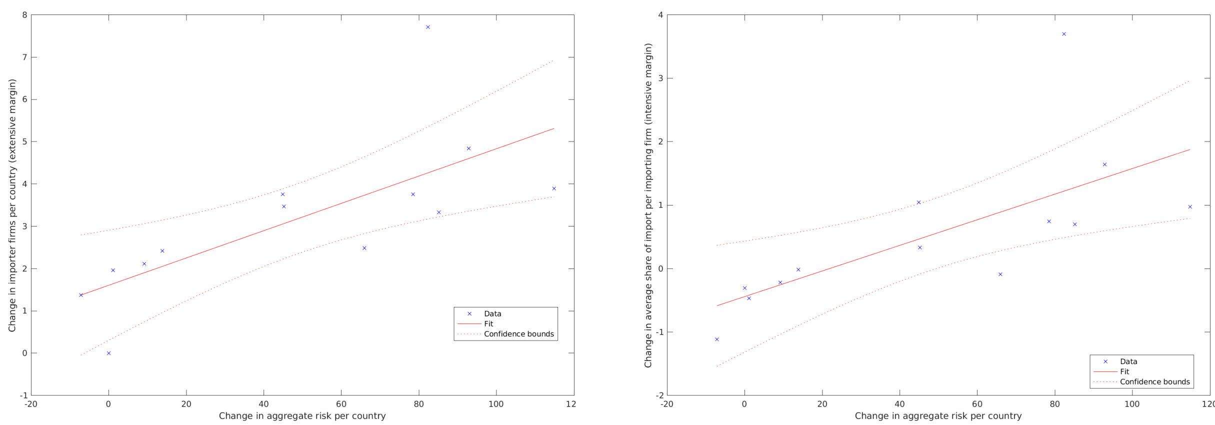
In the figure 14, we hence plot, for each country i, the decomposition:

$$\Delta\%\bar{\chi}_{ij} \approx \Delta\%\lambda_{ij} + \Delta\%\frac{\bar{\chi}_{ij}}{\lambda_{ij}}$$

with the percentage $\Delta\%\bar{\chi}_{ij}$, the extensive margin change, λ_{ij} in red, and the change of $\frac{\bar{\chi}_{ij}}{\lambda_{ij}}$, the intensive margin, in yellow.

From this figure, we observe that most countries increased both their intensive and extensive margin. The total effect of uncertainty on import share ranges from 2%, for the case of the Rest of the World to almost 12% for Taiwan, which supplied the lowest number of firms in the first place. For some countries, like the US, Argentina or France, the entire effect goes through the extensive margin and the intensive margin – i.e. the change in import values for the average firm – is negligeable, or even negative. With an increase of risk, more firms source from these countries ex-ante, despite reducing their import expenditure expost due to the potential occurence of aggregate shocks. Note that for Argentina and France, the increase in aggregate risk is the smallest. This indicates a possible positive relationship between the change in aggregate risk by country and the intensive and extensive margin, which is what we explore next in Figure 15.

Figure 15: Change in aggregate risk and intensive and extensive margins



(a) Extensive margin

(b) Intensive margin

From Figure 15, we observe that there is a positive relationship between the change in aggregate uncertainty and the change in both the extensive and the intensive margins. Most countries, except for two, fall inside the confidence interval, which means that, for most countries, the relationship between uncertainty and the number of importing firms and the expenditure per firm, is positive. We will next explain this correlation in terms of the results from our model.

Starting with the extensive margin in 15a, we observe that the effect of aggregate uncertainty goes in the expected direction for most of the sample. An increase in aggregate uncertainty leads to a rise in the share of firms importing from that country, which can be explained by the option value effect being more significant than the hedging effect: firms prefer to add countries to their sourcing strategy with higher uncertainty because of the chance of getting a lower cost if the country is highly positively shocked.

This occurs because sourcing from more countries allows firms to have access to more Fréchet shocks, so a mean preserving spread variance increases is beneficial for lowering the costs and increasing profits. This effect is even higher for the case of aggregate uncertainty, since that also increases the expected price index and hence the market demand. In summary, more firms are now importing from the countries whose uncertainty increases the most.

The intensive margin is, instead, an ex-post decision, so what's affecting it is the realization of the shock and not the uncertainty surrounding it. However, in this case, we are taking the expected intensive margin. From our model, we expect that, given that the change in the share of value of imports is increasing in the sourcing potential, an increase in the aggregate uncertainty of a country will increase the expected average share because it increases the probability of cost reduction. However, the decrease in the intensive margin for Argentina and France can be explained by the fact that the risk decreased or increased less compared to other countries. In this case, firms preferred to buy more ex-post from countries whose shocks strongly reduced their price. As a result, in expectation this decreases the intensive margin and firms import less in expenditure from those sources.

From Figure 15b, we observe that the effect of aggregate uncertainty is higher for the extensive margin than the intensive margin. This can be explained because the extensive margin is affected by all countries' uncertainty through the sourcing capability, through the option value effect, and because of the impact of uncertainty in the market demand.

Finally, we obtain the average expected HHI for the case of no uncertainty, the average uncertainty for the period from 2012 to 2019, and 2020 to 2023.

Table 5: Average HHI

	No risk	Average 2012-2019 risk	Average 2020-2023 risk
Average HHI	0.9960	0.9626	0.9616

From Table 5, we learn that an increase in uncertainty, either comparing to "no uncertainty" or to the average uncertainty from 2012 to 2019, decreases the average expected HHI. Comparing the average uncertainty from 2012 to 2019 with the average uncertainty from 2020 to 2023, in which the overall average uncertainty seems to have increased, we also find that the average expected HHI decreased. We are able to explain this through the lens of our model because the effect on the extensive margin seems to be mostly positive, and higher than the effect on the intensive margin. This means that, overall, firms are diversifying more and buying from more suppliers, which reduced the HHI. Even though this result can be explain using our model, this is in stark contrast with what we found in our introduction, which is that the increase in uncertainty for the period 2020 to 2023 cause an increase in the HHI. However, we have to take into consideration that in our structural analysis: (i) we have less countries and a big rest of the world, which makes our HHI higher and harder to affect, (ii) we take the expectation, and not the realization of a shock. As a result, upon a realization of a particularly large negative shock, as happened during the Covid-19 crisis with substantial disruptions of international trade, the trade shares of negatively impacted countries decreased substantially, concentrating the import into "non-shocked" countries. As a result, the HHI would have increased strongly in some of these events. In future analysis, we will investigate the role of this reallocation.

8 Conclusion

We develop a multi-country sourcing framework, inspired by Antràs, Fort, and Tintelnot [2017], where firms self-select into importing based on productivity, cost minimization, and trade disruption risk that increases the cost of importing. Using this structural model that we take to firm level data from Chile, we show quantitatively that the decrease in marginal cost is still the main driver of firms' sourcing decisions, but risk affects this choice in a non-trivial way.

In our model, heterogeneous firms face a three stages problem: (i) after they learn their productivity they have to decided if they want to produce, (ii) ex-ante, these final-good producers decide the set of countries to import from, subject to a fixed-cost of initiating the sourcing relationship, by maximizing their expected profits. This creates an extensive margin of firms' import decision as well as an interdependent choice of where to source from: adding an additional country to the sourcing set depends on which countries the firm is already importing from and to which extent it decreases their marginal cost. (iii) Ex-post, trade-shocks affect the cost of importing from a particular country in two ways: first, idiosyncratic shocks affect the firm-specific cost for that good, and second, an aggregate shock also change that price but for all the firms importing from that country as well as the aggregate price level and market demand of the economy. Based on these costs, firms make their ex-post quantity decisions as in Eaton and Kortum [2002], which affects ex-ante decisions where firms maximize expected profits. As in Antràs, Fort, and Tintelnot [2017], we find that even with aggregate or idiosyncratic uncertainty, a pecking order exists, and more productive firms self-select into importing from a larger set of suppliers.

Theoretically, we show that aggregate or idiosyncratic uncertainty affect firms' choice in opposite ways. Firm idiosyncratic import risk creates a positive option value of diversifying the set of suppliers, as firm profit is convex in sourcing cost and firms' decision exhibit risk-loving properties. However, country-specific aggregate shocks also affect market demand, which changes the co-movement between the firms' cost and the aggregate price of other firms. In the states-of-the-world where a firm is hit by a negative shock from a foreign country, the fact that the rest of the economy is very exposed to that same country lowers their profit, incentivizing the firm to hedge against such a risk. As a result, outsourcing and diversification objectives can lead to non-trivial sourcing decisions depending on the price and risk-structure of each country.

Nevertheless, in numerical examples, we see that the change in expected profits is principally driven by a decrease in expected marginal cost that comes from the complementarity. This makes firms want to add more countries to their sourcing strategy to get an extra cost of draw and increase competition, which decreases overall cost. However, uncertainty is not innocuous, and, even though it has two counteracting forces, it is driven mostly by the option value. This implies that firms are risk-lovers and prefer countries with high uncertainty for the chance of getting a high enough positive shock that will reduce the marginal cost.

To evaluate the importance of supply-chain uncertainty on the intensive and extensive margins, we estimate this model using firm-level customs and IRS data from the Chilean Central Bank from 2012 to 2023 at the quarterly level. We then recover the variance of aggregate and idiosyncratic risk using firms' import share and evaluate their relative importance in firms' decision. Moreover, we recover the fixed costs of sourcing from each country using Simulated Method of Moments and show how accounting for risk affect our results. Since the sourcing choice interacts between countries, the dimensionality of our problem is thus very high as it involves solving a combinatorial problem over all possible combination of import sources. However, exploiting the complementarity between countries in firms' marginal cost, we can leverage Jia [2008]'s algorithm to reduce the dimensionality of our problem.

Using our parameters, we re-estimate our model to study how the change in average uncertainty from 2020 to 2023 affected the sourcing decision of firms in Chile compared to their the sourcing strategy obtained using the average estimates from 2012 to 2019. We find that there is a positive correlation between the change in aggregate uncertainty and the change in both the extensive and the intensive margins. In the case of the extensive margin, we find that most of the effect is explained by the fact that the option value is bigger than the hedging effect, so firms prefer countries with higher uncertainty because of the chance of a cost reduction and getting the expected increase in the market demand. For the case of the intensive margin we find a similar, albeit smaller, effect of uncertainty. Then, we find that the expected HHI decreases with uncertainty, which can be explained by the fact that the extensive margin increases more than the intensive margin.

Our model makes strong assumptions about the timing of firms' decision making process, which affects our results. We also obtain a model in which firms behave like they are risk loving, which does not necessarily match what we observe in reality. However, our model is novel in the sense that it allows us to obtain the different forces through which uncertainty is affecting the sourcing decisions of firms. With our model and our data we are able to estimate the parameters and obtain a counterfactual to understand the effect of uncertainty in the extensive and intensive margin.

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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:

$$\begin{aligned} M_{ij}(\bar{\gamma}) &= N_j \int_{\tilde{\varphi}_{ij}}^{\infty} \int_{\tilde{\gamma}(\varphi)} M_{ij}(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi)) d\tilde{\Psi}_i^{\varphi}(\gamma) dG_i(\varphi) \\ &= N_j(\sigma-1)\eta^{\frac{\sigma-1}{\theta}} T_i(\tau_{ij}\bar{\gamma}_{ij}w_i)^{-\theta} B_j(\bar{\gamma}) \times \\ &\quad \int_{\tilde{\varphi}_{ij}}^{\infty} \int_{\tilde{\gamma}(\varphi)} \mathbb{1}_{ij}(\varphi)\varphi^{\sigma-1}(\Theta_j(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi)))^{\left(\frac{\sigma-1}{\theta}-1\right)}(\tilde{\gamma}_{ij}(\varphi))^{-\theta} d\tilde{\Psi}_i^{\varphi}(\gamma) dG_i(\varphi), \end{aligned} \tag{21}$$

so,

$$M_{ij}(\bar{\gamma}) = N_j(\sigma-1)\eta^{\frac{\sigma-1}{\theta}} T_i(\tau_{ij}\bar{\gamma}_{ij}w_i)^{-\theta} B_j(\bar{\gamma})\Lambda_{ij}(\bar{\gamma}), \tag{22}$$

with,

$$\Lambda_{ij}(\bar{\gamma}) \equiv \int_{\tilde{\varphi}_{ij}}^{\infty} \int_{\tilde{\gamma}(\varphi)} \mathbb{1}_{ij}(\varphi)\varphi^{\sigma-1}(\Theta_j(\varphi, \bar{\gamma}, \tilde{\gamma}(\varphi)))^{\left(\frac{\sigma-1}{\theta}-1\right)}(\tilde{\gamma}_{ij}(\varphi))^{-\theta} d\tilde{\Psi}_i^{\varphi}(\gamma) dG_i(\varphi), \tag{23}$$

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,

$$M_{ij}(\bar{\gamma}) = \frac{E_j}{P_j(\bar{\gamma})/N_j} \times \frac{Q_i}{\sum_k \frac{E_k}{P_k(\bar{\gamma})/N_k}(\tau_{ik}\bar{\gamma}_{ik})^{-\theta}\Lambda_{ik}(\bar{\gamma})} \times (\tau_{ij}\bar{\gamma}_{ij})^{-\theta} \times \Lambda_{ij}(\bar{\gamma}), \tag{24}$$

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: $\Xi_j(\bar{\gamma}) \equiv K_j(\bar{\gamma})T_j(\tau_{jj}\bar{\gamma}_{jj}w_j)^{-\theta}N_jB_j(\bar{\gamma})$, with $K_j(\bar{\gamma}) = (\sigma-1)\eta^{(\sigma-1)/\theta}N_jB_j(\bar{\gamma})$ so we can write,

$$\Lambda_{ij}(\bar{\gamma}) = \frac{K(\bar{\gamma})}{\Xi_j(\bar{\gamma})}\int_{\tilde{\varphi}_{ij}}^{\infty}\int_{\tilde{\gamma}_{ij}(\varphi)} \mathbb{1}_{ij}(\varphi)\varphi^{\sigma-1}(\Theta_j(\varphi,\bar{\gamma},\tilde{\gamma}(\varphi))^{\frac{\sigma-1}{\theta}-1}T_j(\tau_{jj}\tilde{\gamma}_{jj}(\varphi)w_j)^{-\theta}d\tilde{\Psi}^{\varphi}_{ij}(\varphi)dG_j(\varphi), \tag{25}$$

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

$$\Phi_j = \frac{f_{ej}}{L_j}\underline{\varphi_j}^{-\kappa}P_j(\bar{\gamma})^{-\kappa}w_j^{\frac{\kappa}{\sigma-1}-1} \tag{26}$$

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:

$$
\begin{aligned}
HHI_j &= \sum_{i=1}^{I} (ms_{ij})^2 \\
&= \sum_{i=1}^{I} \left(\frac{M_{ij}(\bar{\gamma})}{\sum_{k=1}^{I} M_{kj}(\bar{\gamma})} \right)^2 \\
&= \sum_{i=1}^{I} \left(\frac{T_i(\tau_{ij}\bar{\gamma}_{ij}w_i)^{-\theta}\Lambda_{ij}(\bar{\gamma})}{\sum_{k=1}^{I} T_k(\tau_{kj}\bar{\gamma}_{kj}w_k)^{-\theta}\Lambda_{kj}(\bar{\gamma})} \right)^2
\end{aligned} \tag{27}
$$

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 Simple Case: 2 Countries with Aggregate Shocks

To understand the mechanisms that are at play in our model, we develop a simple case with 2 countries where there can be both aggregate and idiosyncratic uncertainty. We simplify everything as much as possible and assume that technology is the same in bot Home and Foreign, and wages, as well as iceberg costs, at Home are all equal to 1 at Home, so $T_H = T_F = w_H = \tau_H = 1$. We denote the countries as Home, H, and Foreign, F, but we only add the country for the origin, and not the destination, since the destination country is always Home. Specifically, we consider the case where the fixed cost of sourcing domestically (f_H) is set to zero, implying that firms invariably prioritize sourcing from the Home country before considering buying from Foreign. Consequently, the sourcing strategy of exclusively procuring from Foreign is not an option. Instead, firms in this simplified setting face a binary choice: either they source solely from Home (H) or opt for a mixed strategy by sourcing from both Home and Foreign (FH), i.e., they diversify.

To simplify things further, supply chain shocks, with $\bar{\gamma}_{ij}$ denoting aggregate shocks, and $\tilde{\gamma}_{ij}^{\varphi}$, denoting idiosyncratic shocks, will follow an independent and identically distributed (i.i.d.) Binomial distribution. Specifically, we concentrate on the scenario of “non-positive” shocks, i.e., shocks that can only maintain or increase the price, so $\tilde{\gamma}_i^{\varphi}, \bar{\gamma}_i > 1$. This case is specified as follows:

$$\bar{\gamma}_i = \begin{cases} 1 & \text{wp } 1-\bar{\pi}_i \\ \bar{\delta}_i & \text{wp } \bar{\pi}_i \end{cases}, \qquad \tilde{\gamma}_i^{\varphi} = \begin{cases} 1 & \text{wp } 1-\tilde{\pi}_i^{\varphi} \\ \tilde{\delta}_i^{\varphi} & \text{wp } \tilde{\pi}_i^{\varphi} \end{cases},$$

with $i \in \{H, F\}$, $1 < \bar{\delta}_H < \bar{\delta}_F$, $1 < \tilde{\delta}_H^{\varphi} < \tilde{\delta}_F^{\varphi}$, and the probability of shock is higher for Foreign than for Home, $\bar{\pi}_F > \bar{\pi}_H$, and $\tilde{\pi}_F^{\varphi} > \tilde{\pi}_H^{\varphi}$. We now compare the expected profits for each of the strategies and understand how aggregate and idiosyncratic uncertainty affects the firm's decision of where to source from.

We proceed to show the expected profits of a firm whose sourcing strategy is to buy only from Home, so the only shocks that affect this firm are the domestic aggregate shock and the firm-domestic specific shock, such that:

$$\mathbb{E}(\pi(\varphi, \bar{\gamma}, \tilde{\gamma}^{\varphi})) = \varphi^{\sigma-1}\ \eta^{\frac{\sigma-1}{\theta}} \sum_{\gamma} \mathbb{P}(\bar{\gamma}_H, \bar{\gamma}_F, \tilde{\gamma}_F^{\varphi}, \tilde{\gamma}_H^{\varphi})(\bar{\gamma}_H\tilde{\gamma}_H^{\varphi})^{1-\sigma} B(\bar{\gamma}_H, \bar{\gamma}_F) \tag{28}$$

where we don't have a fixed cost of sourcing from Home since we set it up to be equal to zero.

We now find the expected profits for a firm whose sourcing strategy includes both Home and Foreign countries. This firm will be affected by both the domestic and foreign countries' aggregate uncertainty as well as firm-origin specific uncertainty for both domestic and foreign countries. The expected profits for a firm with this sourcing behavior are:

$$\mathbb{E}(\pi(\varphi, \bar{\gamma}, \tilde{\gamma}^{\varphi})) = \varphi^{\sigma-1}\eta^{\frac{\sigma-1}{\theta}} \sum_{\gamma} \mathbb{P}(\bar{\gamma}_H, \bar{\gamma}_F, \tilde{\gamma}_F^{\varphi}, \tilde{\gamma}_H^{\varphi})\Big((\tau_F\bar{\gamma}_F\tilde{\gamma}_F^{\varphi}w_F)^{-\theta} + (\bar{\gamma}_H\tilde{\gamma}_H^{\varphi})^{-\theta}\Big)^{\frac{\sigma-1}{\theta}} B(\bar{\gamma}_H, \bar{\gamma}_F) - f_F \tag{29}$$

with $\Theta_H(\varphi, \bar{\gamma}, \tilde{\gamma}^{\varphi}) = (\bar{\gamma}_H\tilde{\gamma}_H^{\varphi})^{-\theta}$, and $\Theta_{HF}(\varphi, \bar{\gamma}, \tilde{\gamma}^{\varphi}) = (\tau_F\bar{\gamma}_F\tilde{\gamma}_F^{\varphi}w_F)^{-\theta} + (\bar{\gamma}_H\tilde{\gamma}_H^{\varphi})^{-\theta}$ the sourcing capabilities for each of the two sourcing strategy. Because shocks are distributed i.i.d Binomial, we have $2^4 = 16$ possible states of the world in this case. This means that we have 16 different probabilities of shocks, e.g., $\mathbb{P}(\bar{\delta}_H, \bar{\delta}_F, \tilde{\delta}_H^n, \tilde{\delta}_F^n) = \bar{\pi}_H\bar{\pi}_F\tilde{\pi}_H^{\varphi}\tilde{\pi}_F^{\varphi}$, or $\mathbb{P}(\bar{\delta}_H, \bar{\delta}_F, \tilde{\delta}_H^n, \tilde{\delta}_F^n) = (1-\bar{\pi}_H)\bar{\pi}_F\tilde{\pi}_H^{\varphi}\tilde{\pi}_F^{\varphi}$, and so on. Finally, since there is no domestic fixed cost, we only consider the foreign fixed cost.

Then, we take a look at the firm-level intermediate input purchases. This is an ex-post decision, so it happens after shocks have already been realized. For a firm that only sources from Home:

$$M_H(\varphi, \bar{\gamma}, \tilde{\gamma}^{\varphi}) = (\sigma-1)\ \eta^{\frac{\sigma-1}{\theta}} \varphi^{\sigma-1}(\bar{\gamma}_H\tilde{\gamma}_H^{\varphi})^{1-\sigma+\theta} B(\bar{\gamma}_H, \bar{\gamma}_F) \tag{30}$$

and for the case of a firm that sources from both Foreign and Home:

$$M_H(\varphi, \bar{\gamma}, \tilde{\gamma}^{\varphi}) = A \times \varphi^{\sigma-1}\Big((\tau_F\bar{\gamma}_F\tilde{\gamma}_F^{\varphi}w_F)^{-\theta} + (\bar{\gamma}_H\tilde{\gamma}_H^{\varphi})^{-\theta}\Big)^{\frac{\sigma-1}{\theta}-1} (\bar{\gamma}_H\tilde{\gamma}_H^{\varphi})^{-\theta} B(\bar{\gamma}_H, \bar{\gamma}_F) \tag{31}$$

$$M_F(\varphi, \bar{\gamma}, \tilde{\gamma}^{\varphi}) = A \times \varphi^{\sigma-1}\Big((\tau_F\bar{\gamma}_F\tilde{\gamma}_F^{\varphi}w_F)^{-\theta} + (\bar{\gamma}_H\tilde{\gamma}_H^{\varphi})^{-\theta}\Big)^{\frac{\sigma-1}{\theta}-1} (\tau_F\bar{\gamma}_F\tilde{\gamma}_F^{\varphi}w_F)^{-\theta} B(\bar{\gamma}_H, \bar{\gamma}_F) \tag{32}$$

with $A \equiv (\sigma-1)\eta^{\frac{\sigma-1}{\theta}}$ a constant. We now take a closer look to what the market demand term includes. We have that

$$B(\bar{\gamma}_H, \bar{\gamma}_F) = K \times P(\bar{\gamma}_H, \bar{\gamma}_F)^{\sigma-1}$$

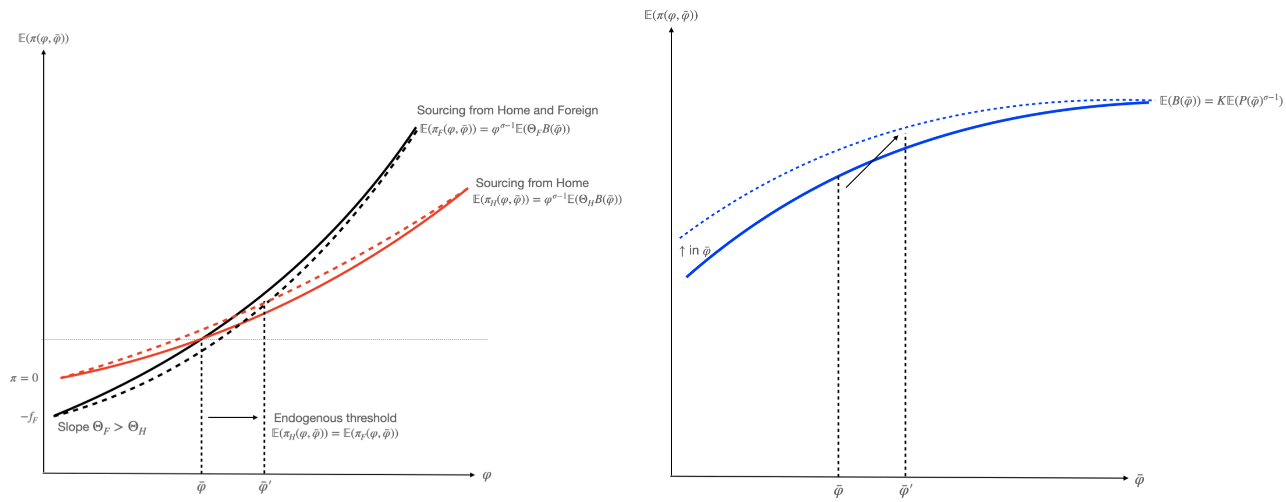
with $K \equiv \left(\frac{1}{\sigma}\right) \times \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} \times E$ a constant.

Then, for each realization of the shocks, we will have different values of the price index $P(\bar{\gamma}_H, \bar{\gamma}_F)$: $P(\bar{\delta}_H, \bar{\delta}_F)$, $P(\bar{\delta}_H, 1)$, $P(1, \bar{\delta}_F)$, $P(1,1)$. Writing them out, we have:

$$\begin{aligned}
P_H(\bar{\delta}_H, \bar{\delta}_F)^{\sigma-1} &= \left(\frac{\sigma-1}{\sigma}\right)\left(\frac{\eta^{\frac{1}{\theta}}}{s_1(\tilde{\varphi}, \bar{\varphi})\ \bar{\delta}_H^{1-\sigma} + s_2(\bar{\varphi})\ (\bar{\delta}_H^{-\theta} + (\tau_{FH}\bar{\delta}_F w_F)^{-\theta})^{\frac{\sigma-1}{\theta}}}\right) \\
P_H(\bar{\delta}_H, 1)^{\sigma-1} &= \left(\frac{\sigma-1}{\sigma}\right)\left(\frac{\eta^{\frac{1}{\theta}}}{s_1(\tilde{\varphi}, \bar{\varphi})\ \bar{\delta}_H^{1-\sigma} + s_2(\bar{\varphi})\ (\bar{\delta}_H^{-\theta} + (\tau_{FH} w_F)^{-\theta})^{\frac{\sigma-1}{\theta}}}\right) \\
P_H(1, \bar{\delta}_F)^{\sigma-1} &= \left(\frac{\sigma-1}{\sigma}\right)\left(\frac{\eta^{\frac{1}{\theta}}}{s_1(\tilde{\varphi}, \bar{\varphi}) + s_2(\bar{\varphi})\ (1 + (\tau_{FH}\bar{\delta}_F w_F)^{-\theta})^{\frac{\sigma-1}{\theta}}}\right) \\
P_H(1,1)^{\sigma-1} &= \left(\frac{\sigma-1}{\sigma}\right)\left(\frac{\eta^{\frac{1}{\theta}}}{s_1(\tilde{\varphi}, \bar{\varphi}) + s_2(\bar{\varphi})\ (1 + (\tau_{FH} w_F)^{-\theta})^{\frac{\sigma-1}{\theta}}}\right)
\end{aligned} \tag{33}$$

where the shares, denoted as $s_1(\tilde{\varphi}, \bar{\varphi})$ and $s_2(\bar{\varphi})$, represent the proportions of firms exclusively sourcing from Home and those diversifying and sourcing from both Home and Foreign, respectively. $\tilde{\varphi}$ and $\bar{\varphi}$ denote the cutoff productivity levels for firms that do not leave the market, and those who buy from both Foreign and Home, respectively. From the equation above, we can see that the effect of an aggregate shock on the price index depends on these shares which, at the same time, depend on the expectation of the shocks, as well as the productivity of the firm and fixed costs. We are interested in understanding what is the effect of expected shocks on the shares and, finally, what is the effect on the price index, which will allow us to comprehend better what are some of the moving pieces that affect firm's sourcing decisions in the case of uncertainty. To find the value of $\bar{\varphi}$ that determines the cutoff productivity level for firms that only import from Home versus firms that import from both Home and Foreign, we set the expected utility of sourcing from Home equal to that of sourcing from both Foreign and Home, with $\mathbb{E}(\pi_H) = \mathbb{E}(\pi_{FH})$. This equality allows us to recover $\bar{\varphi}$, i.e., the productivity value of the marginal firm, which is indifferent, in expectation, between the two sourcing strategies.

Figure 16: Simple 2 countries example



(a) Cutoff

(b) Effect of cutoff on market demand

In Figure 16, we plot the simple case of firms' profits, and expected profits, when there are only two countries in the world, Home and Foreign. We plot both the case with and without uncertainty, and where the productivity parameter, denoted as φ, follows a Uniform distribution. Figure 16a depicts the expected profits of firms that source from either only Home (red line) or Home and Foreign (black line) when there is no uncertainty (solid line) and when there is uncertainty (dotted line). In the absence of uncertainty, firms solely sourcing from Home initially exhibit higher expected profits due to a lower fixed cost. However, because the slope of the firms that diversify (i.e., source from both Home and Foreign) is higher, since higher productivity firms benefit more from sourcing from more countries, there is a productivity level after which the profits obtained from diversifying surpass those from sourcing only from Home. Passed that threshold, all firms with a productivity higher than the cutoff will source from both Home and Foreign because they obtain higher profits choosing to diversify instead of sourcing only from domestic. Now, when there is aggregate uncertainty, we know that the market demand will be affected, since firms that source from both Home and Foreign will have to increase their prices, either by sourcing more from Home, which is more expensive, or sourcing from a now more expensive, in expectation, Foreign country. For firms sourcing only from Home there is no direct effect in their sourcing capability. The only effect they face is through the expected change in the market demand, which increases if Foreign is shocked, so the profits, as well as the slope, increase with uncertainty in the Foreign country. This occurs because a higher uncertainty in Foreign affects the expected price of final goods and hence the overall demand for cheaper goods. This will increase the demand for final goods from firms that source only from Home because now the price difference will be less, i.e., they gain competitiveness. Now, for the firms that source from both Home and Foreign, the result is ambiguous. On the one hand, the increase in uncertainty reduces firms' sourcing capability, decreasing profits and, on the other hand, market demand increases, counteracting the decrease in profits. Then, it could happen that the increase in expected market demand is big enough ($\bar{\varphi}$ is low enough) that high uncertainty does not affect firms' expected profits that much. The illustrated scenario in the figure represents the specific case where the expected profits end up decreasing due to the increase in Foreign uncertainty.

In Figure 16b, we examine the influence of the threshold on the market demand, denoted as $B_j(\bar{\gamma})$. This is a concave function that, for the case of no uncertainty (solid line), increases with the threshold, $\bar{\varphi}$. A higher threshold implies reduced diversification, leading to more firms exclusively relying on Home for inputs, which are costlier in expectation than those from Foreign. Consequently, these firms set higher prices, contributing to an increase in the price index, increasing the market demand for lower priced goods. Then, when there is an increase in uncertainty (dotted line), we observe from Figure 16a that this increases the threshold, and so the market demand, since there are more firms sourcing from the more expensive country, Home. However, this will decrease the impact of the uncertainty, since more firms won't be affected by it. Both the aggregate shock and uncertainty exert an influence on the price, or expected price, consequently affecting the overall expected price index.

In equations (24) and (25), and as depicted in Figure 16b, we observe that aggregate uncertainty affects both the sourcing capability of firm φ in country j as well as the market demand for country j, $B_j(\bar{\gamma})$. However, idiosyncratic uncertainty affects the sourcing capability but not the market demand. Specifically, heightened aggregate uncertainty at Home diminishes the expected sourcing capability of all firms acquiring inputs from Home. This effect is also observed for firms sourcing from both Home and Foreign, albeit to a lesser extent, as their expected sourcing capability depends not only on the Home country but also on Foreign, which allows them to substitute ex-post through the intensive margin, and the increased competition that reduces expected costs. The higher uncertainty will also increase the expected market demand, which acts in the opposite direction as the effect on the expected sourcing capability. This occurs because, if the foreign country does not get negatively shocked, firms that source from both the domestic and foreign countries can sell their goods at a lower cost than the ones that only source from domestic, so they get a higher expected market demand. From this, we learn that the effect of an increase in aggregate uncertainty at Home is ambiguous and depends on these counteracting forces. Whereas, an increase in idiosyncratic uncertainty at Home only impacts the expected sourcing capability and does not affect the expected market demand. Then, ceteris paribus, if there is an increase in idiosyncratic uncertainty the expected sourcing capability will be reduced, as well as ex-ante profits.

Consider now the scenario where, all else equal, the foreign country experiences an increase in aggregate uncertainty (i.e., increase in the variance of aggregate shock). This change affects the expected sourcing capability and market demand for a firm that sources from both Foreign and Home. However, for a firm exclusively importing from Home, while its expected sourcing capability remains unaffected, the increase in market demand positively impacts expected profits through the rise in the price index. Conversely, if only idiosyncratic uncertainty intensifies, it does not influence the expected market demand, as idiosyncratic shocks are averaged out. Nevertheless, it diminishes the sourcing capability, leading to a reduction in expected profits. Then, if both Home and Foreign increase their aggregate uncertainty and there's also an increase in idiosyncratic uncertainty, the first two will affect the market demand, increasing expected profits. However, the negative impact of the decreased in expected sourcing capability counteract these effects, and could even result in a net decrease in expected profits.

Taking a look at equations (26), (27), and (28), we observe that the impact on intermediate input purchases is different due to the ex-post nature of this decision, where uncertainty does not play a role in this case, but the realization of the shocks do. Given $B_j(\bar{\gamma})$, and $\sigma - 1 > \theta$, both idiosyncratic and aggregate shocks to Foreign lead to a reduction in sourcing potential and sourcing capability and subsequently decreases intermediate input purchases from all sources for firms that diversify, while it does not affect purchases from Home for firms that only source from the domestic country. However, the reduction of intermediate input purchases is higher for the foreign intermediate inputs than for the domestic ones. However, an increase in negative aggregate shocks, i.e., $\bar{\gamma}_{ij} > 1$, also results in an increase in $B_j(\bar{\gamma}_H, \bar{\gamma}_F)$, partially mitigating the decline induced by the reduced sourcing potential and capability. Consequently, the negative effect of the shock on firms' profits decreases. Then, higher $\bar{\varphi}$ values lead to more firms increasing sourcing from Home, resulting in a reduced susceptibility of the market demand to an increase in the shock from Foreign ex-post, decreasing the intermediate input purchases from all countries. This ex-post mechanism allows firms to change the quantity they obtain from each country they start a sourcing relationship with so that, if the foreign country is hit by a negative (positive) aggregate shock, then the firms' that source from both domestic and foreign countries decreases (increases) the quantity they import from the foreign country and might either increase or decrease the quantity they buy from the domestic country depending on how big the effect is on the market demand. This increases (reduces) the quantity bought from Home by firms that only buy intermediate inputs from the domestic country, because of the increase (decrease) in market demand.

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 Appendix

Table 7: Extensive and intensive margin

origin	number of firms	value of imports	rank by firms	rank by value
CHN	24755	153955	1	12
USA	17556	140322	2	2
RoW	8286	26033	3	5
ESP	8055	12507	4	12
DEU	7520	25660	5	6
ITA	7493	11571	6	14
BRA	6964	70063	7	3
ARG	6103	36515	8	4
HKG	5652	238	9	45
TWN	5313	2732	10	28

D Estimation Appendix

Figure 17: Country Sourcing Potential and Extensive Margin

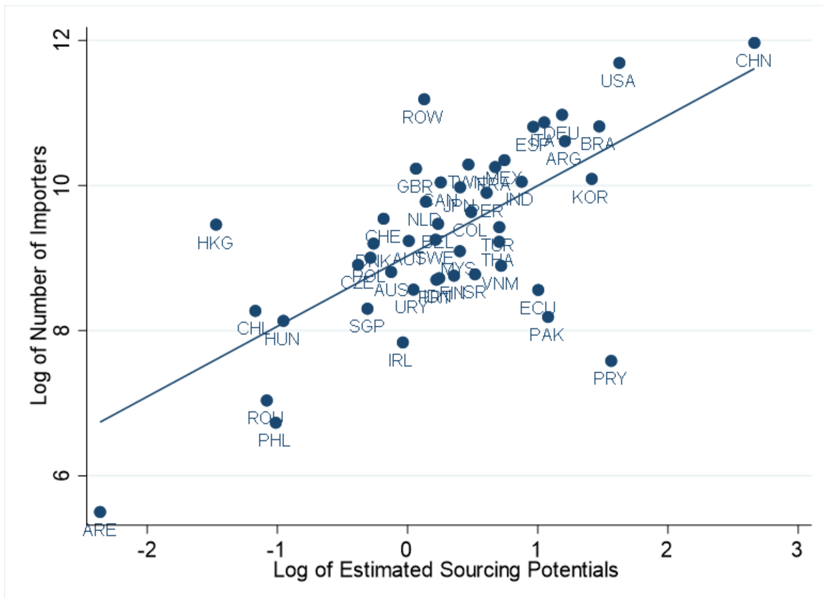


Figure 18: Country Sourcing Potential and Intensive Margin

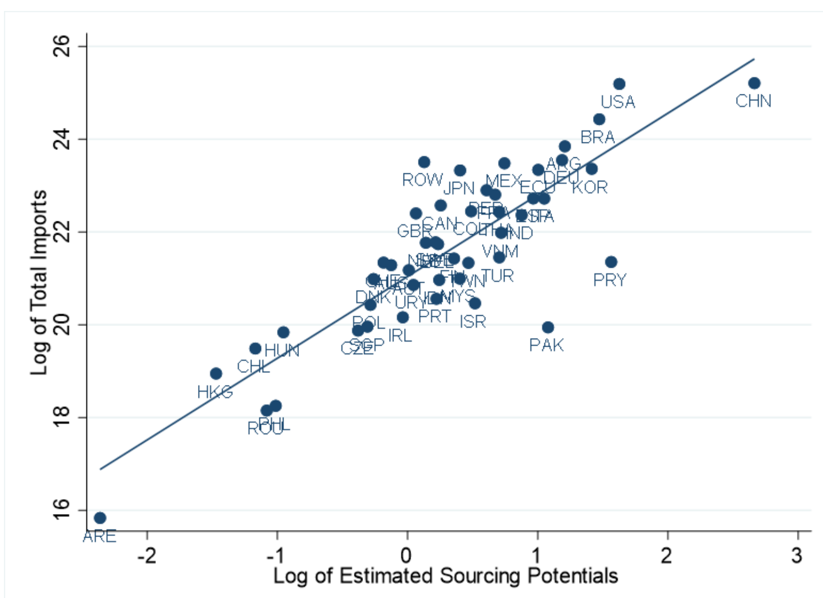


Figure 19: Average Aggregate Shocks All Countries, 2012q1-2023q4

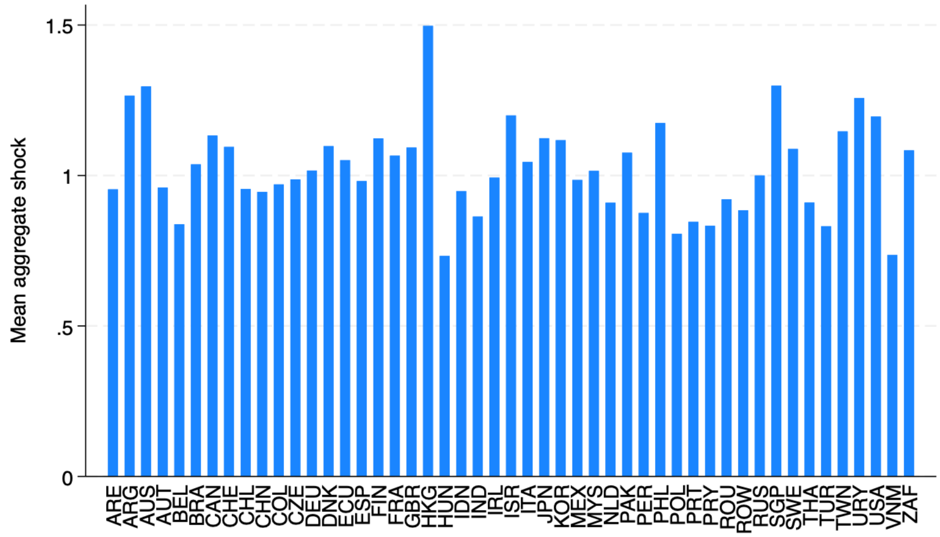


Figure 20: Average aggregate shock all countries, 2012q1-2015q4

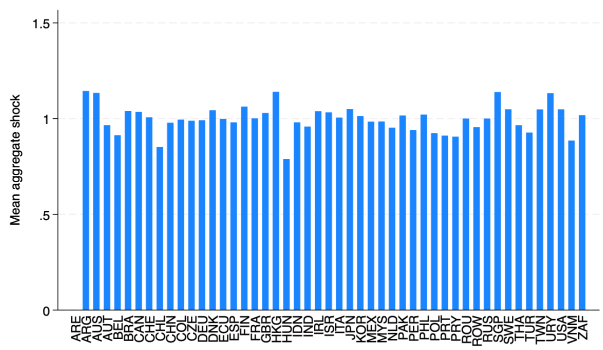


Figure 21: Average Aggregate Shocks All Countries, 2016q1-2019q4

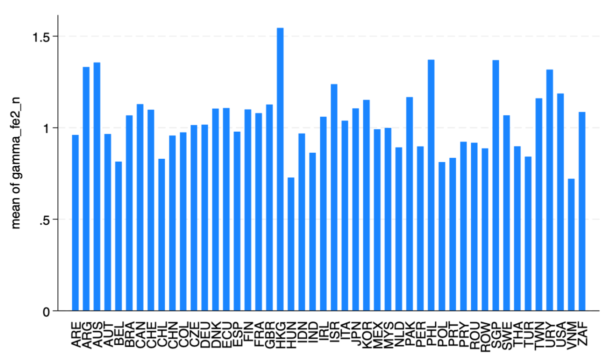


Figure 22: Average Aggregate Shocks All Countries, 2020q1-2023q4

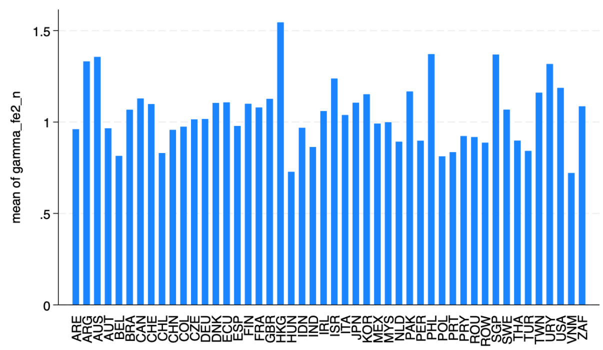


Figure 23: Average Standard Deviation for Aggregate Shocks, 2012q1-2023q4

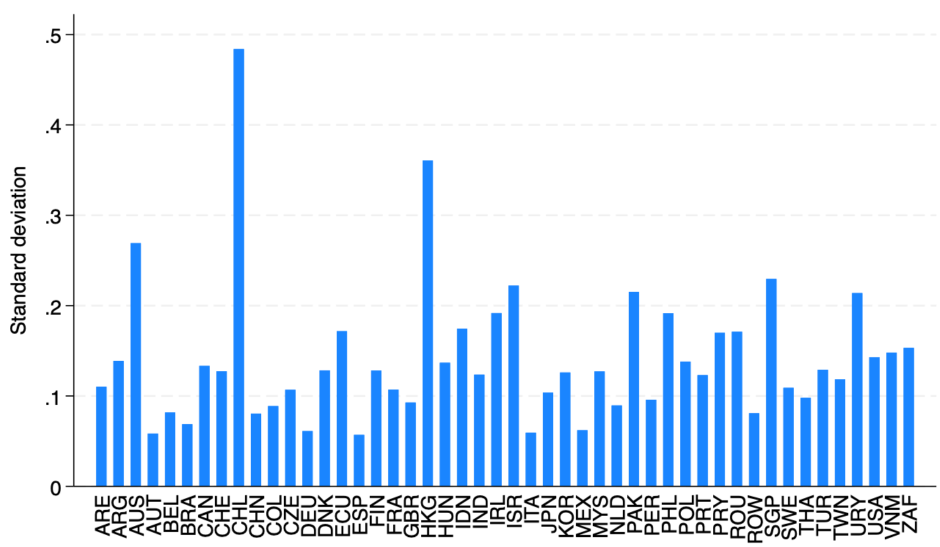


Figure 24: Average Standard Deviation for Aggregate Shocks, 2012q1-2015q4

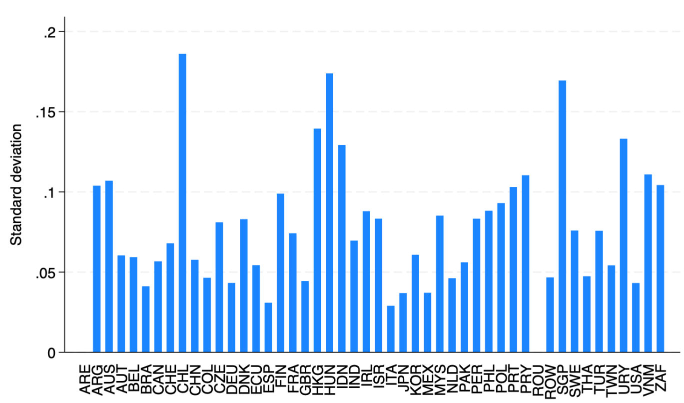


Figure 25: Average Standard Deviation for Aggregate Shocks, 2016q1-2019q4

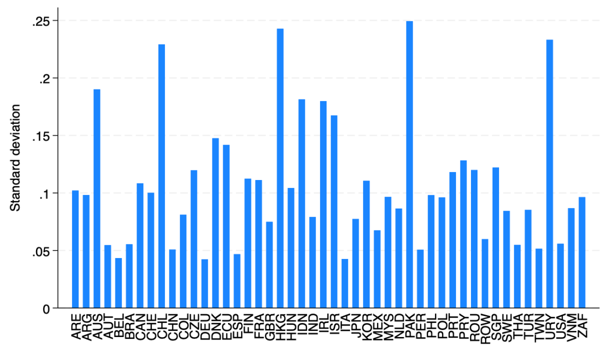


Figure 26: Average Standard Deviation for Aggregate Shocks, 2020q1-2023q4

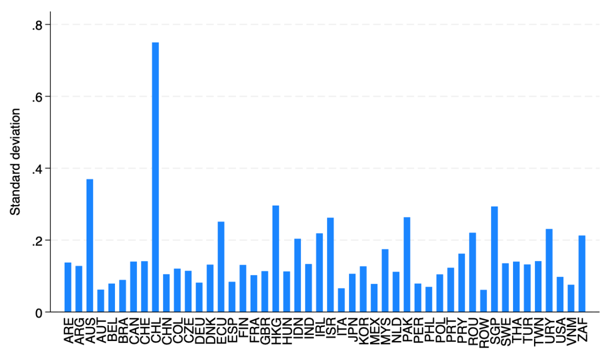


Figure 27: Aggregate Shocks in Time for China and USA

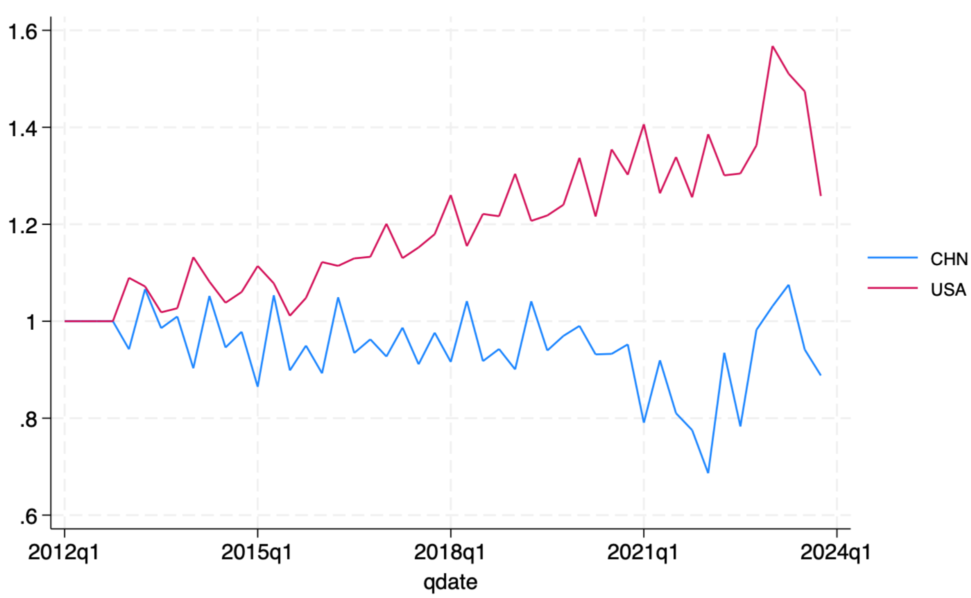


Figure 28: Change in the share of value of imports by importing firms