Essays in International Trade and Macroeconomics

by

José Ramón Morán van Gelderen

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Doctoral Committee:

Professor Andrei Levchenko, Co-Chair
Associate Professor Sebastián Sotelo, Co-Chair
Assistant Professor Zach Brown
Professor Jagadeesh Sivadasan

Jose Ramon Moran
moranvg@umich.edu
ORCID iD 0009-0007-7019-8736

Para Mutti y Vatti, todo esto es gracias a ustedes.

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ABSTRACT

This dissertation contains three essays related to international trade and macroeconomics. Two of these essays explore firm behavior in export markets, while the third one studies the impact of natural disasters. Chapter I examines how firms use a free trade agreement to export and the effects of regulations included in these agreements; Chapter II explores how learning while exporting affects firms' entry and exit decisions in export markets; and Chapter III examines the role natural disasters have on medium-term economic growth.

In Chapter I "Rules of Origin and the Use of NAFTA" Alfonso Cebreros and I explore how rules of origin affect the use of NAFTA. Firms exporting using NAFTA must source specific intermediate inputs from local suppliers to enjoy lower tariffs. Using Mexican data, we find that the smallest and largest firms use NAFTA less. This is rationalized by exporters facing fixed costs of using NAFTA and sourcing from foreign countries. We build a model of global input sourcing and rules of origin, and quantify these fixed costs at the sectoral level. We find that a 25% increase in the strictness of RoO or a 5% tariff on all Mexican imports would result in 0.72% and 13.65% lower US exports of intermediates to Mexico, respectively. On the contrary, removing RoO would increase these exports by 2.98%.

In Chapter II "Information Spillovers in Export Destinations" I study how firms' entry decisions in export markets are affected by export experience when destinations are informative about others. I provide empirical evidence of how export experience leads firms to make better foreign market entry decisions. I build a model of export supply and learning in which firms' behavior depends on their beliefs on their profitability in export markets; beliefs on a particular destination are affected by export experience in other foreign markets. I quantify the model by estimating firms' profitability in select destinations and conduct simulations to evaluate information spillovers' role on export diversification.

Finally, in Chapter III "Natural Disasters and Scarring Effects" Weicheng Lian, Raadhika Vishvesh, and I explore the medium-term scarring effects of natural disasters. We combine the synthetic control approach with the local projections method to quantify the dynamic effects of natural disasters on medium-term economic growth. On average, a severe natural disaster will result in 2.3% lower real GDP per capita five years after the shock. This effect is 1.24 p.p. stronger for countries with high levels of public debt.

CHAPTER I

Rules of Origin and the Use of NAFTA

joint with Alfonso Cebreros

1.0 Abstract

We study how Rules of Origin (RoO) affect the use of NAFTA. Firms exporting using NAFTA have to comply with RoO to enjoy preferential tariff treatment. We document that: (i) the smallest and largest firms use NAFTA less intensively than medium-sized firms, and (ii) the decrease in input sourcing from non-NAFTA countries when using NAFTA to export is increasing in firm size. We rationalize these empirical findings by including fixed costs of using NAFTA and of sourcing from foreign countries in a model of global input sourcing, where the opportunity cost of complying with RoO when using NAFTA increases with firm size. We quantify our model using data on Mexican firms, RoO, and tariffs. We conduct counterfactuals that suggest a 25% increase in the strictness of RoO or a 5% tariff on all Mexican imports would result in 0.72% and 13.65% lower US exports of intermediates to Mexico, respectively. On the contrary, we quantify that removing RoO would increase these exports by 2.98%.

1.1 Introduction

Since the creation of the World Trade Organization (WTO) in 1995, there has been a proliferation of Free Trade Agreements (FTAs) around the World. Bhagwati (1995) terms this as the *Spaghetti Bowl Effect*, describing how international trade is dominated by regional agreements instead of relying on multilateral organizations such as the WTO.[1] One of the regulations included in FTAs are Rules of Origin (RoO), defined as *"the criteria needed to determine the national source of a product."*[2] RoO are highly pervasive, being included in at

[1]According to the WTO, as of 2023 there are 360 active FTAs around the world. Source: WTO's RTA-IS.
[2]Source: WTO's Technical Information on Rules of Origin.

least 62% of existing FTAs according to Kniahin and De Melo (2022).

RoO are implemented to protect local industries, and to increase the amount of regional content in bilateral exports by requiring domestic firms to source some of their intermediate inputs from suppliers in member countries. By doing so, they introduce a key tradeoff between a potential loss of efficiency and lower barriers to trade. On the one hand, firms complying with RoO cannot source their inputs from the most efficient suppliers around the World, increasing their cost of production. On the other hand, RoO allow firms to enjoy preferential tariff treatment, decreasing their cost of exporting to a member country.

This paper studies the effect of RoO on the use of the North American Free Trade Agreement (NAFTA) to export, and their implications for bilateral trade flows. We assemble a unique dataset for the universe of Mexican exporters in which we observe whether they use NAFTA, i.e., benefit from preferential tariffs by complying with RoO, or not for their exports to the US, as well as the inputs these firms source from foreign countries. We complement this dataset with: (i) The Most Favored Nation (MFN) tariffs the US applies to Mexican exporters if they do not export under NAFTA, (ii) The RoO firms had to comply with if using NAFTA, and (iii) The input composition of every product being exported to the US.

We use our data to construct a product-level measure of RoO strictness, defined as the share of a product's input value restricted to be sourced from suppliers within NAFTA countries. For this, we leverage the fact that in the NAFTA agreement, most RoO are written in terms of *Classification Changes*, as documented by Conconi et al. (2018). This type of RoO specifies for each product which inputs must be sourced from suppliers within NAFTA countries, according to the Harmonized System (HS) codes of both the final product and its intermediate inputs.[3]

We begin by documenting three empirical facts. First, there is a positive correlation between RoO strictness and MFN tariffs. Second, there is an inverse U-shaped relationship between the use of NAFTA and firm size, i.e., medium sized exporters are more likely than larger or smaller exporters to export using NAFTA. Third, the proportion of firms that use non-NAFTA input sourcing is lower among NAFTA exporters, and this difference is increasing across exporter size deciles. These findings are robust to controlling for industry fixed effects, which should capture any common sectoral unobservables affecting the use of NAFTA and foreign sourcing. The first empirical fact implies firms do face a tradeoff when choosing whether to use NAFTA to export, that is, if a firm wants to avoid paying a high tariff, it has to source a large share of its inputs exclusively from suppliers within NAFTA

[3]For example, under this type of RoO, a firm exporting a product with HS code 85 has to source all inputs belonging to the same HS code 85 from NAFTA countries, while any input of a different HS code can be freely sourced from around the world.

countries. The second and third empirical facts suggest that Mexican exporters face fixed costs of using NAFTA and sourcing from foreign countries. The former may reflect costs such as complying with labor regulations and learning to use the FTA. The latter should capture costs such as finding a foreign supplier and dealing with foreign bureaucracy.

We include these fixed costs in the model of global input sourcing by Antras et al. (2017), extending it to include distinct sectors and industries within them. In our model, Mexican firms export to the US and choose: (i) whether they use NAFTA or WTO to export, and (ii) the set of countries from which they can source their inputs. Using NAFTA requires them to comply with RoO and pay the associated fixed cost, while using WTO implies they have to pay MFN tariffs. Exporters in Mexico are monopolistically competitive and require a continuum of intermediate inputs that they can source from heterogeneous suppliers around the world. We introduce RoO by assuming that a share of a firm's inputs can only be sourced from NAFTA countries, while the rest of its inputs can be freely sourced from the best suppliers among the set of countries for which firms have paid fixed costs of sourcing. Mexican exporters are heterogeneous in terms of the RoO and MFN tariffs they face, their fixed costs of using NAFTA and sourcing from foreign countries, how attractive it is for them to source inputs from foreign countries, and their export-specific productivity.

The model yields the following natural predictions on how the use of NAFTA is affected by RoO, tariffs, foreign countries' sourcing efficiency, and fixed costs: (i) The use of NAFTA to export is decreasing in RoO, as these increase marginal cost by requiring firms to source a share of their inputs from possibly inefficient suppliers. (ii) Higher tariffs increase the use of NAFTA, as these increase the cost of exporting using WTO. (iii) The use of NAFTA is increasing in how efficient NAFTA countries are in supplying inputs, as this decreases the opportunity cost of RoO. (iv) Conversely, the use of NAFTA is decreasing in how efficient non-NAFTA countries are in supplying inputs. (v) The use of NAFTA is decreasing in its fixed cost, and increasing in fixed costs of sourcing from foreign countries. The latter follows since the larger fixed costs of sourcing are, the lower the likelihood a firm will be able to source from these countries, thereby decreasing the cost of complying with RoO.

In our model, an increase in RoO decreases bilateral trade in final goods, as sourcing from inefficient suppliers results in higher prices which lowers demand, and has ambiguous effects on bilateral trade in intermediate goods. On the one hand, stricter RoO will increase the share of inputs being sourced from suppliers in member countries. On the other, since firms sourcing from possibly less efficient suppliers results in lower trade in final goods, purchases of intermediates decrease as well. The net effect of these two opposing effects depends on the relative efficiency of NAFTA countries in supplying intermediate inputs, and on the extent to which firms can source their inputs from suppliers in non-NAFTA countries.

To quantitatively evaluate these tradeoffs and the impact of RoO, we take the model to the data. We estimate, at the sectoral level, the fixed costs of using NAFTA and sourcing from foreign countries. The moments we target are: (i) The share of firms using NAFTA to export, which pins down its fixed cost, (ii) The share of firms sourcing from each foreign country, which helps us identify fixed costs of sourcing, and (iii) Average exports at the firm level, which pins down US market demand for each sector. We do this by feeding into our model data on the RoO and tariffs that each firm within an industry would either have to comply with or pay. We also estimate how attractive it is for Mexican industries to source their intermediate inputs from foreign countries.

Having calibrated the parameters of our model, we conduct counterfactuals where we study whether the US and Mexico would benefit from a set of policy changes. We explore: (i) An increase in RoO implied in the transition from NAFTA to the United States-Mexico-Canada Agreement (USMCA), (ii) An increase in tariffs on Mexican imports, and (iii) A removal of RoO from the NAFTA agreement. The first two counterfactuals are of interest as they represent the most prominent changes in trade policy that have been either implemented or proposed in recent years between these two countries. The third counterfactual allows us to quantify the inefficiency resulting from restricting firms from sourcing their inputs from the most efficient suppliers. In these counterfactuals, we focus our attention on three key variables policymakers care about: US exports of intermediate goods to Mexico, US prices for Mexican imports, and Mexican firm profits.

Two key factors determine the sectoral heterogeneity in the responses to these counterfactual scenarios. First, the distribution of firm size in a sector. Fixed costs of sourcing from foreign countries imply the opportunity cost of complying with RoO is increasing in size. Therefore, a protectionist policy will be costlier in sectors with relatively larger firms. Second, the efficiency of NAFTA and non-NAFTA countries in supplying intermediate inputs. Sectors sourcing from industries in which NAFTA countries are relatively better suppliers of inputs will be the ones less affected by either an increase or a removal of RoO.

The first counterfactual that we explore is the transition in July 2020 from NAFTA to USMCA, which we implement as an increase of 25% in the RoO strictness faced by all Mexican firms.[4] We do this because: (i) Assuming a common increase across all industries allows us to study how sectoral heterogeneity leads to different outcomes through the lens of our key mechanisms, (ii) Detailed sectoral data on the new RoO in USMCA are not yet available. We evaluate the responses to the increase in RoO in terms of three distinct effects. First, stricter RoO require Mexican exporters to source a larger share of their inputs from suppliers

[4]For example, if a product had a 10% RoO strictness under NAFTA, we assume in USMCA it would have a RoO strictness of 12.5%. This increase is consistent with that experienced by the automobile sector.

in NAFTA countries, this increases US exports of intermediates to Mexico. Second, having to source a larger share of inputs from NAFTA suppliers increases the cost of production, which decreases bilateral trade. Third, some firms will no longer use NAFTA to export. On the one hand, this implies firms can now source from efficient suppliers, potentially decreasing the price of Mexican exports. On the other, not having to comply with RoO decreases the share of inputs sourced from NAFTA countries. Our counterfactual simulations suggest that bilateral trade would decrease across all sectors. On average, US exports of intermediates to Mexico would decrease by 0.72%, together with a 0.16% increase in US prices for imports from Mexico and 0.67% lower profits for Mexican fims.

The second counterfactual analysis that we conduct is one in which all Mexican imports pay at least a 5% tariff, following a US proposal in 2019. We assume firms using NAFTA now pay a 5% tariff, while firms using WTO see their tariff increase to at least 5%. This would result in 47% of the firms originally using NAFTA switching to WTO, as having to pay tariffs even if using NAFTA decreases its benefit. This decreases US exports of intermediates as firms would no longer comply with RoO. Moreover, this would not translate into higher foreign sourcing because paying higher tariffs decreases firms' ability to pay fixed costs of sourcing. In this situation, our model predicts US exports decrease by 13.65%, US prices for imports from Mexico increase by 4.95%, and Mexican firm profits decrease by 11.68%.

The third counterfactual that we study is what would happen if NAFTA had removed RoO on all products. This decreases the cost of using the FTA, increasing its use. For firms that were already using NAFTA, the share of inputs they source from member countries would decrease as RoO are no longer in place, but this effect is dominated by the cost reductions coming from being able to source from more efficient suppliers. Of the firms that were originally using WTO, 9.00% switch to NAFTA, and these firms also increase their foreign sourcing as these firms no longer pay MFN tariffs, which increases their export revenue. Results suggest that US exports would increase by 2.98%, US prices for imports from Mexico decrease by 1.15%, and Mexican firm profits would increase by 5.52%.

This paper is related to several branches of the literature. First, we contribute to the literature on the impact of trade liberalization and Free Trade Agreements. Seminal papers on this topic are those by Trefler (2004), Romalis (2007), Arkolakis et al. (2008), Bustos (2011), Ossa (2011), Antràs and Staiger (2012), Kehoe and Ruhl (2013), Caliendo and Parro (2015), De Loecker et al. (2016), among others. To the best of our knowledge, this is the first paper to provide evidence on which firms are using NAFTA to export, and how this depends on firm characteristics such as their size and industry.

Second, our paper builds on the literature on global sourcing decisions, including Antras and Helpman (2004), Goldberg et al. (2010), Rodríguez-Clare (2010), Garetto (2013), Kee and Tang (2016), Tintelnot (2017), Bernard et al. (2018), and Head and Mayer (2019). Our model builds on Antras et al. (2017), which develops a model of global sourcing in which firms choose the set of countries from which they can import their inputs. We introduce a new margin of decision for firms: their choice of using either NAFTA or WTO to export, which captures the tradeoff between lower tariffs and inefficiencies in production.

Third, our paper speaks directly to the literature on content protection and the effects RoO have on firm behavior, starting with the work by Dixit and Grossman (1982), Grossman and Helpman (2008), Krishna and Krueger (1995), and Estevadeordal (2000). More recent papers are Carrère and De Melo (2004), Anson et al. (2005), Augier et al. (2005), Ju and Krishna (2005), Cadot et al. (2006), Deardorff (2018), Krishna et al. (2021), Acosta and Leal (2022), and Ornelas and Turner (2024). Our work is closely related to Conconi et al. (2018) which finds that the more restricted an input became under RoO, the larger the extent to which Mexico substituted sourcing it from non-NAFTA countries towards NAFTA ones. Head et al. (2024) also builds a model of input sourcing and RoO, which they calibrate to the automotive industry in North America, allowing them to characterize a Laffer Curve between RoO and the amount of regional content in exports. We contribute to their work using data on the universe of the Mexican export transactions, which allows us to document novel stylized facts on the use of NAFTA and structurally estimate a model of NAFTA and compliance RoO with based on these data.

The rest of the paper is organized as follows. Section 1.2 describes the data sources we use and how we combine them to construct a dataset capturing firm behavior and the costs and benefits of using NAFTA. In Section 2.2, we show three empirical facts that we highlight throughout the paper and inform our modeling strategy, as well as provide evidence of Mexican exporters facing fixed costs of using NAFTA and of sourcing from foreign countries. Section 2.3 develops our model for the use of NAFTA and RoO. Section 2.4 details the quantification of our model, while Section 2.5 presents the counterfactual scenarios we explore. Section 1.7 summarizes our main findings and discusses their policy implications.

1.2 Data

This section describes the distinct data sources we use to create a unique dataset on the use of NAFTA and firms' sourcing choices, including the RoO and tariffs exporters to the US face. We study Mexican firms exporting final products to the US using either NAFTA or WTO, and importing intermediate inputs from all over the World. The data sources we use are the following:

Mexican Customs Data: This data are accessed through the Econlab at Banco de México, the country's Central Bank. It contains the universe of exports and imports at the transaction level. For every transaction, we observe the following: Firm ID, product at the HS 6-digit level, trade value, origin/destination of the transaction, and whether the transaction was classified as either for an intermediate or a final good. Crucially for this paper, we also observe whether an export used NAFTA or WTO membership.

US 2022 Harmonized Tariff Schedule: This data set details, at the HS 6-digit level, the MFN tariffs Mexican exporters would have to pay at the border if they choose to export their products using WTO membership.

NAFTA's RoO: This data comes from Annex 401 of the NAFTA agreement, assembled and made available to the public by Conconi et al. (2018). It describes the exact RoO applied to each product at the HS 6-digit level, which Mexican firms had to comply with if they wanted to use NAFTA to export. As Conconi et al. (2018) points out, most of NAFTA's RoO are defined in terms of *Classification Changes*, which implies that for each final product, we observe which of its inputs have to be sourced from NAFTA countries.

Input-Output Tables: We use the Direct Requirement Coefficients (DRC) Tables published in 1997 by the BEA. These tables provide us with a survey-based estimate of the average input composition of each final product. Products are defined following the BEA's own product classification, which is very similar to the 1997 BEA classification system.

We combine these two last data sources to compute a product-level measure of RoO strictness. Since we know the input intensity of every product, and we know which of their inputs are restricted to be sourced exclusively from suppliers in NAFTA countries, our measure of RoO strictness is defined as the share of a product's inputs that have to be sourced from NAFTA countries if a firm chooses to use NAFTA to export.[5]

We study exports between September 2014 and June 2020. The former is the first month for which the NAFTA usage information is available, and the latter is the last month before the transition from NAFTA to USMCA. In these periods, there are 25,572 different firms exporting 1,050 unique products to the US, using either NAFTA or WTO to do so. This results in 1,019,408 unique firm-time-product combinations, which we define as our unit of observation. We restrict our sample in two distinct ways.

First, at the firm level, we drop exporters whose total exports to all destinations are lower than their total imports, which drops 29.27% of firms. We do this because we want to

[5]This requires moving the DRC tables from BEA's classification to HS; details of this are in Appendix A.1.

focus this study on the behavior of Mexican exporters, and hence we want to exclude trade intermediaries or firms that primarily sell in the domestic market.[6]

Second, at the product level, we drop HS 6-digit codes for which: (i) Tariffs are zero, as there would be no benefit of using NAFTA, nor defined in ad-valorem terms.[7] (ii) Exporters can choose to comply with an alternative Value-Added rule instead of RoO. The data in Conconi et al. (2018) includes information on the HS 6-digit codes for which this is the case. Products with positive ad-valorem tariffs represent 63.27% of the total number of products, while for 86.76% of the products exporters have to comply with RoO.

After restricting the data according to these criteria, our final sample includes 410 HS 6-digit products within 48 different HS 2-digit industries, and 9,918 unique firms exporting final goods to the US, using either NAFTA or WTO to do so.

An illustrative example of an observation in our dataset is the following: In our customs data we observe that *Firm A* exported *Product 1* to the US, imported *Input 1* from the US, and imported *Input 2* from China; we also observe that *Firm A* used NAFTA to export. From the DRC Tables we know *Product 1* is made 40 % of *Input 1*, 40 % of *Input 2*, and 20 % of *Input 3*. From RoO data, we know that if a firm uses NAFTA to export *Product 1*, then it has to source *Input 1* and *Input 3* from NAFTA countries. This implies the RoO strictness of *Product A* is 60%. Lastly, MFN tariff data tells us that whenever a firm exports *Product A* to the US using WTO, it has to pay a 10% ad-valorem tariff.

1.3 Three Empirical Facts

This section documents three empirical facts on how RoO affect firm behavior, and discusses how they are rationalized in our model. First, RoO strictness and MFN tariffs are positively correlated. Second, small and large firms use NAFTA less intensively than medium-sized firms. Third, the distortion RoO have on firms' input sourcing is increasing with size.

Empirical Fact 1. *There is a positive correlation between RoO strictness and MFN tariffs.*

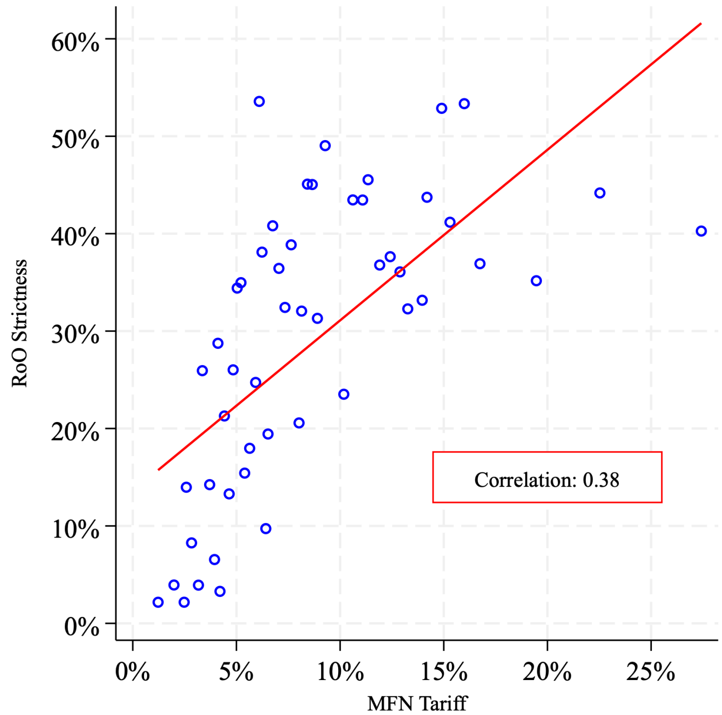
Figure 1.1 shows this correlation at the product level.[8] The fact that it is positive implies that firms are facing a tradeoff when using NAFTA or WTO to export. For example, if a firm has a high benefit of using NAFTA, because it implies not paying a high tariff, it also

[6] These firms have disproportionally large imports, as the median of their imports-to-exports ratio is 254.84.

[7] An example of a non-ad-valorem tariff is *US dollars per pound*, for which it is hard to compare across different products.

[8] This is a binscatter, grouping our sample of 410 HS 6-digit products across 50 distinct MFN tariff bins.

Figure 1.1: Correlation between RoO strictness and MFN tariffs.



faces a high cost of using it, as the RoO on its product will be high as well. In our model, firms will evaluate whether it is worth complying with RoO to avoid paying MFN tariffs.

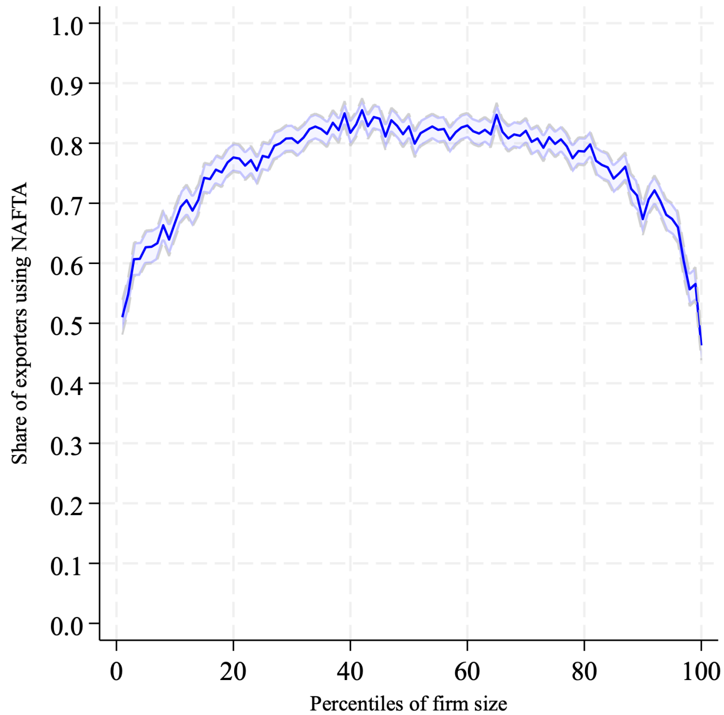
Empirical Fact 2. *The relationship between the use of NAFTA and firm size follows an inverse U-shape.*

Figure 1.2 shows how the use of NAFTA depends on firm size. We proxy firm size by computing average monthly total exports to all destinations. We divide firms into percentiles of size and for each one of these, compute the share of firms that export using NAFTA. Results show that small and large firms use NAFTA less intensively compared to medium-sized firms. This relationship could be driven by selection into industries, e.g. it is not that firm size matters *per se*, but rather that small and large firms are in sectors with relatively lower incentives of using NAFTA. To check for this, we estimate Equation (1.3.1) using OLS:

$$\mathbb{N}_{ikjt} = \beta_0 + \sum_{k=2}^{10} \beta_k \mathbb{I}_{ikt} + \alpha_1 \text{RoO}_j + \alpha_2 \text{MFN}_j + \iota_t + \epsilon_{ikjt} \tag{1.3.1}$$

where $\mathbb{N}_{ikjt} = 1$ if firm i of size decile k exporting product j at time t is using NAFTA to export, and $\mathbb{I}_{ikt} = 1$ if the firm belongs to size decile k. To account for the role that RoO and MFN tariffs have in shaping the firm-level decision to use NAFTA, we control for RoO_j, the

Figure 1.2: Share of exporters using NAFTA by size percentile.



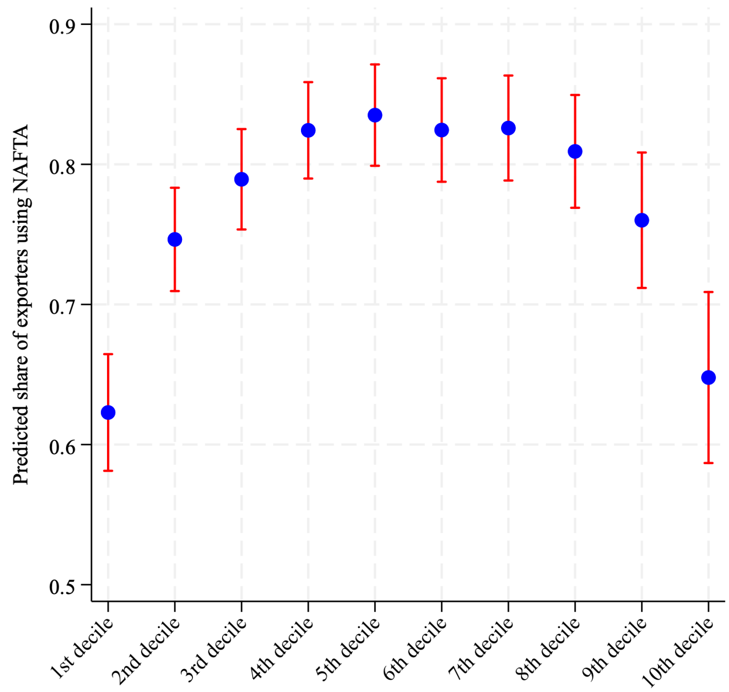
share of restricted inputs for product j if using NAFTA, and MFN_j, product j's ad-valorem tariff if using WTO. We include time fixed effects ι_t to control for any shocks common to all firms. We do not include industry fixed effects as we are also interested in the *ceteris paribus* effect of RoO and MFN tariffs, and there is little industry-level variation in these.[9]

Figure 1.3 shows how the estimated coefficients for intercepts $\hat{\beta}_0 + \hat{\beta}_k$ change across size deciles k. In the figure, the x-axis shows the deciles of firm size, while the y-axis shows the predicted share of firms using NAFTA. We assume $\text{RoO}_j = 0$ and $\text{MFN}_j = 0$ for simplicity, as we are interested in the direct effect that firm size has on the use of NAFTA. Results suggest firm size does partly explain the inverse U-shape relationship, even after controlling for RoO strictness and tariffs. Estimated coefficients $\hat{\alpha}_1$ and $\hat{\alpha}_2$ imply that if RoO strictness or MFN tariffs were to increase by 1 s.d., the probability that a firm uses NAFTA would change on average by -9.03 and 3.66 p.p., respectively.

The estimation output is included in Table A.6 of Appendix A.2, where we also conduct the following robustness checks: (i) Include industry fixed effects, (ii) Use different specifications and proxies for firm size, and (iii) Show a particular industry does not drive our results.

[9]The average coefficient of variation in RoO strictness and MFN tariffs across products within an industry, defined as $CV = \sigma/\mu$, is equal to 0.63 and 0.19, respectively.

Figure 1.3: Predicted share of exporters using NAFTA by size decile.



Empirical Fact 3. *The decrease in the probability of sourcing inputs from non-NAFTA countries when using NAFTA to export is increasing in firm size.*

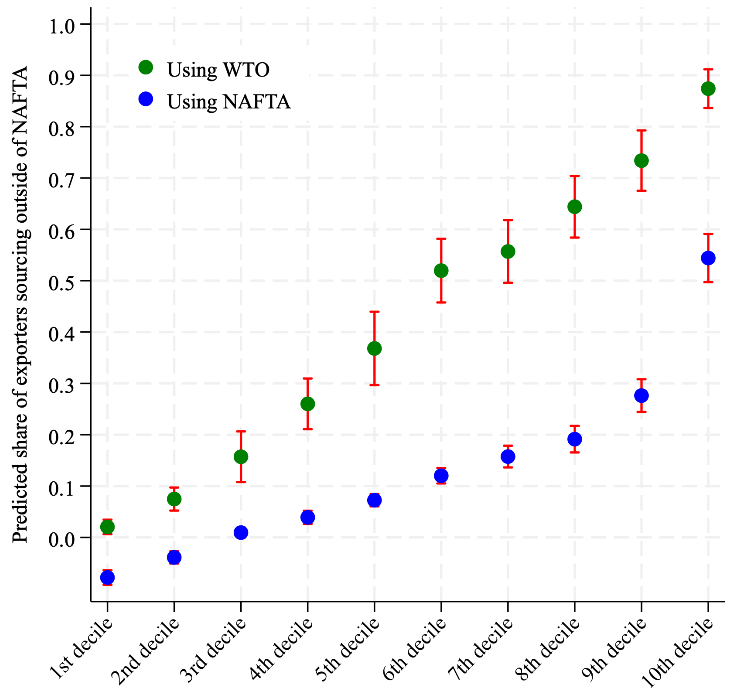
To study the impact RoO have on firms' input sourcing choices, we use OLS to estimate Equation (1.3.2) separately for firms using either NAFTA or WTO membership to export:

$$\mathbb{S}_{ikst} = \beta_0 + \sum_{k=2}^{10} \beta_k \mathbb{I}_{ikt} + \iota_{s,t} + \epsilon_{ijt} \tag{1.3.2}$$

where $\mathbb{S}_{ikst} = 1$ if firm i of size k from industry s at time t sources inputs outside of NAFTA countries, and $\mathbb{I}_{ikt} = 1$ if the firm belongs to size decile k. An exporter sources outside of NAFTA countries if we observe imports of intermediates coming from countries other than the US or Canada. We control for unobservables by including industry-year fixed-effects ι_{st}, which should capture any heterogeneity across industries in terms of how attractive it is to source intermediate inputs from non-NAFTA countries.

Figure 1.4 shows how the estimated coefficients $\hat{\beta}_0 + \hat{\beta}_k$ change across size deciles, for exporters either using NAFTA or WTO. We are interested in the gap between the NAFTA and WTO coefficients, which we interpret as the distortion in sourcing choices induced by RoO. While it is mechanically true that a firm using NAFTA should be less likely to source

Figure 1.4: Predicted share of exporters sourcing outside of NAFTA by size decile.



from non-NAFTA countries, as it has to comply with RoO, results show the distortion RoO have on sourcing choices is increasing with size, suggesting that other mechanisms are present. The estimation output for Equation (1.3.2) is included in Table A.8 of Appendix A.2, and we conduct the same robustness checks as those for Equation (1.3.1).

We rationalize Empirical Facts 2 and 3 as consequences of Mexican exporters facing fixed costs of using NAFTA and sourcing from foreign countries. Fixed costs of using an FTA to export are well documented in the literature; see Demidova et al. (2012), Cherkashin et al. (2015), and Krishna et al. (2021). Using NAFTA to export not only requires complying with RoO, but also with labor, environmental, and health regulations. Exporters also need to learn to use the FTA, and keep track of the sourcing of their inputs by presenting a *Certificate of Origin* at the border.[10] We consider these factors part of the fixed cost of using NAFTA to export. A firm should also find it costly to be able to source inputs from a foreign country, as it needs to find an appropriate supplier, deal with domestic and foreign bureaucracy, agree on product characteristics, etc. We consider these factors part of the fixed costs of sourcing, as discussed in Antras et al. (2017).

When studying the use of NAFTA and the effect RoO have on it, firm size matters. On

[10] A document required under NAFTA to certify that a good being exported qualifies as an originating good, and thus qualifies for preferential tariff treatment.

the one hand, the larger a firm is, the more able it is to pay the fixed cost of using NAFTA; this by itself generates a positive relationship between firm size and the use of NAFTA. On the other, larger firms should find it more profitable to source from foreign countries; suggesting the opportunity cost of complying with RoO is increasing in a firm's ability to pay these fixed costs. This implies by itself a negative relationship between firm size and the use of NAFTA.

These two fixed costs together explain Figures 1.3 and 1.4. For the former, small firms are less able to pay the fixed cost of using NAFTA, while large firms who can source their inputs from all over the world find it too costly to have their input sourcing restricted by RoO. For the latter, small firms are less able to source inputs from foreign countries, thus being restricted by RoO when using NAFTA does not significantly affect their sourcing choices. The larger a firm is, the more it can source inputs from foreign countries, and therefore the larger the distortion RoO have on its probability of sourcing from non-NAFTA countries.[11] This is our key mechanism: the opportunity cost of RoO is increasing in firm size. Our model accounts for this by including fixed costs of using NAFTA and of sourcing from foreign countries.

To provide further evidence on these fixed costs, we exploit cross-product variation in RoO strictness and MFN tariffs across the firm size distribution. In the absence of fixed costs, both the benefit and cost of using NAFTA scale up with firm size. The benefit is not paying the MFN tariff, which is defined in ad-valorem terms. The cost is complying with RoO, which increase a firm's marginal cost. This implies that, without fixed costs, the effects of RoO and MFN tariffs on the use of NAFTA should be homogeneous across the firm size distribution.

To test this, we estimate Equation (1.3.3), which allows the marginal effect of RoO and MFN tariffs on the use of NAFTA to vary across firm sizes:

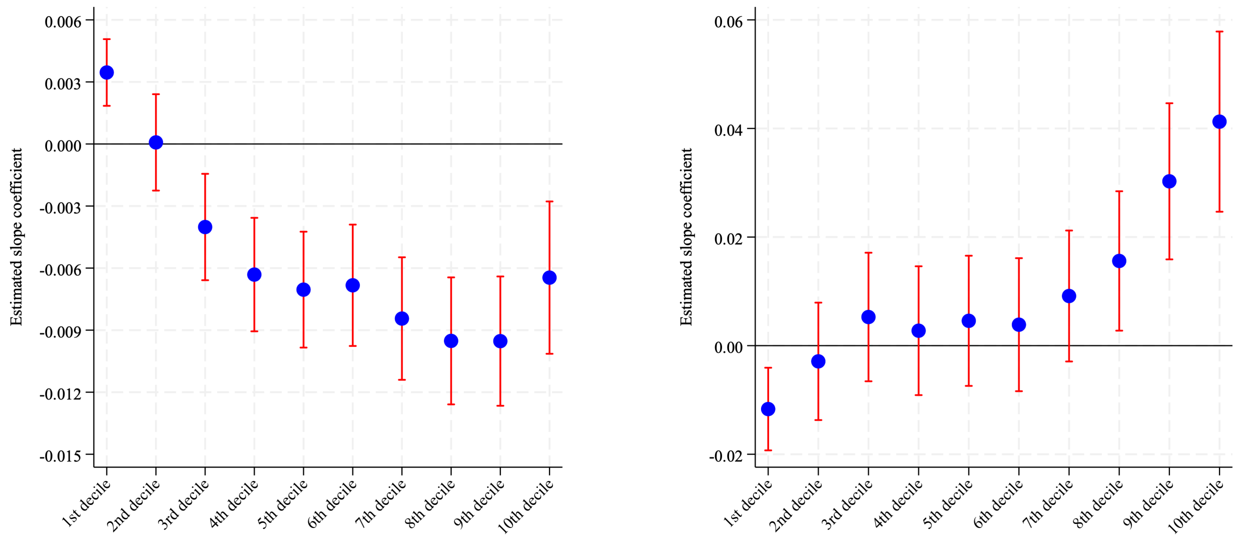
$$\mathbb{N}_{ikjt} = \beta_1 + \sum_{k=2}^{10} \beta_k \mathbb{I}_{ikt} + \alpha_1 \text{RoO}_j + \sum_{k=2}^{10} \alpha_k \mathbb{I}_{ikt} \times \text{RoO}_j + \gamma_1 \text{MFN}_j + \sum_{k=2}^{10} \gamma_k \mathbb{I}_{ikt} \times \text{MFN}_j + \iota_t + \epsilon_{ikjt} \quad (1.3.3)$$

where $\mathbb{N}_{ikjt} = 1$ if firm i of size decile k exporting product j at time t is using NAFTA to export, $\mathbb{I}_{ikt} = 1$ if the firm belongs to size decile k, and RoO_j and MFN_j are product j's RoO strictness and MFN tariff, respectively.

Figure 1.5 shows the absolute value of estimated slope coefficients $\hat{\alpha}_0 + \hat{\alpha}_k$ and $\hat{\gamma}_0 + \hat{\gamma}_k$ weakly increases with size, which we treat as evidence that Mexican firms do face fixed costs

[11] The gap in the estimated coefficients decreases for the 10th decile. This could be the result of the import volume the largest firms have, i.e. the largest firms purchase such a large quantity of inputs that even if restricted by RoO, they still find it profitable to pay fixed costs of sourcing.

Figure 1.5: Marginal effects on the probability of using NAFTA to export.



(a) RoO strictness

(b) MFN tariffs

of using NAFTA and sourcing from foreign countries. The estimation output for Equation (1.3.3) is included in Table A.10 of Appendix A.2.

For smaller firms, RoO and MFN tariffs have a lower effect on their probability of using NAFTA to export, as these firms are less able to pay fixed costs. For example, even if a small firm has high incentives of using NAFTA because it faces a high MFN tariff, it is unable to do so as it cannot pay the fixed cost of it. Likewise, a small firm will not decrease its use of NAFTA even if facing high RoO because the firm was not able to source from foreign countries in the first place. The larger firms are, the less these fixed costs constrain them, and thus the greater the effect RoO and MFN tariffs will have on their probability of using NAFTA, i.e. higher MFN tariffs increase firms' incentives of using NAFTA, while stricter RoO do the opposite.

1.4 A Model of Rules of Origin and NAFTA Usage

We extend Antras et al. (2017) to include RoO and the choice of using NAFTA to export. The key elements of their model are CES preferences over varieties and monopolistically competitive final good producers, as developed in Melitz (2003). Each variety uses a continuum of intermediate inputs $\nu \in [0, 1]$ with competitive global suppliers, as in Eaton and Kortum (2002). Final good producers only sell domestically, and choose from which countries they can source their inputs, their *sourcing strategy*, by paying fixed costs of sourcing.

Our contribution to their model is two-fold: (i) We assume Mexican firms are exporting their final goods to the US, and (ii) We allow firms to also choose whether they export using NAFTA or WTO membership. By choosing the former, firms must comply with RoO, which restrict their sourcing strategies by imposing that a given share of their inputs must come from NAFTA countries. To exploit our product-level data on RoO strictness and MFN tariffs, we include in the model different sectors and industries within them.

1.4.1 US Consumers

Let N be the set of NAFTA countries. We assume that consumers in the US value consumption of domestic good D and Mexican varieties ω across distinct industries and sectors.

$$U = D^{1-\eta} \prod_{s=1}^{S} \Big[\sum_{i=1}^{I_s} \Big(\int_{\omega \in \Omega_{si}} q_{si}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \Big)^{\frac{\sigma(\epsilon-1)}{\epsilon(\sigma-1)}} \Big]^{\frac{\alpha_s \eta \epsilon}{(\epsilon-1)}} \tag{1.4.1}$$

Domestic good D is meant to capture all non-Mexican products. There is a total of S sectors, and an I_s number of industries within each sector. Ω_{si} represents the set of varieties of sector s and industry i being exported to the US. Parameter $\sigma > 1$ is the elasticity of substitution across varieties of a given industry, while $\epsilon > 1$ is the elasticity across industries within a given sector. We assume that $\sigma > \epsilon$, as demand should be more elastic within an industry than across them. Consumers in the US spend a share $\eta \in [0, 1]$ of their income in Mexican imports, and a share $1 - \eta$ in domestic good D. Finally, we assume consumers spend a share α_s of their total expenditure on Mexican imports on goods from sector s:

$$\sum_s \alpha_s = 1$$

Consumers maximize their utility in Equation (1.4.1) subject to their budget constraint:

$$D + \sum_{s=1}^{S} \sum_{i=1}^{I_s} \Big(\int_{\omega \in \Omega_{si}} q_{si}(\omega) p_{si}(\omega) d\omega \Big) = E \tag{1.4.2}$$

where E represents the total income/expenditure of the US, and $p_{si}(\omega)$ stands for the price of variety ω of industry i from sector s. We assume domestic good D acts as a numeraire, and thus the price of a Mexican variety $p_{si}(\omega)$ is expressed relative to it.

Solving the consumer's optimization problem, the demand in the US for variety ω is:

$$q_{si}(\omega) = \frac{\alpha_s \eta E P_{si}^{\sigma-\epsilon}}{\sum_k P_{sk}^{1-\epsilon}} p_{si}(\omega)^{-\sigma} \tag{1.4.3}$$

where $P_{si} \equiv (\int_0^1 p_{si}(\omega)^{1-\sigma} d\omega)^{1/(1-\sigma)}$ is the Dixit-Stiglitz ideal price index for industry i of sector s. Demand for variety ω is increasing in the expenditure level in the US, and increasing in both the share of expenditure spent in Mexican imports η and the share α_i of total expenditure on Mexican imports spent on industry i. Lastly, demand is increasing in the ideal price index, and decreasing in price as $\sigma > 1$.

1.4.2 Mexican Exporters

To introduce RoO and the use of NAFTA in the model, we first define a set of objects. Let $\kappa \in \{0, 1\}$ be an indicator variable equal to 1 when a firm chooses to export using NAFTA, and 0 if it chooses to export using WTO. Denote by $\lambda(\omega) \in [0, 1]$ the share of inputs firm ω has to source from NAFTA countries if it chooses to use NAFTA, and let $\tau(\omega) \in [0, \infty)$ represent the ad-valorem tariff it would have to pay if it chooses to export using WTO. These two objects are exogenous to firms and specific to each variety. Motivated by our discussion in Section 2.2, we assume that if firms use NAFTA, they have to pay a fixed cost represented by $\zeta_{si} \in \mathbb{R}^{++}$. Firms also have to pay fixed cost $f^j_{si}(\omega) \in \mathbb{R}^{++}$ to be able to source inputs from foreign country j. In what follows, we drop the ω index to ease up notation.

For presentation purposes, we assume that firm behavior consists of four distinct stages. First, a firm in industry i of sector s observes its λ and τ, and fixed costs ζ and f^j $\forall j$. Second, the firm chooses whether to enter the US export market. We assume that a firm's export-specific productivity ϕ is unknown to it unless it pays a fixed cost of entry υ. Third, the firm chooses whether to export using NAFTA or WTO membership. Lastly, given the firm's previous choice, it chooses the set of countries from which it can source inputs from, that is, its sourcing strategy.

Final good producers use a continuum of inputs of measure equal to one. These inputs are specific to each industry i and sector s. Marginal costs of producing an input are not only heterogeneous across countries but also across industries and sectors, e.g. China might be better at supplying inputs used by industry i than inputs used by industry i'. We assume that the unit labor cost of producing an input a^j_{si} is Fréchet distributed according to:

$$F^j_{si}(a) = \exp(-T^j_{si} a^{-\theta})$$

where T^j_{si} captures the aggregate productivity level of country j at supplying inputs for industry i of sector s. Let $d^j_{si} > 1$ represent an iceberg-type trade cost between Mexico and country j, and w^j_{si} the wage paid at country j per unit of labor when producing inputs for industry i of sector s. We assume that suppliers of intermediate inputs, both domestic and at foreign countries, are competitive and thus price at marginal cost. The price paid by a

Mexican firm for input $\nu \in [0,1]$ is given by:

$$z_{si}(\nu,\kappa,\lambda,J) = \begin{cases} \min\limits_{j\in N\cap J}\{d^j_{si}a^j_{si}(\nu)w^j_{si}\} & \text{if } \nu \in [0,\kappa\lambda) \\ \\ \min\limits_{j\in J}\{d^j_{si}a^j_{si}(\nu)w^j_{si}\} & \text{if } \nu \in [\kappa\lambda,1] \end{cases} \tag{1.4.4}$$

where $J(\phi,\kappa,\lambda,\tau)$ represents the sourcing strategy of firm ϕ, i.e. the countries from which it can source inputs having paid their fixed costs of sourcing. Equation (1.4.4) states that the price a firm will pay for input ν is the lowest marginal cost among the countries from which it can source input ν. This is where we introduce RoO in the model: If a firm chooses to export using NAFTA, it has to source inputs $\nu \in [0,\lambda)$ exclusively from the NAFTA countries in its sourcing strategy $N \cap J$; whereas the rest of the inputs $\nu \in [\lambda, 1]$ can be freely sourced from any country in J.

The increase in firms' marginal cost when using NAFTA is proportional to the increase in expenditure in intermediate inputs induced by having to comply with RoO:

$$\int\limits_0^{\kappa\lambda}\Big[\min_{j\in N\cap J}\{d^j_{si}a^j_{si}(\nu)w^j_{si}\} - \min_{j\in J}\{d^j_{si}a^j_{si}(\nu)w^j_{si}\}\Big]d\nu \tag{1.4.5}$$

Conditional on using NAFTA, Equation (1.4.5) shows RoO imply an increase in marginal cost, except when: (i) NAFTA countries are the best suppliers of a firm's inputs, and (ii) A firm cannot pay the fixed costs of sourcing from non-NAFTA countries, i.e. $J \subseteq N$.

Within an industry, firms are heterogeneous in terms of their export-specific productivity ϕ, which we assume is drawn from a Pareto distribution with shape parameter χ. Given input prices described in Equation (1.4.4), a firm of productivity ϕ faces marginal costs:

$$c_{si}(\phi,\kappa,\lambda,\tau,J) = \frac{1+(1-\kappa)\tau}{\phi}\left(\int\limits_0^{\kappa\lambda} z_{si}(\nu)^{1-\rho}d^*\nu + \int\limits_{\kappa\lambda}^{1} z_{si}(\nu)^{1-\rho}d\nu\right)^{1/(1-\rho)} \tag{1.4.6}$$

Equation (1.4.6) represents the marginal cost of producing and exporting. This is where we introduce the benefit of using NAFTA to export: if a firm chooses to export using WTO, $\kappa = 0$, then it has to pay MFN Tariff $\tau \geq 0$.

Marginal cost is decreasing in ϕ, and the rest of the expression is a CES aggregation over the price of intermediate inputs, where $\rho > 1$ represents the substitution parameter across these. The measure of inputs is split into two integrals because the distribution of input prices is different depending on whether RoO restricts an input, $\nu \in [0, \lambda)$, or it can be freely sourced, $\nu \in [\lambda, 1]$.

Using the properties of the Fréchet distribution for unit labor costs, we can express the marginal cost of a firm with productivity ϕ in industry i of sector s as:

$$c_{si}(\phi, \kappa, \lambda, \tau, J) = \frac{1}{\phi}\gamma^{-1/\theta}[1 + (1-\kappa)\tau][\kappa\lambda\Psi_{si}(\phi)^{(\rho-1)/\theta} + (1-\kappa\lambda)\Phi_{si}(\phi)^{(\rho-1)/\theta}]^{\frac{1}{1-\rho}} \quad (1.4.7)$$

with:

$$\Psi_{si}(\phi) = \sum_{h \in N \cap J} T_{si}^{h}(d_{si}^{h} w_{si}^{h})^{-\theta} \quad \text{and} \quad \Phi_{si}(\phi) = \sum_{h \in J} T_{si}^{h}(d_{si}^{h} w_{si}^{h})^{-\theta}$$

We refer to $\Psi_{si}(\phi)$ as a firm's *NAFTA sourcing capability*, and $\Phi_{si}(\phi)$ as its *total sourcing capability*. Intuitively, $T_{si}^{h}(d_{si}^{h} w_{si}^{h})^{-\theta}$ captures how attractive it is for a firm in industry i of sector s to include country h in its sourcing strategy. We refer to this term as a country's *sourcing potential*, and it is the incentive a firm has for paying the fixed cost of being able to source inputs from country h. Lastly, γ represents the Gamma function evaluated at $(\theta + 1 - \rho)/\theta$.

The model yields predictions for the share of inputs a firm is going to source from each of the countries in its sourcing strategy J. These shares are subject to a distortion caused by RoO. Using again the properties of the Fréchet distribution, the share of inputs coming from non-NAFTA country $j \in J \setminus N$ is:

$$x_{si}^{j}(\phi, \kappa, \lambda, J) = (1-\kappa\lambda)\frac{T_{si}^{j}(d_{si}^{j} w_{si}^{j})^{-\theta}}{\sum_{h \in J} T_{si}^{h}(d_{si}^{h} w_{si}^{h})^{-\theta}} \quad (1.4.8)$$

while the share of inputs sourced from NAFTA country $j \in J \cap N$ is given by:

$$x_{si}^{n}(\phi, \kappa, \lambda, J) = \kappa\lambda\frac{T_{si}^{j}(d_{si}^{j} w_{si}^{j})^{-\theta}}{\sum_{h \in N \cap J} T_{si}^{h}(d_{si}^{h} w_{si}^{h})^{-\theta}} + (1-\kappa\lambda)\frac{T_{si}^{j}(d_{si}^{j} w_{si}^{j})^{-\theta}}{\sum_{h \in J} T_{si}^{h}(d_{si}^{h} w_{si}^{h})^{-\theta}} \quad (1.4.9)$$

In our model, for a fixed $\kappa = 1$, RoO increase the share of inputs sourced from NAFTA countries, regardless of their sourcing potential. Note that if a firm is choosing to export using WTO, $\kappa = 0$, or faces no RoO, $\lambda = 0$, then the expression for the share of inputs sourced from any country collapses to the standard input shares derived in Eaton and Kortum (2002).

Since firms compete monopolistically, the optimal price a firm sets, taking US demand as given, is a constant markup over the marginal cost of producing and exporting:

$$p_{si}(\phi, \kappa, \lambda, \tau, J) = \frac{\sigma}{\sigma - 1} c_{si}(\phi, \kappa, \lambda, \tau, J) \tag{1.4.10}$$

Combining Equations (1.4.3), (1.4.7), and (1.4.10), a firm's operating profits for a choice of κ and J are given by:

$$\pi_{si}(\phi, \kappa, \lambda, \tau) = \phi^{\sigma-1}\gamma^{(\sigma-1)/\theta}B_{si}[1 + (1-\kappa)\tau]^{1-\sigma}[\kappa\lambda\Psi_{si}(\phi)^{(\rho-1)/\theta} + (1-\kappa\lambda)\Phi_{si}(\phi)^{(\rho-1)/\theta}]^{\frac{1-\sigma}{1-\rho}} \tag{1.4.11}$$

where B_{si} represents US market demand for varieties from industry i of sector s:

$$B_{si} = \frac{1}{\sigma}\left(\frac{\sigma}{\sigma - 1}\right)^{1-\sigma}\left[\frac{\alpha_s \eta E P_{si}^{\sigma-\epsilon}}{\sum_k P_{sk}^{1-\epsilon}}\right] \tag{1.4.12}$$

which the firm takes as given. Equation (1.4.11) shows that if a firm uses NAFTA to export, on the one hand it will avoid paying MFN tariff τ, but on the other it will experience an increase in its marginal cost. This because λ will give some weight to the NAFTA sourcing capability at the expense of total sourcing capability, with $\Psi_{si}(\phi) \leq \Phi_{si}(\phi)$. If firms do not use NAFTA to export nor are there any RoO in place, Equation (1.4.11) collapses to the expression for operating profits in Antras et al. (2017).

As described before, we assume that firm choice occurs in distinct stages i.e. a firm first chooses whether it will use NAFTA or WTO membership to export, then it chooses the set of countries in its sourcing strategy. Assume that a firm has already chosen either NAFTA or WTO. Firms will choose the sourcing strategy that maximizes their operating profits subject to paying a fixed cost of sourcing from each country:

$$\Pi_{si}(\phi, \kappa, \lambda, \tau) = \max_{I_{si}^j \in \{0,1\}_{j=1}^J} \pi_{si}(\phi, \kappa, \lambda, \tau, I^1, ..., I^J) - w\sum_{j=1}^{J} I_{si}^j f_{si}^j(\phi) \tag{1.4.13}$$

where $I_{si}^j = 1$ if the firm chooses country j to be in its sourcing strategy. We assume that fixed costs of sourcing are firm-specific in order to capture any firm-level heterogeneity in these fixed costs. For example, firms located at the border with the US should have a lower fixed cost of sourcing from this country, as it should be easier for them to find a supplier.

The optimization in Equation (1.4.13) is a combinatorial discrete choice problem for firms as they choose the combination of countries that maximizes their profits given their previous choice of using either NAFTA or WTO membership. Therefore, a firm's chosen sourcing strategy will be a function of whether it chose NAFTA or WTO to export, e.g. a firm has fewer incentives to source inputs from Non-NAFTA countries when using NAFTA to export as RoO restrict a share of its inputs to be sourced exclusively from NAFTA countries.

By backwards induction, a firm will choose the κ, either NAFTA where $\kappa = 1$ or WTO where $\kappa = 0$, that maximizes its profits subject to paying a fixed cost if using NAFTA:

$$\kappa^* = \underset{\kappa \in \{0,1\}}{\arg\max} \ \{\Pi_{si}(\phi, \kappa, \lambda, \tau) - \kappa w \zeta_{si}\} \tag{1.4.14}$$

where ζ_{si} is the fixed cost of using NAFTA to export. Note we assume that both fixed costs of sourcing and using NAFTA are expressed in Mexican labor units.

In order to close our model, free-entry into the US export market implies that expected profits of exporting have to be equal to the cost of entry into the export market:

$$\int_{\tilde{\phi}_{is}}^{\infty} \left[\Pi_{si}(\phi, \kappa, \lambda, \tau) - \kappa(\phi) w \zeta_{si}\right] dG(\phi) = w\upsilon \tag{1.4.15}$$

where $G(\cdot)$ is the cdf of the Pareto distribution and $\tilde{\phi}_{si}$ denotes the productivity of the least productive firm from industry i of sector s that chooses to enter.

To summarize firm behavior: Firms observe realizations for their productivity and fixed costs. They also observe the RoO they would have to comply with if using NAFTA, and the MFN tariffs they would have to pay if using WTO. Then they choose whether to enter the US export market, followed by whether they will export using NAFTA or WTO, and their corresponding choice of sourcing strategy. Lastly, firms meet demand, pricing at a constant markup over their marginal cost.

1.4.3 Equilibrium

We assume the measure of non-exporting firms is large enough such that firms exporting to the US treat wages as exogenous; which implies that our model is one of partial equilibrium.

An equilibrium is a set of prices of varieties $p_{si}(\omega)$ and Mexican wages w such that:

1. Consumers maximize utility according to Equation (1.4.1) by choosing $q_{si}(\omega)$
2. Firms maximize profits in Equation (1.4.14) by choosing κ^* and J^* given $\{\lambda, \tau, f, \zeta\}$
3. Firms meet demand for their variety, given by Equation (1.4.3)
4. Expected profits of exporting to the US are zero, as in Equation (1.4.15)

This last condition results in the equilibrium number of firms of industry i from sector s actively exporting to the US being given by:

$$N_{si} = \frac{\alpha_s \eta E[1 - G(\tilde{\phi}_{si})]}{\sigma w \Big[\upsilon + \int\limits_{\tilde{\phi}_{si}}^{\infty} \Big(\kappa(\phi)\zeta_{si} + \sum\limits_{j \in J(\phi)} f_{si}^{j}(\phi) \Big) dG(\phi) \Big]} \times \frac{P_{si}^{1-\epsilon}}{\sum\limits_{k} P_{sk}^{1-\epsilon}} \tag{1.4.16}$$

Equation (1.4.16) shows that the number of Mexican firms exporting to the US in a given industry is increasing in the share of US expenditure in Mexican imports η, the share of expenditure in its particular sector α_s and total US expenditure/income E. The equilibrium number of firms is decreasing in the elasticity of substitution σ, as firm profits are decreasing in it, in wage w, as fixed costs are expressed in labor units, in fixed costs of using NAFTA and sourcing ζ and f, and in the industry-level ideal price index $P_{si}^{1-\epsilon}$ as $\epsilon > 1$.

1.4.4 Input Purchases from Foreign Countries

Our model generates predictions for Mexico's purchases of intermediate inputs from foreign countries. It can be shown that for a firm with productivity ϕ, its purchases of inputs from country j can be expressed as a share of its operating profits:[12]

$$M_{si}^{j}(\phi) = (\sigma - 1) x_{si}^{j}(\phi, \kappa^*, \lambda, J^*) \pi_{si}^{o}(\phi, \kappa^*, \lambda, \tau) \tag{1.4.17}$$

where $x_{si}^{j}(\phi, \kappa^*, \lambda, J^*)$ is the share of inputs purchased from country $j \in J^*$, under optimal choices for κ^* and J^*. As Section 1.4.2 details, the expression for these shares is different between NAFTA and non-NAFTA countries because of the distortionary effects of RoO. Input purchases from non-NAFTA country $j \in J^* \setminus N$ are given by:

$$\begin{aligned} M_{si}^{j}(\phi) = {} & (\sigma - 1)\phi^{\sigma-1}\gamma^{(\sigma-1)/\theta}(1 + (1 - \kappa^*)\tau)^{-\sigma} B_{si}(1 - \kappa^*\lambda)\Phi_{si}(\kappa^*)^{-1} T_{si}^{j}(d^j w_{si}^{j})^{-\theta} \\ & \times \Big(\kappa^*\lambda\Psi_{si}(\kappa^*)^{(\rho-1)/\theta} + (1 - \kappa^*\lambda)\Phi_{si}(\kappa^*)^{(\rho-1)/\theta} \Big)^{\frac{1-\sigma}{1-\rho}} \end{aligned} \tag{1.4.18}$$

while input purchases from NAFTA country $j \in J^* \cap N$ follow:

$$\begin{aligned} M_{si}^{j}(\phi) = {} & (\sigma - 1)\phi^{\sigma-1}\gamma^{(\sigma-1)/\theta}(1 + (1 - \kappa)\tau)^{-\sigma} B_{si} \Big[\kappa^*\lambda\Psi_{si}(\kappa^*)^{-1} + (1 - \kappa^*\lambda)\Phi_{si}(\kappa^*)^{-1} \Big] \\ & \times T_{si}^{j}(d^j w_{si}^{j})^{-\theta} \Big(\kappa^*\lambda\Psi_{i}^{*}(\kappa)^{(\rho-1)/\theta} + (1 - \kappa^*\lambda)\Phi_{i}^{*}(\kappa)^{(\rho-1)/\theta} \Big)^{\frac{1-\sigma}{1-\rho}} \end{aligned} \tag{1.4.19}$$

[12]We include this derivation in Appendix A.5.

and $M_{si}^j(\phi) = 0 \ \forall j \notin J^*$. The model's predictions for a sector's input purchases from country j are:

$$M_s^j = \sum_{i=1}^{I_s} \left[N_{si} \int_{\tilde{\phi}_{si}}^{\infty} M_{si}^j(\phi) dG(\phi) \right] \tag{1.4.20}$$

We are not able to analytically characterize Equation (1.4.20) as it is a highly non-linear object. A firm's input purchases from a country depend not only on its sourcing potential, but also on the sourcing potential of the other countries in the firm's sourcing strategy, which in turn is endogenous to the firm's productivity and the RoO and MFN tariff it faces, affecting whether the firm uses NAFTA or WTO membership to export. In practice, we simulate sectors' input purchases by first computing these at the firm level, following Equation (1.4.17), and then adding across our simulated firms within a sector.

Equations (1.4.19) and (1.4.20) hint at the potentially detrimental effects of a higher λ. An increase in RoO will not necessarily result in higher input purchases from a NAFTA country, as firms could optimally choose to use WTO instead. Moreover, even if a firm chooses to comply with these higher RoO and thus the share of inputs it sources from NAFTA countries increases, the induced increase in marginal costs could offset the increase in input shares and lead to an overall decrease in its imports of intermediates from a given NAFTA country.

1.4.5 Impact on the Use of NAFTA

This section discusses how, according to our model, the use of NAFTA is affected by RoO, MFN tariffs, sourcing potentials, fixed costs, and comparative advantage across countries. In the absence of fixed costs of using NAFTA and sourcing from foreign countries, a firm would choose to export using NAFTA if:

$$(1+\tau)\Phi^{-\frac{1}{\theta}} > \left[\lambda \Psi^{\frac{\rho-1}{\theta}} + (1-\lambda)\Phi^{\frac{\rho-1}{\theta}} \right]^{\frac{1}{1-\rho}}$$

which intuitively states that a firm will export using NAFTA if the benefit of doing so, not paying the MFN tariff, is larger than its cost, the increase in marginal cost because of RoO. Note that if there are no fixed costs, then Ψ and Φ are constant, as firms will always include all countries in their sourcing strategy. It proves convenient to re-write the above as:

$$LHS \equiv \frac{1-(1+\tau)^{1-\rho}}{\lambda} > 1 - \left(\frac{\Psi}{\Phi}\right)^{\frac{\rho-1}{\theta}} \equiv RHS \tag{1.4.21}$$

Proposition 1. The use of NAFTA is decreasing in RoO.

The derivative of the RHS w.r.t. λ is 0 while that of the LHS is negative:

$$-\frac{[1-(1+\tau)^{1-\rho}]}{\lambda^2} < 0$$

making Inequality (1.4.21) less likely to hold. An increase in RoO increases the price a firm has to pay for inputs restricted to be sourced within NAFTA countries. This would not be true in the unlikely case that non-NAFTA countries have zero sourcing potential for a given industry.

Proposition 2. The use of NAFTA is increasing in MFN tariffs.

The derivative of the RHS w.r.t. τ is 0, while that of the LHS is positive:

$$\frac{\rho-1}{\lambda}(1+\tau)^{-\rho} > 0$$

making Inequality (1.4.21) more likely to hold. Not paying MFN tariffs is the benefit of using NAFTA, therefore, an increase in these increases the incentives of using it.

Proposition 3. The use of NAFTA is increasing in the sourcing potential of a NAFTA country.

The sourcing potential of a country is $T^j_{si}(d^j w^j_{si})^{-\theta}$, therefore, for NAFTA country $j \in N \cap J$:

$$\frac{\partial \Psi}{\partial T^j_{si}(d^j w^j_{si})^{-\theta}} = \frac{\partial \Phi}{\partial T^j_{si}(d^j w^j_{si})^{-\theta}} = 1$$

and thus the derivative of the LHS is 0, while that of the RHS is negative given $\Phi > \Psi$:

$$\frac{1-\rho}{\theta}\Big(\frac{\Psi}{\Phi}\Big)^{\frac{\rho-1}{\theta}-1}\Big[\frac{\Phi-\Psi}{\Phi^2}\Big] < 0$$

making Inequality (1.4.21) more likely to hold. This is because the higher the sourcing potential of NAFTA countries relative to that of non-NAFTA countries, the lower the opportunity cost of complying with RoO. For example, if Mexico is the best place for a firm to source its inputs from, then RoO do not increase the firm's marginal cost because regardless it would have been sourcing from Mexico.

Proposition 4. The use of NAFTA is decreasing in the sourcing potential of non-NAFTA countries.

For non-NAFTA country $j \in J \setminus N$:

$$\frac{\partial \Psi}{\partial T_{si}^{j}(d^{j} w_{si}^{j})^{-\theta}} = 0$$

and thus the derivative of the LHS is 0, while that of the RHS is positive:

$$\frac{1-\rho}{\theta}\Big(\frac{\Psi}{\Phi}\Big)^{\frac{\rho-1}{\theta}-1}\Big[-\frac{\Psi}{\Phi^2}\Big] > 0$$

making Inequality (1.4.21) less likely to hold. An increase in the sourcing potential of non-NAFTA countries increases the opportunity cost of RoO. For example, if China is the best place for a firm to source its inputs from, it is very costly to force the firm to source part of its inputs from NAFTA countries.

Propositions 3 and 4 are only neccessarily true if there are no fixed costs, as these make the model difficult to analyze. For example, if Mexico's sourcing potential increases, according to Proposition 3 the use of NAFTA should increase. However, the decrease in marginal cost could give a firm enough revenue so that it can now pay the fixed cost of sourcing from a non-NAFTA country, thereby decreasing the incentives of using NAFTA to export.

Proposition 5. The use of NAFTA is decreasing in the fixed cost of using NAFTA to export, and increasing in the fixed cost of sourcing from a foreign country.

The latter follows because if a firm is unable to source its inputs from a foreign country, RoO will not affect its sourcing strategy. For example, if a firm cannot source its inputs from China, it does not matter if RoO prohibit sourcing from that country.

Proposition 6. The stronger comparative advantage is across countries, the larger the effects RoO have on the use of NAFTA.

Parameter θ is the shape parameter of the Fréchet distribution for a country's unit labor costs, where lower values of θ imply higher variability in these, and thus stronger comparative advantage across countries. Equation (1.4.11) shows that lower values of θ will magnify any difference between firms' NAFTA and total sourcing capabilities, increasing the opportunity cost of complying with RoO. Intuitively, parameter θ acts as an elasticity of substitution across sourcing countries: Lower values of it makes countries more complementary to each other, and thus, increase the cost of being restricted in terms of input sourcing.

1.5 Taking the Model to the Data

This section describes the estimation of our model, which is split in three distinct steps. First, we take several parameters from the literature, decreasing the computational burden of the estimation. Second, we estimate countries' sourcing potentials at the industry level, i.e. how attractive it is for an industry to source its inputs from a given country. For this, we use data on firm-level input shares and regress these against industry-country fixed effects. Third, we use Simulated Method of Moments with a Simulated Annealing algorithm to find the fixed costs and US market demand that best match a set of simulated moments with their data counterparts, following Eaton et al. (2011).

We map industries in the model to the HS 2-digit codes in our data, which we aggregate into 6 sectors: Agriculture and Foods, Minerals and Chemicals, Skins and Textiles, Mining, Manufacturing, and Others.[13] Within a sector, industries are heterogeneous in terms of their RoO strictness, MFN tariffs, number of firms, and sourcing potentials. We take all of these directly from the data, except for sourcing potentials which we estimate in 1.5.2.

For ease of computation, we group the regions from which firms can source their inputs as follows: Mexico, US and Canada, China, Europe,[14] and Rest of the World. We do this to make our SMM estimation computationally feasible, as the set of different sourcing strategies increases exponentially with the number of countries a firm can source from. Unlike Antras et al. (2017), profits in our model are not necessarily supermodular in productivity, and thus, do not satisfy having increasing differences in a firm's sourcing strategy. This results from the non-linearities introduced by the choice of using NAFTA and RoO. As such, we are unable to reduce the dimensionality of the firm's problem as in Jia (2008) and have to compute firm profits for each possible sourcing strategy. Details for this are in Appendix A.6.

1.5.1 Parametrization

We take several parameters from the literature, detailed in Table 1.1. These are the elasticity of substitution across final goods σ, the elasticity of substitution across industries ϵ, the shape parameter of the Frechét distribution for unit-labor costs θ, as well as the shape parameter χ of the Pareto distribution for firm productivity. We set parameter $\rho = 1.05$, the substitution parameter across intermediate inputs, so inputs are complementary to each other in production. The implied elasticity of substitution is given by $1/\rho$.

1.5.2 Estimation of Sourcing Potentials

Estimation of how attractive countries are to source inputs from follows Antras et al. (2017). In Section 1.4.2, we show that the share of inputs a firm sources from region j when

[13] Agriculture and Foods: HS Sections I-IV; Minerals and Chemicals: HS Sections V-VII; Skins and Textiles: HS Sections VIII-XII; Mining: HS Sections XIII-XV; Manufacturing: HS Sections XVI-XVIII; Others: HS Sections XIX-XXII.

[14] This group includes the ten largest exporters of intermediate inputs to Mexico from this continent: DEU, GBR, FRA, ITA, RUS, ESP, NLD, TUR, SWE, and POL.

Table 1.1: Parameters from the literature.

Parameter	Value	Source
σ	3.85	Antras et al. (2017)
ϵ	3.00	Broda and Weinstein (2006)
θ	1.79	Antras et al. (2017)
χ	4.25	Melitz and Redding (2015)

it either uses WTO or faces no RoO is given by:

$$x_{si}^{j}(\phi) = \frac{T_{si}^{j}(d_{si}^{j}w_{si}^{j})^{-\theta}}{\sum\limits_{h\in J} T_{si}^{h}(d_{si}^{h}w_{si}^{h})^{-\theta}}$$

Normalizing Mexico's sourcing potential to one, i.e. $T_{si}^{MEX}(d_{si}^{MEX}w_{si}^{MEX})^{-\theta} = 1$, and taking the ratio between the sourcing potential of region j and that of Mexico results in:

$$\frac{x_{si}^{j}(\phi)}{x_{si}^{MEX}(\phi)} = T_{si}^{j}(d_{si}^{j}w_{si}^{j})^{-\theta} \tag{1.5.1}$$

Taking logs from both sides and assuming an idiosyncratic measurement error ϵ_{si}^{j} yields:

$$lnx_{si}^{j}(\phi) - lnx_{si}^{MEX}(\phi) = lnT_{si}^{j}(d_{si}^{j}w_{si}^{j})^{-\theta} + \epsilon_{si}^{j}(\phi)$$

We regress using OLS the left-hand side, which is data on firm-level input shares, against the right-hand side, using industry-region fixed effects. In this estimation, we restrict our sample to firms either using WTO or facing no RoO, as for these firms the ratio of input shares depends only on region j's sourcing potential, as shown in Equation (1.5.1).

We need to infer input shares as we do not observe the inputs Mexican firms source domestically, only those purchased abroad. We do this in the following way. First, we use the DRC Tables for the input composition of every final product in our sample. Second, we place the key assumption that: (i) Any input that was not imported was sourced from Mexico, and (ii) Any input we observe was purchased from a foreign region, was not sourced from Mexico at all. For example, if a product is made of 60% of input A and 40% of input B, and we observe that a firm exporting this product is importing input B from China, then the share of inputs coming from China is 40% while that of Mexico is 60%. The rest of the countries have an input share of 0% as we do not observe any imports coming from them. As long as the measurement error in this calculation is idiosyncratic across firms and industries, this procedure should give us an unbiased estimation for how attractive it is to source inputs from each foreign region.

The estimation above captures how good a region is at supplying inputs of a given exporting industry i.e. how good is China at supplying electrical components. To better capture the overall benefit of sourcing from a foreign region, we need sourcing potentials to be defined at the importing industry level i.e. how attractive it is to the automotive industry in Mexico to source inputs from China. To compute this, we again use the input composition of each final product. For example, if we estimate that China has a sourcing potential of 0.4 in supplying *Input A* and 0.6 in supplying *Input B*, and we know that an industry in Mexico uses 50% of *Input A* and 50% of *Input B*, the sourcing potential of China specific to this industry in Mexico will be a weighted average equal to 0.5.

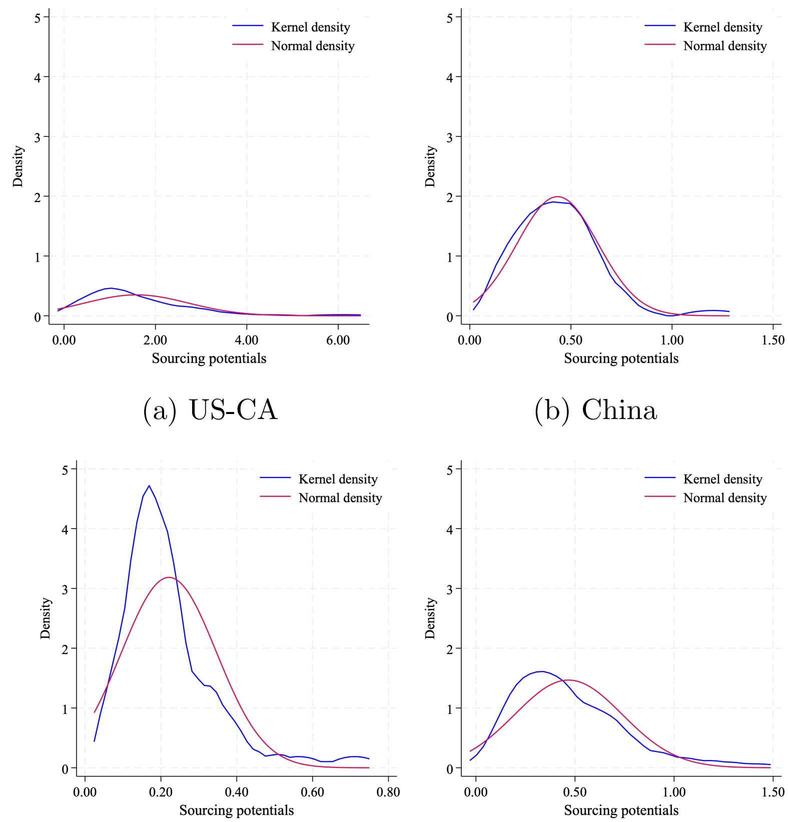
Figure 1.6 shows the estimates for the industry-specific sourcing potentials by region. Averaging across industries, the sourcing potentials of US-CA, China, Europe, and Rest of the World are 1.58, 0.43, 0.22, and 0.47, respectively. This implies that, on average, the total sourcing capability of a firm importing inputs from all countries is 270% higher than that of a firm only sourcing inputs from Mexico.[15] In comparison, Antras et al. (2017) estimate the total sourcing capability of a firm sourcing from all countries to only be 19% higher. The difference in our estimates can be attributed to the fact that it is likely that the US is better than Mexico at supplying inputs to its domestic firms, i.e., estimates are relative to the sourcing potential of the home country.

To illustrate these results, the Mexican industry with the lowest potential sourcing capability is *Wood and articles of wood; wood charcoal* (HS Chapter 44), with an 65% higher total sourcing capability compared to a firm only sourcing from Mexico. The industry with the highest one is *Articles of iron or steel* (HS Chapter 73) with an 830% higher total sourcing capability. The full results for every industry-region pair are presented in Appendix A.7.

The sourcing potential measure captures the attractiveness of particular regions as sources of inputs, so forgoing a regions with high sourcing potential would imply higher marginal costs. Therefore, in industries in which the attractiveness of sourcing from non-NAFTA countries is higher: (i) the use of NAFTA should be lower, because of a higher opportunity cost of RoO, and (ii) the share of firms sourcing from these countries should be higher, as firms find it profitable to pay their fixed costs. Results support this, as Panel 1.7a shows there is a negative industry-level correlation between our estimated sourcing potentials and the share of firms using NAFTA to export, and Panel 1.7b shows a positive one between

[15]By construction, a firm only sourcing inputs from Mexico has a total sourcing capability equal to 1.

Figure 1.6: Kernel Densities for Estimated Sourcing Potentials.



(a) US-CA (b) China

(c) Europe (d) Rest of the World

these sourcing potentials and the share of firms sourcing from non-NAFTA countries.

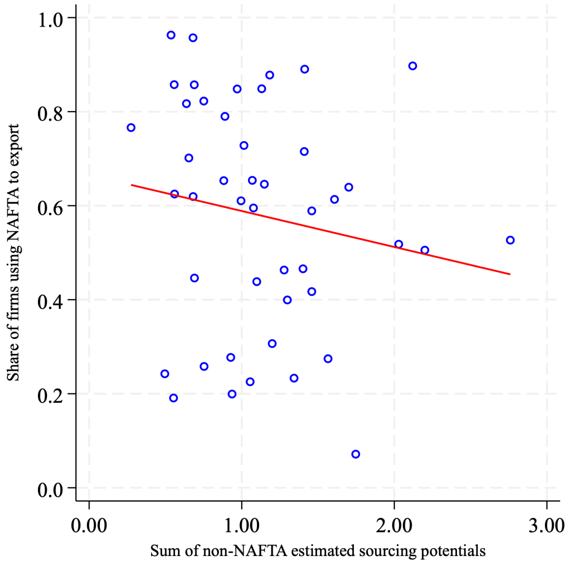
1.5.3 Estimation of Fixed Costs and US Market Demand

We structurally estimate the fixed cost of using NAFTA, fixed costs of sourcing from each foreign region, and US market demand. For computational simplicity, we assume these parameters are sector-specific instead of being defined at the industry-sector level. As in Section 1.4.2, the fixed cost of using NAFTA is constant across firms within a sector, and fixed costs of sourcing from foreign countries are assumed to follow:

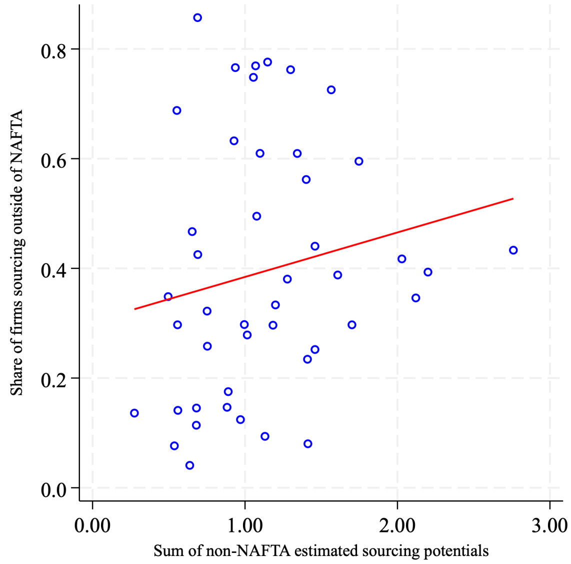
$$f_s^j(\phi) \sim \text{Log-normal}(\mu_s^j, \delta_s^j) \tag{1.5.2}$$

The location parameter $\mu_s^j \in (-\infty, +\infty)$ is allowed to be region-sector specific to capture any differences across countries because of proximity, common language, etc., as well as differences across sectors, e.g. how easy is it for firms to find suppliers abroad, the degree of input customization, etc. We assume $\delta_s^j = \sqrt{\log 2}$ as μ_s^j already influences both the mean and

Figure 1.7: Correlations with estimated non-NAFTA sourcing potentials.



(a) NAFTA Usage



(b) Non-NAFTA Sourcing

the variance of these fixed costs. Since firms, according to our computation in Section 1.5.2, always source inputs from Mexico, we set its fixed cost of sourcing to zero. For every sector s, we separately estimate the fixed cost of using NAFTA, the location parameters of fixed costs of sourcing, and US market demand:

$$\xi_s = [\zeta_s, \mu_s^{US-CA}, \mu_s^{CHN}, \mu_s^{EUR}, \mu_s^{ROW}, B_s]$$

Estimation follows Eaton et al. (2011) in using Simulated Method of Moments together with a Simulated Annealing solution algorithm, which optimally combines random exploration of the parameter space with searching for the parameters that decrease our objective function.[16] Let x_s represent data for a sector and ξ_s a set of sector-specific parameters. Our estimation consists in finding the parameters that minimize the following objective function:

$$\min_{\xi_s} ||e(\tilde{x_s}, x_s|\xi_s)||$$

The moment error function $e(\tilde{x_s}, x_s|\xi_s)$ is expressed as the percent difference between the vectors of simulated and data moments:

$$e(\tilde{x_s}, x_s|\xi_s) = \frac{\hat{m}(\tilde{x_s}|\xi_s) - m(x_s)}{m(x_s)}$$

[16]The algorithm uses a *temperature* which influences the acceptance rate of points that do not reduce the objective function, adapting the Metropolis-Hastings algorithm described in Metropolis et al. (1953).

where $m(\cdot)$ represents a set of R distinct moments, and $\tilde{x}_s$ is simulated data from our model under parametrization ξ_s. We use the L^2 distance norm, and therefore, our implementation of SMM consists in finding the set of parameters that minimizes the sum of squared errors:

$$\hat{\xi}_s = \arg\max_{\xi_s} e(\tilde{x_s}, x_s|\xi_s)^T I_R e(\tilde{x_s}, x_s|\xi_s)$$

with I_R being an $R \times R$ identity matrix. We define our objective function in percentage deviations so that all moments in $m(\cdot)$ are expressed in the same units and no moment receives an unintended larger weight. Informed by the empirical facts described in Section 2.2, the set of sector-specific moments we include to identify the true parameter vector ξ_s are:

1. Share of firms using NAFTA to export: This moment helps us pin down the fixed cost of using NAFTA to export ζ_s, as variation in this parameter will directly affect how many firms can pay the fixed cost of using NAFTA.

2. Share of firms sourcing from each region: Conditional on sourcing potentials, the costlier it is to source from a foreign region, the lower the share of firms sourcing inputs from it. We use this extensive margin of sourcing to pin down the location parameter of the distribution of fixed costs of sourcing from every region.

3. Average firm exports: To identify market demand in the US, we use average exports across all firms of a given sector.[17] In our model, average productivity and market demand are isomorphic in terms of revenue, and since we assume the same distribution of productivity across all sectors, there is a one-to-one relationship between US market demand and firm-level exports.

Our previous discussion on the relationship between the use of NAFTA and firm size being driven by fixed costs motivates us to include additional moments in our estimation. On the one hand, fixed costs of using NAFTA should be large enough to result in small firms using NAFTA less intensively. On the other, fixed costs of sourcing should be large enough to deter medium-sized firms from sourcing intensively from non-NAFTA countries, thereby increasing their use of NAFTA. These additional moments are:

4. Share of firms using NAFTA to export, by quintile of firm size

5. Share of firms sourcing inputs outside of NAFTA, by quintile of firm size

[17] We use a weighted average, with weights based on industries' contribution to the total trade value of a given sector.

Table 1.2: Estimates for Fixed Costs and US Market Demand.

	ζ_s/X	f_s^{CHN}/X	f_s^{EUR}/X	f_s^{US-CA}/X	f_s^{ROW}/X	B_s
Agriculture and Foods	0.54	20.15	16.66	26.51	16.04	0.45
Minerals and Chemicals	0.43	5.15	2.81	12.88	4.26	0.60
Skins and Textiles	0.62	3.40	3.07	8.48	4.52	0.47
Mining	0.04	5.28	3.20	31.96	8.71	0.01
Manufacturing	1.08	1.75	0.71	6.28	1.55	100.00
Others	1.50	2.78	2.06	16.8	4.15	0.13
Average	0.70	6.42	4.75	17.15	6.54	16.94

Our simulation of the model for a particular guess of ξ_s is as follows: (i) For each industry i within sector s, we take N_{si} random draws for productivity from a Pareto distribution with shape parameter χ. We take the number of firms exporting to the US of a given industry N_{si} directly from the data. (ii) For each sector s we take $N_s = \sum_{i=1}^{I_s} N_{si}$ random draws for the fixed costs of sourcing from each region, following Equation (1.5.2), where I_s is the number of industries within sector s. Within a sector, industries are heterogeneous in terms of their RoO, MFN tariffs, and sourcing potentials. Within an industry, firms are heterogeneous in terms of their productivity. (iii) By backwards induction and fixing either the use of NAFTA or WTO, for every firm we find the set of sourcing countries that maximizes their profits subject to paying fixed costs of sourcing, following Equation (1.4.13). (iv) Having found firms' optimal sourcing strategy under NAFTA and WTO, we compare profits under these two and assign firms to the option that yields the largest profits, as described in Equation (1.4.14). Having fully simulated firms' choices for the use of NAFTA and global sourcing strategies, we use Equations (1.4.8), (1.4.9), (1.4.10), (1.4.11), and (1.4.17), to compute predictions for input shares, prices, firm exports and profits, and imports of intermediates.

We present the results of this estimation in Table 1.2. These are not the point estimates resulting from our application of SMM, but rather transformations of them so results are easier to interpret. For the fixed cost of using NAFTA ζ and fixed costs of sourcing f, we show estimates of the average fixed cost as a share of total exports X, e.g. on average for a firm in the *Agriculture and Foods* sector, being able to source inputs from China represents 20.15% of its revenue in the US. For the estimates for US market demand B, we normalize that for *Manufacturing* to be equal to 100, and thus, market demand for the rest of the sectors is relative to it. The estimated parameters are shown in Appendix A.8.

Our results suggest the following. First, there is heterogeneity across sectors in the fixed cost of using NAFTA. This should be driven by sectoral differences in factors such as regulation or learning to use the FTA to export. As mentioned before, when firms export using NAFTA, they have to present a *Certificate of Origin* at the border, detailing the country of origin of all their intermediate inputs. Sectors with more complex products or more complex supply chains, such as the case of *Manufacturing*, should find it costlier to keep track of the sourcing of their inputs. Differences in the cost of complying with regulations should also drive this heterogeneity. For example, sectors with higher capital intensity, such as *Mining*, should find it less costly to comply with the labor regulations in NAFTA.

Second, there is also heterogeneity in fixed costs of sourcing, both across countries and sectors. Heterogeneity across countries should reflect differences in factors such as language, cultural proximity, or the strength of business relationships between Mexico and foreign countries. Heterogeneity across sectors for a given region could reflect differences in the ease with which Mexican exporters can find suppliers in foreign regions, or the degree of input customization needed for a sector's inputs. For example, foreign suppliers of inputs required by the *Manufacturing* and *Skins and Textiles* sectors in Mexico could be more connected to the global economy. Differences in fixed costs across sectors are important as it implies RoO have heterogeneous effects. For example, for sectors where few firms can pay the fixed cost of using NAFTA to export, RoO will not have much of an effect. On the contrary, if a sector has low fixed costs of sourcing from foreign countries, RoO will be very costly as firms could be sourcing from efficient suppliers from around the World.

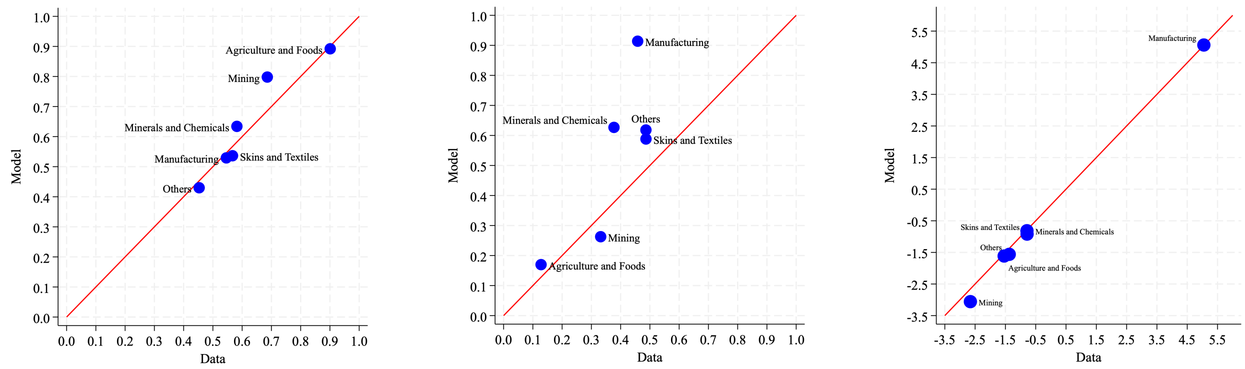
Lastly, US market demand for *Manufactures* is estimated to be much larger compared to other sectors. This is consistent with the fact that in our sample, on average, 77% of export value from Mexico to the US corresponds to this sector. However, this is likely to be partly driven by our assumption of all sectors having the same average productivity.

1.5.4 Fit of the Model

This section evaluates the model's fit at the sectoral and aggregate levels. At the sectoral level, Figure 1.8 shows the predictions of the model for: (a) The share of firms using NAFTA to export, (b) The share of firms sourcing inputs outside of NAFTA, (c) Average of log firm exports. In these figures, the x-axis shows the data moment, and the y-axis the simulated one. Therefore, the closer to the 45-degree line, the better the fit for that particular sector. Across all sectors, the model is able to fit these moments, and thus capture firm behavior regarding the use of NAFTA to export and how firms choose their sourcing strategies in response to RoO.

For the fit at the aggregate level we present Figure 1.9, where we ignore sectors and instead compute size quintiles according to export revenue, consistent with our empirical facts presented in Section 2.2. Panel 1.9a shows the model's replication of the inverse U-shape

Figure 1.8: Sectoral fit of the model.



(a) NAFTA Usage (b) Non-NAFTA Sourcing (c) Average Log Exports

relationship between the use of NAFTA and firm size. Consistent with Empirical Fact 2, our model predicts that small and large firms will use NAFTA to export less intensively compared to medium-sized firms. This is the result of the fixed cost of using NAFTA being too expensive for small firms, and the fixed costs of sourcing resulting in the opportunity cost of complying with RoO being increasing in firm size.

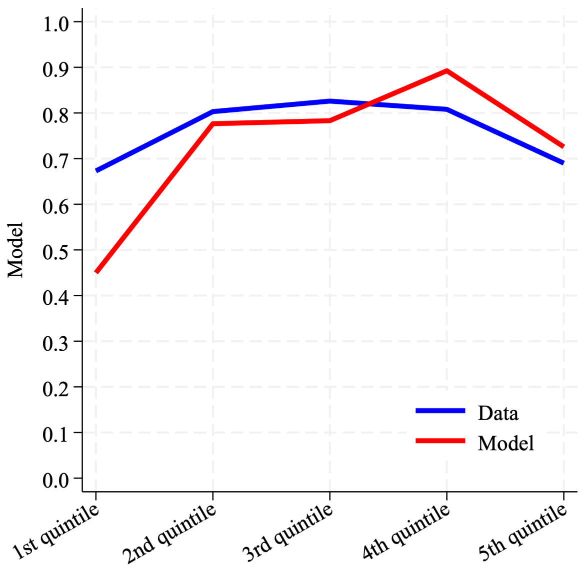
Regarding the share of firms sourcing inputs outside of NAFTA, Panel 1.9b shows we replicate its increasing relationship with firm size at the aggregate level. This relationship is driven by firm size, as larger firms are more likely to be able to pay the fixed cost of sourcing from foreign countries, and by the use of NAFTA, as it decreases the incentives firms have for sourcing from non-NAFTA countries. As in the data, the model predicts that even though the largest firms use NAFTA less intensively than medium-sized firms, almost all of the largest firms source inputs from non-NAFTA countries. This should be the result of large firms finding it profitable to pay these costs, even if restricted by RoO, because of their large export and import volume. Other results for the fit of the model, both at the sectoral and aggregate levels, are presented in Appendix A.9.

1.6 Effects of Trade Policies

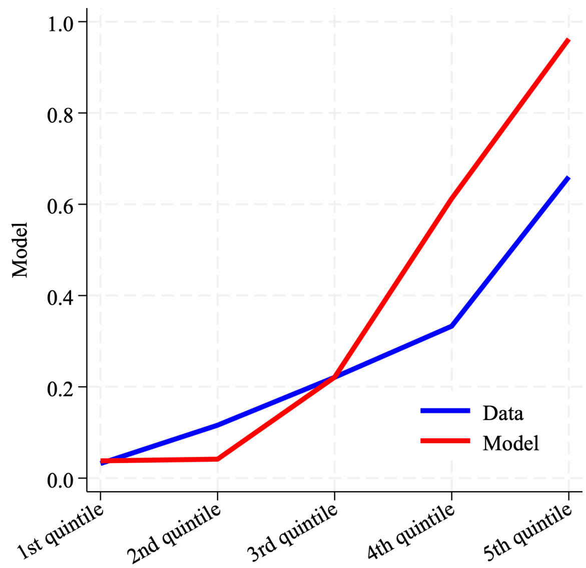
This section describes the counterfactuals we explore in our paper. Given the richness of our product-level data and our model capturing diverse aspects of trade policy, such as RoO and tariffs, we can conduct a wide range of policy-relevant counterfactual simulations.

The counterfactuals we study are: (i) The transition from NAFTA to USMCA, (ii) An increase in tariffs on Mexican imports, and (iii) NAFTA without RoO. Our counterfactuals study how the US and Mexico are affected from the policy change, focusing our attention on

Figure 1.9: Aggregate fit of the model.



(a) NAFTA Usage



(b) Non-NAFTA Sourcing

the effects over US exports of intermediates, US price index for Mexican imports, and Mexican firm profits; as these are the key variables policymakers care about the most. We emphasize the heterogeneity in responses to these policy changes across different firm sizes, highlighting the primary mechanism discussed in our paper: Firm size determines the opportunity cost of complying with RoO, thus affecting firms' use of NAFTA.

In these counterfactuals we are silent on other margins of adjustment not captured by our model. For example, we implicitly assume countries' sourcing potentials are not endogenous to policy changes. This idea is presented in Ornelas and Turner (2024) which studies how RoO can result in higher investment whenever an industry has high productivity, which could indeed be what policymakers have in mind when they implement RoO to protect domestic industries from foreign competition.

1.6.1 Transition to USMCA

In July 2020, NAFTA, which had been in place since 1994, was replaced by USMCA. This revised FTA brought changes both in terms of regulation and in terms of a general increase in RoO. We consider the latter in this counterfactual, in which we ask if the US and Mexico benefit from an increase in RoO. We assume the same increase in RoO across all industries. There are two reasons for this. First, assuming a common increase across all industries allows us to study how sectoral heterogeneity leads to different outcomes because

Table 1.3: Percent change in key variables due to an increase in RoO.

	US-CA Exports of inputs to Mexico	US-CA Price index for Mexican imports	Mexican firm profits
Agriculture and Foods	-0.42	0.27	-0.85
Minerals and Chemicals	-0.08	0.05	-0.24
Skins and Textiles	-2.93	0.24	-1.45
Mining	-0.03	0.06	-0.08
Manufacturing	-0.05	0.05	-0.08
Others	-0.80	0.32	-1.29
Average	-0.72	0.16	-0.67

of sectoral differences in firm size, sourcing potentials, and fixed costs. Second, while it is feasible to code the change in the RoO strictness for all HS 6-digit products, as USMCA's RoO are detailed in the documentation for the treaty, it is out of the scope of this paper to do so.

We assume a general increase of 25% in the strictness of RoO on all products. For example, if a particular product had a RoO strictness of 10% under NAFTA, under USMCA we will assume it has a 12.5% RoO strictness. This increase of 25% is in line with the increase in RoO for the automotive industry, studied in Head et al. (2024). They find that the increase in RoO decreased the share of regional content in the automotive sector, as the new rule fell to the right side of the Laffer Curve.

Table 1.3 shows the results for our variables of interest in terms of their percentage change. Averaging across sectors, US exports of intermediates would decrease on average by 0.72%, while the US Price index for imports from Mexico would increase on average by 0.16%. For Mexico, firm profits would be 0.67% lower. These results suggest that neither the US nor Mexico benefited from the increase in RoO that the transition to USMCA implied.

To study the mechanisms behind these effects, we focus on discussing the change in US exports of intermediates, as the explanation for the effects on the other key variables follows from our discussion. We identify three distinct effects: A (i) Substitution effect, a (ii) Scale effect, and a (iii) Switching effect, which can either increase or dampen the first two effects. First, when higher RoO are implemented across all sectors, firms are forced to substitute some of the inputs they were sourcing from non-NAFTA countries towards NAFTA countries if they want to keep using NAFTA. This should have been the main mechanism policymakers had in mind when implementing higher RoO in the USMCA agreement. This substitution does not necessarily imply higher US exports of intermediates, as Mexican firms could choose

Table 1.4: Share of firms of each quintile in each sector.

	1st quintile	2nd quintile	3rd quintile	4th quintile	5th quintile
Agriculture and Foods	0.18	0.37	0.21	0.14	0.09
Minerals and Chemicals	0.00	0.13	0.10	0.48	0.30
Skins and Textiles	0.07	0.11	0.21	0.28	0.33
Mining	0.66	0.02	0.15	0.12	0.04
Manufacturing	0.00	0.00	0.00	0.00	1.00
Others	0.03	0.01	0.38	0.42	0.17

to start sourcing these inputs either from Mexico or Canada, still complying with RoO. The extent to which this substitution effect does imply an increase in US exports depends on whether firms can source their inputs from the US, and on the relative sourcing potential of the US to that of Mexico, e.g. Mexican sectors with the largest increases in their import from the US are those for which the US is better than Mexico at sourcing their inputs.

Second, as our model suggests, an increase in RoO should lead to an increase in firms' marginal cost, unless firms are either unable to source from non-NAFTA countries or are already sourcing all their inputs from NAFTA countries. Increases in marginal cost directly imply higher US import prices, leading to lower demand for Mexican imports, and thus, lower input purchases from all countries, including the US. This is our scale effect because of the increase in RoO; this effect is stronger in sectors with either larger firms, as these firms were able to source from cheaper non-NAFTA suppliers, or sectors for which NAFTA countries have a relatively lower sourcing potential compared to non-NAFTA countries. For this purpose, we present Tables 1.4 and 1.5. The former shows shows the distribution of firm size across sectors, while the latter shows the relative sourcing potential of US-CA to that of non-NAFTA countries.

The third mechanism proposed in these counterfactuals is a switching effect. When RoO increase, some firms might no longer find it optimal to export using NAFTA and switch to export using WTO. It is unclear whether these firms will increase or decrease their purchases of inputs from the US. On the one hand, these purchases might increase as firms can now source from the cheapest suppliers around the World, leading to lower marginal costs and higher demand. On the other, switching to WTO implies firms will source a smaller share of their inputs from the US as they do not comply with RoO, and will now have to pay MFN tariffs which increase the price of US imports from Mexico.

For sectors with a higher US-CA sourcing potential, such as *Manufacturing* or *Mining*, the positive substitution effect on US exports of inputs should be higher as it is more likely

Table 1.5: Relative sourcing potential, RoO strictness, and MFN tariffs by sector.

	SP of US-CA to non-NAFTA	RoO Strictness	MFN Tariff
Agriculture and Foods	0.99	0.09	0.08
Minerals and Chemicals	1.39	0.02	0.04
Skins and Textiles	0.91	0.34	0.11
Mining	2.68	0.07	0.07
Manufacturing	1.96	0.01	0.03
Others	2.29	0.12	0.06

that firms will source from the US when required to source from NAFTA countries. In terms of the negative scale effect, sectors in which US-CA has a relatively higher sourcing potential should experience less of a decrease in demand as for these sectors, the increase in marginal cost because of higher RoO should be lower compared to sectors for which NAFTA countries are poor suppliers of their inputs.

For sectors with larger firms, such as *Manufacturing* or *Skins and Textiles*, the positive substitution effect on US exports should be higher, as these firms can source from the US when required to comply with stricter RoO. However, the negative scale effect should also be higher, as these sectors were importing more intensively from non-NAFTA countries and thus face larger increases in marginal cost when having higher RoO. Additionally, sectors with a higher share of larger firms should benefit from firms switching from NAFTA to WTO as these firms can now access non-NAFTA sourcing, leading to lower marginal cost and increased exports. Table 1.6 shows the responses to the increase in RoO by quintiles of firm size. Consistent with Panel 1.5a, medium to large firms are the ones for which the use of NAFTA decreases the most, while smaller firms experienced smaller effects. This ties back to Table 1.4 as sectors with larger firms should be the ones for which both the substitution and scale effects are the strongest.

For the switching effect, we present Table 1.7. It shows the share of firms that either keep using NAFTA or switch to WTO to export their products. On average, firms that keep using NAFTA do increase the share of their inputs coming from US-CA, implying the substitution effect is positive. However, these same firms experience an increase in marginal cost because of lower non-NAFTA sourcing, indicating a negative and detrimental scale effect. Firms that switch to WTO no longer comply with RoO, which results in higher sourcing from non-NAFTA countries. However, these firms now have to pay MFN tariffs, which ultimately results in their marginal cost increasing as well.

To conclude our discussion on the effects of the increase in RoO as a result of the transition

Table 1.6: Responses to the increase in RoO by firm size.

	Change						
	1st quintile	2nd quintile	3rd quintile	4th quintile	5th quintile	Aggregate	Units
Share of firms using NAFTA	-0.02	-0.21	-2.18	-4.25	-4.73	-2.28	p.p. Δ
Share of firms sourcing from China	-0.03	0.04	-0.90	-1.90	-0.65	-0.69	p.p. Δ
Share of firms sourcing from Europe	-0.01	-0.01	-0.22	-0.45	0.41	-0.06	p.p. Δ
Share of firms sourcing from US-CA	0.01	-0.04	-0.41	-0.26	-0.01	-0.14	p.p. Δ
Share of firms sourcing from ROW	-0.02	0.07	-0.91	-2.45	-0.65	-0.79	p.p. Δ
Share of inputs coming from US-CA	0.01	-0.01	-0.25	0.12	-0.12	0.02	p.p. Δ
Average Marginal Cost	0.00	0.21	1.05	1.34	2.31	0.70	% Δ
Average Exports	-0.04	-0.13	-1.20	-1.87	-0.15	-0.17	% Δ

Table 1.7: Responses to the increase in RoO by transitions between NAFTA and WTO.

	NAFTA to WTO	WTO to NAFTA	Stayed WTO	Stayed NAFTA	Units
Share of firms	0.02	0.00	0.21	0.77	-
	Change				
Share of firms sourcing from China	5.11	0.00	0.00	-1.04	p.p. Δ
Share of firms sourcing from Europe	11.34	0.00	0.00	-0.41	p.p. Δ
Share of firms sourcing from US-CA	-5.22	0.00	0.00	-0.03	p.p. Δ
Share of firms sourcing from ROW	3.9	0.00	0.00	-1.14	p.p. Δ
Share of inputs coming from US-CA	-8.67	0.00	0.00	0.19	p.p. Δ
Average Marginal Cost	17.94	0.00	0.00	0.22	% Δ
Average Exports	-7.83	0.00	0.00	-0.15	% Δ

from NAFTA to USMCA, across all sectors, purchases of inputs from the US would decrease, even if for some sectors the share of inputs coming from the US would indeed increase. The detrimental effects of higher prices for Mexican imports, coupled with the fact that 2.28% of firms would stop using NAFTA, dominate any potential gains from stricter RoO and thus, result in lower bilateral trade and higher prices for US consumers.

1.6.2 Increase in tariffs on Mexican imports

On May 30$^{\text{th}}$ 2019, Donald Trump published a tweet[18] announcing that the US would impose a 5% tariff on all goods coming into the country from Mexico. The objective of this

[18] Source: https://twitter.com/realDonaldTrump/status/1134240653926232064

measure was to exert political pressure on Mexico to address the issue of illegal immigration. On June 7th of that same year, it was announced that an agreement had been reached, with Mexico accepting to adopt stricter measures at the border. In this counterfactual, we quantify the effects a 5% tariff policy would have had on the US and Mexico.

It is hard to interpret precisely what Donald Trump meant in those *tweets*, as "all Mexican imports will pay a 5% tariff"' does not provide much detail on the exact implementation of the policy. For the purposes of this counterfactual, we interpret it as if all Mexican firms had to pay at least a 5% tariff. If a firm uses NAFTA to export, it will have to pay a 5% tariff. If a firm uses WTO to export, then it would have had to pay at least a 5% tariff, i.e. if in the baseline a firm had to pay a tariff lower than 5%, then we increase the tariff to 5%; whereas if a firm had to pay a higher tariff, then the counterfactual implies no change.

Table 1.8 details the results for the key variables policymakers should care for in terms of their percentage change given the increase in tariffs.[19] Averaging across sectors, US exports of intermediates would have decreased by 13.65%, while the US price index for Mexican imports would have increased by 4.95%. For Mexico, firm profits would have been 11.68% lower. These results suggest it would have been very costly for the US to implement this measure as Mexico is one of its main trading partners, even if it gains political leverage. From Mexico's point of view, the policy would have also been highly detrimental as exports to the US represent, on average, 80.1% of Mexico's total export value.

Table 1.8: Percent change in key variables due to an increase in tariffs.

	US-CA Exports of inputs to Mexico	US-CA Price index for Mexican imports	Mexican firm profits
Agriculture and Foods	-17.04	4.86	-13.42
Minerals and Chemicals	-15.07	5.58	-13.92
Skins and Textiles	-12.04	4.16	-8.95
Mining	-13.53	5.74	-14.82
Manufacturing	-12.15	4.79	-11.25
Others	-12.05	4.57	-7.74
Average	-13.65	4.95	-11.68

For discussing the mechanisms behind these results, Table 1.9 presents the change in key moments by quintiles of size. When exporters have to pay a tariff even if using NAFTA, the incentive for it decreases, which lowers the share of firms using NAFTA across all firm sizes.

[19] We do not include results for the change in US tariff revenue as we do not consider this was the motivation behind the intended policy change.

Lower NAFTA usage does not result in higher non-NAFTA sourcing, as higher tariffs decrease revenue, which lowers the ability to source from foreign countries. Therefore, marginal costs increase because of higher tariffs on all Mexican imports and less efficient sourcing. These two effects are the largest for medium-sized firms, which explains why these firms experience the largest decrease in their exports. The largest firms experience the lowest increase in their marginal costs as for them foreign sourcing decreases the least. Therefore, sectors with a higher share of smaller to medium-sized firms, as detailed in Table 1.4, are those for which bilateral trade decreases the most, namely *Agriculture and Foods* and *Mining*.

Table 1.9: Responses to the increase in tariffs by firm size.

	Change						
	1st quintile	2nd quintile	3rd quintile	4th quintile	5th quintile	Aggregate	Units
Share of firms using NAFTA	-46.09	-48.65	-46.35	-54.61	-40.64	-47.27	p.p. Δ
Share of firms sourcing from China	-0.23	-0.85	-1.33	0.92	-0.68	-0.43	p.p. Δ
Share of firms sourcing from Europe	-0.07	-0.13	-1.04	-1.47	-1.74	-0.89	p.p. Δ
Share of firms sourcing from US-CA	-1.34	-1.16	-12.18	-1.98	-0.20	-3.37	p.p. Δ
Share of firms sourcing from ROW	-0.24	-1.16	-0.84	0.56	-0.80	-0.50	p.p. Δ
Share of inputs coming from US-CA	-0.88	-0.43	-5.59	-1.12	-0.69	1.39	p.p. Δ
Average Marginal Cost	6.36	6.31	8.64	6.53	4.71	6.63	% Δ
Average Exports	-15.43	-16.19	-17.59	-14.43	-12.3	-12.34	% Δ

Table 1.10 shows the same moments but according to whether firms would keep using the same trade regime or switch to a different one as a result of the increase in tariffs. Around 47% percent of the firms would switch from NAFTA to WTO. For these firms, no longer being constrained by RoO would not translate into higher sourcing from Europe, but sourcing from China and the Rest of the World would increase. According to our estimates in Section 1.5.2, Europe's sourcing potential for Mexican firms is lower than that of other countries, so firms would not find it profitable to source from Europe even if no longer restricted by RoO. Moreover, as these firms would no longer use NAFTA, the share of firms sourcing from the US and Canada would have decreased by 5.15 percentage points, which, together with the increase in marginal cost, would have decreased purchases of inputs from these countries.

Firms that would keep using NAFTA to export, 32% of firms, would decrease their sourcing from all foreign countries even if not restricted by higher RoO. The fact that now they would have to pay tariffs even if using NAFTA, would decrease their revenue and therefore their ability to pay fixed costs of sourcing. Lastly, firms that would keep using WTO would exhibit the smallest changes, as some of these firms would not experience any change because of

Table 1.10: Responses to the increase in tariffs by transitions between NAFTA and WTO.

	NAFTA to WTO	WTO to NAFTA	Stayed WTO	Stayed NAFTA	Units
Share of firms	0.47	0.00	0.21	0.32	-
	Change				
Share of firms sourcing from China	0.63	0.00	-0.21	-2.14	p.p. Δ
Share of firms sourcing from Europe	-0.50	0.00	-0.11	-1.97	p.p. Δ
Share of firms sourcing from US-CA	-5.15	0.00	-0.31	-2.71	p.p. Δ
Share of firms sourcing from ROW	0.62	0.00	-0.22	-2.32	p.p. Δ
Share of inputs coming from US-CA	-3.09	0.00	-0.08	-0.83	p.p. Δ
Average Marginal Cost	10.20	0.00	0.62	6.23	% Δ
Average Exports	-13.36	0.00	-5.68	-13.95	% Δ

the counterfactual, i.e. firms that were already paying tariffs higher than 5%. Firms that had MFN tariffs lower than 5% also would experience an increase in marginal cost because of the higher tariffs, which would decrease their revenue, decreasing their foreign sourcing and further increasing their marginal cost. As a summary, sectors with the largest share of firms using NAFTA to export, namely *Agriculture and Foods*, *Minerals and Chemicals*, and *Mining* according to Figure 1.8, are those for which purchases of inputs from the US would have decreased the most, and the ones that would have experienced the largest price increases. These results highlight the significant costs policies aimed at gaining political leverage would have, to the detriment of a country's own manufacturers of intermediate goods and consumers.

1.6.3 NAFTA without Rules of Origin

The purpose of RoO is to protect local industries and to encourage bilateral trade among FTA member countries. While these effects can be achieved, as discussed in Ornelas and Turner (2024), sourcing potentials are likely fixed in the short run. Therefore, RoO have a detrimental effect on trade as they restrict exporters from being able to take advantage of comparative advantage across the World. This section quantifies the efficiency gains from removing RoO and allowing Mexican exporters to source their inputs freely from the best suppliers. Importantly, we do not ask what would happen today if NAFTA had not had RoO to begin with, as sourcing potentials today might be different. If RoO had never been implemented, the sourcing potential of NAFTA countries could be lower today, implying our results can be interpreted as a lower bound for the effects of NAFTA never having RoO.

Table 1.11: Percent change in key variables due to the removal of RoO.

	US-CA Exports of inputs to Mexico	US-CA Price index for Mexican imports	Mexican firm profits
Agriculture and Foods	1.89	-1.41	4.32
Minerals and Chemicals	0.33	-0.19	0.97
Skins and Textiles	12.44	-3.50	21.34
Mining	0.10	-0.26	0.35
Manufactures	0.19	-0.14	0.34
Others	2.93	-1.36	5.82
Average	2.98	-1.15	5.52

For this counterfactual, we set RoO strictness to be equal to zero across all industries. However, we still assume fixed costs of using NAFTA and MFN tariffs whenever firms choose to export using WTO membership. If RoO are removed, the cost of using NAFTA to export decreases while the benefit of it, not paying MFN tariffs, remains the same. Table 1.11 shows the changes in the key variables policymakers in the US and Mexico likely care about.

Across all sectors, the removal of RoO would be beneficial for both countries. The US would increase its exports of intermediates, and its consumers would face lower prices for their Mexican imports. Mexican firms would see their profits increase. The US firms that would benefit the most are those supplying inputs to the *Skins and Textiles* and *Others* sectors in Mexico. US consumers of goods from these sectors would experience the largest decrease in the price of their imports, as well as the ones for which Mexican firms would experience the largest increase in profits. The sectors that would benefit the least are *Mining* and *Manufacturing*, which could be the result of: (i) Already having lower RoO, as shown in Table 1.5. (ii) US-CA are good suppliers of inputs for the *Mining* sector, so the removal of RoO does not matter as much because they were already sourcing from NAFTA. (iii) Firms in the *Mining* sector are smaller in size, according to Table 1.4, therefore they were less likely to source from non-NAFTA countries, and thus the removal of RoO would have a small effect. As in Section 1.6.1, we discuss the effects on US exports of intermediates in terms of three mechanisms: A substitution, an income, and a switching effect.

For the substitution effect, intuitively the removal of RoO should decrease the share of inputs being sourced from US-CA. Inspection of Table 1.12 reveals this is not necessarily the case, as smaller firms would actually increase the share of their inputs coming from US-CA. The removal of RoO would induce smaller firms to use NAFTA, decreasing marginal costs as they would no longer pay MFN tariffs, and in turn, increasing revenue so these firms can now

Table 1.12: Responses to the removal of RoO by firm size.

	Change						
	1st quintile	2nd quintile	3rd quintile	4th quintile	5th quintile	Aggregate	Units
Share of firms using NAFTA	1.80	3.52	9.29	6.22	22.44	8.65	p.p. Δ
Share of firms sourcing from China	0.13	-0.59	7.25	16.35	4.17	5.46	p.p. Δ
Share of firms sourcing from Europe	0.02	0.21	2.78	5.61	6.66	3.06	p.p. Δ
Share of firms sourcing from US-CA	0.02	1.16	3.09	0.95	0.04	1.05	p.p. Δ
Share of firms sourcing from ROW	0.10	-0.79	8.33	16.17	3.90	5.54	p.p. Δ
Share of inputs coming from US-CA	0.01	0.55	1.31	-3.9	-2.34	-0.11	p.p. Δ
Average Marginal Cost	-0.31	-2.03	-6.85	-4.75	-8.07	-3.52	% Δ
Average Exports	1.25	4.45	14.08	16.79	0.99	1.17	% Δ

pay the fixed cost of sourcing from US-CA. For larger firms, the substitution effect is indeed negative, as they would decrease the share of inputs they source from US-CA. Since larger firms are able to source from non-NAFTA countries, once RoO no longer restrict them, they increase the share of their inputs coming from these countries, as shown in Table 1.12. US suppliers selling to Mexican sectors in which there is a higher share of smaller firms actually experience a beneficial substitution effect, while firms selling to sectors with larger firms will see their exports of intermediates decrease.

In this counterfactual, a stronger scale effect benefits the US and Mexico. The removal of RoO implies firms can now source their inputs from the cheapest suppliers across the World, which should decrease marginal cost, increasing demand and input purchases from the US. The extent to which this is the case depends on firms' ability to source from non-NAFTA countries. Table 1.12 shows that larger firms are the ones that would increase their sourcing from these countries the most, thus experiencing the largest decreases in marginal cost. US firms selling to Mexican sectors with larger firms should experience the strongest scale effect, as even if the share of inputs sourced from them decreases, these sectors experience an increase in their exports and thus, increase their purchases of intermediates from the US. In summary, the beneficial scale effect should be negligible for sectors with smaller firms, but beneficial for those with larger firms.

Lastly, for discussing the switching effect we present Table 1.13. Firms that would benefit the most from the removal of RoO are those that switch from WTO to NAFTA, experiencing on average a 21.57% increase in their exports. Their marginal cost would decrease significantly as they would no longer pay MFN tariffs, and their increased revenue would now allow them to source from foreign countries. Firms that would keep using NAFTA do increase their

Table 1.13: Responses to the removal of RoO by transitions between NAFTA and WTO.

	NAFTA to WTO	WTO to NAFTA	Stayed WTO	Stayed NAFTA	Units
Share of firms	0.00	0.09	0.12	0.79	-
	Change				
Share of firms sourcing from China	0.00	6.56	0.00	6.17	p.p. Δ
Share of firms sourcing from Europe	0.00	7.33	0.00	3.05	p.p. Δ
Share of firms sourcing from US-CA	0.00	8.67	0.00	0.38	p.p. Δ
Share of firms sourcing from ROW	0.00	6.34	0.00	6.29	p.p. Δ
Share of inputs coming from US-CA	0.00	2.43	0.00	-1.37	p.p. Δ
Average Marginal Cost	0.00	-25.43	0.00	-2.10	% Δ
Average Exports	0.00	21.57	0.00	0.84	% Δ

exports but to a lower extent, as the removal of RoO would allow them to source a larger share of inputs from non-NAFTA countries, decreasing their marginal cost by 2.10%. US firms selling to Mexican sectors in which firms use NAFTA less intensively, and US consumers purchasing goods from them, would be the ones that benefit the most. Likewise, sectors benefiting the most would be those for which non-NAFTA countries are relatively better suppliers of their inputs, as it is the case of the *Skins and Texiles* sector according to Table 1.5.

This counterfactual suggests that removing RoO would benefit the US and Mexico across all sectors. The degree to which a sector benefits depends on the size of its firms, the relative sourcing potential of NAFTA countries, and how strict were RoO. For sectors with larger firms, the removal does imply a lower share of intermediates being sourced from the US. However, the effect of lower marginal costs achieved by firms being able to source from cheaper suppliers would be larger, and thus, US exports of intermediates would increase. Sectors in which firms are smaller would also benefit, as removing RoO would still lead to an increase in the share of firms using NAFTA, decreasing their marginal cost as these firms would no longer pay MFN tariffs.

1.7 Conclusions and Policy Implications

The main message of this paper is that firm size matters for the effect RoO have on the use of NAFTA. This is rationalized by the fact that Mexican exporters face: (i) Fixed costs of using NAFTA, and (ii) Fixed costs of sourcing from foreign countries. The former implies small firms are less able to pay the fixed cost of using NAFTA, while the latter implies large firms are more able to source from foreign countries, making the opportunity cost of complying with RoO increasing in firm size.

Restrictive trade policies have detrimental effects on the US and Mexico, with sectoral heterogeneity in these responses being the result of: (i) The distribution of firm size, and (ii) How good suppliers of inputs NAFTA countries are relative to non-NAFTA ones. On average, across sectors, we quantify that a 25% increase in the strictness of RoO would lead to 0.72% lower US exports of intermediates to Mexico, 0.16% higher US prices for imports coming from Mexico, and 0.67% lower Mexican exporter profits. Imposing an ad-valorem tariff of at least 5% on all Mexican imports would decrease US exports by 13.65%, increase US prices for imports coming from Mexico by 4.95%, and decrease Mexican exporter profits by 11.68%. On the contrary, efficiency gains from removing RoO would imply 2.98% higher US exports of intermediates to Mexico, 1.15% lower US prices for imports coming from Mexico, and 5.52% higher Mexican exporter profits.

Our paper has two policy implications. First, it is costly to protect local industries from foreign competition, as RoO result in lower sourcing efficiency precisely in sectors in which NAFTA countries have a comparative disadvantage. Moreover, RoO should be especially costly for developing countries such as Mexico, as these are likely to have less diversified economies and less efficient suppliers of intermediates. Second, RoO do not necessarily result in higher regional content in exports, as firms could choose to no longer use the FTA to export. Moreover, even if the share of regional content increases, bilateral trade could decrease as a result of lower sourcing efficiency. The objective of trade policy should not be to maximize the share of the pie countries within an FTA get but rather maximize the amount of pie these countries are getting in the end.

CHAPTER II

Information Spillovers in Export Destinations

2.0 Abstract

We study how information spillovers, in terms of learning about other destinations when exporting, affect firms' entry and exit decisions in export markets. We provide empirical evidence on the existence of these spillovers and how firms use their export experience to make better choices when selling to foreign markets. We build a dynamic model of export supply and learning in which firms choose to which countries to export based on their beliefs about their profitability in these destinations. We quantify our model by estimating firms' export profitability and fixed costs of exporting, and conduct counterfactual simulations to evaluate the contribution of these spillovers to the diversification of export destinations. Without information spillovers, the share of Mexican firms exporting to destinations other than the US would decrease by 21.6%. We also find that lowering the fixed costs of exporting to a particular country could increase the share of firms exporting and exports to other destinations.

2.1 Introduction

Several distinct factors determine a firm's export supply, such as its productivity or the trade costs it faces. Moreover, in a world with imperfect information, one could also consider a firm's perceived profitability in export destinations an essential factor. This is because uncertainty in demand could lead a firm not to enter a destination when it was profitable to do so, or on the contrary, lead a firm to enter a destination only to exit after discovering it was not profitable to export there, that is, an exporting failure. If uncertainty is present in export markets and therefore firms learn while exporting, one could also ask if learning about a destination is only possible when exporting there or if learning occurs not only when exporting to that destination but also when exporting to other similar export markets. This is precisely the central question of this paper: how information spillovers affect firms' entry and exit decisions from export markets.

The literature on the geographic expansion of a firm's exports considers two mechanisms: the first is that exporting tenure lowers the costs of exporting and thus increases the profitability of entering other export destinations. The second is that there are information spillovers across potential destinations; therefore, previous experience may lead a firm to enter new markets. This paper follows the second mechanism. On one hand, I provide empirical evidence of information spillovers affecting firm dynamics in export markets. On the other hand, using this empirical evidence as motivation, I built a structural model of export supply with learning to explore the mechanisms behind the geographical spread of a firm's exports. More work needs to be done on how export destinations shape the pattern of entry into other destinations and on building empirical models that allow us to ask interesting questions regarding firms' export choices under uncertainty.

For example, assume a Mexican firm is considering exporting to Germany and Switzerland but is uncertain about its profitability. Given some prior beliefs, the exporter chooses to enter Germany and, while exporting there, starts to learn about its true profitability in that country. However, the firm learns about Germany and Switzerland because of the similarity between these two countries. Therefore, the experience of exporting to Germany also leads the firm to export to Switzerland. This is what I call information spillovers, the fact that when exporting to a particular destination, a firm learns about that specific destination and other similar potential export destinations. If this mechanism is accurate, these information spillovers could generate the geographic spread of a firm's exports.

This paper contributes to the literature on uncertainty and entry choices such as the work by Das et al. (2007), Impullitti et al. (2013) and Dickstein and Morales (2018), to the literature on extended gravity such as the work by Morales et al. (2019) which remarks the importance of export experience when trying to explain exporter dynamics and to the literature on firm's destination choices such as the work by Nguyen (2012) where it is assumed that there is demand uncertainty across potential destinations -which is immediately resolved once a firm enters a market-, but only explores a two country static model. In contrast, we are proposing a dynamic framework in which demand shocks are imperfectly correlated across destinations and firms do not immediately discover their profitability but rather start a learning process, which seems more akin to the stylized facts for new exporters identified in the data as in Ruhl and Willis (2017). Another key difference is that the author only performs numerical simulations to evaluate, on average, how many destinations a firm enters; in contrast, this paper structurally estimates a model and conducts counterfactual simulations to assess the effect of information spillovers.

In Albornoz et al. (2012), the authors consider a two-period, two-country model with perfectly correlated demand shocks and immediate learning. In contrast, this paper explores an environment with multiple potential destinations where demand is imperfectly correlated across these. Defever et al. (2015) provide reduced-form evidence of how it is more likely a firm will enter a destination geographically close to another destination the firm has previously exported to. Another paper in this line is that of Evenett and Venables (2002). Still, they consider that past export experience only affects the cost side of firms and that firms need to be forward-looking, i.e., when deciding whether to enter a new destination, it is not taking into account that the new location will provide information on other destinations.

The work by Schmeiser (2012) also considers the geographic expansion of a firm's exports but rather than being a story of demand uncertainty, it is a story about learning to export in which the fixed costs of entry into a destination are decreasing in the number of destinations previously served. Because of this, a destination that previously was not profitable to export might become profitable once sufficient experience is acquired, thus generating geographical expansion. This differs from the framework we present since their work is more about firms getting the know-how of exporting -through reduced fixed costs of doing so- rather than firms acquiring more information while exporting to a given market.

The rest of the paper is organized as follows. Section 2.2 describes the data we use, discusses how we compute a similarity measure of export destinations, and provides reduced-form evidence on information spillovers and how these affect firms' entry and exit choices in export destinations. In Section 2.3, we present a model of export supply and information spillovers, in which we describe how firms choose their export destinations and learn according to their experience in these markets. Section 2.4 details the quantification of our model, while Section 2.5 presents the counterfactual scenarios we explore to evaluate the role of information spillovers. Section 2.6 summarizes our main findings and discusses their policy implications.

2.2 Empirical Evidence

This section describes how we use Mexican customs data on the universe of exporting firms, with which we compute a similarity index between export destinations and present reduced-form evidence on the existence of information spillovers and how they affect firm behavior in export markets. The most prominent empirical work regarding how past destination choices affect entry into new export markets is that of Defever et al. (2015), which tests if having previously exported to a given country increases the probability of entering a similar destination, e.g., if a firm has exported to Germany, the firm is more likely to start exporting to Switzerland given that Germany and Switzerland are similar countries. This approach is standard in the literature, and even though it is intuitive, we need to take a different approach in this paper.

While the sign of the coefficient for the effect of export experience on entry is positive in the work mentioned above, we are silent about it. Having previously exported to a destination may only sometimes lead to entry into a similar destination. Still, it should allow the firm to make more informed decisions. For example, suppose a firm, while exporting to Germany, learns that exporting to Switzerland would not be profitable. In that case, export experience decreases the probability of a firm entering Switzerland after entering Germany. Under this argument, all that exporting to Germany does is give the firm more information about Switzerland: whether it is profitable to export to Switzerland. Moreover, if destinations provide information about other export markets, the information a destination provides might incentivize firms to enter that particular export market.

2.2.1 Data

The data used in this paper comes from the Exporter Dynamics Database published by the World Bank and constructed by Fernandes et al. (2016). The Mexican data contains yearly information on export destination, value of sales, year, product -at the HS 6-digit disaggregation level- and, for some observations, quantity. As shown in Table 2.1, data is for the period between 2000 and 2012 and covers 203,869 distinct firms exporting to 226 destinations and 2,879 unique markets. A market is defined as a unique destination-product combination aggregating products into a 2-digit disaggregation level.

Table 2.1 also provides a brief overview of some exporter characteristics relevant to this paper. The average number of destinations exported by a firm in a single period is 2.08 destinations -standard deviation of 3.63-, while the average number of exported destinations for all years in the sample is 2.54 -standard deviation of 4.57-. These low values for the mean number of destination countries reflect the small diversity in export destinations for Mexico. Mexican exports are concentrated in a small number of destinations, e.g., exports to the United States account for 82.63% of total export value during this period. This fact is only reinforced by the medians shown in parenthesis, which indicate that half of all Mexican firms only export to one country in their tenure as exporters.

As for the number of periods a firm exports to a particular destination, which we refer to as tenure in an export market, the average firm exports only for 1.93 years -with a standard deviation of 1.60-. This points out that most firms experience exporting failures since they only enter an export market for a few periods and exit from it. Meanwhile, the average tenure as an exporter is 2.36 years -with a standard deviation of 1.99 years-, which again

Table 2.1: Descriptive Statistics.

Statistic	Value
Years	2000 - 2012
# of firms	201,739
# of destinations	226
# of markets	2,879
Average # of destinations served per period	2.04
	(1.00)
Average # of markets served per period	3.38
	(1.00)
Average # of destinations served in total	2.47
	(1.00)
Average # of markets served in total	4.57
	(2.00)
Average tenure of a firm in an export destination	1.87
	(1.00)
Average tenure of a firm in an export market	1.67
	(1.00)
Average tenure of a firm as an exporter	2.25
	(1.00)

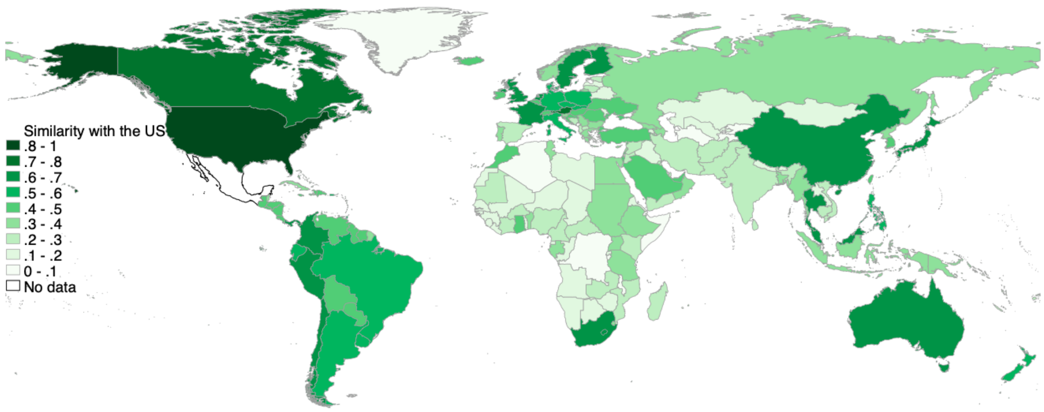
shows that most firms only engage in international trade for a few periods. This fact has been well documented in the literature. As for why this behavior persists in the data, rather than a story of demand shocks driving firms out of export markets, it is one of uncertainty when engaging in international trade, which further motivates this paper.

2.2.2 Similarity of Export Destinations

To calculate a similarity index between export destinations, We follow the work by Finger and Kreinin (1979) in which the authors develop an export similarity index. Their index measures the similarity of two countries regarding their exports to a common third country and is defined as:

$$S_X(i,j;k) = \sum_l \min\left(\frac{X_{ik}^l}{X_{ik}}, \frac{X_{jk}^l}{X_{jk}}\right) \tag{2.2.1}$$

Figure 2.1: The US compared to the ROW in terms of their imports from Mexico.



where i and j are the two origin countries in consideration, k is the third country that is exported to, l represents some trade classification system and X represents the value of exports. For this work, rather than using this export similarity index, we define and calculate an import-based similarity index. We are using imports rather than exports since Mexican firms serving a particular destination care about how similar that destination is to others regarding their exports to those countries, which can be seen as imports from their perspective. The import-based similarity index is thus defined as:

$$S(i, j; k) = \sum_{l} \min\left(\frac{M_{ik}^{l}}{M_{ik}}, \frac{M_{jk}^{l}}{M_{jk}}\right) \tag{2.2.2}$$

The index takes values such that $S \in [0, 1]$, where higher values of S represent a higher degree of similarity between countries i and j with respect to their imports from k. If the index equals 0, then i's and j's import patterns from k are entirely dissimilar. If the index equals 1, then the commodity distribution of i's and j's imports from country k is identical. To calculate the import-based similarity index, we use our customs data as firm exports can be aggregated at the product-destination level, and thus, we can calculate the value of imports of a particular country coming from Mexico for every product in the data. Products are defined following the HS classification system at a 2-digit disaggregation level.

Figure 2.1 shows how similar the United States is to the rest of the world regarding their imports from Mexico. The index predicts intuitive results such as the similarity between the US and Canada or Commonwealth countries such as the United Kingdom, Australia, South Africa, etc. The complete end-product of this exercise is a symmetric matrix that shows how similar every country-pair is for the destinations to which Mexican firms exported between the years 2000 and 2012. The index is calculated yearly but then averaged over all periods in the data for our reduced-form estimations.

2.2.3 Effects of Information Spillovers on Exporter Behavior

This section provides empirical evidence on information spillovers and whether these affect firms' choices in export markets. If destinations contain information about other potential destinations, then the following testable implications should follow:

Implication 1: *If destinations provide information about other similar destinations, then a firm that has previously exported to countries similar to i should be less likely to make a wrong decision regarding entry into i.*

Assuming there is uncertainty on destination-specific profitability and information spillovers across similar destinations, a firm with higher export experience relevant to a certain destination is less likely to make a wrong decision regarding entry into that destination.

Implication 2: *If destinations provide information about other similar destinations, then destinations are valuable for how much information about other countries they provide. More informative destinations should be more likely to be entered.*

In the presence of information spillovers, and assuming firms are aware of these spillovers and are forward-looking, destinations are valuable not only because of their expected profitability but also because of how informative they are about destinations that firms have not previously exported to. A firm might enter a destination even when expecting non-positive profits if the destination will lead to lower uncertainty concerning other destinations and, thus, higher profits or at least better decisions in the future.

2.2.3.1 Relevant Export Experience and Wrong Decisions

The ideal identification strategy would be regressing the probability of making a "wrong decision" concerning entry into a destination on a measure of how much information a firm has about this destination, where we use export experience as a proxy for the amount of information a firm has. However, estimating or defining what making a wrong decision means is challenging, even more so when we only have customs data without firm characteristics.

Testing this implication first requires us to define what we mean by a wrong decision. We will consider the case in which a firm enters a particular market, realizes it is not profitable to export there, and thus decides to exit. That is, entry when entry was not profitable. This requires us to define what we consider an exit from a market and how to proxy for the firm being profitable or unprofitable. For the case of exit, we will consider two distinct cases:

- An exit is when a firm enters a market and exits from it in the next period.

- An exit is when we observe entry and then exit at some point before the last year in the data.

Measuring when a firm is profitable or not in an export market poses a greater challenge. Given the lack of firm characteristics in our data, we proxy for it using whether a firm exited -continued- the market when demand was increasing -decreasing-. That is:

- The firm was profitable if it did not exit the market despite a negative demand shock.

- The firm was not profitable if it exited the market despite a positive demand shock.

The reasoning behind this is if the firm exited the market even with a positive demand shock, it could indicate that it was not profitable in that market and thus exited. On the contrary, if we observe that a firm did not exit the market even with a negative demand shock, then it might be the case that the firm was profitable, that is, if the firm was able to withstand a negative demand shock then it is likely that the firm was profitable in that market.

Lastly, we define a positive/negative demand shock using changes in demand. Even though the analysis is conducted at the market level, a product-destination combination, we define demand shocks at the destination level to account for the fact that a few firms might serve a market. Thus, a firm's exit would generate a negative market shock, which would cause a problem of reverse causality. We propose two measures of what a positive demand shock is:

- The growth rate of demand is positive.

- The growth rate of demand is above its average growth rate.

And equivalently for a negative demand shock. With these definitions in hand, Table 2.2 shows how our dependent variable is constructed. We ignore the cases in which the firm exited with a negative demand shock and when it continued with a positive demand shock since it is less clear if the firm was or was not profitable in these cases. Suppose the firm exited the market, but there was a negative demand shock. In that case, We cannot say that the firm was not profitable since its exit might be driven precisely by a negative demand

Table 2.2: Definition of a wrong decision.

	Positive demand shock	**Negative demand shock**
Exit	Wrong decision	-
Continue	-	Right decision

shock and not by its profitability in that export market. The same intuition applies to the case in which a firm continued, and there was a positive demand shock.

Now, we turn our attention to the independent variable of this analysis, the measure of relevant export experience. We emphasize the word relevant to acknowledge the fact that not all previously exported destinations provide the same amount of information about a particular destination, but rather, it depends on how similar those destinations are to the one in consideration. Suppose the destinations a firm has previously exported are more similar to the one in consideration. In that case, the firm should have more information about this destination and thus be more likely to make a better decision concerning entry.

The measure of relevant export experience should be a function of two things: which destinations firm i has exported before period t and the similarity of each of these destinations with market m. Defining z_{imt} to be the amount of export experience that firm i has with respect to market m at time t, then:

$$z_{imt} = \sum_{j \in V_{i,t-1}} S(m, j) \tag{2.2.3}$$

where we sum across all destinations j in set $V_{i,t-1}$, which is the set of destinations to which firm i has exported up to period $t-1$. z_{imt} is increasing in the size of V_{it-1} as long as its elements are such that $S(m, j) > 0$, that is, if firm i has previously exported to countries somewhat similar to m. The specification to test whether having more information leads to better decision-making regarding entry into a destination is:

$$\mathbb{P}_{imt} = \alpha_0 + \alpha_1 z_{imt} + \epsilon_{imt} \tag{2.2.4}$$

where $\mathbb{P}_{imt}$ represents the probability of firm i having made a wrong decision concerning entry into market m at time t, where wrong decision is defined according to one of the criteria above, that is, we are estimating a linear probability model of how relevant export experience affects the likelihood of making a wrong decision regarding entry into a destination.

The specification in Equation (2.2.4) is not without problems, as other factors could affect entry into export markets. In particular, two issues are of concern. The first one is that a positive demand shock could be driving entry into a destination and thus threatening the identification of the effect of export experience on entry. For example, imagine a demand shock affecting Germany and Switzerland, perhaps with different timing. The shock could lead to entry into Germany, and then, as the shock hits Switzerland, it could also lead to entry into Switzerland. If this is the case, the estimated coefficient for export experience would have an upward bias and, thus, yield an incorrect estimate of the effect of export experience on how the firm makes entry decisions.

The second issue is that of firms learning how to export. The literature has found evidence that the more a firm has exported in the past, the better it is at exporting. If this is the case, export destinations' profitability would increase in export experience and thus, again, threaten the identification of the effect of increased information on a firm's entry choices. An example of this could be that a firm does not start exporting to Switzerland because by exporting to Germany, it has learned that it is profitable to do so, but rather because by exporting to Germany, it becomes more efficient in exporting, which later drives entry into Switzerland.

To control for both of these concerns, we propose the following specification:

$$\mathbb{P}_{imt} = \alpha_0 + \alpha_1 z_{imt} + \eta_1 \%\Delta x_{dt} + \eta_2 \%\Delta x_{it} + \phi_{f,m,t} + \epsilon_{imt} \tag{2.2.5}$$

where $\%\Delta x_{dt}$ represents the percentage change in demand from destination d and time t and $\%\Delta x_{it}$ represents firm i's aggregate exports in time t. We also include product, market, and time-fixed effects to capture any unobservables that our explanatory variables might not capture. On one hand, variable $\%\Delta x_{dt}$ controls for demand shocks driving entry. If there is a demand shock in destination d at time t, this will affect all other firms in that destination and thus will be picked up by this variable. On the other, variable $\%\Delta x_{it}$ controls for learning how to export effects and quality upgrading. If export experience makes the firm more efficient at exporting, this should increase exports to all other destinations the firm serves, which the firm's aggregate exports will thus pick up.

Results for a random sample of firms are shown in Table 2.3. In it, each column represents a different definition of a wrong decision. Here, dependent variable $\mathbb{P}_{x,y}$ should be read as the probability of making a wrong decision according to criteria x, y, where x represents when the firm exited the market and y how is a positive demand shock measured. The case in which $x = inm$ is when a firm exited the market immediately. The case in which $y = pdg$ is when a positive demand shock is defined as positive demand growth and $y = dgaa$ is when demand growth is above average. Other combinations for these definitions can be explored and would serve as robustness checks.

Table 2.3: Relevant Export Experience.

	(1) $\mathbb{P}_{inm,pdg}$	(2) $\mathbb{P}_{inm,pdg}$	(3) $\mathbb{P}_{inm,dgaa}$
Export Experience	-0.00527***	-0.0118***	-0.0120***
	(-18.41)	(-5.78)	(-5.34)
$\%\Delta x_{dt}$		-1.85e-08	-7.93e-08
		(-0.79)	(-1.46)
$\%\Delta x_{it}$		1.22e-09*	1.87e-09**
		(2.84)	(3.23)
Constant	0.187***	0.216***	0.435***
	(81.78)	(21.79)	(51.05)
Fixed Effects		✓	✓
Observations	40,984	25,561	17,922

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.3 shows results both for the specification in Equation (2.2.4), without any controls or fixed effects, and for the full specification according to Equation (2.2.5). The coefficient for our measure of relevant export experience seems biased if we do not control for other factors affecting a firm's entry behavior. Columns (2) and (3) are the exact full specifications, but they differ in the definition of a wrong decision we use. Comparing them, the coefficient for export experience is robust to changes in this definition.

As can be seen, the coefficient for relevant export experience is significant and has the expected sign, indicating that higher relevant export experience results in a lower likelihood of a firm making a wrong decision regarding entry into an unprofitable export market. Moreover, the magnitude of the coefficient is also reasonable, as it implies that if relevant export experience increases by one standard deviation -5.4 points- then a firm is 6.4% less likely to make a wrong decision. In the last two specifications, standard errors are clustered at the firm, market, and time level to capture any correlation on unobservables among these groups. It should also be noted that the decrease in observations when including controls is because some destinations are not exported to in contiguous years, combined with many firms not exporting two years in a row. Additionally, the size of the estimated coefficients on the control variables results from having significant growth rates of demand again because of the high turnover rates in some export markets.

In summary, there is evidence of firms acquiring information about other potential destinations when exporting and using that information to make better decisions regarding their entry into export markets. This supports the hypothesis claimed in **Implication 1**.

2.2.3.2 Informativeness of Destinations and Entry

The objective of this section is to provide evidence that if destinations offer information about other potential destinations, then forward-looking firms might enter destinations to acquire information about other destinations. That is, testing whether the informativeness of a destination affects the probability of entry into it. To do this, Equation 2.2.6 defines our measure of the informativeness of an export destination. The index represents how informative destination d is for firm i at period t by considering the destinations to which firm i has not exported before and the similarity of those destinations to the destination in consideration. It is defined as:

$$I_{idt} = \sum_{j \notin V_{i,t-1} \cup \{d\}} S(d, j) \tag{2.2.6}$$

With the same notation as in Section 2.2.3.1 except that now we are summing over destinations that firm i has not exported before. The relationship we test is the following:

$$\mathbb{P}[\text{entry}_{idt}] = \beta_0 + \beta_1 I_{idt} + \epsilon_{idt} \tag{2.2.7}$$

We expect the sign of the coefficient for informativeness to be positive, representing that the more informative a destination is for a firm, the higher the probability the firm will enter that destination, given that it would allow it to learn about other potential markets. As with the analysis for the effect of relevant export experience, the specification in 2.2.7 could be misleading as other factors can potentially affect the probability of entry into a destination. One of these factors, as discussed in Section 2.2.3.1, is demand shocks driving entry into a destination, i.e., if a firm entered a given destination, it might be just because of a positive destination demand shock, which now made the destination profitable.

Considering this issue, we propose the specification in Equation (2.2.8). If the profitability of a destination is increasing -proxying profitability with positive demand shocks- it should be captured by variable $\%\Delta x_{dt}$. Furthermore, we add destination and time-fixed effects to account for any other unobserved source of variation in entry choices.

$$\mathbb{P}[\text{entry}_{idt}] = \beta_0 + \beta_1 I_{imt} + \eta_1 \%\Delta x_{dt} + \phi_{d,t} + \epsilon_{idt} \tag{2.2.8}$$

Table 2.4 shows these specifications' results for a random sample of firms. The first column represents the specification in Equation (2.2.7), and the second includes our control variable. Still, it does not account for fixed effects, and lastly, the third column is the full specification as stated in Equation (2.2.8).

Table 2.4: Informativeness Index.

	(1) $\mathbb{P}(entry)$	(2) $\mathbb{P}(entry)$	(3) $\mathbb{P}(entry)$
Informativeness	0.0000577***	0.0000782***	0.00338***
	(166.70)	(160.07)	(10.93)
$\%\Delta x_{dt}$		7.67e-10***	2.52e-09*
		(124.68)	(2.37)
Constant	-0.00152***	-0.00265***	-0.163***
	(-151.87)	(-145.95)	(-10.85)
Fixed Effects			✓
Observations	33,132,504	27,671,505	27,671,505

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Focusing on the results for the third specification, the estimated coefficient associated with our measure of informativeness is positive, which supports the hypothesis that if destinations contain information about other potential export markets, more informative destinations are more likely to be entered. Moreover, the magnitude of the estimated coefficient is reasonable; it implies that if the informativeness of a destination increases by one standard deviation -20.06 points- then a firm is 6.8% more likely to enter that destination. One important thing to note here is that looking at the standard errors for the first and second columns, there is evidence of the need to cluster our standard errors since there is a correlation between unobservables. We do this for the third column, the full specification, by clustering our standard errors at the firm and destination levels. As in Section 2.2.3.1, there is a loss in the number of observations because some destinations do not have observations in contiguous years, given our random sample and the high turnover rates in export markets.

In summary, there is evidence in favor of **Implication 2**, that is, if destinations are informative about other potential destinations and assuming firms are forward-looking, more informative destinations are more likely to be entered since firms value this information as it can lead them to make better choices in terms of their entry into export market choices.

2.3 A Model of Export Supply and Information Spillovers

The most prominent papers that develop models of information spillovers and firm entry into export markets are that of Nguyen (2012), Albornoz et al. (2012), and Morales et al. (2019). We follow the model developed in Cebreros (2016) but generalize it to multiple export destinations and allow for information spillovers across them. The model builds on the standard heterogeneous firms framework by Melitz (2003) but adds uncertainty regarding destination-specific demand shocks. Exporters can discretely choose which destination to export based on their prior beliefs, which they update according to Bayes' Rule.

2.3.1 Consumer Demand at Export Destinations

For the demand side, we assume that CES preferences describe utility in export destination j:

$$U_j = \left(\int_{\Omega} \epsilon_j(\omega) q_j(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}} \tag{2.3.1}$$

where $\sigma > 1$ is the elasticity of substitution across varieties, $q_j(\omega)$ is consumption of variety ω and $\epsilon_j(\omega)$ is a demand shifter. Given aggregate expenditure X_j, the demand function firm ω faces from country j is:

$$q_j(\omega) = \epsilon_j(\omega)^{\sigma} p_j(\omega)^{-\sigma} X_j P_j^{\sigma-1} \tag{2.3.2}$$

where P_j is the Dixit-Stiglitz price index:

$$P_j \equiv \left(\int_{\Omega} \epsilon_j(\omega)^{\sigma} p_j(\omega)^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \tag{2.3.3}$$

Using the fact that revenue is given by $r(\omega) \equiv p_j(\omega) q_j(\omega)$, we can use the expression for demand to rewrite an exporter's revenue in market j as:

$$r(q_j) = \epsilon_j(\omega) X_j^{\frac{1}{\sigma}} P_j^{\frac{\sigma-1}{\sigma}} q_j^{\frac{\sigma-1}{\sigma}} \tag{2.3.4}$$

We assume that all uncertainty in export market j depends on underlying export profitability θ_{jt} which is unknown to the firm. This allows us to rewrite the demand shifter a firm faces in export market j as $h(\theta_{jt})$, which captures both aggregate $X_j^{\frac{1}{\sigma}} P_j^{\frac{\sigma-1}{\sigma}}$ and idiosyncratic $\epsilon_j(\omega)$ determinants of demand. For simplicity, we assume a firm faces no uncertainty in the domestic market and normalize its demand shifter to unity. Given these assumptions, a firm faces the following revenue functions:

$$\text{Domestic Revenue: } r(q_j) = q_j^{\frac{\sigma-1}{\sigma}} \tag{2.3.5}$$

$$\text{Export Revenue: } r(q_j) = h(\theta_{jt}) q_j^{\frac{\sigma-1}{\sigma}} \tag{2.3.6}$$

2.3.2 Static Exporter Behavior

For now, we will describe a firm's profit maximization problem as static in nature. Conditional on vector θ_t, a firm's total revenue is the sum of revenue in every market:

$$r_t = q_{ht}^{\frac{\sigma-1}{\sigma}} + \sum_{j \in D} d_{jt} h(\theta_{jt}) q_{jt}^{\frac{\sigma-1}{\sigma}} \tag{2.3.7}$$

where:

$$d_{jt} = \begin{cases} 1 & \text{if the firm exports to destination } j \text{ in period } t, \\ 0 & \text{otherwise.} \end{cases}$$

with q_{ht} and q_{jt} being quantities sold at home and at export market j respectively. Conditional on export status $d_t \in \mathbb{R}^D$, profit-maximizing firms will equate marginal revenue at home and every export destination:

$$q_{jt} = d_{jt} h(\theta_{jt})^{\sigma} q_{ht} \quad \forall j \in D \tag{2.3.8}$$

and thus we can define a firm's total output as:

$$q_t = \Big(1 + \sum_{j \in D} d_{jt} h(\theta_{jt})^{\sigma}\Big) q_{ht} \tag{2.3.9}$$

Equations (2.3.8) and (2.3.9) allow us to rewrite a firm's total revenue as:

$$\begin{aligned} r_t &= q_{ht}^{\frac{\sigma-1}{\sigma}} + \sum_{j \in D} d_{jt} h(\theta_{jt}) [d_{jt} h(\theta_{jt})^{\sigma} q_{ht}]^{\frac{\sigma-1}{\sigma}} = q_{ht}^{\frac{\sigma-1}{\sigma}} + \sum_{j \in D} d_{jt} h(\theta_{jt})^{\sigma} q_{ht}^{\frac{\sigma-1}{\sigma}} \\ &= \Big(1 + \sum_{j \in D} d_{jt} h(\theta_{jt})^{\sigma}\Big) q_{ht}^{\frac{\sigma-1}{\sigma}} = \Big(1 + \sum_{j \in D} d_{jt} h(\theta_{jt})^{\sigma}\Big) \Big[\Big(1 + \sum_{j \in D} d_{jt} h(\theta_{jt})^{\sigma}\Big)^{-1} q_t\Big]^{\frac{\sigma-1}{\sigma}} \\ &= \Big(1 + \sum_{j \in D} d_{jt} h(\theta_{jt})^{\sigma}\Big)^{\frac{1}{\sigma}} q_t^{\frac{\sigma-1}{\sigma}} \end{aligned} \tag{2.3.10}$$

Let f_j denote the fixed costs of exporting to destination j, which we assume a firm must pay every period it is in the market. Conditional on θ_t and the firm's export status d_t, firms choose their total quantity to maximize profits:

$$\max_{q_t}\left\{\left(1+\sum_{j\in D}d_{jt}h(\theta_{jt})^{\sigma}\right)^{\frac{1}{\sigma}}q_t^{\frac{\sigma-1}{\sigma}}-\left(f+\sum_{j\in D}d_{jt}f_j\right)-\left(1+\sum_{j\in D}\tau_{jt}d_{jt}h(\theta_{jt})^{\sigma}\right)\left(1+\sum_{j\in D}d_{jt}h(\theta_{jt})^{\sigma}\right)^{-1}q_t\right\} \tag{2.3.11}$$

where the first term in parenthesis is total revenues, the second term is the fixed costs of serving the domestic and export markets, and the third represents the firm's variable costs. The only source of heterogeneity between firms is differences in export profitability. We normalize the marginal cost of serving the domestic market to unity; thus, the marginal cost of serving export market j equals τ_{jt}.

Solving the firm's maximization problem, the optimal scale of operation for a firm is given by:

$$q_t=\left(\frac{\sigma-1}{\sigma}\right)^{\sigma}\left(1+\sum_{j\in D}\tau_{jt}d_{jt}h(\theta_{jt})^{\sigma}\right)^{-\sigma}\left(1+\sum_{j\in D}d_{jt}h(\theta_{jt})^{\sigma}\right)^{1+\sigma} \tag{2.3.12}$$

From which we can obtain an expression for profits as a function of export status d_t conditional on export profitability:

$$\Pi(d_t|\theta_t)=\frac{1}{\sigma}\left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1}\left(1+\sum_{j\in D}\tau_j d_{jt}h(\theta_{jt})^{\sigma}\right)^{1-\sigma}\left(1+\sum_{j\in D}d_{jt}h(\theta_{jt})^{\sigma}\right)^{\sigma}-\left(f+\sum_{j\in D}d_{jt}f_j\right) \tag{2.3.13}$$

Given that the firm has uncertainty concerning its export profitability θ_t, the firm's expected profits are given by:

$$\tilde{\Pi}(d_t|\Gamma_t)=\frac{1}{\sigma}\left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1}\mathbb{E}_{\theta_t}\left[\left(1+\sum_{j\in D}\tau_j d_{jt}h(\theta_{jt})^{\sigma}\right)^{1-\sigma}\left(1+\sum_{j\in D}d_{jt}h(\theta_{jt})^{\sigma}\right)^{\sigma}|\Gamma_t\right]-\left(f+\sum_{j\in D}d_{jt}f_j\right) \tag{2.3.14}$$

where Γ_t represents the firm's information set at period t, a function of its export experience up until that point. Equation (2.3.14) is a crucial object as it represents a firm's expected profits as a function of its export status d_t given information set Γ_t. That is, in every period a firm is going to choose its export status $d_t=[d_{1t},...,d_{Dt}]$ such that the expression in Equation (2.3.14) is maximized given information set Γ_t, which is a function of its export experience. Defining:

$$A_t(d_t|\Gamma_t)\equiv\mathbb{E}_{\theta_t}\left[\left(1+\sum_{j\in D}\tau_j d_{jt}h(\theta_{jt})^{\sigma}\right)^{1-\sigma}\left(1+\sum_{j\in D}d_{jt}h(\theta_{jt})^{\sigma}\right)^{\sigma}|\Gamma_t\right]^{\frac{1}{\sigma}} \tag{2.3.15}$$

Results in the final expression for a firm's expected profits given d_t:

$$\tilde{\Pi}(d_t|\Gamma_t) = \frac{1}{\sigma}\Big(\frac{\sigma-1}{\sigma}\Big)^{\sigma-1} A_t(d_t)^{\sigma} - \Big(f + \sum_{j\in D} d_{jt} f_j\Big) \tag{2.3.16}$$

where $A_t(d_t)$ captures all possible uncertainty regarding a firm's export profitability in export markets. Notice that this expression represents a static optimization problem for the firm; that is, it does not consider the dynamic implications of its entry choices. Dynamics have to be taken into account because if information spillovers are present and firms are forward-looking, then a firm might choose to enter a destination not only because of its expected profits but also because of the information content the destination has.

2.3.3 Learning and Information Spillovers

This section shows how firms acquire information and update their beliefs according to Bayes' Rule. Assuming that firms know the exact functional form of $h(\cdot)$, once a firm chooses to export to destination j and observes realized demand in t, it receives a noisy signal of its export profitability in destination j:

$$s_{jt} = \theta_j + \epsilon_{jt} \quad \text{where } \epsilon_{jt} \overset{\text{i.i.d.}}{\sim} \mathbb{N}(0, \sigma_\epsilon^2) \tag{2.3.17}$$

where the vector of a firm's true export profitability $\theta \in \mathbb{R}^D$ follows by assumption a multivariate normal distribution $\mathbb{N}(\mu_\theta, \Sigma_\theta)$. Firms knows both μ_θ and Σ_θ, as well as the distribution of ϵ_{jt}.

True export profitability is constant through time but is subject to random shocks unobservable to firms. Every period a firm exports to destination $j \in D$, it receives signal s_{jt} and uses it to update its beliefs on the entire distribution of θ. Suppose there were no information spillovers among export destinations. In that case, the only belief that would be updated is precisely that for θ_j since exporting to j would give no information on the profitability of exporting to any other destination. The way we introduce information spillovers among export destinations is by assuming that true export profitabilities $\{\theta_j\}_{j\in D}$ are correlated with each other, that is, covariance Σ_θ is a symmetric and non-diagonal matrix. In particular, the covariance between θ_j and θ_k is a function of the similarity between destinations j and k.

Learning works in the model as follows: At $t = 0$ every firm gets a random draw of their

θ from distribution $\mathbb{N}(\mu_\theta, \Sigma_\theta)$. Firms know this distribution, and thus, it represents firms' prior beliefs about their export profitability. At $t = 1$ and based on these prior beliefs, firms choose export status d_1 to maximize Equation (2.3.15). For any $t > 1$, firms will choose which destinations to export in that particular period according to their updated beliefs on their export profitability, which are a function of their export history up to that point. The derivation of a firm's learning process for any export history $d^t = (d_1, ..., d_t)$ is as follows.

Bayes' Rule states that the distribution of θ conditional on observing signals s_t is proportional to the likelihood of observing those signals times the prior distribution of θ:

$$\pi(\theta|z_t) \propto L(s_t|\theta)\pi(\theta) \tag{2.3.18}$$

where s_t is the vector of signals observed during period t and $\pi(\theta)$ is the distribution of θ, which is common knowledge. Define $\Phi_t = \{j|d_{jt} = 1\}$ as the set of destinations a firm exported to in period t, then:

$$s_{jt} = \theta_j + \epsilon_{jt} \ \ \forall j \in \Phi_t \tag{2.3.19}$$

$$\Rightarrow s_{jt}|\theta_j \sim \mathbb{N}(\theta_j, \sigma_\epsilon^2) \tag{2.3.20}$$

Conditional on θ, realizations of s_t are i.i.d. due to the distribution of error term ϵ_{jt} and therefore we can express the likelihood of s_t conditional on θ as follows:

$$\begin{aligned} L(s_t|\theta) &= \prod_{j\in\Phi_t} \mathbb{N}(\theta_j, \sigma_\epsilon^2) \\ &\propto \exp\Big(-\frac{1}{2}\sum_{j\in\Phi_t}\Big(\frac{s_{jt}-\theta_j}{\sigma_\epsilon}\Big)^2\Big) \end{aligned} \tag{2.3.21}$$

Define $\Omega_t \equiv \text{diag}((1/\sigma_\epsilon^2)d_t)$ which is a diagonal and therefore symmetrical matrix such that $\Omega_{t_{jj}} = 0$ if $d_{jt} = 0$. We can then rewrite the likelihood above as:

$$L(s_t|\theta) \propto \exp\Big(-\frac{1}{2}(\theta_t - \theta)'\Omega_t(\theta_t - \theta)\Big) \tag{2.3.22}$$

Beliefs are updated after a firm has chosen its export status, which are the beliefs it carries into the next period. Using Equation (2.3.18), the posterior distribution of a firm's export profitability given any export history d^{t-1} can be expressed as:

$$\pi(\theta|d^{t-1}) = \pi(\theta)\prod_{i=1}^{t-1} L(s_i|\theta) \tag{2.3.23}$$

where $\pi(\theta)$ is common knowledge and thus acts as firms' prior beliefs at the beginning of the learning process. Conditional on θ, the s_i terms are i.i.d. which allows us to express the above as the product of likelihood functions and therefore:

$$\begin{aligned}
\pi(\theta|d^{t-1}) &\propto \pi(\theta)\prod_{i=1}^{t-1}\exp\Big(-\frac{1}{2}(s_i-\theta)^{'}\Omega_i(s_i-\theta)\Big)\\
&\propto \exp\Big(-\frac{1}{2}(\theta-\mu_\theta)^{'}\Sigma_\theta^{-1}(\theta-\mu_\theta)\Big)\times\prod_{i=1}^{t-1}\exp\Big(-\frac{1}{2}(s_i-\theta)^{'}\Omega_i(s_i-\theta)\Big)\\
&\propto \exp\Big(-\frac{1}{2}(\theta-\mu_\theta)^{'}\Sigma_\theta^{-1}(\theta-\mu_\theta)-\frac{1}{2}\sum_{i=1}^{t-1}(s_i-\theta)^{'}\Omega_i(s_i-\theta)\Big)
\end{aligned} \tag{2.3.24}$$

For the sake of convenience, we take the natural logarithm of the whole expression and multiply both quadratic terms, resulting in the following:

$$\begin{aligned}
\ln\pi(\theta|d^{t-1}) &\propto -\frac{1}{2}(\theta-\mu_\theta)^{'}\Sigma_\theta^{-1}(\theta-\mu_\theta)-\frac{1}{2}\sum_{i=1}^{t-1}(s_i-\theta)^{'}\Omega_i(s_i-\theta)\\
&= -\frac{1}{2}\Big[\theta^{'}\Sigma_\theta^{-1}\theta-\theta^{'}\Sigma_\theta^{-1}\mu_\theta-\mu_\theta^{'}\Sigma_\theta^{-1}\theta+\mu_\theta^{'}\Sigma_\theta^{-1}\mu_\theta\\
&+\sum_{i=1}^{t-1}s_i^{'}\Omega_i s_i-\sum_{i=1}^{t-1}s_i^{'}\Omega_i\theta-\sum_{i=1}^{t-1}\theta^{'}\Omega_i s_i+\sum_{i=1}^{t-1}\theta^{'}\Omega_i\theta\Big]\\
&= -\frac{1}{2}\theta^{'}\Big(\Sigma_\theta^{-1}+\sum_{i=1}^{t-1}s_i^{'}\Omega_i\Big)\theta+\frac{1}{2}\Big(\sum_{i=1}^{t-1}s_i^{'}\Omega_i\theta+\sum_{i=1}^{t-1}\theta^{'}\Omega_i s_i\Big)\\
&+\frac{1}{2}\Big(\theta^{'}\Sigma_\theta^{-1}\mu_\theta+\mu_\theta^{'}\Sigma_\theta^{-1}\theta\Big)-\frac{1}{2}\Big(\mu_\theta^{'}\Sigma_\theta^{-1}\mu_\theta+\sum_{i=1}^{t-1}s_i^{'}\Omega_i s_i\Big)
\end{aligned} \tag{2.3.25}$$

Since μ_θ, Σ_θ, Ω_i and s_i are either observed or known by the firm, we can ignore the last term in parenthesis. Moreover, because of the dimensions of these matrices, we have that $s_i^{'}\Omega_i\theta = \theta^{'}\Omega_i s_i$ and $\mu_\theta^{'}\Sigma_\theta^{-1}\theta = \theta^{'}\Sigma_\theta^{-1}\mu_\theta$ and therefore:

$$\begin{aligned}
\ln\pi(\theta|d^{t-1}) &\propto -\frac{1}{2}\theta'\Big(\Sigma_\theta^{-1}+\sum_{i=1}^{t-1}\theta_i'\Omega_i\Big)\theta+\sum_{i=1}^{t-1}\theta'\Omega_i s_i+\theta'\Sigma_\theta^{-1}\mu_\theta \\
&= -\frac{1}{2}\theta'\Big(\Sigma_\theta^{-1}+\sum_{i=1}^{t-1}s_i'\Omega_i\Big)\theta+\theta'\Big(\Sigma_\theta^{-1}\mu_\theta+\sum_{i=1}^{t-1}\Omega_i s_i\Big)
\end{aligned} \tag{2.3.26}$$

which yields the following proportional expression:

$$\begin{aligned}
\ln\pi(\theta|d^{t-1}) &\propto -\frac{1}{2}\Big(\theta-\mu_\theta^p\Big)'\Big(\Sigma_\theta^{-1}+\sum_{i=1}^{t-1}\Omega_i\Big)\Big(\theta-\mu_\theta^p\Big) \\
\text{with } \mu_\theta^p &= \Big(\Sigma_\theta^{-1}+\sum_{i=1}^{t-1}\Omega_i\Big)^{-1}\Big(\Sigma_\theta^{-1}\mu_\theta+\sum_{i=1}^{t-1}\Omega_i s_i\Big)
\end{aligned} \tag{2.3.27}$$

All of this results in the firm's posterior beliefs for its export profitability at the beginning of period t given export history d^{t-1} being:

$$\theta|d^{t-1}\sim\mathbb{N}\Big(\Big(\Sigma_\theta^{-1}+\sum_{i=1}^{t-1}\Omega_i\Big)^{-1}\Big(\Sigma_\theta^{-1}\mu_\theta+\sum_{i=1}^{t-1}\Omega_i s_i\Big),\Big(\Sigma_\theta^{-1}+\sum_{i=1}^{t-1}\Omega_i\Big)^{-1}\Big) \tag{2.3.28}$$

The posterior distribution in Equation (2.3.28) holds for any $t>0$. In particular, note from the mean and covariance matrix that in period $t=1$, when the firm has not had any export experience before, the beliefs a firm has on its export profitability collapse to:

$$\begin{aligned}
\theta|d^0 &\sim\mathbb{N}\Big(\Big(\Sigma_\theta^{-1}\Big)^{-1}\Big(\Sigma_\theta^{-1}\mu_\theta\Big),\Big(\Sigma_\theta^{-1}\Big)^{-1}\Big) \\
&=\mathbb{N}\Big(\mu_\theta,\Sigma_\theta\Big)
\end{aligned} \tag{2.3.29}$$

That is, as discussed earlier, a firm's beliefs when it has not had any export experience are precisely the distribution of θ, which by assumption is common knowledge to all firms. As a summary, a firm's beliefs at period t on its export profitability as a function of its export history d^{t-1} are as follows:

$$\Gamma_t(d^{t-1})=\begin{cases}(\mu_\theta,\Sigma_\theta) & \text{if } t=1\\ (\mu_\theta^p,\Sigma_\theta^p) & \text{if } t>1\end{cases} \tag{2.3.30}$$

where:

$$
\begin{aligned}
\Omega_i &= \mathrm{diag}((1/\sigma_\epsilon^2)d_i) \\
\mu_\theta^p &= \Big(\Sigma_\theta^{-1} + \sum_{i=1}^{t-1}\Omega_i\Big)^{-1}\Big(\Sigma_\theta^{-1}\mu_\theta + \sum_{i=1}^{t-1}\Omega_i s_i\Big) \\
\Sigma_\theta^p &= \Big(\Sigma_\theta^{-1} + \sum_{i=1}^{t-1}\Omega_i\Big)^{-1}
\end{aligned}
\tag{2.3.31}
$$

Note that we use Γ_t to refer to the firm's learning process as in Equation (2.3.15) because we assume that the information set that a firm has in period t is precisely its updated beliefs on the distribution of its true export profitability given its export history up until that period. This is where the learning process ties to the firm's discrete choice problem. At period t, a firm will choose export status d_t such that the expression in Equation (2.3.16) is maximized. To compute the expected value in Equation (2.3.15), the firm is simply going to use its posterior beliefs which evolve according to Equation 2.3.31 as a function of its export history d^{t-1}.

2.3.4 Dynamic Exporter Behavior

We have discussed the firm's problem as static, but this is not the case. As the learning process shows, export decisions have dynamic implications. Once a firm decides to enter an export market, it will affect its beliefs about its profitability in every export market and, thus, affect future entry and exit decisions.

Data shows that some firms reenter an export market after exiting from it. Since a firm's precision concerning its true export profitability θ is non-decreasing in tenure, one way to rationalize this behavior is to assume the fixed costs a firm has to pay when exporting to a destination are subject to random shocks. As in Cebreros (2016), we assume that the fixed costs of exporting to market j at time t are constant but subject to some random shock:

$$
f_{jt} = f_j + \eta_{jt} \quad \text{where } \eta_{jt} \overset{\text{i.i.d.}}{\sim} \mathbb{N}(0, \sigma_\eta^2)
\tag{2.3.32}
$$

Using Equation (2.3.16), expected profits in t given export status d_t will now be given by:

$$
\tilde{\Pi}(d_t|\Gamma_t) - \sum_{j\in D} d_{jt}\eta_{jt}
\tag{2.3.33}
$$

where η_{jt} is observed $\forall j \in D$ by a firm before choosing export status d_t. Importantly, a firm's recursive problem regarding its entry and exit choices from export markets is characterized by the following Bellman equation:

$$\mathbb{V}_{\Psi}(\mu_{\theta}^{p}, \Sigma_{\theta}^{p}, \eta) = \max_{d \in \Xi}\{\tilde{\Pi}(d|\mu_{\theta}^{p}, \Sigma_{\theta}^{p}) - \sum_{j \in D} d_j \eta_j + \beta \mathbb{E}_{\mu_{\theta}^{p'}, \Sigma_{\theta}^{p'}, \eta'}[\mathbb{V}_{\Psi}(\mu_{\theta}^{p'}, \Sigma_{\theta}^{p'}, \eta')]\} \tag{2.3.34}$$

subject to the evolution of a firm's beliefs about its profitability in export markets according to Equation (2.3.31). In this recursive formulation, Ξ is the set of all possible combinations of export status d, β represents a discount factor, and Ψ represents the vector of parameters of the model.

As discussed in Section 2.2.3.2, firms are forward-looking and thus exporting to a particular destination is not only valuable because of the effect it has on expected profits $\tilde{\Pi}(d|\mu_{\theta}^{p}, \Sigma_{\theta}^{p})$ but also because of the information it provides about other potential destinations; this is contained in the continuation value of the Bellman equation. Since entry into j will update a firm's beliefs on its export profitability in every potential destination, it affects its choice to enter the export market j.

2.4 Quantification of the Model

Estimation of the model presented in Section 2.3 proves to be computationally challenging as the state variables a firm has when choosing to which countries to export in a given period are its beliefs for its profitability for all export markets, i.e., a vector of means and a covariance matrix, and a vector of shocks to fixed costs of exporting. Suppose a Mexican firm can export to D different countries, then the number of state variables a firm has equals $2D + D * (D + 1)/2$.

This is challenging for two reasons. First, our model being dynamic implies that we must perform value function iteration when estimating it. Even for a relatively small number of export destinations, e.g., ten countries, we would have to implement a value function iteration algorithm including 75 state variables, which, as of today, is unfeasible from a computational perspective. Second, our model is one of combinatorial discrete choice, which implies firms have to choose the best combination of export countries out of the set of all possible combinations, and the size of this set increases exponentially with the number of possible export destinations.

We address these challenges in the following way. First, we assume that Mexican firms can only export to 5 countries, that is, $D = 5$. These five destinations will be the top five export destinations from the Mexican customs data: the United States, Canada, Spain, Germany, and China. Second, we assume there are no iceberg-type trade costs, resulting in the choice of entering export markets being independent across them. Under this assumption, the expression for expected total profits in Equation (2.3.14) becomes:

$$\tilde{\Pi}(d_t|\Gamma_t) = \Big\{\frac{1}{\sigma}\Big(\frac{\sigma-1}{\sigma}\Big)^{\sigma-1} - f\Big\} + \sum_{j\in D} d_{jt}\Big\{\frac{1}{\sigma}\Big(\frac{\sigma-1}{\sigma}\Big)^{\sigma-1}\mathbb{E}_{s_t}\big(h(s_{jt})^{\sigma}|\Gamma_t\big) - f_j\Big\} \tag{2.4.1}$$

which shows that firms' entry problem is separable across export destinations. Lastly, we assume firms are myopic in the sense that they are not aware of these information spillovers, i.e., when choosing to enter a particular export destination, they are not aware of how this decision will affect their beliefs regarding other export destinations, nor how their experience exporting to similar destinations is informative on their profitability in the export market in consideration. This assumption results in firms only having three state variables when deciding to enter a particular export market: their beliefs on the mean and variance of export profitability and the current shock to fixed costs of exporting, which is observable to the firm. The downside of this assumption is that the quantification of our model will not capture firm behavior as described in Section 2.2.3.2 where firms are forward-looking and might choose to enter a particular destination because of the information it provides about other export markets.

2.4.1 Independent Export Destinations and Myopic Firms

We characterize firms' optimization problem and derive expressions for their beliefs when the choice of entry is independent for each export market and firms are myopic regarding information spillovers. For this section, we drop the subindex notation in favor of a recursive one to distinguish between variables' current and future values.

Following Equation (2.3.34), a firm's Bellman equation in a particular export market is:

$$\mathbb{V}_{\Psi}(\mu,\Sigma,\eta) = \max_{d\in\{0,1\}}\{\tilde{\Pi}(d|\mu,\Sigma) - d\eta + \beta\mathbb{E}_{\mu',\Sigma',\eta'}[\mathbb{V}_{\Psi}(\mu',\Sigma',\eta')]\} \tag{2.4.2}$$

where μ and μ' stand for current and future beliefs for the expected value of a firm's export profitability, Σ and Σ' represent current and future beliefs for the variance of export profitability, and η and η' are the current and future value of the shock to fixed costs of exporting.

Expected profits of exporting to a given destination are given by:

$$\tilde{\Pi}(d|\mu, \Sigma) = d\Big\{\frac{1}{\sigma}\Big(\frac{\sigma - 1}{\sigma}\Big)^{\sigma-1}\mathbb{E}_s\big(h(s)^{\sigma}|\mu, \Sigma\big) - f\Big\} \tag{2.4.3}$$

As detailed in Equation (2.3.17), a firm's profits in a given export destination depend on signal s, which is comprised of a firm's export profitability and some noise. Firms observe this signal by observing realized export profits if they choose to export in a given period.

In terms of how firms form their expectations for signal s, and thus on how profitable they expect to be when choosing to export to a particular destination, recall that the signal each firm receives is given by:

$$s = \theta + \epsilon \tag{2.4.4}$$

where we are assuming that $\theta \sim \mathbb{N}(\mu_\theta, \sigma_\theta^2)$ and $\epsilon_{jt} \sim \mathbb{N}(0, \sigma_\epsilon^2)$, and both these distributions are known to the firm. The expected value of signal s conditional on a firm's current beliefs for the mean μ and variance Σ of export profitability θ is:

$$\begin{aligned} \Rightarrow \mathbb{E}(s|\mu, \Sigma) &= \mathbb{E}(\theta + \epsilon|\mu, \Sigma) \\ &= \mathbb{E}(\theta|\mu, \Sigma) + \mathbb{E}(\epsilon|\mu, \Sigma) = \mu + 0 \end{aligned} \tag{2.4.5}$$

while the variance of the signal, again conditional on a firm's current beliefs, is given by:

$$\begin{aligned} \Rightarrow \mathbb{V}(s|\mu, \Sigma) &= \mathbb{V}(\theta + \epsilon|\mu, \Sigma) \\ &= \mathbb{V}(\theta|\mu, \Sigma) + \mathbb{V}(\epsilon|\mu, \Sigma) \\ &= \Sigma + \sigma_\epsilon^2 \end{aligned} \tag{2.4.6}$$

Using the assumption that θ and ϵ are independent. The observed signal is believed by firms to be distributed according to:

$$s|\mu, \Sigma \sim \mathbb{N}(\mu, \Sigma + \sigma_\epsilon^2) \tag{2.4.7}$$

For computing the expectation of the continuation value in Equation (2.4.2), it is useful to characterize the distribution of the next period's beliefs μ' and $\Sigma^{'}$ given a firm's current beliefs. When export destinations are independent, Equation (2.3.31) for current beliefs implies that:

$$\mu = \Big(\frac{1}{\sigma_\theta^2} + \frac{n}{\sigma_\epsilon^2}\Big)^{-1}\Big(\frac{\mu_\theta}{\sigma_\theta^2} + \frac{1}{\sigma_\epsilon^2}\sum_{i=1}^{t-1} d_i s_i\Big) \tag{2.4.8}$$

$$\Sigma = \Big(\frac{1}{\sigma_\theta^2} + \frac{n}{\sigma_\epsilon^2}\Big)^{-1} \tag{2.4.9}$$

We can see that the updated beliefs for the covariance matrix Σ are deterministic in the sense that it only depends on known parameter Σ_θ and the number of periods a firm has exported to a destination in the past n. For a given realization of s' in the next period, the updated mean will then be given by:

$$\mu' = \Big(\frac{1}{\sigma_\theta^2} + \frac{n+d}{\sigma_\epsilon^2}\Big)^{-1}\Big(\frac{\mu_\theta}{\sigma_\theta^2} + \frac{1}{\sigma_\epsilon^2}\sum_{i=1}^{t-1} d_i s_i + \frac{d}{\sigma_\epsilon^2}s'\Big) \tag{2.4.10}$$

Note that if a firm decides not to export today, $d = 0$, then beliefs are not updated, i.e., $\mu' = \mu$. Since s' is not observed until the next period, the expected value of tomorrow's beliefs for the mean, conditional on today's beliefs and today's export choice, is given by

$$\mathbb{E}(\mu'|\mu, n, d) = \Big(\frac{1}{\sigma_\theta^2} + \frac{n+d}{\sigma_\epsilon^2}\Big)^{-1}\Big(\frac{\mu_\theta}{\sigma_\theta^2} + \frac{1}{\sigma_\epsilon^2}\sum_{i=1}^{t-1} d_i s_i + \frac{d}{\sigma_\epsilon^2}\mathbb{E}(s'|\mu, n)\Big) \tag{2.4.11}$$

which using Equation (2.4.7) gives us:

$$\mathbb{E}(\mu'|\mu, n, d) = \Big(\frac{1}{\sigma_\theta^2} + \frac{n+d}{\sigma_\epsilon^2}\Big)^{-1}\Big(\frac{\mu_\theta}{\sigma_\theta^2} + \frac{1}{\sigma_\epsilon^2}\sum_{i=1}^{t-1} d_i s_i + \frac{d}{\sigma_\epsilon^2}\mu\Big) \tag{2.4.12}$$

The variance of the updated beliefs for the mean μ' is given by:

$$\begin{aligned}\mathbb{V}(\mu'|\mu, n, d) &= \Big(\frac{d}{\sigma_\epsilon^2}\Big)^2\Big(\frac{1}{\sigma_\theta^2} + \frac{n+d}{\sigma_\epsilon^2}\Big)^{-2}\mathbb{V}(s'|\mu, n) \\ &= \Big(\frac{d}{\sigma_\epsilon^2}\Big)^2\Big(\frac{1}{\sigma_\theta^2} + \frac{n+d}{\sigma_\epsilon^2}\Big)^{-2}\Big(\Big(\frac{1}{\sigma_\theta^2} + \frac{n}{\sigma_\epsilon^2}\Big)^{-1} + \sigma_\epsilon^2\Big) \qquad (2.4.13)\end{aligned}$$

Note that if a firm chooses not to export today, e.g. $d = 0$ then $\mathbb{V}(\mu'|\mu, n) = 0$ which is intuitive as there is no uncertainty regarding the future value of μ', as beliefs will not be updated and will stay at μ.

2.4.2 Parametrization of the Model

We use the following functional form for demand shifter $h(\cdot)$ in Equation (2.3.15):

$$h(s) = \kappa \exp(-\lambda \exp(-gs)) \quad \text{where} \quad \kappa, \lambda, g > 0 \tag{2.4.14}$$

in which κ controls the upper-bound of the $h(\cdot)$ function and λ and g control its growth rate. This parametrization has the advantage of being a continuous, differentiable, bounded, positive, and monotone function.

Table 2.5 details the value of specific parameters of our model. We take from the literature the elasticity of substitution σ and parameters of the $h(\cdot)$ function λ and g. We use the estimates in Cebreros (2016) for the parameters of this function as their paper also uses Mexican data for their estimation. We set discount factor β to be equal to 0.95 and assume a value of 2.5 for κ such that the model can replicate observed firm-level exports while still having exports being bounded from above. Lastly, we set the variance of the shocks to export profitability σ_ϵ^2 to 0.23 as this value helps us match the observed variance of export revenue.

Table 2.5: Parameters from the literature.

Parameter	**Value**	**Source**
β	0.95	-
σ	3.85	Antras et al. (2017)
λ	2.64	Cebreros (2016)
g	2.69	Cebreros (2016)
κ	2.50	Calibrated
σ_ϵ^2	0.23	Calibrated

We assume that the correlation coefficient between the export profitability of two countries is captured by our import-based similarity index $S(i,j) \in [0,1]$ described in Section 2.3.3, thus reflecting that the more similar two export destinations are, the higher the correlation coefficient between firms' export profitability in these countries. Given these correlation coefficients, and our estimates for the variances of export profitability, we can later recover the covariance of export profitability between a pair of countries and construct the entire covariance matrix Σ_θ for a firm's export profitability, which we will then use once we simulate our model and perform counterfactual scenarios.

Finally, to lower the computational burden of our estimation, we assume that the shock to fixed costs of exporting η as shown in Equation (2.4.2) can only take two different values, either $-\bar{\eta}$ or $\bar{\eta}$; these values having equal probabilities. As argued before, this shock to fixed costs of exporting is needed to rationalize why some firms might re-enter an export market after exiting from it.

2.4.3 Estimation of Export Profitability and Fixed Costs

This section describes how we structurally estimate firms' export profitability and the fixed costs of exporting to each export destination, as discussed in Section 2.4.1. We use the Nested Fixed-Point algorithm, first introduced by Rust (1987). The algorithm consists of two distinct loops: an outer loop that implements the estimation routine and an inner loop that solves the firms' problem for each particular guess for our estimates.

First, for the outer loop, we use the Simulated Method of Moments (SMM) to find the element of the parameter space that best matches a simulation of the model with a set of moments observed in our Mexican customs data. We choose to use SMM as is in our model we do not have closed-form solutions to firm behavior and thus need to resort to simulation. Let x represent data and ξ a point in the parameter space. Our implementation of SMM consists in finding the ξ that minimizes the following objective function:

$$\min_{\Psi} ||e(\tilde{x}, x|\Psi)||$$

The moment error function $e(\tilde{x}, x|\Psi)$ is expressed as the percent difference between the vectors of simulated and data moments:

$$e(\tilde{x}, x|\Psi) = \frac{\hat{m}(\tilde{x}|\Psi) - m(x)}{m(x)}$$

where $m(\cdot)$ represents a set of R distinct moments, and $\tilde{x}$ is simulated data from our model under parametrization Ψ. We use the L^2 distance norm, and therefore, our implementation of SMM consists in finding the point in the parameter space that minimizes the sum of squared errors:

$$\hat{\Psi} = \arg\max_{\Psi} e(\tilde{x}, x|\Psi)^T I_R e(\tilde{x}, x|\Psi)$$

with I_R being an $R \times R$ identity matrix. We define our objective function in percentage deviations so that all moments in $m(\cdot)$ are expressed in the same units, and no moment receives an unintended larger weight.

The vector of parameters we estimate using SMM for each of the export destinations included in our quantification is the following:

$$\Psi = [\mu_\theta, \sigma_\theta^2, f, \bar{\eta}]$$

that is, the means and variances of export profitability, the fixed costs of exporting, and the size of the shocks to fixed costs of exporting. The set of destination-specific moments we include to identify parameter vector $\hat{\Psi}$ are:

1. Average log exports at the firm level: We use this moment to identify mean of export profitability μ_θ as larger values of this parameter will result in larger draws for signals s and thus, larger export revenue.

2. Standard deviation of log exports at the firm level: This moment helps us identify the variance of export profitability σ_θ^2 since the higher this variance is, the greater the variability in signals s and thus, the larger the variance of export revenue becomes.

3. Share of firms exporting: We use this moment to identify the fixed cost of exporting f, as larger values will result in a larger share of firms being unable to cover it with their operating profits.

4. Average length of export spells: The moment helps identify the shock to fixed costs of exporting $\bar{\eta}$ as the larger it is, the more it can compensate adverse shocks to signal s.

Second, for the inner loop of the estimation algorithm, we use Value Function Iteration. For a particular point Ψ_j in the parameter space and starting from an arbitrary initial guess $\mathbb{V}^0_{\Psi_j}(\cdot)$, according to Equation (2.4.2) we can recursively iterate as follows:

$$\mathbb{V}^{t+1}_{\Psi_j} = \max_{d \in \{0,1\}} \{\tilde{\Pi}(d) - d\bar{\eta} + \beta \mathbb{E}[\mathbb{V}^t_{\Psi_j}]\} \tag{2.4.15}$$

where superscript t represents a particular iteration. Because of our choice of $h(\cdot)$ being a continuous and bounded function, expected profits $\tilde{\Pi}(d)$ also inherit these properties and thus, for a sufficiently large number of iterations, a fixed-point is found in which $\mathbb{V}^{t+1}_{\Psi_j} = \mathbb{V}^t_{\Psi_j}$.

At every iteration, we compute $\mathbb{V}^t_{\Psi_j}$ for every point of the state space, with a firm's state variables being its current beliefs for mean profitability μ, the number of periods it has exported in the past n, and the current shock to fixed costs of exporting $\bar{\eta}$. As Equations (2.4.7), (2.4.9), and (2.4.10) show, these variables are sufficient for computing $\tilde{\Pi}(d)$ and the expectation of the continuation value in Equation (2.4.15). The only control variable firms have is their choice of entry d into an export market.

We discretize the state space using grids with 50 different values for μ, 20 different values for n -which implicitly assumes firms can export up to twenty different time periods-, and two different values for the shock to fixed costs of exporting, $-\bar{\eta}$ and $\bar{\eta}$. Note that these grids are different for every point Ψ_j of the parameter space, i.e., for every guess of the outer loop. We compute $\tilde{\Pi}(d)$ using Monte-Carlo integration, and construct transition probability matrices using Equations (2.4.12) and (2.4.13) to compute the expectation of the continuation value in Equation (2.4.15).

Once the algorithm has converged to a fixed point of the value function, we proceed to simulate firm behavior. For a particular guess of Ψ_j, we take 10,000 random draws from $\mathbb{N}(\mu_\theta, \sigma_\theta^2)$, which are firms' profitabilities in the export market, and simulate for 20 periods how firms choose to enter or exit from it. In each period, firms choose whether to export, and if they do so, they observe signal s, which is again a random draw, and use it to update their beliefs as described in Section 2.4.1. We use the results of this simulation to compute moments $\hat{m}(\tilde{x}|\Psi)$, which we then compare to data moments $m(x)$. If these two sets of moments are sufficiently close, given some tolerance level, we have found $\hat{\Psi}$.

Our estimation results are shown in Table 2.6. According to the model, Canada, China, and Spain have the same export profitability for a Mexican exporter on average. It is not striking that the US is estimated to be significantly more profitable for Mexican firms, reflecting that it is a huge export market and its consumers are likely to have a stronger preference for Mexican varieties than the rest of the countries. Estimates for the variance of export profitability are larger for Canada and the US. Since these destinations have the largest share of firms exporting to them, the sets of exporters to these countries feature the largest heterogeneity, which results in higher estimates for the variance of export profitability for these destinations.

Table 2.6: SMM Estimated Parameters.

Parameter	**Canada**	**China**	**Germany**	**Spain**	**USA**
μ_θ	0.96	0.99	0.85	0.96	1.25
σ_θ^2	0.33	0.29	0.27	0.21	0.35
f	3.34	3.04	2.61	2.95	0.39
$\bar{\eta}$	0.95	0.42	0.61	0.72	0.90

For both the fixed cost of exporting and its shock, units are log USD. These estimates show that Mexican firms find exporting to the US much cheaper than the rest of the destinations. This, together with the higher mean of export profitability, is reflected in most Mexican firms exporting to the US at some point. In contrast, these firms have much lower entry rates to other destinations. Lastly, regarding the shock to the fixed cost of exporting, we estimate lower values for China and Germany, consistent with these countries having export spells last the least on average.

Table 2.7: Estimated Covariance Matrix of Export Profitability.

	Canada	**China**	**Germany**	**Spain**	**USA**
Canada	0.33	0.16	0.18	0.06	0.27
China	0.16	0.29	0.11	0.08	0.20
Germany	0.18	0.11	0.27	0.04	0.15
Spain	0.06	0.08	0.04	0.21	0.07
USA	0.27	0.20	0.15	0.07	0.35

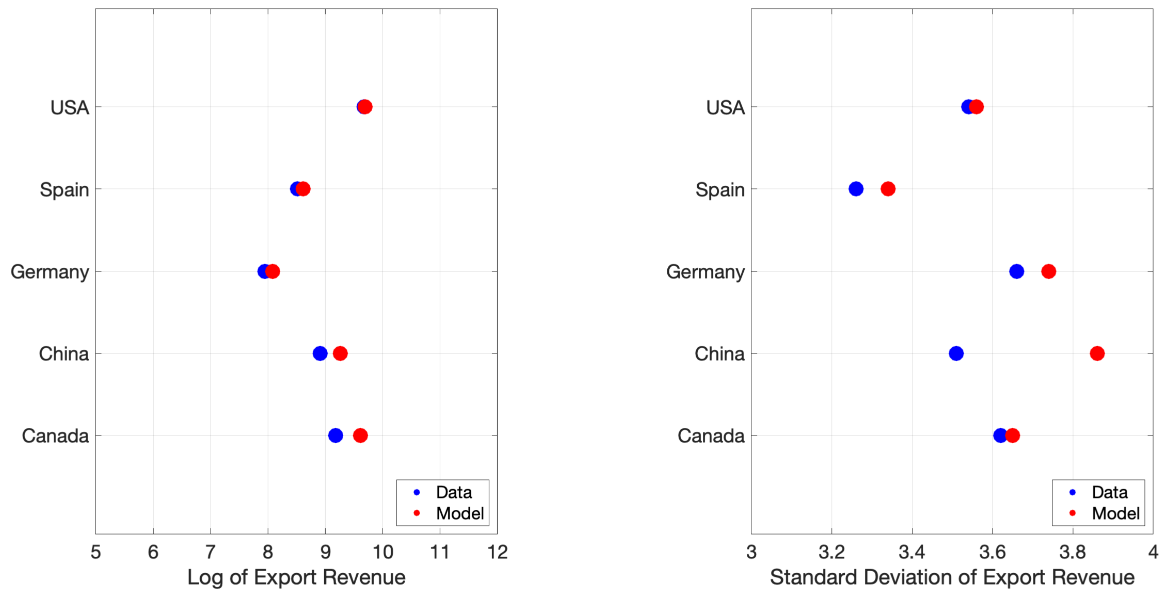
As detailed in Section 2.4.2, we proxy correlation coefficients in export profitability using our similarity index across export destinations, which, together with our estimates for the variances, allows us to construct covariance matrix of export profitability $\hat{\Sigma}_\theta$, shown in Table 2.7. Results show that the largest covariances, and thus the largest information spillovers, are between the US and Canada, Canada and Germany, and the US and China. Surprisingly, the covariance between Germany and Spain is very low, as both European countries are geographically close, although they possibly have very different preferences for Mexican varieties.

Figures 2.2 and 2.3 compare several moments between the data and our simulation to evaluate the model's performance. Overall, the model does a satisfactory job of matching these moments, except for China's standard deviation of log exports and the average length of export spells in the US. The former could be the result of overestimating China's variance in export profitability. In contrast, the former indicates we could be overestimating the size of the shock to fixed costs of exporting to the US.

2.4.4 Evolution of Entry Shares and Beliefs

To show how our model's simulation works, we present its results in Figures 2.4 and 2.5. Regarding the former, Panel 2.4a shows the share of firms exporting to each destination against tenure in that same market. This figure shows that from the moment a firm first exports in our data sample, it is unlikely to last several periods exporting to a particular destination. Panel 2.4b shows the simulation of our model, in which we can replicate the decreasing relationship between entry shares and tenure. In our model, initial entry into the export market is partly driven by a positive shock to the fixed costs of exporting. However, once firms learn about their export profitability, a large share of them choose to export no

Figure 2.2: Fit of the model regarding the mean and variance of log exports.



(a) Average log exports

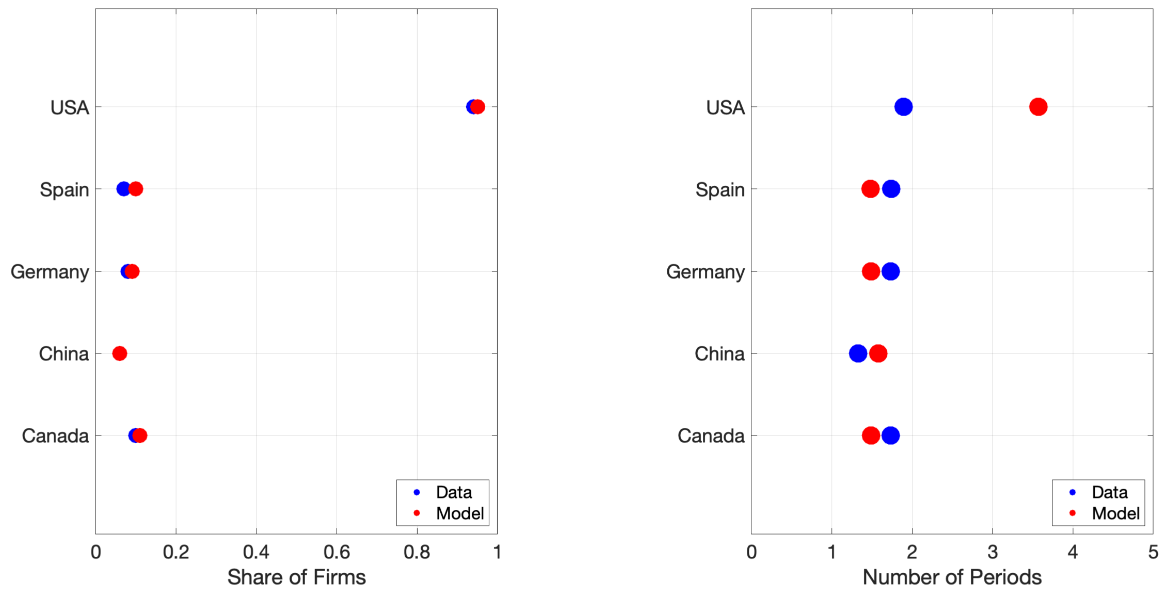
(b) Standard deviation of log exports

longer. For the case of the US, the model cannot replicate this decreasing relationship, as it predicts that only a few firms will stop exporting to the US over time.

Figure 2.5 shows how average export profitability and beliefs for it change over time. Panel 2.5a shows Canada, China, and Germany, and Panel 2.5b shows Spain and the US. Solid lines represent firms' beliefs about the expected value of their export profitability, and dashed lines represent their actual export profitability. While export profitability is constant across time, the composition of the firms that export does change. This explains why export profitability changes across time: when a larger share of firms chooses not to export, Panel 2.4b suggests that the firms that remain in the export market are the more profitable ones and thus, average export profitability increases with tenure in the export market.

Dashed lines are not necessarily consistent with the estimated means shown in Table 2.6 as the former represent mean export profitability conditional on exporting, while the latter correspond to unconditional means. Figure 2.5 shows us the relationship between export spells and the precision of the signals. As firms accumulate experience, their uncertainty regarding their profitability decreases, leading their beliefs to converge towards firms' true export profitability, i.e., the solid and dashed lines get closer as the number of time periods increases. While variation in the set of firms that export to a particular destination affects average export profitability and firms' beliefs, the latter also change because of the noise around export profitability. For example, even if a firm is profitable in a particular destination,

Figure 2.3: Fit of the model regarding entry shares and export spells.



(a) Share of firms exporting

(b) Length of export spells

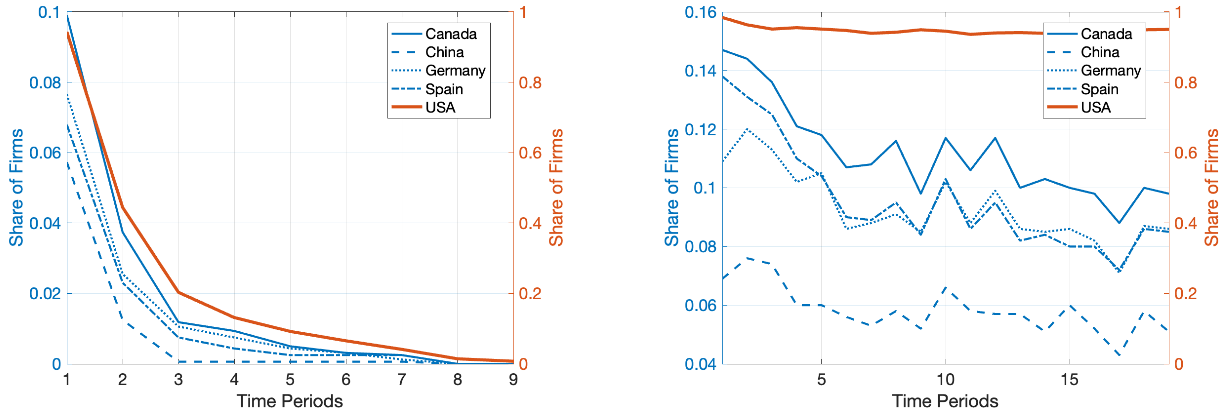
it could receive a negative demand shock that results in the firm believing it is not profitable to export and exit the market. This firm would only re-enter the export destination if it experiences a positive shock to fixed costs of exporting, which would result in the firm acquiring more information and perhaps discovering it is profitable to export.

2.5 Counterfactual Scenarios

In this section, we conduct two distinct sets of counterfactual simulations. First, we explore the role of information spillovers on export diversification. In our first counterfactual, we remove information spillovers, and using our estimates found in Section 2.4, we evaluate how key moments of our model change relative to the baseline simulation with information spillovers. The second set of counterfactuals uncovers the effects of reductions in fixed costs of exporting on the same key moments of the model, particularly on the average number of destinations a firm exports to. Reductions to fixed costs of exporting can result from policies such as governments facilitating domestic firms to engage in international trade or countries enacting free trade agreements which reduce the costs firms face of entering export markets.

The results of the second set of counterfactual scenarios provide evidence for a potential second-order effect of free trade agreements: the diversification of a country's exported destinations. We stress the word potential as information spillovers do not necessarily result

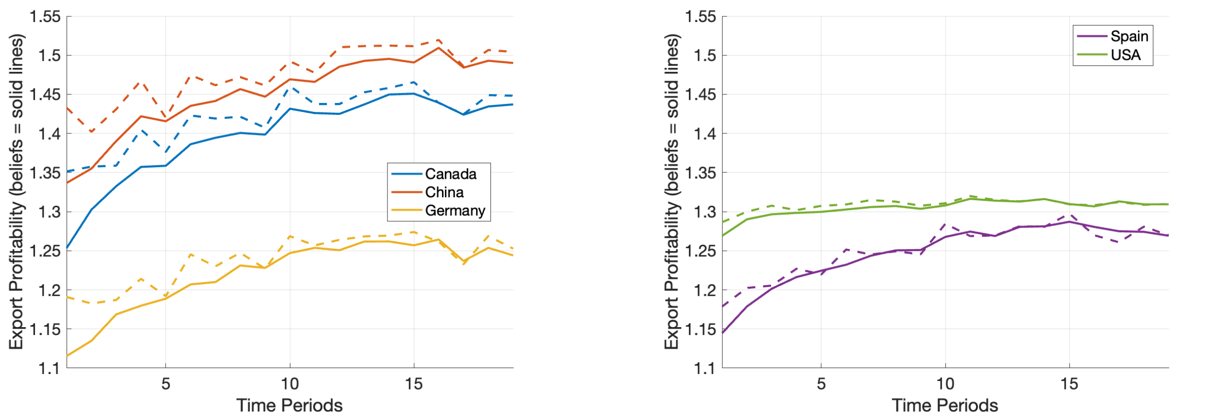
Figure 2.4: Data and simulation of the model for the share of firms exporting.



(a) Data for the share of firms exporting

(b) Simulation for the share of firms exporting

Figure 2.5: Simulation of the model for export profitability.



(a) Simulation for export profitability

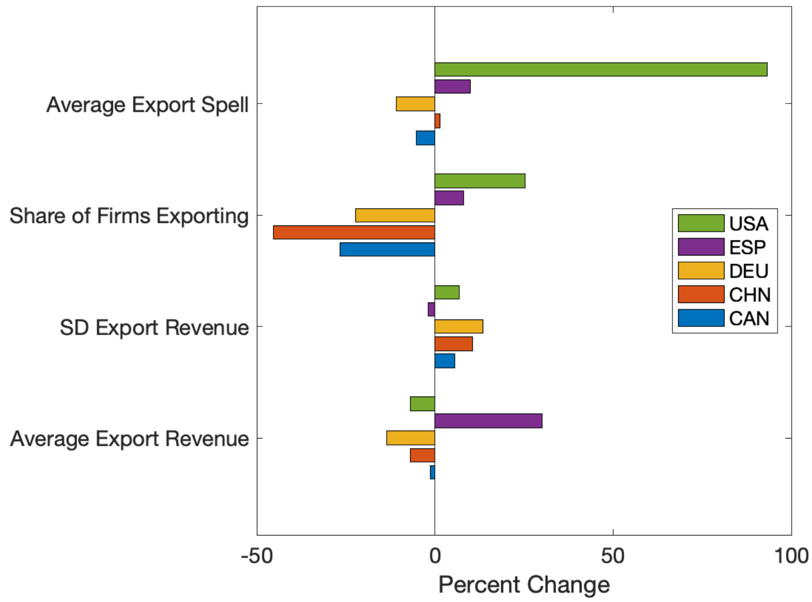
(b) Simulation for the share of firms exporting

in a larger share of firms exporting to a particular destination. As argued in Section 2.2, all that learning should do is provide firms with better information on demand conditions in foreign markets, leading them to make better decisions regarding entry and exit from export markets.

2.5.1 Removing Information Spillovers

We remove information spillovers by assuming that even if firms' export profitability is correlated across destinations, they are unaware of this. To do so, we assume the covariance matrix shown in Table 2.7 holds, but it is no longer common knowledge for firms when forming beliefs on their export profitability. This implies that a firm's prior beliefs on its export

Figure 2.6: Effects of removing information spillovers.



profitability, when the firm has not had any export experience, are distributed according to:

$$\theta | d^0 \sim \mathbb{N}(\hat{\mu}_\theta, \tilde{\Sigma}_\theta) \quad \text{where } \tilde{\Sigma}_\theta \equiv I_D \odot \hat{\Sigma}_\theta \tag{2.5.1}$$

Effectively, even if export profitability is still correlated across export destinations according to $\hat{\Sigma}_\theta$, the fact that firms believe profitability is distributed according to the diagonal covariance matrix $\tilde{\Sigma}_\theta$ results in them not learning about other markets when exporting to a particular one. For performing this counterfactual, we simulate a large number of firms as described in Section 2.4.3 but assuming all firms have prior beliefs as in Equation (2.5.1). Results for this counterfactual exercise are shown in Figure 2.6, which compares the key moments of the model between our baseline simulation against those for this alternative specification for the covariance matrix of prior beliefs.

First, without information spillovers, the share of firms exporting to Canada, China, and Germany, would decrease by 26.6%, 45.42%, and 22.3%, respectively. For Spain and the US, the share of firms exporting to these destinations would increase by 8.1% and 25.2%, respectively. These results suggest the significant role that exporting to the US and information spillovers have on the diversification of Mexican exports. It is in the US where Mexican exporters learn about their profitability in other foreign markets, leading some of them to export to these destinations.

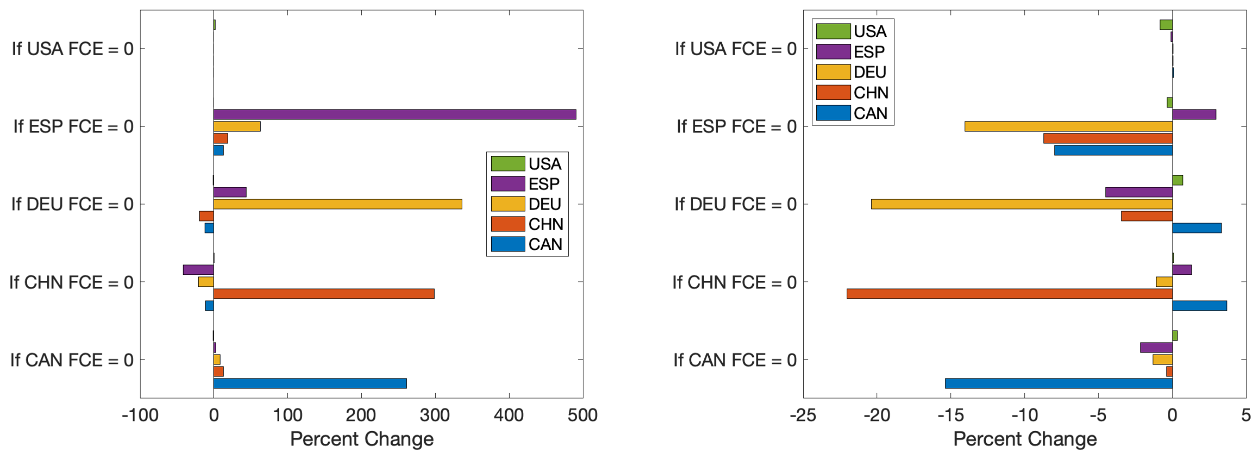
The intuition behind these results is as follows. Recall that our estimates for the fundamentals of export profitability, as shown in Table 2.6, constitute firms' prior beliefs when they have no export experience. Under these common prior beliefs, exporting to destinations such as Canada, China, and Germany, is not profitable, i.e., the average firm would not be profitable in these countries. Since removing information spillovers implies firms only learn about their profitability in a particular market when exporting to it, sustained exporting to a destination only happens when a profitable firm, one with a large enough random draw for its export profitability, experiences a positive shock to fixed costs of exporting. This results in a much slower learning process compared to the case with information spillovers when firms can learn in the US, a profitable destination for the average firm, about their profitability in non-US destinations.

Average firm-level export revenue, conditional on exporting, would decrease in all destinations except for Spain, resulting from the change in the composition of firms that keep exporting to these destinations. When there are no information spillovers and therefore, firms do not learn about their profitability while exporting to other markets, entry into destinations such as China or Germany is mainly driven by positive shocks to fixed costs of exporting, and these shocks are independent from firms' export profitability in a particular market.

Lastly, the average length of export spells would decrease for Canada and Germany. This is consistent with entry into these destinations now being mainly driven by shocks to fixed costs of exporting, which results in firms exporting for a shorter amount of time. In particular, the length of export spells in Canada and Germany would decrease by 5.3% and 10.8%, respectively. However, the length of export spells would increase for China, Spain, and the US by 1.4%, 9.9%, and 93.2%, respectively. The considerable increase in the length of average export spells in the US is explained by the decrease in the share of firms exporting to other destinations. When firms export to fewer foreign markets, learning about their profitability becomes slower regarding the time periods it takes for firms' beliefs to be sufficiently precise. In the case of the US, a large share of firms would enter the export market incentivized by the large mean export profitability and the low fixed costs of exporting, only to take some firms longer to realize they are not profitable in the US.

Overall, this counterfactual shows information spillovers' critical role in export markets, particularly in export diversification. Our results suggest entry into smaller, less profitable markets is mainly driven by the experience Mexican firms have while exporting to the US. On average, without information spillovers, the number of non-US destinations Mexican firms export would be 21.6% lower, corresponding to a decrease of 1.08 in the number of export destinations.

Figure 2.7: Effects of a reduction in the fixed costs of exporting.



(a) Share of firms exporting

(b) Firm-level exports

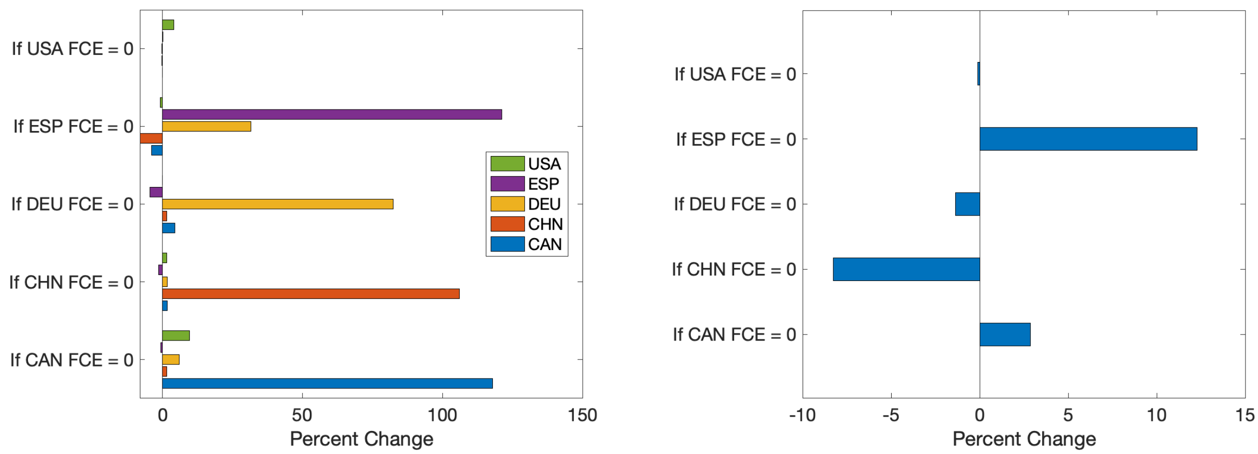
2.5.2 Reductions in the Fixed Costs of Exporting

This counterfactual quantifies the effects of decreased fixed costs of exporting (FCE) to a particular country. To do so, we set $f = 0$ for one destination at a time and then simulate how firms would make their entry and exit choices from our chosen export destinations. Intuitively, these results depend on which destination experienced the decrease in FCE and its similarity with the rest of the destinations. Entry into destinations is still partially driven by shocks to FCE $\bar{\eta}$ and we assume that the covariance matrix of export profitability is again the one shown in Table 2.7.

Figure 2.7 shows the results of these counterfactual simulations for average firm-level exports and the share of firms exporting. Each group of bars in these panels shows the effects over all export destinations resulting from lowering FCE to a particular foreign market, as indicated in the y-axis. Panel 2.7a shows how the share of firms exporting to each destination would change when lowering a particular FCE. Unsurprisingly, this share dramatically increases for the destination that experienced the decrease in FCE.

For the case of the decrease in FCE to Canada, the share of firms exporting to China, Germany, and Spain would increase by 12.7%, 8.7%, and 2.9%, respectively. Higher entry into a destination would not necessarily result in higher entry into other ones; it might even decrease entry, such as in the case of the decrease in China's FCE. These decreases in entry could be driven by firms discovering they are not profitable in China and assuming that, therefore, they would not be profitable in other export markets as well. The reduction in FCE to Germany would result in 43.6% higher entry into Spain, and the decrease for the case of Spain would result in 62.9% higher entry into Germany. Even if, according to our results,

Figure 2.8: Effects of a reduction in the fixed costs of exporting.



(a) Length of export spells

(b) Number of exported destinations

Germany and Spain are not very similar in terms of export profitability, the correlation among these European countries is sufficient for generating higher entry. Results also show that the reduction in FCE to the US would not yield higher entry into this destination since many Mexican exporters have already exported to the country. Intuitively, the share of firms exporting to other destinations remains the same since entry into the US is not affected, and thus, firms do not acquire additional information on their profitability in other export destinations.

Panel 2.7b shows the effects on firm-level exports. Overall, average exports decrease due to the larger shares of firms exporting when FCE decrease. This is again a composition effect. When the less profitable firms face lower fixed FCE, they enter the foreign market and lower the firm-level average. This effect is the strongest for the destination that experienced the decrease in FCE since this is the destination that experiences the largest increase in entry shares. Panel 2.8a shows the effects on the average length of export spells. Overall, the length of export spells increases in line with the increases in the share of firms exporting. This effect is present in the country experiencing the decrease in FCE and other destinations. Higher entry results in more precise beliefs about profitability because of information spillovers, leading firms to make better choices regarding entry and, thus, longer export spells.

Lastly, Panel 2.8b shows the effects on export diversification. For this figure, we compute the firm-level average number of exported destinations excluding the destination for which FCE decreased. The reason for this is that we want to quantify the effects on diversification coming exclusively from information spillovers, and if we do not exclude the country that experienced the decrease in FCE, the results will be driven mainly because of it. Results show that decreases in FCE to Canada and Spain lead to higher export diversification. In particular, lowering FCE to Canada would increase the number of destinations Mexican firms export on average by 0.14 countries, while decreasing FCE to Spain would increase the number of destinations on average by 0.61 countries.

In the case of lower FCE to China, diversification would decrease following the decrease in the share of firms exporting to destinations other than China, while in the case of lower FCE to Germany, diversification would also slightly decrease since the effect of lower entry into Canada and China dominates the increased entry into Spain. Again, lowering FCE to the US does not significantly affect diversification since the decrease does not generate changes in entry shares.

This counterfactual shows that lowering FCE to foreign markets can result in higher shares of exporting firms and greater diversification in destinations. The magnitude of these changes depends on how similar countries are to the one experiencing the lower FCE and the experience firms receive while exporting, e.g., a firm experiencing adverse demand shocks in a destination will result in lower entry shares into similar destinations. These results suggest that policies that facilitate domestic firms engaging in international trade or multilateral free trade agreements that lower the cost of exporting could indeed result in greater export diversification or, at the very least, lead domestic firms to make better choices regarding the destination of their exports.

2.6 Conclusions

This paper explores how information spillovers across foreign markets affect firms' entry and exit decisions. When demand conditions are correlated across destinations, firms learn about how profitable they are when exporting and form their beliefs based on these experiences. Using data on the universe of Mexican exporters, we provide empirical evidence on how the probability that a firm makes a wrong decision concerning entry into an unprofitable export market is lower the higher the amount of relevant export experience a firm has. Conversely, since export destinations allow firms to learn about other markets, the higher the informativeness of a destination, the more likely a firm will start exporting to it.

We build and quantify a dynamic model of export supply and information spillovers. In our model, Mexican firms choose in each period to which countries to export, and accumulate experience which affects their beliefs on their profitability in other markets, therefore affecting future entry decisions. We quantify firm-level export profitability in five export markets and the fixed costs Mexican firms face when exporting to them. Having estimated our model, we conduct counterfactual simulations to quantify the effects of information spillovers across export destinations. Without information spillovers, the share of firms exporting to destinations other than the US would decrease by 96.6%. This suggests that exporting to the US is critical for Mexican firms because it allows them to learn about their profitability in export markets. In a different set of counterfactuals, we show how decreased fixed costs of exporting to a particular destination can result in increased export diversification and increased exports and longer export spells in destinations other than the one experiencing the shock.

The results of this paper highlight the importance of learning in foreign markets on firm behavior and export diversification, and how trade policies aimed at increasing firms' participation in international trade can improve outcomes such as their exports or how long they sell to foreign markets. Policies such as free trade agreements that decrease barriers to entry or governments incentivizing firms to export to foreign markets should give firms better information on their profitability, ultimately leading them to make better decisions regarding entry into export markets.

CHAPTER III

Natural Disasters and Scarring Effects

joint with Weicheng Lian and Raadhika Vishvesh

3.0 Abstract

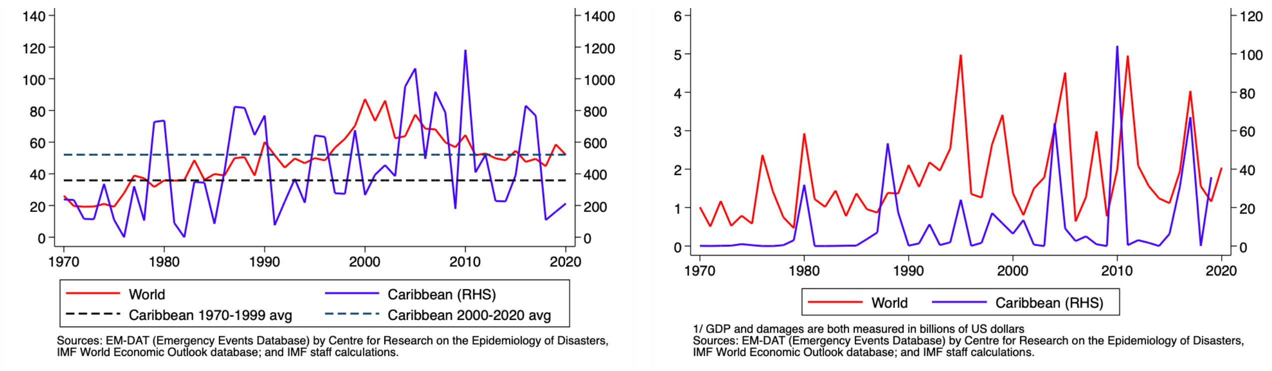
This paper uses a novel empirical approach, following the literature on hysteresis, to explore medium-term scarring of natural disasters for countries vulnerable to climate change. By quantifying the dynamic effects of natural disasters on real GDP per capita for a large number of episodes using a synthetic control approach (SCA) and focusing on severe shocks, we demonstrate that a persistently large deviation of real GDP per capita from the counterfacutal trend exists five years after a severe shock in many countries. The findings highlight the importance and urgency of building ex-ante resilience to avoid scarring effects for countries prone to natural disasters, such as those in the Caribbean region.

3.1 Introduction

Natural hazards present significant macroeconomic challenges for small countries, especially for vulnerable developing island states, where natural disasters occur frequently and inflict large damage to their economy.[1] To illustrate this, we present in Figures 3.1 some stylized facts about the Caribbean region. The disaster frequency in the Caribbean, measured as the number of natural disasters every year per billion people, is around 10 times the world average. The economic damage each year in the Caribbean, relative to the GDP size, can be around 20 times higher than the world average in recent decades. The disaster frequency and total disaster cost have had upward trends, which can be intensified by climate change going forward.

[1] Severe natural hazards may or may not cause severe natural disasters, depending on the resilience of the economy system. Strobl (2011) uses a wind-filed model to measure the destructiveness of hurricanes.

Figure 3.1: Frequency of Natural Disasters and the Economic Damage in the Caribbean Region.



(a) Frequency of Natural Disasters (disasters per billion population)

(b) Damage Caused By Natural Disasters (in percent of GDP[1/])

The large total damage of natural disasters in Caribbean countries reflects their high exposure to severe natural disasters, as we document in this paper. Potentially, severe disasters can cause a persistent disruption to aggregate production for these economies, an issue that is, however, not clearly understood in the current literature on the economic impact of natural disaster shocks. Existing studies tend to focus on short-run output effects, an average natural disaster event rather than severe ones, or severe disasters in countries that seem to have a strong capacity to recover from the shock.[2]

This paper has two goals. First, we use a technique to quantify the dynamic impact of severe natural disaster shocks on real GDP per capita that, to the best of our knowledge, has not been applied to small island developing economies.[3] We use the Synthetic Control Approach (SCA), which was developed by Abadie and Gardeazabal (2003) and Abadie et al.

[2] An incomplete list of recent studies includes Noy (2009), Cavallo et al. (2013), Acevedo-Espinoza (2014), Felbermayr and Gröschl (2013), Barone and Mocetti (2014), Tran and Wilson (2021), and Cavallo et al. (2021).

[3] Analytical tools have evolved in quantifying the growth impact of natural disasters. An early attempt was made by Albala-Bertrand et al. (1993), who compares macro indicators before and after natural disaster shocks (Crowards (2000), Charvériat (2000), and Rasmussen (2004)). The panel VARX method is later utilized by several studies to analyze the dynamic impact (Raddatz (2009), Fomby et al. (2013), and Acevedo-Espinoza (2014)). These studies tend to find negative impact for a severe shock in developing countries as opposed to in developed countries but no consistent patterns regarding the role of the disaster type. Fomby et al. (2013) find that "droughts have a negative effect on both agricultural and non-agricultural growth. In contrast, floods tend to have a positive effect on economic growth in both major sectors. Earthquakes have a negative effect on agricultural growth but a positive one on non-agricultural growth. Storms tend to have a negative effect on gross domestic product growth but the effect is short-lived and small." By contrast, Acevedo-Espinoza (2014) notes that both storms and floods have a negative effect on growth. More recently, several studies make use of the synthetic control approach. Cavallo et al. (2013) analyze severe disasters in a global sample and find no significant impact of natural disasters on economic growth in either the long or short term, except in events succeeded by political instability. Barone and Mocetti (2014) study two earthquakes in Italy and find no significant short-term growth impact but better long-run growth when institutional quality is stronger.

(2010), and combine this technique with a local projection method (LPM) (Jordà (2005)) to do the estimation. Second, we not only estimate the effects, but also try to reveal the underlying channels for persistent effects of natural disaster shocks on real GDP per capita to emerge. We document several patterns to differentiate across competing explanations.

We design our analysis as a two-step approach. In the first step, we apply the SCA to 370 natural disaster episodes that happened in our sample (which mainly consists of small island developing economies) after 1980.[4] For each of these episodes, the SCA allows us to use countries at a similar stage of economic development and with a similar exposure to global shocks to construct a synthetic control unit for the country affected by the disaster in that episode. The high exposure to global shocks of our sample makes such an application of the SCA resemble those that study regions having similar exposure to aggregate shocks at the country level. Despite this similarity, unlike existing regional studies that use the SCA, we find it difficult to get a very good match between the synthetic control and the treated country in terms of the trajectory of real GDP per capita before the natural disaster shock for many episodes, an issue we refer to as that of an imperfect synthetic control later.

In the second step, we mitigate this issue of an imperfect synthetic control using various econometric techniques, especially by utilizing an LPM. We utilize the LPM to obtain an impulse response of real GDP per capita to the natural disaster shock, following the literature on hysteresis in output, and for example, the analysis conducted by Cerra and Saxena (2008) on the persistent effects of financial crises and political conflicts on output. The results from the first step help the LPM exercise in two ways. First, we use the decline in real GDP per capita on impact, which is estimated using the SCA in the first step, rather than the immediate economic damage to measure the size of the natural disaster shock. Since the medium-term output effects come from a persistent disruption to production capacity, which should show up also in the initial period, we would argue that our shock measure is a better one than the immediate economic damage in terms of capturing the medium-term output effects. Our estimation results support this argument.

Second, the SCA results from the first step help us control for post-shock noises in the LPM exercise. Instead of using real GDP per capita in different periods after the shock as the dependent variables in the LPM regressions, we use the difference between real GDP per capita of the treated country and that of the synthetic control in corresponding periods as the dependent variables. This helps control for the effects of global shocks on real GDP per capita that happened after the natural disaster shock for which we try to understand its

[4]Our sample also consists of countries in the Caribbean region, and small developing countries in Latin America, given they are exposed to similar business cycles as small island developing economies in the Caribbean. Few severe natural disasters, however, happened in these economies.

dynamic effects.

We have several findings. First, there is a suggestive pattern to supports the use of the decline in real GDP per capita on impact as the shock size in the LPM exercise: it is significantly and positively correlated with the damage of natural disasters reported by the EM-DAT. For example, the real GDP per capita declines by around 2 percent on impact, for an immediate economic damage of 30 percent of GDP. The relationship seems plausible in economic terms, noting that the decline in real GDP per capita on impact may underestimate the full-year impact as many severe natural disasters in our sample happened in the second half of the year.

Second, we find that severe natural disasters lead to a persistent deviation of real GDP per capita from the counter-factual trend, with little sign of converging back towards the trend even five years after the shock. When a natural disaster shock causes an immediate economic damage of 30 percent of GDP, after the initial decline of real GDP per capita by 2 percent, its deviation from the (counter-factual) trend is estimated to widen in the five-year horizon after the shock, reaching around 8 percent of GDP in the fifth year. One caveat is that we use the intercept of the LPM estimation results and the coefficient of the initial decline in real GDP per capita on impact to reach this finding, but the results are qualitatively the same if we use the coefficient of the initial decline in real GDP per capita only.

We obtain three sets of patterns to help differentiate the underlying channels. First, we find that unlike severe natural disasters, small shocks (i.e. those with small immediate economic damage) do not have persistent effects on real GDP per capita. This pattern suggests that real GDP per capita in our sample does not follow a stochastic trend (otherwise, shocks always cause a persistent deviation of real GDP per capita from the counter-factual trend). Second, we find that if a country's public debt as a share of GDP is high, the medium-term effects of severe natural disaster shocks on real GDP per capita are amplified.[5] Third, we find that natural disasters of large immediate economic damage tend to drive the value-added of agriculture and tourism sectors to be persistently below the pre-shock trend, which is not the case for other sectors

These findings have strong policy implications, with three aspects. First, they point to a larger benefit from building resilience ex ante to natural disasters compared with a "counter-factual" world in which even severe natural disasters do not cause persistent

[5]We obtain this result by defining a dummy based on whether the public debt exceeds a certain threshold (70 percent of GDP), and from a triple interaction term, defined based on this dummy, a dummy indicating whether the immediate economic damage of the natural disaster is large, and the initial decline in real GDP per capita on impact. The results are not sensitive to this choice of public debt threshold, which is not surprising as they are driven by the comparison between an average episode below the threshold and that above the threshold.

output loss. Second, by making severe disasters more frequent and intense, climate change would imply stronger benefits of avoiding scarring effects of natural disasters. Third, other ramifications of scarring effects further add to the benefit of building resilience ex ante. One possibility is that persistent output loss causes a lower tax base, which by exacerbating the indebtedness of the country, can potentially create vicious cycles. Avoiding such vicious cycles is also an important benefit of building resilience ex ante.

Our findings contribute to the literature on hysteresis in output, as is recently summarized by Cerra et al. (2023).[6] Existing studies in this literature have not systematically look at the scarring effects of natural disaster shocks, an issue that urgently needs to understand given the challenges presented by climate change. As elaborated later, our findings in this paper reveal interesting issues for future research.

The rest of the paper is organized as follows. Section 3.2 presents empirical methodology. Section 3.3 describes the data and sample. Section 3.4 reports the findings regarding the dynamic effects of natural disasters on real GDP per capita. Section 3.5 explores the underlying channels of medium-term output effects. Section 3.6 concludes.

3.2 Empirical Methodology

Quantifying the dynamic effects of natural disaster shocks on real GDP per capita for small island developing countries is challenging. Cavallo et al. (2013) discuss the advantage of the SCA relative to conventional econometric techniques for obtaining such effects. For small island developing economies, one may further argue that they are highly exposed to global shocks and are experiencing economic convergence, the SCA tries to use countries at a similar stage of economic development and having a similar exposure to global shocks to form a control unit for the country affected by the natural disaster shock. These features further favor the SCA over conventional econometric tools.

3.2.1 The Synthetic Control Approach

Consider a sample that consists of $J+1$ units. Without loss of generality, the unit $J=1$ is the treated unit, i.e., affected by a shock at time T_0, and the rest of the sample is referred to as the donor pool.

The SCA tries to estimate the impact of the shock on outcome variable Y for this unit at time t:

[6] For example, two empirical studies in this literature are Cerra and Saxena (2008) and Cerra and Saxena (2017)

$$\tau_{1t} = Y_{1t}^I - Y_{1t}^N \tag{3.2.1}$$

where Y_{1t}^I is the outcome observed at time t and Y_{1t}^N the outcome should the shock have not occurred. The challenge is Y_{1t}^N is not directly available in the data for $t \geq T_0$.

The SCA deals with this challenge by replacing Y_{1t}^N with a weighted average of the outcomes of other units. It estimates $\hat{\tau_{1t}}$ (instead of τ_{1t}):

$$\hat{\tau}_{1t} = Y_{1t}^I - \sum_{j=2}^{J+1} w_j Y_j t \tag{3.2.2}$$

where the weights $\mathbf{W} = (w_2, ..., w_{J+1})$ are non-negative and add up to one. They are estimated in two steps.

In the first step, given a set of non-negative constants $\mathbf{V} = \{\nu_1, ..., \nu_k\}$, the SCA minimizes the following objective by choosing $\{w_2(\mathbf{V}), ..., w_{J+1}(\mathbf{V})\}$:

$$\sum_{h=1}^{k} \left(v_h (X_h 1 - w_2(\mathbf{V}) X_h 2 - ... - w_{J+1}(\mathbf{V}) X_{hJ+1})^2 \right)^{1/2} \tag{3.2.3}$$

where $\{X_1, X_2, ..., X_k\}$ are referred to as the predictor variables, which are chosen to ensure that the synthetic control and the treated unit share similar characteristics that can affect the outcome Y.

In the second step, the SCA chooses $\mathbf{V} = \{\nu_1, ..., \nu_k\}$ that minimize the following objective:

$$\sum_{\tau \in \tau_0} \left(Y_{1t} - w_2(\mathbf{V}) - ... - w_{J+1}(\mathbf{V}) \right)^2 \tag{3.2.4}$$

for some set $\tau_0 \in \{1, 2, ..., T_1\}$ where $T_1 \leq T_0$. The confidence band of $\hat{\tau}_{1t}$ can be obtained through a permutation method and see Cavallo et al. (2013) for an example.

Our application of the SCA follows closely that of Cavallo et al. (2013), who quantify the dynamic effects of natural disasters also in a cross-country context, but with a focus on the natural disaster episodes of large countries. We follow them in choosing predictor variables, and in a similar spirit, in restricting episodes to be those whose outcome trajectory of the synthetic control matches that of the treated country well.

Predictor variables: We choose the same list of predictor variables: trade openness, capital stock, land, population, schooling, latitude, and a democracy index, as in Cavallo et al. (2013). Moreover, we add tourism sector's share in GDP as an additional one, as several other studies in the SCA literature have sector share as a predictor variable. Table 3.1 provides a summary for selected studies. Given a data quality issue, we do not have a good coverage of all the predictor variables for our countries.

Donor pools: We construct episode-specific donor pools. For each episode, the donor pool is chosen by restricting the sample countries to those at a similar development stage as the treated country. To deal with a data coverage issue, predictor variables are not available for all countries, which can affect the match between the synthetic control and the treated country (in terms of the trajectory of real GDP per capita), we construct the donor pool as the combination of potential donor pool countries that has the best match between the synthetic control and the treated country. An algorithm, presented in Appendix B.2, explains the details.

Dropping episodes with a poor match: We exclude episodes whose fifth-year effect $\hat{\tau}_{1,i,T_0^i+5}$ falls into the first or the fourth quartiles of the distribution of $\hat{\tau}_{1,i,T_0^i+5}$. Large medium-term effects are unlikely to be a consequence of natural disaster shocks but reflect a poor fit of the SCA or large post-event episode-specific shocks. By truncating the sample by half, we do not try to get the match to be "perfect" for all the episodes in our exercises.[7] By contrast, Cavallo et al. (2013) seem to use a more restrictive selection, to get a very good fit for each episode kept in their exercises.[8]

3.2.2 Quantifying the Dynamic Effects of Natural Disaster Shocks

The impact of a natural disaster shock on real GDP per capita is assumed to satisfy the following relationship:

$$\tau_{i,k} = \alpha_k + \beta_{k,1_{(\text{disaster i is severe})}} \tau_{i,0} + \epsilon_{i,k} \tag{3.2.5}$$

where $\tau_{i,k}$ is the impact of a natural disaster shock on real GDP per capita k^{th} period after the shock in the episode i. For small natural disasters, $\beta_{k,0}$ converges to zero when k increases. By contrast, for severe ones, $\beta_{k,1}$ can be persistently large even with k rising.

[7]Arguably, the measurement error for the estimated causal effects of natural disasters should make it harder for us to find medium-term output effects, and we may get a lower bound for the true coefficient of the decline in real GDP per capita on impact in our second step.

[8]They keep 4 out of 8 events for disasters above the 99th percentile of the damage, 18 out of 164 for the 90th percentile, and 22 out of 444 for the 75th percentile.

Table 3.1: The Design of SCA in Selected Studies.

	Intervention	Outcome variable	Predictor variables	Donor pool
Abadie and Gardeazabal (2003)	Terrorism in a Spanish state	Real GDP per capita, 1986 USD thousand	Investment ratio, population density, sectoral shares and human capital measures	Spanish states (positive weights to Madrid and Cataluña)
Cavallo et al. (2013)	Natural disasters	Real GDP per capita, normalized to ND	Trade openness, capital stock, land, population, schooling, latitude and democracy index	Countries in the EM-DAT database (196 countries)
Barone and Mocetti (2014)	Earthquakes in regions of Italy	Real GDP per capita, 1985 euro equivalent prices	Investment ratio, sectoral shares, population density, schooling, institutional quality measures	Regions in Italy
Abadie et al. (2015)	German reunification	Real GDP per capita, 2002 USD PPP	Inflation, industry share, investment rate, schooling and trade openness	Developed countries

We estimate the following equation:

$$\hat{\tau}_{1,i,T_0^i+k} = \beta_{0,k} + \beta_{1,k}\hat{\tau}_{1,i,T_0^i} \times (1 - D_i) + \beta_{2,k}\hat{\tau}_{1,i,T_0^i} \times D_i + \beta_{3,k} \times D_i + \gamma_k Z_i + \epsilon_i \qquad (3.2.6)$$

where $\hat{\tau}_{1,i,T_0^i+k}$ is the estimated impact of the natural disaster on real GDP per capita in country i for the k^{th} year after its occurrence (in period T_0^i), which is estimated using the SCA; D_i is a dummy indicating whether the damage-to-GDP ratio is larger than 10 percent. This threshold implies a significant fraction of the sample whose damage-to-GDP ratio is above the threshold (as is suggested by Figure 3.2). The results, however, are not sensitive to changing this threshold. Z_i is the damage-to-GDP ratio. Controlling for the damage in the equation helps identify medium-term scarring effects, given that reconstruction activities can boost GDP despite scarring effects and can be captured by the damage to GDP ratio.[9]

We focus on the impulse response of the medium-term output loss to the decline of GDP on impact to measure the scarring effects of natural disaster shocks. This captures better the disruption to production and its propagation over time. By contrast, previous studies

[9] We do not have many controls in Equation (3.5.1), given a relatively small regression sample, which is significantly smaller than the number of episodes we have due to two factors: (i) we drop those whose medium-term effects fall into the tails of the distribution; (ii) only around half of the episodes report pecuniary damage.

use the immediate economic damage as a measure for the size of the damage of natural disaster shocks to study their short-term output effects (Noy (2009)).[10] As the immediate economic damage can involve non-productive assets, it is a noisier measure of the disruption to aggregate production capacity.

3.3 Data and Sample

3.3.1 Sample Selection and Data Sources

We have three sets of countries in our sample: small island developing states, other countries in the Caribbean, and developing countries in Latin America. For small island developing countries, they all have relatively small GDP size and relatively high dependency on tourism, and for those in Latin America and the Caribbean, they are affected by similar regional business cycle shocks. Having a broad sample helps the construction of the donor pools.

We examine disasters that can be classified at least as being mild. We use a classification similar to Munich Re (2006) at least one of the following variables: total deaths, total injured, total affected, or total damage, is above the 50^{th} percentile of the empirical distribution of its own region/group of countries according to the *EM-DAT (Emergency Events)* database, a commonly used data source in the literature on natural disasters that is constructed by the Centre for Research on the Epidemiology of Disasters.[11] This gives us a total of 370 natural disasters since 1980, which includes all types of natural disasters (storm, flood, drought, earthquake, and volcanic eruption).

We use the IMF's *World Economic Outlook* dataset, the World Bank's *World Development Indicators* database, and the Penn World Tables (version 10.0) to construct real GDP per capita, the size of population, and land area for the sample countries. We also use data on countries' geographic latitudes from Google's Dataset Publishing Language Guide (DSPL). These indicators are used as the predictor variables in the synthetic control approach, as is explained in the next section.

3.3.2 Summary Statistics

Table 3.2 lists basic characteristics of countries in our sample, including real GDP, real GDP per capita, land area, population, pecuniary damage caused by natural disasters, and damage as share of GDP, versus those of an average country in the world. Our sample

[10] Noy (2009) adjusts the cost-of-damage using a scaling factor based on the month of year of the event. We do not do so since we study the impact on real GDP per capita after the year of the shock.

[11] Felbermayr and Gröschl (2013) explores severe disaster episodes not covered by the EM-DAT.

Table 3.2: Summary Statistics.

	Our Sample	All Countries
Real GDP (USD in billion)	46	2,252
Real GDP per capita (USD in thousand)	5.3	12
Land area (in millions of square kms)	0.3	2
Population (in millions of persons)	8.6	195
Pecuniary damage (USD in billion)	0.2	0.8
Damage ratio (in percent of GDP)	1.8	0.3

Sources: EM-DAT (*Emergency Events database*), IMF's *World Economic Outlook* database, World Bank's *World Development Indicators*, and authors' calculations.

countries have a much smaller economic size than the world average, as they are not only poorer but also have a smaller population size (residing in a smaller land area). Specifically, the real GDP is USD 46 billion for the average country in our sample and USD 2,252 billion for the world average. The real GDP per capita is USD 5,300 for the average country in our sample and USD 12,000 for the world average. For the population size, it is 8.6 million vs. 195 million, and for the land area, 0.3 million square kms vs 2 million square kms. The pecuniary damage caused by natural disasters also differs substantially between our sample and the world average. In level terms, the average damage is smaller for our sample (USD 0.2 billion for the average country vs. USD 0.8 billion for the world average) but as share of GDP, it is higher (1.8 percent vs. 0.3 percent).

The larger damage-to-GDP ratio in our sample relative to the global sample reflects two sharply different distributions. Figure 3.2 plots the distribution of damage-to-GDP ratio for disasters that occurred after 1970 and whose damage exceeded 0.1 percent of GDP and shows that the distributions are different between our sample and the global sample. For the global sample, two-thirds of these events have the ratio below 0.5 percent. For our sample, only around a quarter had their damage falling into this range. Meanwhile, our sample has a much thicker right tail of the distribution. An average country in the global sample rarely experienced a disaster whose damage exceeds 10 percent of GDP, and by contrast, a quarter does so in our sample of the distribution plotted in Figure 3.2. Therefore, our sample countries not only suffer from larger average damage but also have a large exposure to extremely severe disasters.

We further zoom into the most damaging natural disasters in history when measured based on damage as share of GDP. Figure 3.3 plots all the events in the EMDAT with the damage larger than 10 percent of GDP. We highlight two patterns: First, five of the top ten high-damage events and nine of the top twenty between 1970 and 2020 occurred in the Eastern Caribbean Currency Union (ECCU).[12] The most extreme of these occurred recently: Hurricane Maria hit Dominica in 2017, causing an immediate damage around 224 percent of GDP.[13]

3.4 Results

3.4.1 Synthetic Controls for Selected Episodes

Figure 3.4 shows the performance of the SCA for selected countries and provides suggestive evidence of medium-term scarring effects. ECCU countries are selected as they tend to be much less resilient and have limited resources to recover from a large damage.

We have a good fit of synthetic controls for episodes such as Antigua and Barbuda (1995) and St. Kitts and Nevis (1998), which are shown in the upper panel of Figure 3.4. The solid and dashed lines match very well before the events. The two lines diverge after the year of the disaster, taking around 5 to 10 years for the solid line to return to the counterfactual dashed line. This pattern is likely driven by scarring effects of the disaster shocks. For both events, there were extremely large damages as share of GDP: 60 percent for Antigua and Barbuda in 1995, and 49 percent for St. Kitts and Nevis in 1998.

Interestingly, there are also patterns of long-run scarring. In both episodes, the gap in real GDP per capita between the affected country and the synthetic control widened substantially in the long run. While such patterns may be driven by scarring effects on long-run growth, it may not necessarily be the case. Other shocks may be behind this strong divergence. We leave such issues for future research to investigate but focus on medium-term impact of disaster shocks, i.e., five years after the shocks.[14]

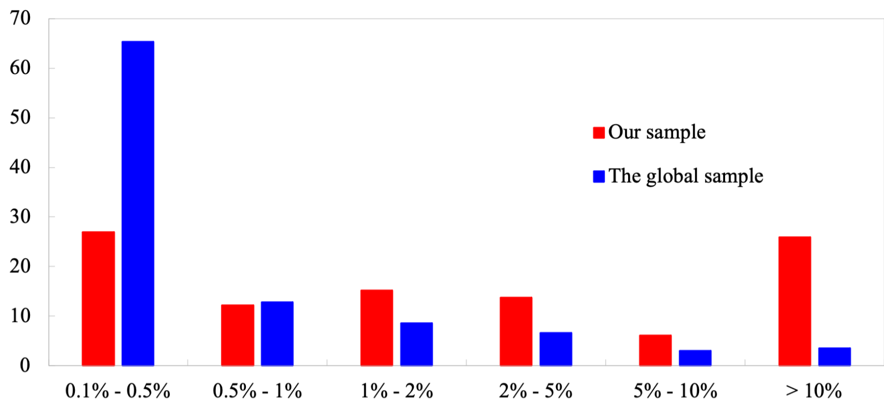
The lower panel of Figure 3.4 shows the episodes for Dominica in 1995 and 2007 respectively. The damage-to-GDP ratio was 64 percent in the 1995 episode but only 5 percent in the

[12]See Rasmussen (2004) assessment of disasters in the Caribbean, especially those in the ECCU.

[13]Figure 3.3 shows a smaller number as the denominator is GDP in PPP term.

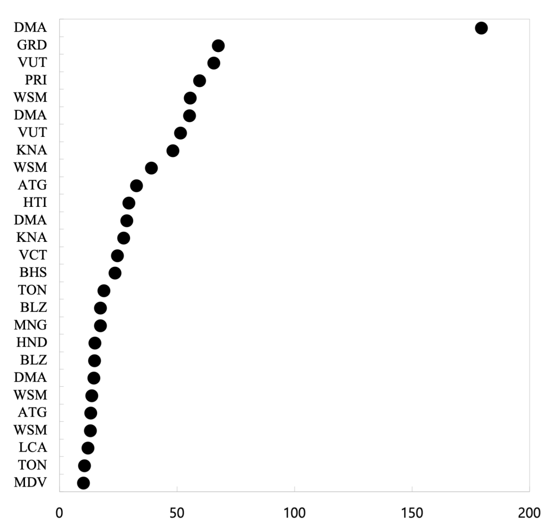
[14]The global financial crisis occurred during the post-disaster windows of these episodes. It is possible that Antigua and Barbuda and St. Kitts and Nevis were disproportionately affected by the GFC. The large divergence between Antigua and Barbuda and its synthetic control started after 2010. On the other hand, the disproportionately large exposure to the GFC could stem from the difficulty of recovering fully from its extremely large shocks that happened earlier. A closer look at the tourism and FDI data in Antigua and Barbuda suggests that tourism arrivals did not experience a sharp slowdown after the GFC, but the FDI crashed and was slow to recover.

Figure 3.2: Distribution of Damage over GDP: The Caribbean and SIDs v/s the World. (In percent; share in events with damage over GDP exceeding 0.1%)



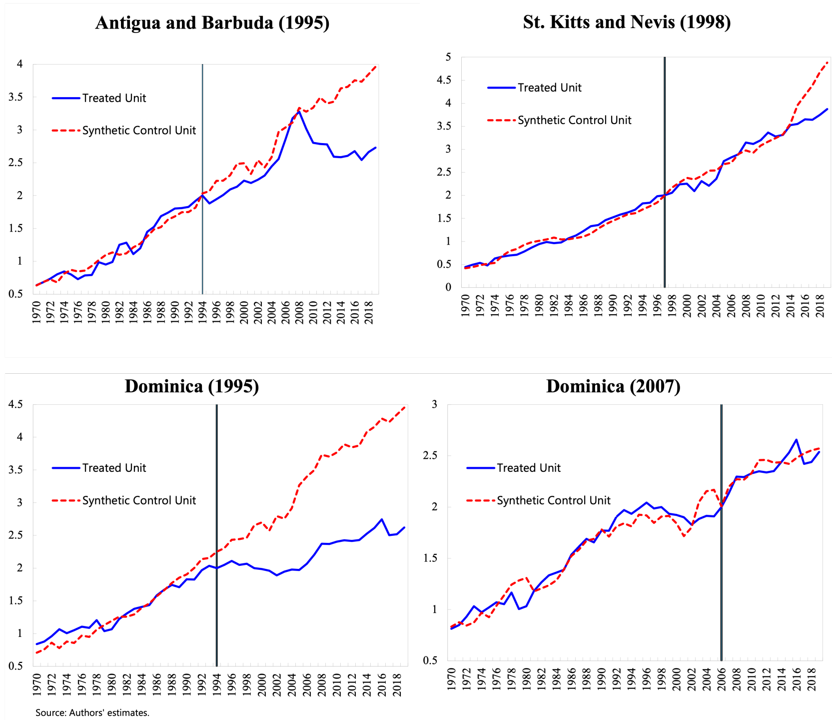
Note: SIDs are Small Island Developing countries.
Sources: EM-DAT, *World Economic Outlook* database, and authors' calculations.

Figure 3.3: Highly Damaging Natural Disasters. (Disasters with damage over 10 percent of GDP)



Note: Except for an episode in Mongolia and in Honduras, all highly damaging disasters occurred either in the Caribbean or small island developing countries.
Sources: EM-DAT, *World Economic Outlook* database, and authors' calculations.

Figure 3.4: Synthetic Control Estimation Results for Selected Episodes.



2007 episode. Consistent with the dramatic difference in the damage, the 1995 episode has a stronger divergence between the solid line and the dash one.

One may notice that the pre-event fit is not perfect for these episodes, but they should not drive our results, as we explain earlier in describing the DID strategy. We also conduct placebo tests to further mitigate the concern.

3.4.2 Quantifying Medium-Term Effects of Natural Disasters on Real GDP per Capita

Table 3.3 reports the results of estimating Equation (3.5.1). The impact on real GDP per capita is transitory for low-damage events, i.e, those whose cost of damage is below 10 percent of GDP. For example, if, on impact, the real GDP per capita declines by 1 percent more relative to the trend, its deviation from the trend will be larger by 0.841 percent one year after the shock, but then decline over time: 0.769 percent in the second year, 0.574 percent the third, 0.478 percent the fourth, and 0.203 percent the fifth. Such a pattern suggests little scarring effects of small disaster shocks.

By contrast, the impact on real GDP per capita is much more persistent for events whose cost of damage exceeds 10 percent of GDP. For a larger decline of 1 percent of real GDP per capita on impact, the effects in the first year to the fifth year after the shock are: 1.357

Table 3.3: Impulse Response of Real GDP per Capita to a Natural Disaster Shock.

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5
Change in GDPPC on impact × Low-Damage Dummy	0.841***	0.769***	0.574***	0.478***	0.203**
	(0.0620)	(0.0720)	(0.0906)	(0.103)	(0.0956)
Change in GDPPC on impact × High-Damage Dummy	1.357***	1.049***	0.943***	0.891***	0.911***
	(0.184)	(0.214)	(0.269)	(0.306)	(0.284)
High-Damage Dummy	0.0226	0.00929	0.00513	0.00537	0.0117
	(0.0155)	(0.0180)	(0.0226)	(0.0257)	(0.239)
Constant	-0.0145*	-0.0253***	-0.0400***	-0.0506***	-0.0577***
	(0.00726)	(0.00845)	(0.0106)	(0.0121)	(0.0112)
Observations	71	71	71	71	71
R-squared	0.786	0.677	0.442	0.311	0.181

Standard errors in parenthesis
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

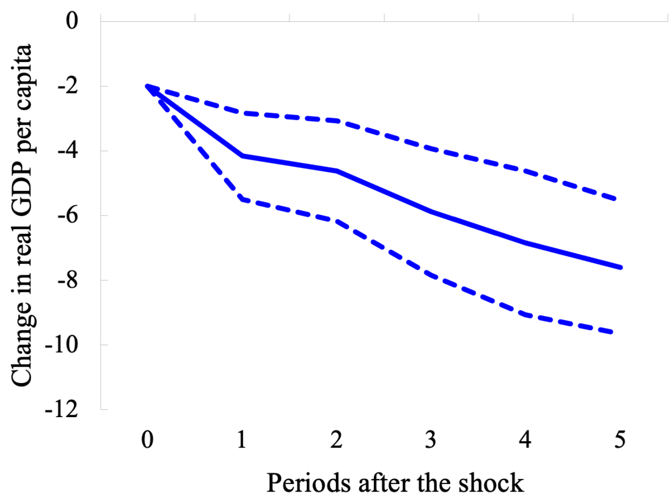
percent, 1.049 percent, 0.943 percent, 0.891 percent, and 0.911 percent. Moreover, one cannot reject the hypothesis that the effects are constant over time.

To illustrate the magnitude of medium-term output effects, we study a shock that inflicts an economic damage that is around 30 percent of GDP. This is a very severe shock in our sample and causes a 2 percent decline in real GDP per capita in the year of the disaster. We estimate the elasticity by regressing the decline in real GDP per capita on impact on the reported pecuniary damage, without applying the intercept. This decline in real GDP per capita in the year of the disaster, however, should not be interpreted as the full impact of the disaster, because natural disasters tend to occur in the second half of the year in our sample.[15]

We calculate the impulse response to this shock by combining the coefficients of the change

[15] One may further raise concern about why there is no jump in the impulse responses of the first and second years if the disaster only "partially" affects the output in the year of the disaster. One possibility is that reconstruction activities boost GDP in these years, which is supported not only by the empirical pattern we document in the appendix D that the construction GDP had a surge after disasters in ECCU countries but also by previous findings in the literature (Crowards (2000) and Charvériat (2000)). Crowards (2000) and Charvériat (2000) do before-after comparisons of macro indicators for natural disaster episodes. Crowards (2000) compares the growth rates of key macro variables like GDP, imports, exports, and tourist arrivals before and after 21 major storms in the Caribbean between 1976 and 1996. He finds a rise in GDP growth of approximately 3 percent in the year succeeding a disaster, and attributes this to a surge in construction and rehabilitation activity, and the inflow of external aid. This is then followed by a slowdown of about 2.5 percent in the second year, suggesting that the effects of the temporary boom are short-lived. Charvériat (2000) finds similar results when she analyzes 35 disaster cases between 1980 and 1996 in 20 Latin American and Caribbean countries to assess their effects on real GDP growth. Median growth decreases by 2 percent in the year of the disaster and increases sharply by 3 percent in the two years that follow.

Figure 3.5: The Impulse Response of Real GDP per Capita to a Shock with 2% Decline in Real GDP per Capita on Impact.



Source: Authors' estimates.

in real GDP per capita on impact and the intercepts.[16] We consider the intercept term, as the initial drop in real GDP per capita, $\tau_{i,0}$, may only capture the damage to assets critical for the aggregate production rather than all factors that can influence the speed of post-disaster recovery in real GDP per capita (such as international aid, the size of self-insurance funds accumulated by the government ex ante, and the migration of people out of the affected country affecting the composition of workers). These factors may not be perfectly correlated with the size of the damage to the critical productive assets.

Figure 3.5 shows that five years after the shock, real GDP per capita is still around 8 percent below the trend, with around 2.3 percent from the contribution of the decline in real GDP per capita on impact, and 5.7 percent from the intercept. It is beyond the scope of our current paper to explore what is behind the large intercept, an issue we leave for future research.

3.4.3 Placebo Tests

To alleviate any potential concern that our results are driven by poor pre-event fits of synthetic controls, we conduct the following placebo test. We regress the GDP gap in years -5 to -1 on the GDP gap in year -6, with year $-k$ referring to the k^{th} year before the disaster event. We employ the same specification as Equation (3.5.1), with the only difference being

[16] The impulse response in the kth year after the shock is calculated as the sum of the intercept and the coefficient of the change in the real GDP per capita on impact in the k^{th} column of Table 3.1 multiplied by 2 percent.

that no natural disasters occurred in these years. If results were driven by a poor fit of the SCA creating a gap between the treated unit and the synthetic control before the shock, we should observe similar results as what we see in Table 3.3.

Table 3.4, however, suggests that this is not the case, the only significant effect is on the GDP gap of year -5. It is also useful to recognize that the intercept is insignificantly different from zero in this exercise.[17]

Table 3.4: Placebo Test: Limited response in GDP per capita to a Year -6 shock.

	(1) Year -5	(2) Year -4	(3) Year -3	(4) Year -2	(5) Year -1
Change in GDPPC on impact × Low-Damage Dummy	0.691*** (0.197)	0.0309 (0.223)	-0.0153 (0.232)	-0.0711 (0.208)	0.308 (0.227)
Change in GDPPC on impact × High-Damage Dummy	-0.0266 (0.244)	-0.299 (0.276)	0.00288 (0.287)	-0.187 (0.258)	0.227 (0.280)
High-Damage Dummy	0.0496* (0.0260)	0.0611** (0.0295)	0.0388 (0.0306)	0.0426 (0.0275)	0.0223 (0.0299)
Constant	0.00563 (0.0139)	-0.00678 (0.0157)	-0.0128 (0.0163)	-0.0145 (0.0147)	-0.0241 (0.0160)
Observations	35	35	35	35	35
R-squared	0.366	0.123	0.069	0.074	0.131

Standard errors in parenthesis
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.5 Exploring Underlying Channels

3.5.1 Channels for Natural Disasters to Cause Scarring Effects in Small Island Developing Economies

There are multiple reasons why adverse shocks can have persistent negative effects on output (Cerra et al. (2023)). For developing countries, a simple mechanism is that real GDP per capita follows a stochastic trend, implying that it declines persistently after any adverse shock. However, this mechanism seems to be inconsistent with our finding that small natural disasters only have transitory effects.

[17]Here, we have a further restriction of the sample based on the SCA fit. If we use a coarser fit, the placebo test results are broadly the same. The results in Table 3.3 are also robust to having the same sample as those in Table 3.4.

Another channel mentioned in the literature is radical political evolution. Cavallo et al. (2013) analyze large countries and find that "only very large natural disasters, followed by radical political revolution, show long-lasting negative economic effects on economic growth. Even very large natural disasters, when not followed by disruptive political reforms that alter the economic and political system, including the system or property rights, do not display significant effects on economic growth." Given the frequency of severe disasters in our sample, this political revolution channel is, however, unlikely to be a major source of negative medium-term output effects.

A third possibility is lacking resources to recover from the damage inflicted by a severe disaster, which seems to be plausible to explain why such shocks caused no significant effects on economic growth for most episodes studied by Cavallo et al. (2013), but suppressed output per capita persistently whenever the damage is large in countries of our sample, as they tend to face more binding resource constraints for post-disaster reconstruction.

This channel is supported by the finding of Von Peter et al. (2012). They analyze a global sample and find that "major natural catastrophes have large and significant negative effects on economic activity, both on impact and over the longer run." and that "it is mainly the uninsured losses that drive the subsequent macroeconomic cost, whereas sufficiently insured events are inconsequential in terms of foregone output." Countries in our sample tend to have limited insurance protection. For example, Duarte and Munoz (2022) shows that Caribbean countries, which had the majority of severe natural disaster episodes in our sample, have limited protection from disaster insurance instruments.

There are two testable hypotheses if the cause of medium-term output effects is a lack of resources to repair damaged infrastructure.

Hypothesis I: *High indebtedness of a country can exacerbate the medium-term output loss of a severe natural disaster.*

Hypothesis II: *During a severe natural disaster episode, tourism and agriculture sectors have stronger medium-term output loss than other sectors.*

An implicit assumption behind Hypothesis II is that the physical assets of tourism and agriculture sectors are more exposed to a severe natural disaster than those of other sectors. This assumption is consistent with the anecdote for our sample countries that these sectors tend to suffer more during hurricanes, floods, and droughts, the type of disaster events causing severe damage in these countries.

3.5.2 Testing Hypothesis I: Roles of Initial Conditions

To test the Hypothesis I, we estimate the following equation:

$$\hat{\tau}_{1,i,T_0^i+5} = \beta_{0,j} + \beta_{1,j}\hat{\tau}_{1,i,T_0^i} \times D_i \times S_{i,j,T_0^i-1} + \beta_{2,j}\hat{\tau}_{1,i,T_0^i} \times D_i + \beta_{3,j}\hat{\tau}_{1,i,T_0^i} \times S_{i,T_0^i-1} + \beta_{4,j}D_i \times S_{i,T_0^i-1} + \beta_{5,j}D_i + \beta_{6,j}S_{i,j} + \epsilon_i \quad (3.5.1)$$

where S_{i,j,T_0^i-1} is the structural indicator j in the year prior to the natural disaster shock in episode i and can be one of four variables: (1) a dummy indicating whether the ratio of public debt over GDP exceeds 70 percent, (2) political stability indicator, (3) the government effectiveness indicator, and (4) tourism dependency. Other variables have the same definitions as those in Equation (3.5.1).

For the high debt dummy, we choose 70 percent as the threshold to capture the idea that developing countries whose debt exceeds this level may "on average" face tighter borrowing constraints than those whose debt level is below it. The results are not sensitive to the choice of this threshold. It is worth highlighting that this choice does not mean that 70 percent is a level deemed appropriate from other considerations. For example, Greenidge et al. (2012) estimate that gross debt beyond the threshold of 55-56 percent of GDP is associated with lower economic growth for Caribbean countries.[18] Therefore, one should not conflate the debt threshold chosen here with, for example, the medium-term debt target of a fiscal rule.

If resource constraints for repairing assets damaged by natural disasters are the key channel for medium-term output effects of natural disasters to emerge, we should expect the other triple interactions to be statistically insignificant. Here, political stability and the level of governance try to mimic the radical political revolution channel by Cavallo et al. (2013). Tourism dependency is captured as the ratio of tourism receipts over GDP, and we include it to study whether high tourism dependency, a key feature of small island developing economies, can strengthen medium-term output effects of natural disasters.

Table 3.5 suggests that highly indebted countries have stronger medium-term output loss after a severe natural disaster shock than other countries. The triple interaction term between the high-debt dummy, the high-damage dummy, and the change in real GDP per capita on impact is significant both statistically and economically. For example, for one percent decline in real GDP per capita on impact (caused by a high-damage event, i.e., one with the damage-to-GDP ratio exceeding 10 percent), the fifth-year impact would be stronger by 1.24 percent of GDP for countries whose public debt exceeds 70 percent of GDP than the rest of the sample. By contrast, we do not find a significant role for political stability,

[18]See Guerson (2018) and Lissovolik (2018) for a discussion on the need to build resilience against natural disasters and implications for the fiscal framework in ECCU countries.

government effectiveness, or tourism dependency in affecting medium-term output effects of natural disasters.

3.5.3 Testing Hypothesis II: Heterogeneous Natural Disaster Output Effects across Sectors

We test Hypothesis II by analyzing natural disaster output effects at the sector level. Sectoral GDP is available for 15 economies in the Caribbean region: the eight ECCU members plus Haiti, The Bahamas, Barbados, Jamaica, Belize, Guyana, and Trinidad and Tobago, and five sectors: tourism, agriculture, construction, manufacturing, and high skilled services (which include real estate and financial services sectors). The earliest data available is from 1977 for the ECCU countries, with some regional differences (for example, data for Anguilla is available from 1984 onwards, data for Guyana is available from 1988, and data for Trinidad and Tobago is available from 2000).

Sample selection: As earlier results suggest that medium-term output effects are statistically significant only for severe natural disasters, we only keep natural disasters whose damage-to-GDP ratio exceeds the medium of this ratio within this sectoral exercise sample.

Empirical methodology: We choose the following two-step approach to study the dynamic effect of natural disasters at the sector level. In the first step, we estimate the following equation:

$$Y_{i,t} = \sum_{k=-K}^{K} \beta_k I_{i,k,t} + \delta_i + \epsilon_{i,t} \tag{3.5.2}$$

where $Y_{i,t}$ is the logarithm of the sectoral GDP, with i indicating an episode-sector pair. $I_{i,k,t}$ is a dummy that is equal to one if year t is the k^{th} year after the shock, and zero otherwise, and δ_i is the episode-sector fixed effect.

In the second step, we estimate a linear trend based on β_k in the 10-year pre-event window and extrapolate the trend to the post-event window. To get the standard error of the extrapolated values, we bootstrap β_k in the 10-year pre-event window based on the standard error of β_k (for simplicity, we ignore the potential correlation between β_i and β_j for $i \neq j$). We use the bootstrapped coefficients to calculate the confidence band.

Figure 3.6 suggests that natural disasters have significantly negative impact on the GDP of the tourism sector for ECCU countries and countries whose debt-to-GDP ratio is above the median of this sectoral exercise sample. Such patterns, however, do not exist for non-ECCU countries or those whose debt-to-GDP ratio is below the median. Such a pattern is less

Table 3.5: Role of Structural Indicators in Medium-Term Output Effects of Natural Disasters.

	(1) Debt exceeding 70 percent of GDP	(2) Tourism Receipts	(3) Political Stability	(4) Government Effectiveness
Δ real GDP per capita	0.0403***	0.539***	0.413**	0.0422*
	(0.148)	(0.196)	(0.189)	(0.216)
Triple interaction term: Δ real GDP per capita × Dummy damage × Structural Indicator	1.147*	0.0628	17.70	-0.991
	(0.598)	(0.130)	(54.72)	(18.37)
Δ real GDP per capita × Dummy damage	0.378	0.402	-18.90	10.98
	(0.316)	(0.961)	(59.84)	(9.735)
Δ real GDP per capita × Structural Indicator	-0.913***	-0.0540*	-0.0154	0.125
	(0.254)	(0.0273)	(0.344)	(0.421)
Dummy damage × Structural Indicator	0.0189	0.00246	-1.762	-1.755
	(0.0470)	(0.00775)	(4.404)	(2.315)
Dummy damage	-0.00129	-0.0101	1.877	-0.161
	(0.0354)	(0.0639)	(4.773)	(0.250)
Structural Indicator	0.0227	0.00292	0.0396**	0.0285
	(0.0253)	(0.00202)	(0.0159)	(0.0185)
Constant	-0.0599***	-0.0756***	-0.0505***	-0.0447***
	(0.0123)	(0.0159)	(0.0135)	(0.0147)
Observations	68	53	42	42
R-squared	0.345	0.341	0.393	0.285

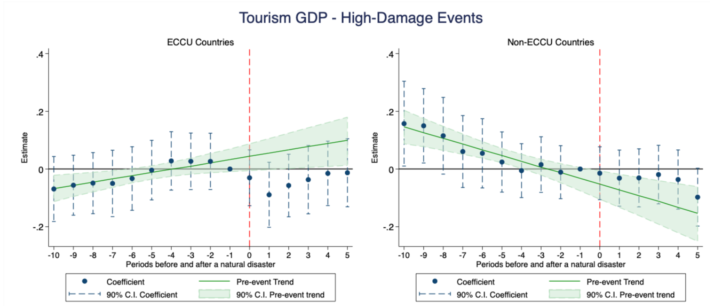
Standard errors in parenthesis
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

salient for Agriculture as shown in Figure 3.7, and even weaker for other sectors as shown in Figures 3.8, 3.9, and 3.10.

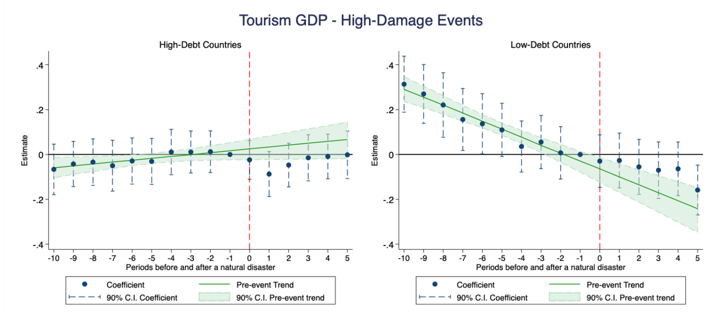
3.5.4 The Impact of Natural Disasters on the Import of Machinery and Equipment

We use the same exercise as in the previous section to study the impact of natural disasters on the import of machinery and equipment (M&E). We replace the dependent variable in Equation (3.5.2) with the import of M&E as share of GDP. This channel can be interesting to study because resource constraints in repairing assets damaged by natural disasters may crowd out the investment in M&E, which can then affect long-term growth through slower capital accumulation and TFP growth. Figure 3.11 find some weak evidence for ECCU countries.

Figure 3.6: Natural Disaster Impact on Sectoral GDP (Tourism).

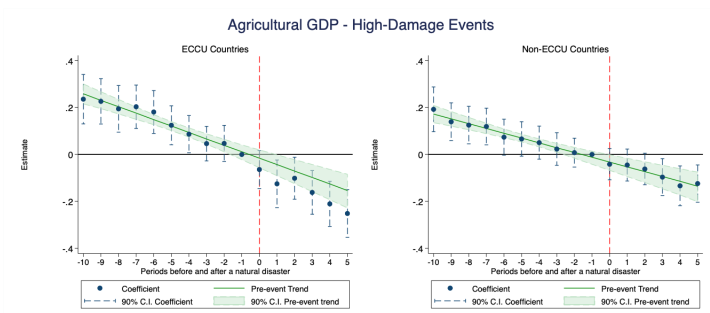


(a) ECCU vs. Non-ECCU Countries

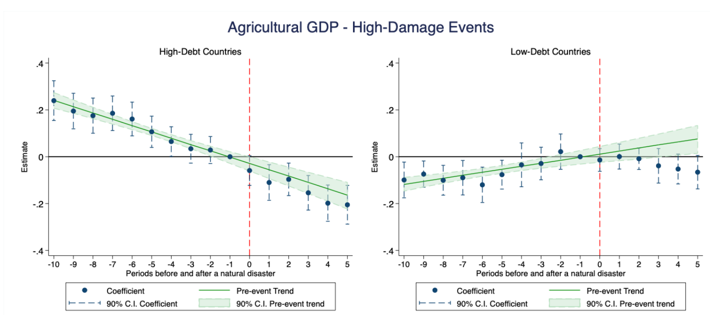


(b) High Debt vs. Low Debt Countries

Figure 3.7: Natural Disaster Impact on Sectoral GDP (Agricultural).

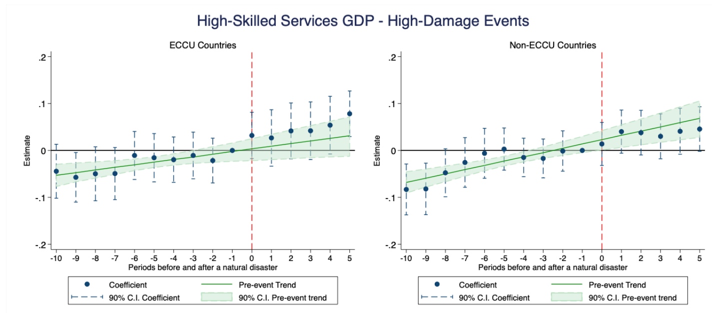


(a) ECCU vs. Non-ECCU Countries

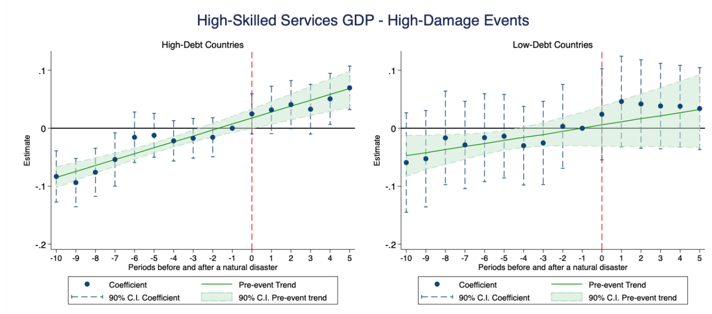


(b) High Debt vs. Low Debt Countries

Figure 3.8: Natural Disaster Impact on Sectoral GDP (High-Skilled Services).

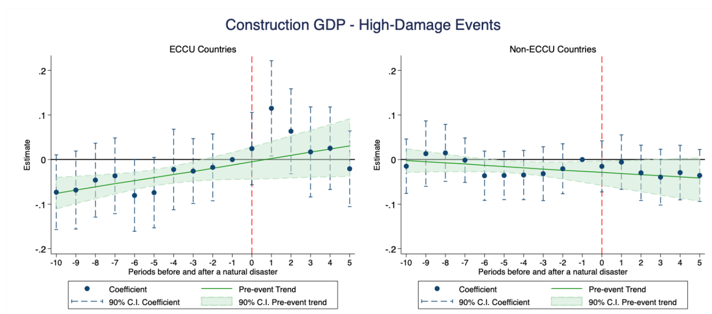


(a) ECCU vs. Non-ECCU Countries

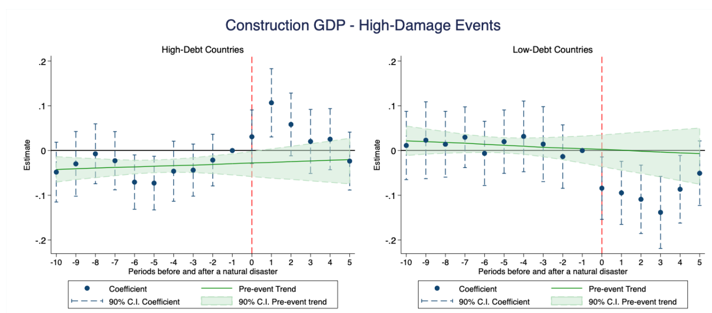


(b) High Debt vs. Low Debt Countries

Figure 3.9: Natural Disaster Impact on Sectoral GDP (Construction).

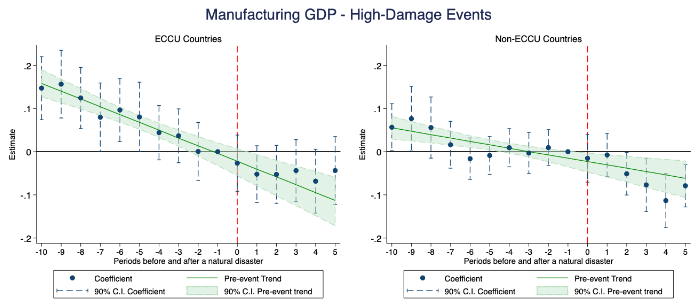


(a) ECCU vs. Non-ECCU Countries

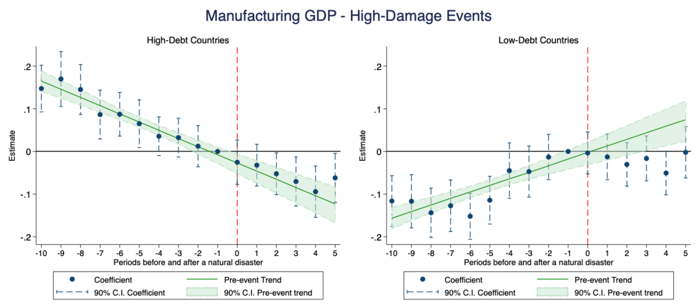


(b) High Debt vs. Low Debt Countries

Figure 3.10: Natural Disaster Impact on Sectoral GDP (Manufacturing).

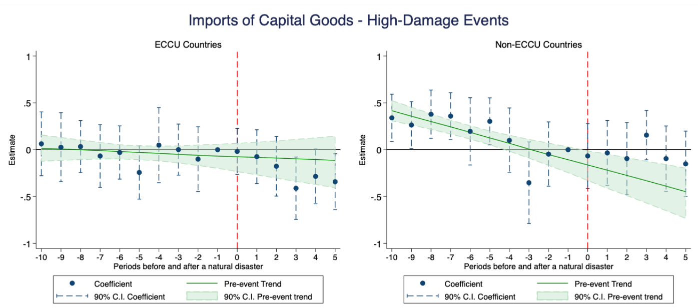


(a) ECCU vs. Non-ECCU Countries

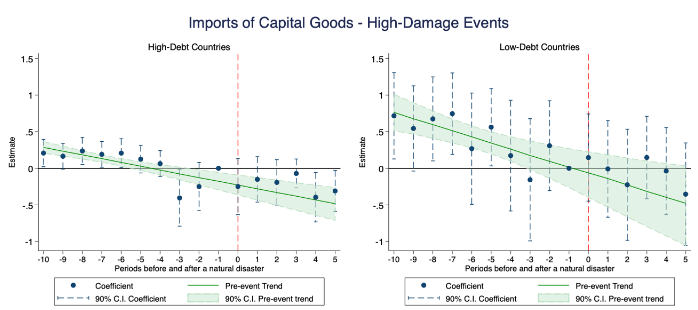


(b) High Debt vs. Low Debt Countries

Figure 3.11: Natural Disasters Impact on the Imports of Capital Goods.



(a) ECCU vs. Non-ECCU Countries



(b) High Debt vs. Low Debt Countries

3.6 Conclusions

This paper studies whether natural disasters caused persistent medium-term output loss in small island developing economies, given their high exposure to severe natural disasters, an issue that can be aggravated by climate change, which could make natural disasters more frequent and intense.

We combine the SCA and the LPM to estimate the dynamic effects of natural disaster shocks on real GDP per capita and find that for an extremely severe event, real GDP per capita is persistently lower than the counter-factual trend even five years after the shock. We find suggestive evidence to support a lack of resources to repair damaged assets as the cause of such persistent effects.

Our findings, arguably, provide a strong support for strengthening resilience building ex-ante to reduce scarring effects of severe natural disasters. Future research can further compare the post-disaster economic dynamics of small island developing economies after severe shocks and those of disaster-prone regions in large economies, to further understand these issues.

APPENDICES

APPENDIX A

Appendix to Chapter I

A.1 Direct Requirement Coefficients in HS

According to the BEA, Direct Requirement Coefficients "show the amount of inputs purchased directly to produce one dollar of output." That is, the exact input composition of every final product, where the sum of these coefficients across a product's inputs adds up to one. As described in Section 1.2, Direct Requirement Coefficient (DRC) Tables are in the BEA's own product classification, while the rest of the data used in this paper is in HS. Correspondence tables between these two classification systems are readily available, however the match is of the many-to-many type i.e. a BEA code can match to multiple HS 6-digit codes, and an HS 6-digit code can match to multiple BEA codes.

Whenever a BEA code for an input corresponds to more than one HS code, we uniformly distribute the direct requirement coefficient, i.e. how much does a particular output use of a given input, across all of its corresponding HS codes. This procedure yields a correspondence table where outputs are defined in BEA's classification, inputs are defined in HS, and the shares across inputs each output uses add up to one. Lastly, whenever an HS code for an output corresponds to more than one BEA code, we take the average of the direct requirement coefficients across all the BEA codes corresponding to this particular HS 6-digit code. The end-product of this computation is the exact input composition of every product at the HS 6-digit level.

To illustrate how we construct HS input composition tables, we use the following example. Suppose the DRC Tables look like Table A.1.

While the BEA-HS correspondence looks like that of Table A.2. Notice that the BEA-HS match is of the many-to-many type, e.g. BEA code A corresponds to more than one HS code,

Table A.1: Example of Direct Requirement Coefficients Tables.

BEA Code Output	BEA Code Inputs	DR Coefficient
A	C	0.6
A	D	0.4
B	C	0.8
B	D	0.2

it corresponds to HS codes 1 and 2; while HS code 1 corresponds to more than one BEA code, it corresponds to BEA codes A and B.

Table A.2: Example of the BEA-HS Correspondence.

BEA Code	HS Code
A	1
A	2
B	1
B	3
C	3
C	4
D	4
D	5

The first step is to create a match where outputs are defined in BEA and inputs are in HS. We expand Table A.1 by uniformly distributing the direct requirement coefficients of each BEA input code across its corresponding HS codes, according to Table A.2. This is shown in Table A.3. By construction, note that for each BEA output, the sum of the DR coefficients across its HS inputs adds up to one. We include BEA-HS input combinations for which DR coefficients are implicitly equal to 0, e.g. HS code 5 does not correspond to BEA code C.

We add the DR coefficients across every BEA output - HS input combination, and then match BEA outputs to HS outputs according to Table A.2. Note that HS code 1 corresponds to both BEA codes A and B. Table A.4 shows how the DR coefficients table would look for HS output code 1.

Lastly, we average the DR coefficients across every HS output-input combination; this is not necessary whenever an HS code corresponds to a unique BEA code. Table A.5 shows the final product of this computation, the exact input composition of HS output code 1 in terms of its HS input codes. It is important that the HS direct requirement coefficients add up to

Table A.3: BEA Outputs - HS Inputs Correspondence.

BEA Output	BEA Inputs	HS Inputs	Adjusted BEA DR Coefficient
A	C	3	0.3
A	C	4	0.3
A	C	5	0.0
A	D	3	0.0
A	D	4	0.2
A	D	5	0.2
B	C	3	0.4
B	C	4	0.4
B	C	5	0.0
B	D	3	0.0
B	D	4	0.1
B	D	5	0.1

Table A.4: HS Outputs - HS Inputs Correspondence.

HS Output	HS Inputs	Adjusted HS DR Coefficient
1	3	0.3
1	4	0.5
1	5	0.2
1	3	0.4
1	4	0.5
1	5	0.1

one because our computation of RoO strictness is a weighted average of the inputs restricted under RoO for each final product.

A.2 Regression Tables and Robustness Checks

In this appendix we include the estimation tables and robustness checks we conduct for the empirical facts in our paper. Table A.6 shows the estimation results for the probability of using NAFTA to export, both for Equation 1.3.1 and for a regression where instead of controlling for the product-level RoO strictness and MFN tariffs, we control for industry fixed-effects to account for any unobserved heterogeneity at the industry-level. These fixed effects should already capture variation across industries in their RoO and MFN tariffs.

Figure A.1 shows the predicted share of firms using NAFTA by deciles of firm size,

Table A.5: Input Composition of HS Code 1.

HS Output	HS Inputs	Adjusted HS DR Coefficient
1	3	0.35
1	4	0.50
1	5	0.15

Table A.6: Regression Output for the Probability of using NAFTA.

	(1) Pr(NAFTA)	(2) Pr(NAFTA)	(3) Pr(NAFTA)
2nd decile	0.124*** (7.11)	0.0981*** (3.57)	0.103*** (3.61)
3rd decile	0.166*** (8.16)	0.129*** (3.99)	0.135*** (4.02)
4th decile	0.201*** (9.72)	0.148*** (4.45)	0.155*** (4.54)
5th decile	0.212*** (9.95)	0.144*** (4.24)	0.152*** (4.36)
6th decile	0.202*** (9.26)	0.125*** (3.52)	0.136*** (3.72)
7th decile	0.203*** (9.34)	0.123*** (3.43)	0.136*** (3.70)
8th decile	0.186*** (8.23)	0.111** (3.01)	0.129*** (3.38)
9th decile	0.137*** (5.35)	0.0317 (0.67)	0.0463 (0.95)
10th decile	0.0249 (0.78)	0.0168 (0.33)	0.0476 (0.91)
RoO Strictness	-0.00508*** (-10.64)		0.00191 (1.41)
MFN Tariff	0.00818*** (4.81)		-0.00967*** (-5.26)
Constant	0.623*** (29.33)	0.621*** (20.36)	0.663*** (15.83)
HS Chapter F.E.	✗	✓	✓
Observations	105,959	159,104	146,081

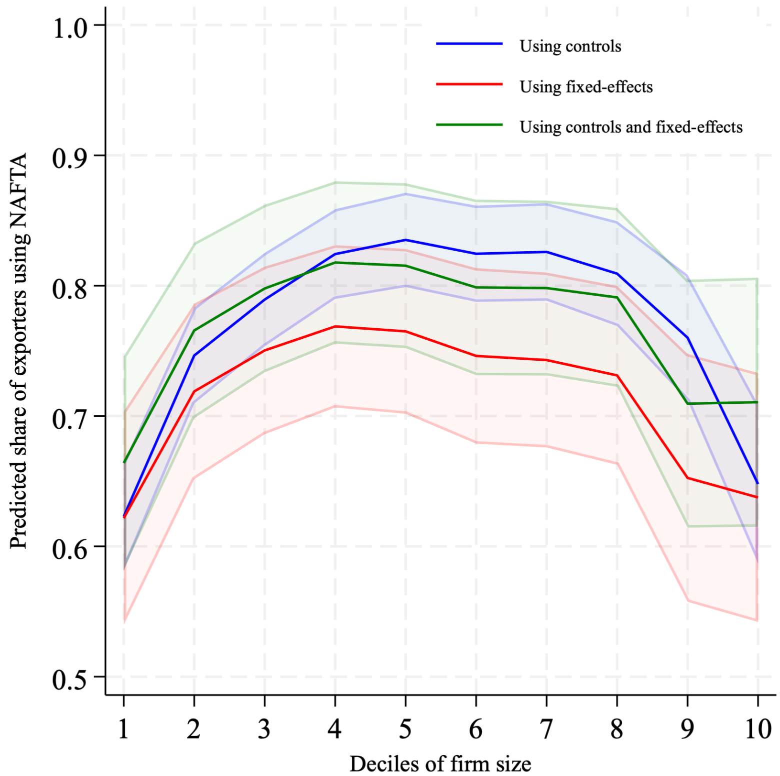
t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

assuming for simplicity that RoO strictness and MFN tariffs are equal to zero. In blue are the same results as in Figure 1.3, in red we show the estimated coefficients when controlling for industry fixed effects, and in green when we control for both RoO strictness, MFN tariffs, and industry fixed effects. Results show that our result of an inverse U-shape relationship between the use of NAFTA and firm size is result to controlling for industry fixed effects, thus to any source of heterogeneity at the industry-level. To further check the robustness of these findings, we estimate the following relationship:

$$\mathbb{N}_{ikjt} = \beta_0 + \beta_1 \text{Size}_{it} + \beta_2 \text{Size}_{it}^2 + \alpha_1 \text{RoO}_j + \alpha_2 \text{MFN}_j + \iota_t + \epsilon_{ikjt} \tag{A.1}$$

where $\mathbb{N}_{ikjt} = 1$ if firm i of size k exporting product j at time t is using NAFTA to export,

Figure A.1: Predicted share of exporters using NAFTA by size decile.



and Size_{it} represents a proxy for firm i's size at time t. We consider two different proxies: (i) Percentiles of firm size, as described in Section 2.2. (ii) The log of a firm's total exports. We also either control for RoO strictness and MFN tariffs, or include industry fixed effects. Results of these estimations are shown in Table A.7.

In our data, we cannot identify firms that are part of either Global Value Chains or Maquilas. It is a possibility that these types of firms are unable to choose whether to use NAFTA or WTO, or choose their sourcing strategy and compliance with RoO. Therefore, including them in our data sample could introduce a bias in our estimates, e.g. if a Maquila firm has to export using NAFTA, then the probability of using NAFTA to export is not affected by RoO strictness, and thus, this will introduce a downward bias in our estimates for the marginal effect of RoO strictness over the probability of using NAFTA to export. This same intuition applies to firms that are part of a GVC, where Mexican firms might not have enough market power for them to choose their use of NAFTA and their sourcing strategy. To address these concerns, we perform the following additional robustness checks: (i) Estimate Equation 1.3.1 but excluding the automotive and textiles industries,[1] as anecdotal evidence

[1]For textiles, we drop all observations corresponding to HS Chapters 61, 62, and 63. For automobiles,

Table A.7: Robustness Checks for the Probability of using NAFTA.

	(1) Pr(NAFTA)	(2) Pr(NAFTA)	(3) Pr(NAFTA)	(4) Pr(NAFTA)
Size percentile	0.0104***	0.00607***		
	(11.51)	(6.79)		
Percentile sq	-0.000100***	-0.0000529***		
	(-11.01)	(-6.77)		
RoO Strictness	-0.00508***		-0.00520***	
	(-10.64)		(-10.94)	
MFN Tariff	0.00793***		0.00769***	
	(4.67)		(4.54)	
Log of exports			0.161***	0.0701***
			(10.63)	(4.96)
Log of exports sq			-0.00697***	-0.00287***
			(-9.96)	(-4.33)
Constant	0.586***	0.685***	-0.105	0.405***
	(25.95)	(30.06)	(-1.30)	(5.29)
HS Chapter F.E.	✗	✓	✗	✓
Observations	105,959	70,935	105,959	70,935

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

suggests these are the industries in which most of the Mexican firms that are part of either GVCs or Maquilas concentrate. (ii) Estimate the same equation but now remove one industry at a time, thus providing evidence that a particular industry does not drive our results for the inverse U-shape relationship.

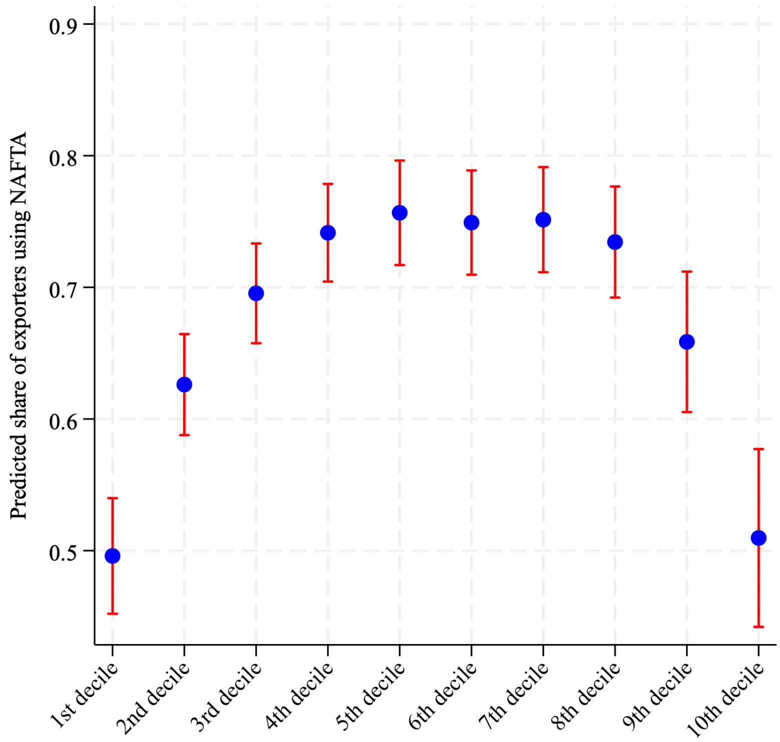
Figure A.2 shows our results for the inverse U-shape relationship between the use of NAFTA and firm size, excluding observations for either the Textiles or Automotive industries. Results for removing one industry at a time and studying how the inverse U-shape relationship changes are shown in Figure A.3, which plots the *convex hull* of the predicted share of firms using NAFTA by size decile, i.e. we estimate Equation 1.3.1 removing one industry at a time. Then for each estimation we predict the share of firms using NAFTA to export by size decile. Then for each decile, we find the lowest and the highest prediction. Figure A.3 plots the area between these two predictions.

These results support our empirical findings for the inverse U-shape relationship between the use of NAFTA and firm size. This relationship is robust to controlling for product-level incentives of using NAFTA, including industry fixed effects to account for any industry-level heterogeneity, using alternative proxies for firm size, and showing that the results does not depend on particular industries, which might be affected by the presence of GVCs or Maquilas.

In terms of the effect of firm size on the probability of sourcing inputs outside of NAFTA,

we drop HS Chapter 87.

Figure A.2: Predicted share of exporters using NAFTA removing Textiles and Automotive.



estimation results for Equation 1.3.2 are shown in Table A.8. We conduct the same robustness checks as those for the probability of using NAFTA to export. First, Table A.9 shows estimates for the following equation:

$$\mathbb{S}_{ist} = \beta_0 + \beta_1 \text{Size}_{it} + \beta_2 \text{Size}_{it}^2 + \iota_{st} + \epsilon_{ikjt} \tag{A.2}$$

where $\mathbb{S}_{ist} = 1$ if firm i of industry s is sourcing inputs outside of NAFTA at time t, and Size_{it} represents again different proxies for firm size. Results are robust to using these alternative measures. Next, we estimate the same relationship but again: (i) Removing observations for Textiles or Automotive industries from our sample. (ii) Estimating the relationship by removing one industry at a time.

Results for (i) are shown in Figure A.4, which provides evidence on our empirical finding for the distortion caused by RoO not driven by the Textiles or Automotive industries. For (ii), we estimate Equation A.3 but instead of separately estimating the relationship for firms using NAFTA and those using WTO, we explicitly control for the effect of using NAFTA to export and allow it to change by firm size:

Table A.8: Regression Output for the Probability of Non-NAFTA sourcing.

	(1) Firms using WTO	(2) Firms using NAFTA
2nd decile	0.0557***	0.0408***
	(5.06)	(7.56)
3rd decile	0.140***	0.0892***
	(5.56)	(11.60)
4th decile	0.241***	0.119***
	(9.18)	(11.81)
5th decile	0.348***	0.152***
	(9.43)	(14.43)
6th decile	0.492***	0.200***
	(15.23)	(16.23)
7th decile	0.527***	0.237***
	(16.00)	(15.38)
8th decile	0.620***	0.271***
	(18.71)	(15.38)
9th decile	0.708***	0.356***
	(22.29)	(17.65)
10th decile	0.854***	0.623***
	(40.76)	(24.04)
Constant	0.0214**	-0.0793***
	(3.06)	(-11.00)
HS Chapter F.E.	✓	✓
Observations	13,293	57,642

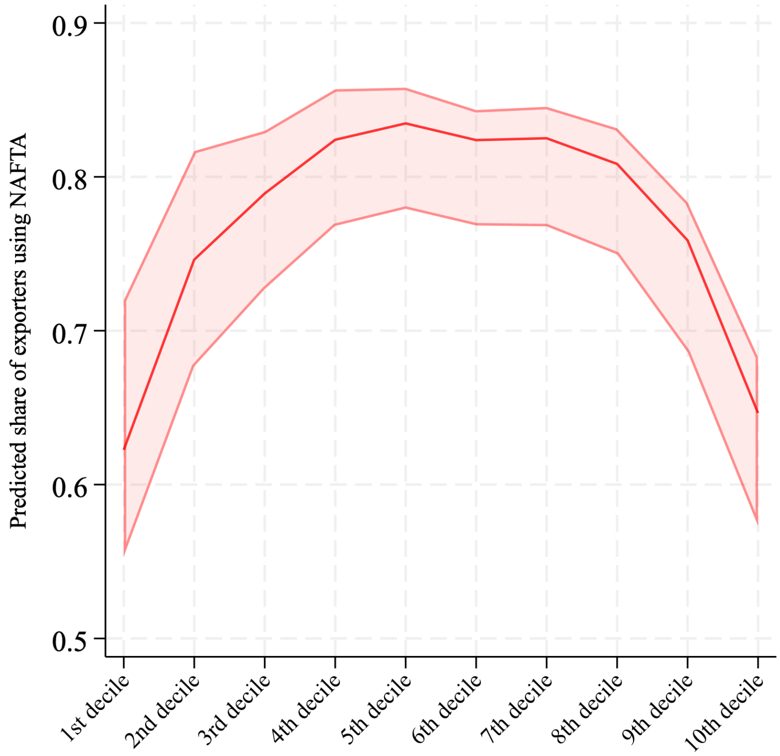
t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.9: Robustness Checks for the Probability of non-NAFTA Sourcing.

	(1) Firms using WTO	(2) Firms using NAFTA	(3) Firms using WTO	(4) Firms using NAFTA
Size percentile	0.0131***	-0.000320		
	(10.90)	(-0.28)		
Percentile squared	-0.0000364**	0.0000610***		
	(-3.11)	(4.53)		
Log of exports			0.120***	-0.0963***
			(7.04)	(-4.87)
Log of exports sq			-0.00113	0.00756***
			(-1.56)	(7.29)
Constant	-0.00446	-0.0145	-0.687***	0.243**
	(-0.25)	(-0.82)	(-7.48)	(2.67)
HS Chapter F.E.	✓	✓	✓	✓
Observations	45,339	111,347	45,339	111,347

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A.3: Predicted share of exporters using NAFTA removing one industry at a time.



$$\mathbb{S}_{ikst} = \beta_0^n + \sum_{k=2}^{10} \beta_k^n \mathbb{I}_{ikt} + \sum_{k=1}^{10} \alpha_k^n \mathbb{I}_{ikt} \mathbb{N}_{ikt} + \iota_{st}^n + \epsilon_{ijt} \tag{A.3}$$

Figure A.5 shows the mean and convex hull for α_k across size deciles. There are 53 industries in our sample, therefore we have 53 sets of $\{\alpha_k^n\}_{k=1}^{10}$. For a given decile k, the line in the middle is the average across estimations:

$$\bar{\alpha}_k = \frac{1}{53} \sum_{n=1}^{53} \alpha_k^n$$

The colored area shows both the lowest estimated effect $\alpha_k^{min} = \min_n \alpha_k^n$ and the largest one $\alpha_k^{max} = \max_n \alpha_k^n$, i.e. the colored area does not represent the size of the distortion, but rather the set of predicted distortions obtained by removing one industry at a time. The distortion induced by RoO is the distance between the zero line and any point inside the convex hull of the predictions.

These results provide evidence on the robustness of our empirical fact for the U-shape relationship between firm size and the distortion in non-NAFTA sourcing induced by RoO.

Figure A.4: Predicted non-NAFTA sourcing removing Textiles and Automotive.

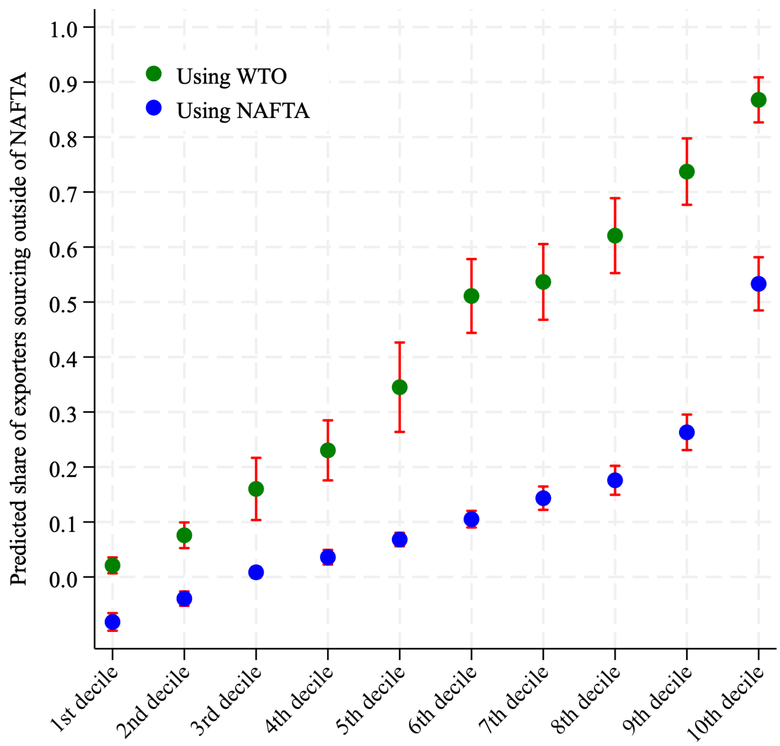


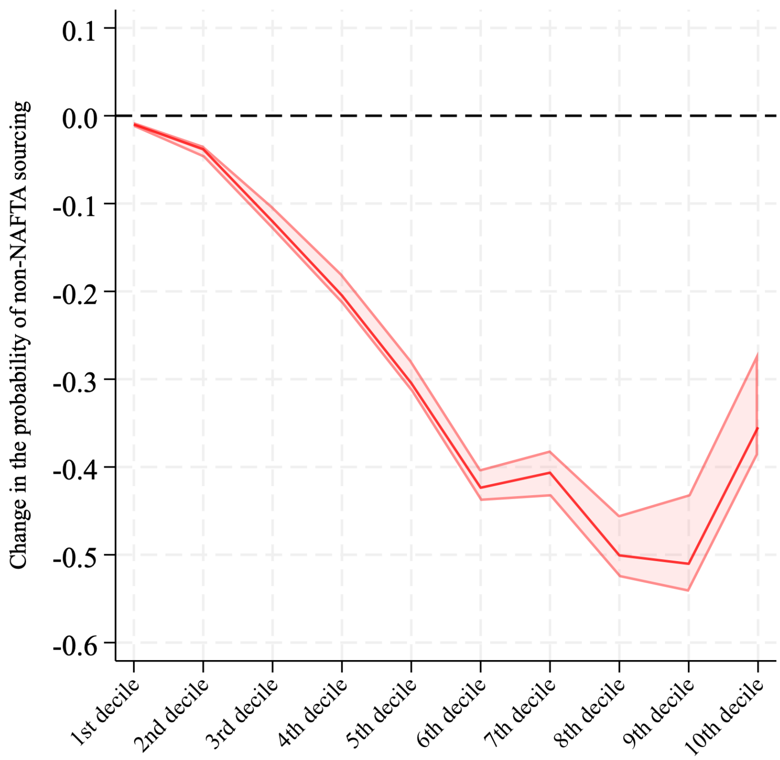
Table A.10 shows the full results of estimating Equation 1.3.3, where we omit including a dummy for the first decile for the intercept and for the interactions with RoO strictness and MFN tariffs, thus the results should be interpreted relative to the first decile.

A.3 Additional Empirical Facts

This section provides additional empirical facts we observe in the data. Figure A.6 shows the time series for the share of firms using NAFTA to export by export destination. The share of using NAFTA remained constant over our sample periods, although a degree of seasonality can be observed in the Figure. This seasonality is likely driven by changes in the composition of Mexican exports throughout the year, e.g. if vegetables are mostly exported during Winter months, and vegetable producers use NAFTA more intensively. The Figure also shows that the intensity of the use of NAFTA is mostly the same whether exporting to the US or to Canada, although volatility is higher for the latter.

Consistent with our structural model, there is industry-level heterogeneity in both the use of NAFTA and sourcing from non-NAFTA countries, which is presented in Figures A.7 and A.8, respectively. Industries correspond to an HS 1-digit level of disaggregation.

Figure A.5: Distortion in non-NAFTA sourcing removing one industry at a time.



In the case of the use of NAFTA, this observed heterogeneity intuitively should be driven either by heterogeneity in the benefits of using NAFTA or in its costs. In terms of benefits, industries are heterogeneous in terms of the MFN tariffs they would have to pay if exporting using WTO membership, and in terms of the costs either in terms of their RoO or the fixed cost of using NAFTA. In our model, we incorporate these features by directly feeding in RoO and MFN tariffs at the industry level and allowing the fixed cost of using NAFTA to be industry-specific. Turning our attention to sourcing outside of NAFTA countries, once again, the heterogeneity should be driven by the different benefits and costs of sourcing from non-NAFTA countries. Industries should be heterogeneous in terms of how attractive it is to source from non-NAFTA countries, depending on the patterns of comparative advantage across the World e.g. if for Mexican firms, the US is a great supplier of their inputs, then there is not much of an incentive to source from a non-NAFTA region. Costs of sourcing outside of NAFTA should also be heterogeneous across industries, as some of them should find it easier to source inputs from foreign countries due to the nature of their inputs, how connected worldwide is their industry, etc. In our model, we allow for the attractiveness of sourcing from foreign countries and the fixed costs of sourcing to be heterogeneous.

Table A.10: Estimated Marginal Effects of RoO and MFN tariffs.

	(1) Pr(NAFTA)
2nd decile	0.0966** (3.15)
3rd decile	0.137*** (3.55)
4th decile	0.235*** (6.04)
5th decile	0.242*** (5.91)
6th decile	0.236*** (5.69)
7th decile	0.216*** (5.24)
8th decile	0.157*** (3.49)
9th decile	-0.0340 (-0.54)
10th decile	-0.266*** (-3.95)
RoO strictness	0.00346*** (4.20)
2nd decile × RoO strictness	-0.00338*** (-3.94)
3rd decile × RoO strictness	-0.00747*** (-7.31)
4th decile × RoO strictness	-0.00977*** (-8.63)
5th decile × RoO strictness	-0.0105*** (-8.98)
6th decile × RoO strictness	-0.0103*** (-8.23)
7th decile × RoO strictness	-0.0119*** (-9.38)
8th decile × RoO strictness	-0.0130*** (-9.74)
9th decile × RoO strictness	-0.0130*** (-9.51)
10th decile × RoO strictness	-0.00992*** (-5.87)
MFN Tariff	-0.0117** (-3.01)
2nd decile × MFN Tariff	0.00879* (2.24)
3rd decile × MFN Tariff	0.0170*** (3.66)
4th decile × MFN Tariff	0.0144** (3.11)
5th decile × MFN Tariff	0.0162*** (3.44)
6th decile × MFN Tariff	0.0155** (3.17)
7th decile × MFN Tariff	0.0208*** (4.36)
8th decile × MFN Tariff	0.0273*** (5.17)
9th decile × MFN Tariff	0.0419*** (6.74)
10th decile × MFN Tariff	0.0529*** (7.04)
Constant	0.661*** (22.60)
Observations	105,959

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A.6: Share of exporters using NAFTA by export destination.

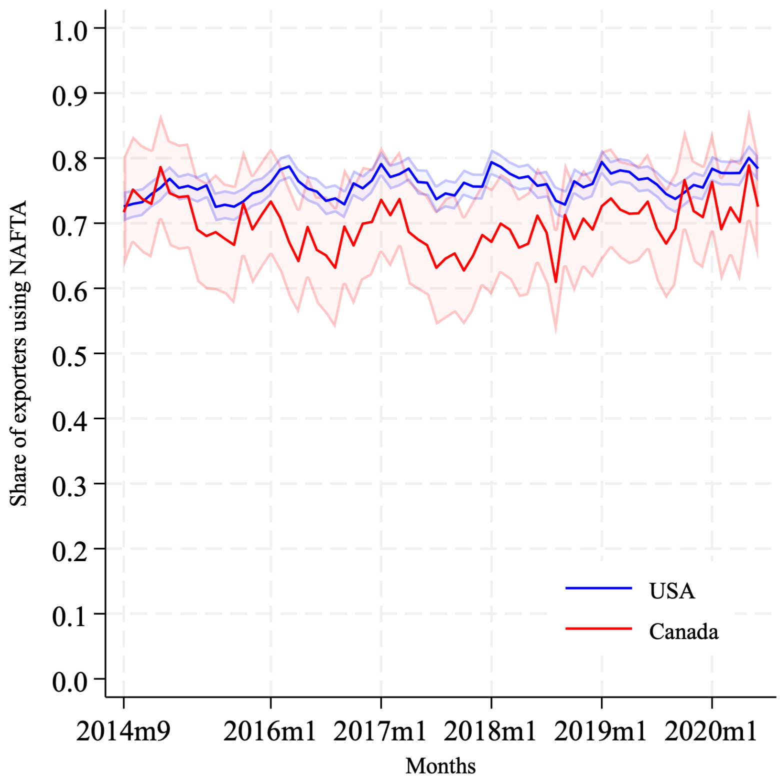


Figure A.7: Share of exporters using NAFTA by HS Section.

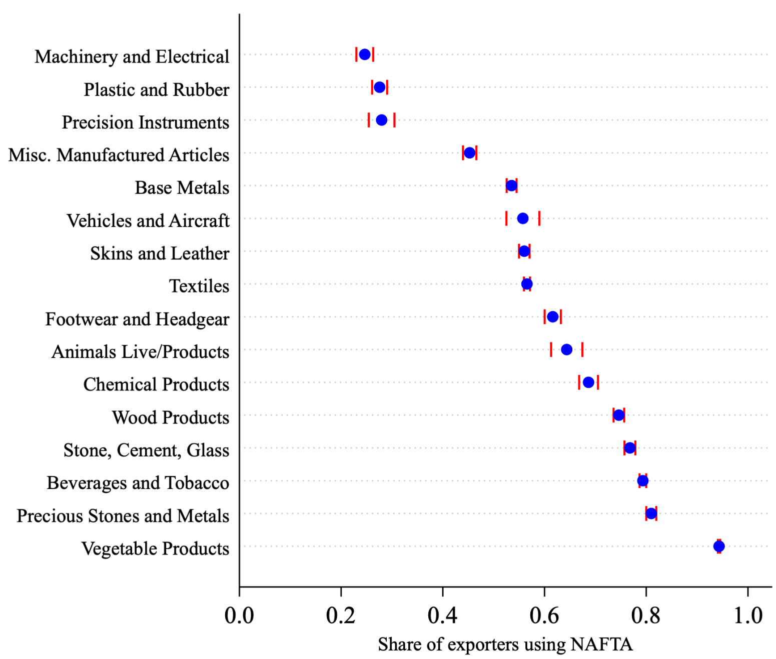
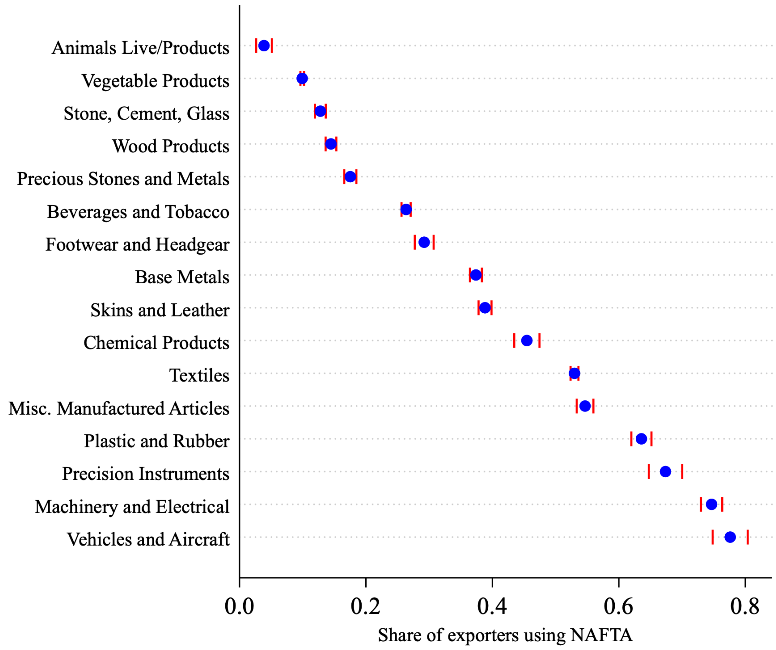


Figure A.8: Share of exporters sourcing outside of NAFTA by HS Section.



A.4 Marginal Cost of Producing and Exporting

According to Equation (1.4.6), the marginal cost of producing and exporting is given by:

$$c_{si}(\phi, \kappa, \lambda, \tau, J) = \frac{1 + (1-\kappa)\tau}{\phi} \left(\int_0^{\kappa\lambda} z_{si}(\nu)^{1-\rho} d^*\nu + \int_{\kappa\lambda}^{1} z_{si}(\nu)^{1-\rho} d\nu \right)^{1/(1-\rho)}$$

which we can rewrite as:

$$c_{si}(\phi, \kappa, \lambda, \tau, J) = \frac{1 + (1-\kappa)\tau}{\phi} \left(\kappa\lambda \int_0^{\infty} z^{1-\rho} dG^*_{si}(z) + (1-\kappa\lambda) \int_0^{\infty} z^{1-\rho} dG_{si}(z) \right)^{1/(1-\rho)}$$

Taking into account the distribution for prices depends on whether it is an input restricted under RoO, $G^*_{si}(z)$, or an unrestricted one, $G_{si}(z)$. Following Eaton and Kortum (2002):

$$\int_0^{\infty} z^{1-\rho} dG^*_{si}(z) = \Gamma\Big(\frac{\theta - 1 - \rho}{\theta}\Big) \left[\sum_{h \in N \cap J} T^h_{si} (d^h w^h_{si})^{-\theta} \right]^{\frac{-(1-\rho)}{\theta}}$$

and:

$$\int_0^\infty z^{1-\rho} dG_{si}(z) = \Gamma\Big(\frac{\theta - 1 - \rho}{\theta}\Big)\Bigg[\sum_{h \in J} T_{si}^h (d^h w_{si}^h)^{-\theta}\Bigg]^{\frac{-(1-\rho)}{\theta}}$$

which allows us to rewrite marginal cost as:

$$c_{si}(\phi, \kappa, \lambda, \tau, J) = \frac{1}{\phi}\gamma^{-\frac{1}{\theta}}\Big[1 + (1-\kappa)\tau\Big]\Bigg[\kappa\lambda\Psi^{\frac{\rho-1}{\theta}} + (1-\kappa\lambda)\Phi^{\frac{\rho-1}{\theta}}\Bigg]^{1/(1-\rho)}$$

with:

$$\gamma = \Gamma\Big(\frac{\theta - 1 - \rho}{\theta}\Big)^{-\frac{\theta}{1-\rho}}$$
$$\Psi = \Bigg[\sum_{h \in N \cap J} T_{si}^h (d^h w_{si}^h)^{-\theta}\Bigg]^{\frac{-(1-\rho)}{\theta}}$$
$$\Phi = \Bigg[\sum_{h \in J} T_{si}^h (d^h w_{si}^h)^{-\theta}\Bigg]^{\frac{-(1-\rho)}{\theta}}$$

A.5 Purchases of Intermediate Inputs

This section shows how firm ϕ's purchases of inputs from country j can be expressed as a share of its operating profits, as stated in Equation (1.4.17). Using (1.4.10) we can write operating profits as:

$$\begin{aligned} \pi_{si}^o(\phi, \kappa^*, \lambda, \tau) &= [p_{si}(\phi, \kappa, \lambda, \tau, J) - c_{si}(\phi, \kappa, \lambda, \tau, J)]q_{si}(\phi) \\ \Rightarrow c_{si}(\phi, \kappa, \lambda, \tau, J)q_{si}(\phi) &= (\sigma - 1)\pi_{si}^o(\phi, \kappa^*, \lambda, \tau) \end{aligned} \tag{A.1}$$

As firm ϕ is sourcing share x_{si}^j of its inputs from country j, the share of its marginal cost coming exclusively from its purchases from j will be then given by:

$$\begin{aligned} c_{si}^j(\phi, \kappa, \lambda, \tau, J) &= x_{si}^j(\phi, \kappa, \lambda, J)c_{si}(\phi, \kappa, \lambda, \tau, J) \\ \Rightarrow c_{si}(\phi, \kappa, \lambda, \tau, J) &= \frac{c_{si}^j(\phi, \kappa, \lambda, \tau, J)}{x_{si}^j(\phi, \kappa, \lambda, J)} \end{aligned}$$

and then rewrite Equation (A.1) as:

$$q_{si}(\phi)\frac{c^j_{si}(\phi,\kappa,\lambda,\tau,J)}{x^j_{si}(\phi,\kappa,\lambda,J)} = (\sigma-1)\pi^o_{si}(\phi,\kappa^*,\lambda,\tau)$$
$$\Rightarrow q_{si}(\phi)c^j_{si}(\phi,\kappa,\lambda,\tau,J) = (\sigma-1)x^j_{si}(\phi,\kappa,\lambda,J)\pi^o_{si}(\phi,\kappa^*,\lambda,\tau)$$

Since c^j_{si} is the marginal cost exclusively coming from j, i.e. the value of inputs purchased from j for the production of one unit of the final good, and $q_{si}(\phi)$ represents the number of units sold, it follows that:

$$M^j_{si}(\phi) = (\sigma-1)x^j_{si}(\phi,\kappa,\lambda)\pi^o_{si}(\phi,\kappa,\lambda,\tau)$$

A.6 Firm profits are not Supermodular

This section shows how in our model, firm profits are not necessarily supermodular in productivity and thus could not feature increasing differences in a firm's sourcing strategy. For this reason, we cannot reduce the dimensionality of the firm's problem as in Antras et al. (2017), following Jia (2008), and have to compute firm profits under each possible sourcing strategy.

According to Topkis's Modularity Theorem, if the expression for profits in Equation (1.4.13) satisfies being supermodular in $(I^j_{si}(\phi), \phi)$ where $I^j_{si}(\phi) = 1$ if firm ϕ sources inputs from j, then $I^*_{si}(\phi) = (I^1_{si}(\phi), ..., I^J_{si}(\phi))$ is non-decreasing in ϕ, i.e. the cardinality of a firm's sourcing strategy is increasing in its productivity. For profits to be supermodular, two conditions have to be satisfied:

1. Let $X = [0,1]^J$ and $Y = \mathbb{R}^+$, where X and Y are lattices and thus $X \times Y$ is a lattice as well. $\pi_{si}(\phi)$ has to have increasing differences in $(I_{si}(\phi), \phi) \iff \pi_{si}(\phi)$ features increasing differences in $(I^j_{si}(\phi), \phi)$ $\forall j \in J$, given $I^k_{si}(\phi)$ for $k \neq j$.
2. $\pi_{si}(\phi)$ features increasing differences in $(I^j_{si}(\phi), I^k_{si}(\phi))$, given $I^h_{si}(\phi)$ for $h \neq j, k$.

Our proof relies on showing that our profit function does not necessarily satisfy increasing differences in $(I^j_{si}(\phi), \phi)$, therefore it does not have to be supermodular, implying that the cardinality of a firm's sourcing strategy might not increase with firm productivity. Let $\phi_H > \phi_L$, for profits to feature increasing differences in $(I^j_{si}(\phi), \phi)$ the following has to hold true:

$$\mathbb{E}\Big[\pi_{si}(1,\phi_H)-\kappa(\phi_H)w\zeta_{si}-\pi_{si}(0,\phi_H)+\kappa(\phi_H)w\zeta_{si}\Big]\geq\mathbb{E}\Big[\pi_{si}(1,\phi_L)-\kappa(\phi_L)w\zeta_{si}$$
$$-\pi_{si}(0,\phi_L)+\kappa(\phi_L)w\zeta_{si}\Big] \tag{A.1}$$
$$\Rightarrow\mathbb{E}\Big[\pi_{si}(1,\phi_H)-\pi_{si}(0,\phi_H)\Big]\geq\mathbb{E}\Big[\pi_{si}(1,\phi_L)-\pi_{si}(0,\phi_L)\Big]$$

since $I_{si}^{j'}\geq I_{si}^{j}\Rightarrow I_{si}^{j'}=1\wedge I_{si}^{j}=0$. We do not consider the case for which $I_{si}^{j'}=I_{si}^{j}=0$ as it is trivially satisfied. Note that we are fixing other countries in the firm's sourcing strategy, i.e. $I_{si}^{k'}=I_{si}^{k}\ \forall k\neq j$. Using the objective function in Equation (1.4.13), each side of the inequality can be expressed as:

$$\phi^{\sigma-1}\gamma^{(\sigma-1)/\theta}B_{si}[1+(1-\kappa)\tau]^{1-\sigma}[\Lambda(1,\phi)-\Lambda(0,\phi)]-w\mathbb{E}\Big[f_{si}^{j}(\phi)\Big]-w\sum_{k\neq j}I_{si}^{j}\mathbb{E}\Big[f_{si}^{j}(\phi)\Big]+w\sum_{k\neq j}I_{si}^{j}\mathbb{E}\Big[f_{si}^{j}(\phi)\Big]$$

where:

$$\Lambda(I_{si}^{j},\phi)\equiv[\kappa\lambda\Psi_{si}(I_{si}^{j},\phi)^{(\rho-1)/\theta}+(1-\kappa\lambda)\Phi_{si}(I_{si}^{j},\phi)^{(\rho-1)/\theta}]^{\frac{1-\sigma}{1-\rho}}$$

which allows us to rewrite Inequality (A.1) as:

$$\phi_H^{\sigma-1}[\Lambda(1,\phi_H)-\Lambda(0,\phi_H)]-w\mathbb{E}\Big[f_{si}^{j}(\phi_H)\Big]\geq\phi_L^{\sigma-1}[\Lambda(1,\phi_L)-\Lambda(0,\phi_L)]-w\mathbb{E}\Big[f_{si}^{j}(\phi_L)\Big]$$

Since we assume that fixed costs of sourcing do not depend on firm size, expectations cancel and we get:

$$\phi_H^{\sigma-1}[\Lambda(1,\phi_H)-\Lambda(0,\phi_H)]\geq\phi_L^{\sigma-1}[\Lambda(1,\phi_L)-\Lambda(0,\phi_L)]$$

By assumption $\phi_H>\phi_L$ and $\sigma>1$, so for the above to necessarily hold true it needs to be the case that:

$$\Lambda(1,\phi_H)-\Lambda(0,\phi_H)\geq\Lambda(1,\phi_L)-\Lambda(0,\phi_L) \tag{A.2}$$

Following the definition for $\Lambda(I_{si}^{j},\phi)$ and since $\sigma>\rho$, Inequality (A.2) is true if $\phi_L\leq\phi_H\Rightarrow\Lambda(\phi_L)\leq\Lambda(\phi_H)$. Assume $\phi_L\leq\phi_H$, firms' chosen sourcing strategies $J^*(\phi_H)$ and $J^*(\phi_L)$ have to satisfy that for the high productivity firm:

$$\phi_H^{\sigma-1}\gamma^{(\sigma-1)/\theta}B_{si}[1+(1-\kappa(\phi_H))\tau]^{1-\sigma}\Lambda(J^*(\phi_H)) - w\sum_{j\in J^*(\phi_H)} I_{si}^j\mathbb{E}\Big[f_{si}^j(\phi_H)\Big] - \kappa(\phi_H)w\zeta_{si}$$
$$\geq \phi_H^{\sigma-1}\gamma^{(\sigma-1)/\theta}B_{si}[1+(1-\kappa(\phi_L))\tau]^{1-\sigma}\Lambda(J^*(\phi_L)) - w\sum_{j\in J^*(\phi_L)} I_{si}^j\mathbb{E}\Big[f_{si}^j(\phi_L)\Big] - \kappa(\phi_L)w\zeta_{si}$$

and for the low productivity firm:

$$\phi_L^{\sigma-1}\gamma^{(\sigma-1)/\theta}B_{si}[1+(1-\kappa(\phi_L))\tau]^{1-\sigma}\Lambda(J^*(\phi_L)) - w\sum_{j\in J^*(\phi_L)} I_{si}^j\mathbb{E}\Big[f_{si}^j(\phi_L)\Big] - \kappa(\phi_L)w\zeta_{si}$$
$$\geq \phi_L^{\sigma-1}\gamma^{(\sigma-1)/\theta}B_{si}[1+(1-\kappa(\phi_H))\tau]^{1-\sigma}\Lambda(J^*(\phi_H)) - w\sum_{j\in J^*(\phi_H)} I_{si}^j\mathbb{E}\Big[f_{si}^j(\phi_L)\Big] - \kappa(\phi_H)w\zeta_{si}$$

The above follows from the fact that for the high productivity firm ϕ_H sourcing strategy $J^*(\phi_H)$ yields larger profits, and correspondingly for the low productivity firm ϕ_L. Adding these two inequalities and using the fact that fixed costs of sourcing do not depend on firm productivity, gives us:

$$[\phi_H^{\sigma-1} - \phi_L^{\sigma-1}]\Big([1+(1-\kappa(\phi_H))\tau]^{1-\sigma}\Lambda(J^*(\phi_H)) - [1+(1-\kappa(\phi_L))\tau]^{1-\sigma}\Lambda(J^*(\phi_L))\Big) \geq 0$$

Since $\phi_L \leq \phi_H$ and $\sigma > 1$, this implies that:

$$[1+(1-\kappa(\phi_H))\tau]^{1-\sigma}\Lambda(J^*(\phi_H)) \geq [1+(1-\kappa(\phi_L))\tau]^{1-\sigma}\Lambda(J^*(\phi_L))$$

For $\Lambda(\phi_H) \geq \Lambda(\phi_L)$ to necessarily be the case, it has to be true that:

$$[1+(1-\kappa(\phi_H))\tau]^{1-\sigma} \leq [1+(1-\kappa(\phi_L))\tau]^{1-\sigma}$$
$$\Rightarrow (1-\kappa(\phi_H))\tau \geq (1-\kappa(\phi_L))\tau$$
$$\Rightarrow \kappa(\phi_H) \leq \kappa(\phi_L)$$

that is, that whenever a firm uses NAFTA to export, $\kappa(\phi_H) = 1$, any other firm with lower productivity has to use it as well, $\kappa(\phi_L) = 1$. In our model, this is not necessarily true. Because of fixed costs of using NAFTA, it could be the case that a medium-sized is using NAFTA to export, while a smaller less-productive firm is not. Since $\phi_L \leq \phi_H \not\Rightarrow \Lambda(\phi_L) \leq \Lambda(\phi_H)$, profits in our model do not necessarily feature increasing differences in $(I_{si}^j(\phi), \phi)$, and thus are not necessarily supermodular in productivity. This implies we cannot invoke Topkis's Modularity Theorem to argue that the cardinality of a firm's sourcing strategy is increasing in its productivity, and have to brute-force the firm's optimization problem by computing profits for each possible sourcing strategy.

Intuitively, this is the case because the use of NAFTA and RoO introduce additional non-linearities in our model. For example, a low productivity firm might not be able to pay the fixed cost of using NAFTA, and therefore it chooses to source from non-NAFTA countries. A more productive firm might be able to pay this fixed cost and choose to use NAFTA, which then could lead to the firm choosing to source its inputs exclusively from member countries. In this example, the set of countries from which the lower productivity firm can source inputs from is larger than that of the higher productivity firm.

A.7 Full Results for Sourcing Potentials

For some industries in foreign countries, Mexican firms never imports some of their inputs from them, which implies that the input shares for these product-region combinations are equal to 0. When regressing the log-difference with respect to the corresponding input share for Mexico against industry-region fixed effects, if we ignored these observations for which input shares are equal to 0, we would introduce an upward bias in our estimates for sourcing potentials. For example, suppose in China *Industry A* is made of *Inputs* 1-100. Mexico does not import from China any product from *Industry A* except for *Input* 100, and it coincides with Mexico barely sourcing this product domestically. This implies the relative input share of China to that of Mexico for *Input* 100 is large, and since *Inputs* 1-99 are not imported at all, the observation for *Inputs* 100 is the only one used in the estimation. A bias is introduced as *Input* 100 is just a small part of *Industry A*, but we would estimate a large sourcing potential of China for this industry. To avoid dropping observations and introducing these biases, whenever an input is not sourced from a foreign region, we assign an input share equal to 0.1 to this input-region combination.

Table A.11 shows the full results of our estimation for foreign countries' sourcing potentials. As a reminder, these estimates are interpreted as relative to the sourcing potential of Mexico, which is normalized to be equal to 1. For US-CA, the industry (HS Chapter) with the lowest sourcing potential is *Sugars and sugar confectionery* with 0.26, while the one with the highest one is *Articles of iron or steel* with 6.10. For China, the industry (HS Chapter) with the lowest sourcing potential is *Wood and articles of wood* with 0.10, while the one with the highest one is *Other made up textile articles* with 1.20. For Europe, the industry (HS Chapter) with the lowest sourcing potential is *Wood and articles of wood* with 0.06, while the one with the highest one is *Preparations of meat, or fish, or crustaceans* with 0.71. For the Rest of the World, the industry (HS Chapter) with the lowest sourcing potential is *Cocoa and cocoa preparations* with 0.08, while the one with the highest one is *Other made up textile articles* with 1.38. Lastly, for the total sum of estimated sourcing potentials, the industry (HS Chapter) with the lowest sourcing potential is *Wood and articles of wood* with 0.65, while the one with the highest one is *Articles of iron or steel* with 8.30.

Table A.11: Industry-level Sourcing Potentials by Foreign Country.

HS Chapter	Description	Sector	HS Section	SP US-CA	SP China	SP Europe	SP ROW	Total SP
03	Fish and crustaceans	1	1	0.70	0.24	0.07	0.32	1.33
04	Dairy Produce, Eggs, Natural Honey	1	1	0.86	0.28	0.18	0.27	1.60
06	Live trees and other plants	1	2	0.51	0.43	0.36	0.62	1.92
07	Edible vegetables	1	2	0.69	0.22	0.19	0.27	1.37
08	Edible fruits and nuts	1	2	0.68	0.18	0.14	0.22	1.21
09	Coffee, tea, mate and spices	1	2	0.34	0.22	0.19	0.27	1.03
16	Preparations of meat, or fish, or crustaceans	1	4	1.45	0.65	0.71	0.76	3.57
17	Sugars and sugar confectionery	1	4	0.26	0.33	0.20	0.21	1.01
18	Cocoa and cocoa preparations	1	4	1.06	0.65	0.45	0.08	2.24
19	Preparations of cereals, flour, starch or milk	1	4	0.58	0.26	0.19	0.23	1.26
20	Preparations of vegetables, fruit, or nuts	1	4	1.30	0.34	0.28	0.39	2.32
21	Mischellaneous edible preparations	1	4	0.59	0.21	0.15	0.20	1.15
32	Tanning or dyeing extracts	2	6	2.90	0.37	0.33	0.50	4.10
33	Essential oils and resionoids, perfumery, cosmetics	2	6	1.09	0.25	0.15	0.25	1.74
36	Explosibes, pyrothehnic products	2	6	0.81	0.21	0.11	0.18	1.31
38	Mischellaneuous chemical products	2	6	1.43	0.28	0.16	0.31	2.18
39	Plastics and articles thereof	2	7	0.92	0.20	0.11	0.24	1.47
40	Rubber and articles thereof	2	7	1.11	0.39	0.19	0.35	2.04
42	Articles of leather	3	8	1.82	0.72	0.23	0.65	3.43
43	Furskins and artificial fur	3	8	1.27	0.69	0.56	0.78	3.30
44	Wood and articles of wood	3	9	0.38	0.10	0.06	0.11	0.65
46	Manufactures of straw, esparto or other plaiting materials	3	9	0.72	0.20	0.11	0.25	1.28
54	Man-made filaments	3	11	1.36	0.52	0.10	1.12	3.11
56	Wadding, felt and nonwovens, special yarns, ropes	3	11	1.16	0.57	0.10	0.90	2.72
61	Articles of appareal and clothing accessories, knitted	3	11	0.88	0.47	0.11	0.52	1.98
62	Articles of appareal and clothing accessories, not knitted	3	11	0.77	0.48	0.11	0.49	1.84
63	Other made up textile articles	3	11	2.06	1.20	0.18	1.38	4.82
64	Footwear, gaiters and the like	3	12	1.02	0.51	0.19	0.30	2.02
65	Headgear and parts thereof	3	12	1.62	0.61	0.18	0.62	3.03
66	Umbrellas, walking sticks, whips	3	12	2.50	0.51	0.35	0.60	3.96
67	Prepared feathers and down articles	3	12	2.50	0.51	0.35	0.60	3.96
69	Ceramic products	4	13	1.66	0.34	0.21	0.34	2.54
70	Glass and glassware	4	13	0.46	0.38	0.19	0.39	1.43
71	Precious stones, precious metals	4	14	1.45	0.42	0.20	0.28	2.34
73	Articles of iron or steel	4	15	6.10	0.79	0.39	1.01	8.30
74	Copper and articles thereof	4	15	2.13	0.53	0.29	0.31	3.26
83	Mischellaneous articles of base metal	4	15	4.37	0.63	0.31	0.77	6.08
84	Nuclear reactors, boilers, machinery and mechanical appliances	5	16	2.93	0.52	0.22	0.56	4.23
85	Electrical machinery and equipment and parts thereof	5	16	2.04	0.44	0.18	0.44	3.10
87	Vehicles other than railway or tramway	5	17	2.42	0.44	0.19	0.53	3.57
90	Optical, photographic, precision, medical apparatus	5	18	1.60	0.40	0.16	0.38	2.53
91	Clocks and watches and parts thereof	5	18	1.69	0.52	0.20	0.35	2.76
92	Musical instruments	5	18	1.39	0.26	0.14	0.29	2.08
94	Furniture, bedding, mattresses, cushions, lamps	6	20	3.21	0.53	0.23	0.64	4.61
95	Toys, games and sports requisites	6	20	3.38	0.47	0.22	0.64	4.72
96	Miscellaneous manufactured articles	6	20	2.67	0.46	0.27	0.55	3.95
Average				0.26	0.10	0.06	0.08	0.65
Maximum				1.58	0.43	0.22	0.47	2.71
Minimum				6.10	1.20	0.71	1.38	8.30

A.8 Point-Estimates using SMM

Table A.12 shows the point estimates resulting from our estimation using SMM. The estimates for the location parameter of the log-normal distribution for fixed costs of sourcing depend on our simplifying assumption for the shape parameter, i.e. $\delta_s^j = \sqrt{log2}$, which results in the variance of fixed costs of sourcing being given by $\mathbb{V}(f_{si}^j) = exp(2\mu_{si}^j + log2)$

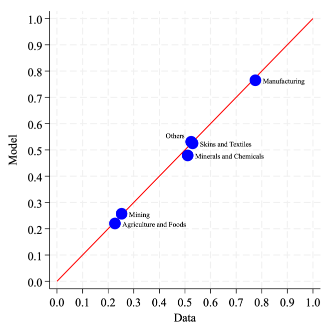
Table A.12: Point Estimates for Fixed Costs and US Market Demand.

	ζ_s	μ_s^{CHN}	μ_s^{EUR}	μ_s^{US-CA}	μ_s^{ROW}	B_s
Agriculture and Foods	0.001	-3.490	-3.681	-3.216	-3.718	0.007
Minerals and Chemicals	0.002	-4.101	-4.707	-3.185	-4.292	0.009
Skins and Textiles	0.003	-4.513	-4.614	-3.599	-4.227	0.007
Mining	0.000	-5.943	-6.443	-4.143	-5.443	0.000
Manufactures	1.687	0.657	-0.243	1.935	0.535	1.566
Others	0.004	-5.304	-5.604	-3.504	-4.901	0.002

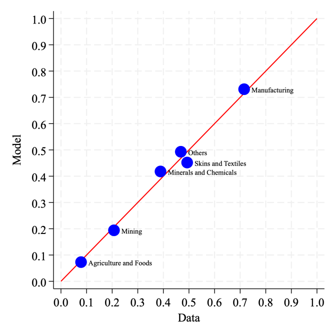
A.9 Further Details on the Fit of the Model

Figure A.9 shows the model's predictions in terms of the extensive margin of sourcing: The share of firms, for each sector, that source inputs from either NAFTA, China, Europe, or the Rest of the World.

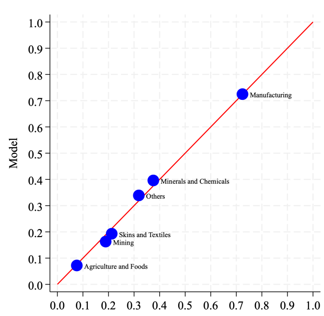
Figure A.9: Sectoral fit of the model in terms of the extensive margin.



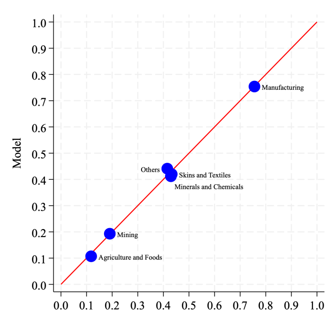
(a) US-CA



(b) China



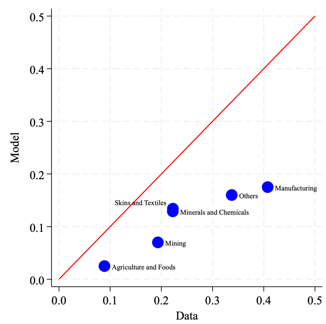
(c) Europe



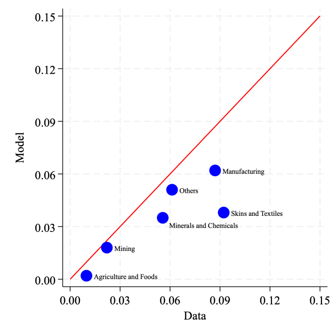
(d) Rest of the World

Figure A.10 shows the model's fit regarding the share of inputs sourced from each foreign region. These moments relate to those in Figure A.9, as a firm choosing not to source from a given region implies that its input share is equal to zero. On the other hand, if a firm decides to source inputs from a region, then input shares are determined by the estimated sourcing potentials discussed in Section 1.5.2. In this figure, we observe that the prediction for firms' input shares from foreign countries are mostly in line with the data except for the case of input shares from the NAFTA region, where the model predicts a lower share of inputs being sourced from these countries. Additionally, we over predict input shares from Europe and Rest of the World for the *Manufacturing* sector. We interpret this as the result of overestimating these countries' sourcing potentials for this sector.

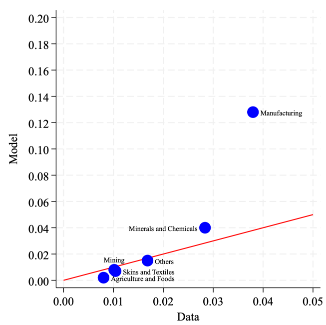
Figure A.10: Sectoral fit of the model in terms of input shares.



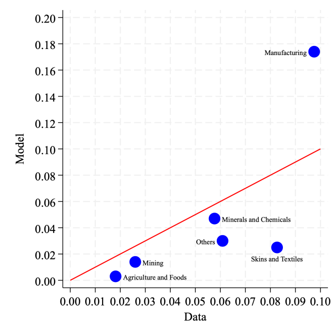
(a) US-CA



(b) China



(c) Europe



(d) Rest of the World

Table A.13 shows the aggregate fit in terms of the share of firms using NAFTA and sourcing from non-NAFTA countries, both by quintiles of firm size. These moments are the ones shown in Figures 1.9a and 1.9b. The table also shows the share of firms sourcing inputs from each foreign region and input shares for these countries.

Table A.13: Fit of the Model at the aggregate level.

	Data	Model
Share of firms using NAFTA	0.76	0.73
... 1st quintile	0.67	0.45
... 2nd quintile	0.80	0.78
... 3rd quintile	0.83	0.78
... 4th quintile	0.81	0.89
... 5th quintile	0.69	0.73
Share of firms sourcing outside of NAFTA		
... 1st quintile	0.03	0.04
... 2nd quintile	0.12	0.04
... 3rd quintile	0.22	0.22
... 4th quintile	0.33	0.61
... 5th quintile	0.66	0.96
Share of firms sourcing from...		
... Mexico	1.00	1.00
... China	0.07	0.28
... Europe	0.04	0.18
... US and Canada	0.27	0.37
... Rest of the World	0.09	0.27
Share of inputs coming from...		
... Mexico	0.77	0.73
... China	0.03	0.04
... Europe	0.03	0.01
... US and Canada	0.12	0.17
... Rest of the World	0.05	0.05

APPENDIX B

Appendix to Chapter III

B.1 Data Sources and Definitions

B.1.1 Data Sources

The primary data sources for this paper are the April 2021 vintage of the IMF World Economic Outlook (WEO) database and the *EM-DAT (Emergency Events)* Database constructed by the Centre for Research on the Epidemiology of Disasters (CRED).

Supplemental datasets used include the Penn World Tables (version 10.0), the World Bank's *World Governance Indicators* and World Development Indicators, and Google's Dataset Publishing Language data repository. Additional data on sectoral GDP from the Caribbean country authorities, and detailed import data from the United Nations' COMTRADE database, were also used to study the transmission channels of natural disaster shocks.

B.2 An Algorithm for Constructing Donor Pools

This section explains the algorithm for constructing the donor pool. For an episode i, with country 1 being affected by the natural disaster in time T_0^i:

Step 1: Keep countries that have non-missing values for each of the predictor variables for at least one year between 1970 and year T_0^i.

Table B.1: Data Sources and Indicators.

Indicators	**Sources**
Natural disaster data	*EM-DAT (Emergency Events Database* created by the Centre for Research on the Epidemiology of Disasters (CRED), Universite Catholique de Louvain, Belgium.
Cross country data on GDP, population, inflation, public debt	IMF's *World Economic Outlook database* (April 2021 vintage)
Latitude data	IMF's *Google Dataset Publishing Language (DSPL) repository*
Land area and tourism expenditures data	World Bank's *World Development Indicators* (WDI)
Institutional quality indicators	World Bank's *World Governance Indicators* (WGI)
Missing historical GDP data	*Penn World Tables 10.0*
Sectoral GDP data	Caribbean country authorities
Import data	United Nations' *COMTRADE* database

Source: Authors' compilation.

Step 2: Keep countries whose nominal GDP is between 10 percent and 15 times that of country 1 during the episode. Select ten countries whose real GDP per capita is closest to that of country 1, and whenever possible have five countries that are richer than country 1 and five poorer.

Step 3: Sort the ten countries selected in Step 2 based on the growth rate of real GDP per capita between $T_0^i - 15$ and T_0^i. Select six countries whose growth rate is closest to that of country 1.

Step 4: Define 31 country sets as follows:

- One set consists of six countries selected in Step 3.
- Six sets consist of five countries, with the six countries selected in Step 3 being excluded one at a time.
- Twenty four sets consist of removing each of the six countries selected in Step 3 one at a time, but add each of the four countries eliminated in Step 3.

The donor pool is then defined as the country set that has the lowest pre-event MSPE for the synthetic control corresponding to this country set (i.e. we apply the SCA to it to get the synthetic control). The key results are robust to choosing the country set with the second lowest pre-event MSPE and other variations of our algorithm for the donor pool construction.

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