The Dynamics of Global Sourcing

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Abstract

Though input trade accounts for a significant share of global trade, little has been done to study the movement of firms in and out of import markets. To fill in the gap, this paper presents and estimates a dynamic, multi-country model of input imports with heterogeneous firms. The model incorporates intra-temporal interdependence across countries, while an inter-temporal link is embedded in the country-specific sunk entry costs. Using a sample of Chinese chemical producers between 2000 and 2006, I obtain the bounds for the fixed and sunk costs of importing by applying a partial identification approach under the revealed preferences assumption. The baseline results indicate that source countries are complementary in the sense that sourcing from an additional country increases the marginal benefits of other countries. Furthermore, a continuing importer pays between 7.81% and 27.06% of the average marginal revenue gain, while the average importing cost for a new importer is higher, ranging between 12.87% and 39.75% of the revenue gain of importing from a new source. The existence of interdependence across countries and location-specific sunk costs implies that temporary trade policy changes in one market can have long-lasting externalities on other markets.

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1 Introduction

Input trade accounts for a significant share of international trade. At the same time, changes in the firm-level extensive margin can explain much of the variation in imports across countries (Bernard, Jensen, Redding, & Schott, 2009) and long-run changes in aggregate trade flows (Eaton, Eslava, Kugler, & Tybout, 2008). There is also strong evidence for the impact of foreign inputs on firm-level productivity, varieties of final goods, and product quality (Amiti & Konings, 2007; Kasahara & Rodrigue, 2008; Goldberg, Khandelwal, Pavcnik, & Topalova, 2010; Gopinath & Neiman, 2014), and aggregate welfare gains from trade (Caliendo & Parro, 2015; Blaum, Lelarge, & Peters, 2018; Ramanarayanan, 2020). Understanding the dynamics of firm-level input imports across international markets is important for these reasons.

Nevertheless, little has been done to study the movement of firms into and out of import markets. Related studies from the literature on export dynamics have found strong support for the presence of sunk entry costs, which in combination with future profit uncertainty introduces an option value in the decision to enter or exit the export market.[1] It is plausible that there is a similar startup cost for importing intermediate inputs as firms have to incur costs to search for new suppliers, negotiate contracts with foreign partners, or adapt the production process to utilize foreign inputs. The exporter and importer's problems, however, are not equivalent. While the canonical export model ensures that a firm's decision to enter each market can be analyzed separately by assuming constant marginal costs, import decisions have direct implications for the firm's marginal costs. Foreign sourcing decisions are thus interdependent across markets. With the sunk entry costs of importing, the firm's decision to import from one country depends on its sourcing decisions from other markets *and* its past import locations. Previous studies, however, have failed to simultaneously account for both features of the firm's sourcing decision in one coherent framework.

The paper aims to fill in this gap in the literature by characterizing the propagation of a firm's import path over time and across international markets. To be more specific, I answer two

[1] The early theoretical work by R. Baldwin (1988), R. Baldwin and Krugman (1989), Dixit (1989a), and Dixit (1989b) emphasizes the importance of sunk costs to explain firm-level decisions to participate in export markets. Empirical evidence of exporting sunk costs was initially provided by Roberts and Tybout (1997) in the context of Colombia and Bernard and Jensen (2004) for US manufacturing plants. More recently, Das, Roberts, and Tybout (2007) structurally estimate the sunk export costs and find them to be substantial.

questions: (1) How does a firm choose its set of input sources in a particular year? (2) Does its current decision have implications for the firm's subsequent sourcing strategy? Preliminary examination of the data patterns presented in Section 2 indicates that a firm's import decision in one market is not independent from its decision in other markets. Moreover, there is persistence over time with regards to where firms import intermediate inputs, consistent with the sunk entry cost hypothesis.

To study these questions in more depth, I propose a dynamic partial equilibrium framework of imports with heterogeneous firms in a multi-country setting. The model incorporates two crucial features of firm-level import decisions: (a) input sources are interdependent in production and (b) firms pay a sunk entry cost when importing from a new location. The mechanism for interdependence across input sources is similar to Antràs, Fort, and Tintelnot (2017) (hereafter AFT), which considers the firm's sourcing decision in a static setting. The decision to incur the fixed costs of sourcing inputs from one country gives the firm access to lower-cost suppliers, which reduces firm production costs and prices. These lower prices in turn imply a larger scale of operation, which makes it more likely that the firm will find it profitable to incur the fixed costs of sourcing inputs from other countries. Conversely, sourcing from an additional country leads to market shares shifting away from the current sources, thus diminishing the value of each current source. In a static environment, the firm decision is essentially to balance the gain in static variable profits and the increase in the fixed costs of importing.

In addition to the static interdependence, my model includes sunk entry costs of importing, which introduces an inter-temporal linkage between current and future decisions.[2] The dynamic solution thus depends not only on the static profit gains and fixed costs, but also on sunk costs and expected future profit gains. Alternatively, one can think of firm-specific sunk costs as heterogeneity in firms' information sets. Given the differences in their import history, firms acquire different information about potential import sources, which gives rise to different sequential import decisions even if they have the same level of core productivity. In other words, firms are not only heterogeneous in terms of productivity, but also in the information set that they acquire given their previous import experience.

[2]In Section 6.1, I provide an extension of the model which allows for dynamic productivity gains from importing. This added feature thus generates another inter-temporal linkage through which current decision affects future profits.

Estimating the model constitutes a challenging task due to (i) the large dimensionality of the firm choice set (with J countries, the firm faces with 2^J choices), which is complicated by (ii) the evaluation of dynamic implications for each choice and (iii) the interdependence across markets in the marginal cost. To address (i) and (ii), I employ a moment inequality approach based on the revealed preference assumption similar to Morales, Sheu, and Zahler (2019) (hereafter MSZ). For each firm in a particular year, I change its import status in each market, one at a time, and compute the difference in observed profits and counterfactual profits in order to estimate the bounds for the fixed and sunk costs. Consequently, for a firm-year pair, the number of deviations I have to analyze is only J, which sharply contrasts with the standard method. The moment inequality method also avoids estimating the value function for each choice, despite the model's dynamic structure. To address (iii), I build on results from AFT's static model to derive the counterfactual static profits. This method allows me to identify the sourcing potential of each import market and thus, the ratio between the firm's marginal cost at the observed import path and its marginal cost at the counterfactual import path.[3] Due to this feature, even in the presence of interdependence across markets, I can estimate the fixed and sunk costs of importing as if markets are independent.

The main findings indicate that countries are complementary in the sense that the marginal revenue gain of an input source increases with the total number of sources a firm imports from. This is consistent with previous studies. Moreover, the marginal revenue gain of a source country is correlated with a firm's status in that country. The revenue gain is particularly high for new and continuing importers, at 7.9 and 6.6 million of 1998 RMB, respectively. For exiting importers and firms that never import, adding a new source increases revenues by about 2.5 and 3.6 mil RMB. The fixed cost of importing is between 0.52 and 1.80 mil RMB for each market, meaning firms pay between 7.81% and 27.06% of the marginal revenue gain of continuing to import from an old source. Finally, a new importer pays between 1.03 and 3.18 mil RMB for both fixed and sunk entry costs when importing from a new market, which accounts for 12.87%-39.75% of the revenue gain from adding a new import source.

The existence of interdependence across markets and sunk entry costs has significant implications for trade policies. Changing trade barriers in one market not only influences entry in its own

[3]Though Morales et al. (2019) also present a model with interdependence across export markets, they only allow for interdependence in the sunk costs while there is no linkage in the marginal costs. This means deviations from a firm's observed path would not change its marginal cost. This is a stark contrast between their model and my paper.

country, but also affects trade flows in other markets. While this third-market effect of targeted trade policies is inherent in standard gravity models (cf. Anderson and Van Wincoop (2003)), the channels are different. In those models, the effect on third markets manifests indirectly through general equilibrium forces, i.e., prices and terms of trade. However, even when we ignore the general equilibrium channel, there can still be externalities in a partial equilibrium framework due to the interdependence across markets at the firm level (Antràs et al., 2017; Morales et al., 2019).[4]

Furthermore, the persistence in the firm-level decisions implies that even temporary trade policy changes can have permanent impacts. Even though this effect is present in standard models of exporting with sunk entry costs, it is often contained to a single market. On the other hand, the path dependence coupled with the interdependence across markets generates widespread and long lasting effects on both the targeted and non-targeted markets.

There are three main contributions in this paper. First, I document a new set of stylized facts about Chinese chemicals producers between 2000 and 2006. Chemicals is an important industry to study for a few reasons. In 2007, China became the world's second largest chemicals manufacturer, just behind the US and ahead of Japan and Germany (Griesar, 2009). In 2017, China's chemical industry accounts for $1.5 trillion of sales, equivalent to 40 percent of the global chemical-industry revenue. Furthermore, the industry also provides critical inputs to pharmaceutical and plastic industries, especially in the US. The chemicals industry accounts for 10.8 billion of US exports and 15.4 billion of Chinese exports that are subject to increased tariffs during the current US-China trade war.

Second, I provide a new theoretical framework that unifies the theory from the import literature with the export dynamics literature. Most theoretical frameworks of importing have been static in nature (Goldberg et al., 2010; Halpern, Koren, & Szeidl, 2015; Antràs et al., 2017), and therefore unable to address the path dependence of import decisions.[5] Kasahara and Lapham (2013) study

[4]There is, however, a subtle difference between my model and supply chain frameworks in which tariffs that are imposed on goods in one stage might influence trade at other stages of the value chains (Blanchard, Bown, & Johnson, 2016; Erbahar & Zi, 2017; Bown, Conconi, Erbahar, & Trimarchi, 2020). In my baseline model, the effect takes place across producers at the same stage of production. Nevertheless, Section 6 provides an extension of the baseline model that accounts for linkages across countries and along the supply chains by allowing firms to import intermediate goods and export final goods.

[5]This literature emphasizes the interdependence across inputs/markets. For example, Halpern et al. (2015) and Goldberg et al. (2010) build on an Armington-style model, in which inputs are complementary in production. AFT provide micro-foundations for the interdependence by allowing for countries' technology levels to affect the input prices, and thus firms' choice of import sources and marginal costs.

a dynamic model of exports and imports, but their model does not consider the choice of locations and thus cannot capture the interdependence across input sources. Similarly, Ramanarayanan (2017), Lu, Mariscal, and Mejia (2016), and Imura (2019) develop dynamic models of importing with sunk entry costs and find that these costs can be substantial and critical to explain the slow adjustments of trade flows. Nonetheless, these papers overlook the interdependence across spatial markets. To my knowledge, this paper is the first to combine both the spatial interdependence and path dependence in a model of importing.

Third, I estimate country-specific sunk costs in the presence of interdependence across markets using a partial identification approach.[6] While many canonical trade models portray firm-level participation in international trade as a series of binary decisions, there is strong evidence that a firm's decision in one market depends on its decision in other markets (Antràs et al., 2017; Morales et al., 2019). Furthermore, as firms have been increasingly engaged in the global markets through many channels as reported in Bernard, Jensen, Redding, and Schott (2018), it is necessary for researchers to be able to study the breadth and richness of the global firm's decisions. Allowing for a multi-country setting with multiple trade margins, nevertheless, gives rise to a complex combinatorial problem, which cannot be addressed with most conventional estimation methods. As a result, the current studies have reduced the dimensions of firm's actions and/or set of possible locations where it can operate. Instead, I employ a partial identification approach that allows for both model complexity and flexible assumptions on the firm's optimization behaviors. In Section 6, I show how this method can be extended to account for multiple trade margins while preserving the range of feasible spatial choices.

The remaining of the paper is organized as follows. Section 2 provides a description of the data sources and several data patterns. Section 3 presents a model that is consistent with the data patterns. Section 4 discusses the identifying assumptions. In Section 5, I provide a detailed description of the estimation procedures and results. Section 6 presents two extensions of the baseline model. Section 7 concludes.

[6] In this sense, the paper contributes to a small but growing number of papers that employ moment inequalities in international trade, including Dickstein and Morales (2018), Morales et al. (2019), Ciliberto and Jäkel (2020), and Bombardini, Li, and Trebbi (2020).

2 Data and Stylized Facts

2.1 Description of the Data Sources

To explore the firm's import decisions across global markets and over time, I construct a rich data set that contains detailed firm-level characteristics and trade flows. My sample combines several sources. The information on firm-level trade flows was collected by the Chinese Customs Office. The data report the activities of the universe of Chinese firms participating in international trade between 2000 and 2006. They consist of transaction-level information, including trade volumes, partner countries, and f.o.b values in U.S. dollars. The second crucial data source for my project is China's National Bureau of Statistics (NBS), which conducts annual surveys cover the population of registered firms with sales above 5 million RMB. The data report detailed firm-level information on total sales, export values, intermediate costs, and wages. Other sources include CEPII for distance and country characteristics to construct standard gravity variables, Penn World Tables for international exchange rates and capital stocks, World Development Indicators for educational attainment and R&D spending at the national level, International Labor Organization for manufacturing wages, and Barro and Lee (2013) for educational attainment.[7]

A key step in the data construction is to match the customs data with the NBS annual surveys. Since the two data sets do not have a common firm identifier, I follow the procedure in Feng, Li, and Swenson (2016) to match the customs data with the firm surveys using firm name, zipcode, and telephone number. About 60% of firms in the customs data can be matched with the NBS firm surveys. Data are then aggregated at the firm-country-year level. Monetary values are converted to RMB 1998 using input and output deflators from Brandt, Van Biesebroeck, and Zhang (2012).

Importers are defined as firms that imported at least once during 2000-2006 and non-importers are defined as those that did not import during any of those years. Since there is not a perfect match between the customs data and the manufacturing survey, a fraction of importers would be mis-classified as non-importers since they cannot be identified in the customs data.[8] As a result, I restrict my estimation to importers only to prevent biased estimates that come from misclassification of firms, but acknowledge that importers and non-importers may be inherently

[7] See Appendix for a detailed description of variable construction.

[8] Another reason for why not all importers can be identified in the NBS data is the latter only surveys above-scale firms, and as a result excludes many small importers.

different and excluding the latter will potentially lead to selection bias.[9] Nevertheless, since the focus of the paper is the firm's sourcing decisions and how the choice of source countries evolves over time, including firms that never import may not add much additional information. Furthermore, a proportion of the firms did not start importing until the latter sample years, and exploiting the years when they did not import gives us some information on non-importers' behavior.[10]

In the final sample, I exclude intermediary firms from the sample as these firms do not face the same production decisions as the typical manufacturing firms. Following Ahn, Khandelwal, and Wei (2011), I identify intermediary firms by searching for Chinese characters in firms' name that mean "trading", "exporter", or "importer". I also exclude firms that do not report domestic sales and total input costs.[11] Finally, I focus on the chemicals industry for reasons provided in Section 1.[12] The final data set comprises of 1,537 unique importers between 2000 and 2006 that imported from the 40 most popular import sources in terms of number of importers. The inclusion of the top 40 countries is to ensure sufficient observations per market. Nevertheless, the main results largely remain the same when I include all 96 import markets that appear in the customs data.

During 2000-2006, China's economy experienced significant growth. The total domestic sales for the Chemicals sample grew by 400% from 840 to 4,239 billion RMB, total import values grew from 10 to 60 billion, and the number of importers more than doubled between the first and the last year of the sample period. This implies that static models under the assumption of stable aggregate environment might not be suitable to apply to the context of China during this period of time. Furthermore, the fast growth rate guarantees high turn-over rates and large variation in terms of exit and entry rates to study the dynamics of firms' importing behaviors.[13]

In the next section, I document a number of facts about the importing behavior of Chinese chemical producers during the sample period.

[9] The NBS data does not contain information about firms' import status and thus it is impossible to identify unmatched importers and non-importers in the firm-level surveys.

[10] See Appendix for the number of importers and share of total importers for each year between 2000 and 2006.

[11] This effectively removes processing firms as they export all of their outputs and do not sell in the domestic market.

[12] Chemicals producers are defined based on both the customs data and the firm surveys. I include firms whose chemicals exports account for at least 50% of their total exports and firms that reported to be in the chemical feedstock and chemical manufacturing industry (China Industry Classification code 26).

[13] Descriptive statistics are provided in Appendix B.

2.2 Stylized Facts

Stylized fact 1: *There is persistence in firm-level import decisions. Firms are more likely to import from a country if it has imported from the same country in the past, even after accounting for different combinations of firm-country, country, and year fixed effects.*

I present the evidence for the persistence in import status at country level in Table 1. Columns 1 and 2 report transition probabilities in year t for source country j given that firm does not import from country j in year $t-1$. Columns 3 and 4 report the transition probabilities when firms import from country j in the previous year. The probabilities in Column 1 are overwhelmingly higher than those in Column 2. This means once a firm chooses not to import from a certain market, it is highly unlikely that the firm will enter in the following year. On the other hand, once a firm enters an import market, it is more likely to keep importing from that market in the following year. The pattern is consistent across all sample years. The persistence in firm-country level import status implies that there may be country-specific sunk costs of importing.

Nevertheless, the persistence we observe in the data may be caused by persistence in country or firm-country-specific components. If these characteristics induce a firm to self-select into certain markets but choose not to enter others, then as long as these characteristics stay constant over time this firm will continue to import from the same set of countries. If this is the case, we might misattribute the path dependence exhibited in the data to sunk costs of importing. To investigate these possibilities, in Table 2 I run a dynamic linear probability model of a firm's current entry decision in each import market on past entry, while accounting for firm-country fixed effects and country dummies. The inclusion of these fixed effects ensures that the effect of past entry on current entry does not come from time-invariant factors that also affect the firm's import decision. In column 4, I also include a set of year dummies to control for macroeconometric trends that might influence the likelihood of importing in a particular year.

Regardless of the specification, the coefficient on past import status remains positive and significant, implying that the persistence in importing cannot be entirely explained by the time-invariant factors or larger economic trends. The estimates range between .308 and 0.571, meaning that if a firm imported from country j in the previous period, it is at least 30 percentage points more likely to continue importing from country j. Notice that there is a big decrease in the effect of past import status when including firm-country-specific fixed effects. This implies that firm-country-specific components might be important in explaining the persistence in firms' importing decisions. In the theoretical framework developed in Section 3, I allow for firm-country-specific components that can account for the pattern observed here.

Finally, it is possible that firms only pay a one-time global sunk cost regardless of the number of countries that they import from and the country-specific past entry variable simply picks up the effect of previously entering the import market. For this reason, in the last column of Table 2, I include an additional dummy that takes the value of unity if the firm imported from any country in the previous year. I find that the estimated coefficient on this variable is negligible, albeit statistically significant, whereas the effect of importing from country j in year $t-1$ on importing from j in year t is largely unchanged. This suggests that its magnitude might be small compared to country-specific sunk costs.[14] Hence, I focus on the country-specific sunk costs in the main analysis of the paper.

Table 1: Transition probability

	$P(d_{ijt}=0 \mid d_{ijt-1}=0)$	$P(d_{ijt}=1 \mid d_{ijt-1}=0)$	$P(d_{ijt}=0 \mid d_{ijt-1}=1)$	$P(d_{ijt}=1 \mid d_{ijt-1}=1)$
2000-2001	0.9962	0.0038	0.3499	0.6501
2001-2002	0.9953	0.0047	0.3727	0.6273
2002-2003	0.9943	0.0057	0.3664	0.6336
2003-2004	0.9938	0.0062	0.3885	0.6115
2004-2005	0.9943	0.0057	0.3979	0.6021
2005-2006	0.9941	0.0059	0.3686	0.6314
All	0.9947	0.0053	0.3766	0.6234

$d_{ijt}=1$ if firm i imports from country j in year t and 0 otherwise.

Stylized fact 2: *The average importer sources from multiple countries. The set of countries from which a firm sources cannot be explained by random entry.*

On average, a firm imports from one to two countries per year and firms that import in at least two consecutive years import from more than three countries. Table 3 reports the ranking of the top ten countries by number of importers and total import values in 2000 and 2006. Surprisingly, the ranking is stable across years, with the most five common import sources being Japan, United States, Germany, South Korea, and Taiwan in both 2000 and 2006. This pattern is not particular

[14] Moxnes (2010) finds that country-specific sunk costs of exporting are about three times larger than global sunk cost.

Table 2: Persistence in import status

	(1)	(2)	(3)	(4)	(5)
Import to j in $t-1$	0.616***	0.571***	0.308***	0.313***	0.299***
	(0.00423)	(0.00429)	(0.0107)	(0.0106)	(0.0106)
Import in $t-1$					0.0244***
					(0.000920)
Constant	0.00744***	0.0000465	0.0120***	0.0141***	0.000731
	(0.0000920)	(0.000125)	(0.000227)	(0.000397)	(0.000579)
Observations	885312	885312	737760	737760	737760
Country Dummies		Yes	Yes	Yes	Yes
Firm-Country FE			Yes	Yes	Yes
Year Dummies				Yes	Yes

This table reports results on regressing current import status on past import status at the firm-country level. Columns 3-5 account for firm-country unobserved heterogeneity using the Arellano-Bond (1991) GMM estimator. In the last column, both country-specific and global import status terms are treated as endogenous variables.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

to chemicals producers. Indeed, the ranking constructed from the universe of Chinese importers also shows similar stability over time, despite China's WTO accession at the end of 2001.[15]

In Table 4, I follow Eaton, Kortum, and Kramarz (2011) to examine firms importing from different sets of sources. I compute the probability of entry that follows a hierarchy in the sense that firms that import from the $k+1$st most popular source also import from the kst popular source. Columns 1 and 3 report the share of firms that import from each set of countries as observed in the data, whereas columns 2 and 4 predict these entry probabilities if firms enter import markets randomly based on the patterns in Table 3. As in Eaton et al. (2011) and AFT, under the assumption that a firm's decisions to import from different countries are independent (i.e., random entry), the fraction of firms that follow a pecking order is much lower than what is presented in the data. This implies certain countries or combinations of countries have characteristics that make them more attractive to Chinese firms compared to others.

[15] Country rankings using all industries are reported in Table A1.

Table 3: Top 10 source countries by number of importers

2000			2006		
Country	**Rank**	**Firms**	**Country**	**Rank**	**Firms**
Japan	1	128	Japan	1	302
United States	2	113	United States	2	234
Germany	3	89	Germany	3	209
South Korea	4	72	South Korea	4	187
Taiwan	5	67	Taiwan	5	160
Singapore	6	37	Singapore	6	88
France	7	36	India	7	73
United Kingdom	8	32	United Kingdom	8	72
Italy	9	26	Netherlands	9	64
Belgium	10	26	Italy	10	62

Table 4: Percent of Chinese chemicals firms importing from strings of top 10 countries

	2000		2006	
	Data	**Random entry**	**Data**	**Random entry**
1	13.83	4.92	13.85	4.76
1-2	2.37	3.97	2.84	3.38
1-2-3	1.19	2.15	1.42	2
1-2-3-4	0.40	.86	1.07	.99
1-2-3-4-5	1.98	.31	1.78	.39
1-2-3-4-5-6	0.40	.05	1.07	.07
1-2-3-4-5-6-7	0.40	.01	0.18	.01
1-2-3-4-5-6-7-8	0	0	0.18	0
1-2-3-4-5-6-7-8-9	0	0	0	0
1-2-3-4-5-6-7-8-9-10	0	0	0.71	0
% following pecking order	20.55	12.26	23.09	11.62

Countries are indexed by their ranks (by number of importers) reported in Table 3.

3 Model

To explain the empirical patterns documented in Section 2, I propose a model in which sourcing locations affect firm-level marginal costs. This allows for interdependence across countries in the spirit of AFT 2017. I further impose that firms have to pay sunk entry costs for each country that it starts sourcing from in order to explain the persistence in firm-country level import status.

3.1 Setup

There are J countries (including home) with standard symmetric CES preferences and two markets: intermediate and final goods. The intermediate-good market is perfectly competitive and firms make zero profit by selling intermediate goods. The final-good market, however, is characterized by monopolistic competition. All final-good producers active in time t are indexed by $i = 1, ..., N_t$. Time is discrete and indexed by t. I focus on the final-good producers located in the home market (i.e., China). The exit and entry of firms in the domestic market is treated as endogenous. The labor wage in the manufacturing sector is pinned down by non-manufacturing sector and is normalized to one.

A firm's optimization problem in each period involves (1) the set of countries to source intermediate goods from, (2) how much to source from each market, and (3) how much to charge for each unit of final goods. Throughout the paper, I denote b as the generic set of import sources, $\mathcal{J}$ as the optimal set, and o as the observed set.

3.1.1 Demand

Individuals in country j value the consumption of differentiated varieties of manufactured goods according to a standard symmetric CES aggregator

$$U_{jt} = \left(\int_{\psi \in \Psi_{jt}} q_{jt}(\psi)^{\sigma/(\sigma-1)} d\psi \right)^{\sigma/(\sigma-1)}, \sigma > 1, \tag{1}$$

where Ψ_{jt} is the set of varieties available to consumers in country j in year t, σ is the elasticity of substitution between varieties. These preferences give rise to the following demand for variety ψ

$$q_{jt}(\psi) = p_{jt}(\psi)^{-\sigma} P_{jt}^{\sigma-1} Y_{jt} \tag{2}$$

where $p_{jt}(\psi)$ is the price of variety ψ, P_{jt} is the standard price index, and Y_{jt} is the aggregate expenditure in country j.

3.1.2 Technology and Market Structure

There exists a measure N_t of final-good producers in year t, each produces a single differentiated variety. The final-good market is monopolistically competitive, and I assume that the final-good varieties are non-traded.[16]

[16] In Section 6, I provide an extension of the baseline model in which final goods are also traded. Final-good producers determine the set of countries to purchase inputs and at the same time choose the set of destinations to export outputs. The inclusion of export platforms provides an additional channel for the interdependence across markets.

Production of final goods requires the assembly of a bundle of intermediates, which contains a continuum of measure one of firm-specific inputs. These inputs are imperfect substitutes for each other, with a constant and symmetric elasticity of substitution of ρ. All intermediates are produced with labor under CRS technologies. Let $a_{ikt}(v)$ denote the unit labor required to produce firm i's intermediate v in country k in year t. Also let τ^m_{ikt} be the iceberg trade cost firm i pays to offshore in k, while w_{kt} is the labor wage in country k in year t. Since the intermediate good market is perfectly competitive, a firm will buy from the lowest-price producer for each input v. The price of input v paid by firm i in year t is then

$$z_{it}(v; \mathcal{J}^m_{it}) = \min_{k \in \mathcal{J}^m_{it}} \{\tau^m_{ikt} a_{ikt}(v) w_{kt}\} \tag{3}$$

where $\mathcal{J}^m_{it}$ denotes the set of source countries that firm i imports from in year t. Let φ_{it} denote firm i's productivity in year t. The marginal cost of firm i to produce a final-good variety is

$$c_{it} = \frac{1}{\varphi_{it}} \Big(\int_0^1 z_{it}(v; \mathcal{J}^m_{it})^{1-\rho} dv \Big)^{1/(1-\rho)} \tag{4}$$

As in Eaton and Kortum (2002), the value of $1/a_{ikt}(v)$ is drawn from a Frechet distribution

$$P(a_{ikt}(v) \geq a) = e^{-T_k a^{\theta}}, \quad \text{with } T_k > 0 \tag{5}$$

These draws are assumed to be independent across locations and inputs. T_k governs the state of technology in country k, while θ determines the variability of productivity draws across inputs, (with lower θ generating greater comparative advantage within the range of intermediates across countries).

As discussed in Section 2, persistence in firm-country-specific characteristics can be important for explaining path dependence in firm-level importing behavior. Here I allow for two sources of heterogeneity at the firm-country level in input prices: variable trade costs τ^m_{ijt} and unit labor required to produce an input variety a_{ijt}. It is possible to impose either or both components to be time-invariant. For example, we can assume variable trade costs are constant over time, or that firms get one permanent productivity draw for each input variety in each market. I remain agnostic about the source of heterogeneity. However, each assumption has different implications in equilibrium. Whereas variable trade costs affect the total value a firm imports from each market, input production efficiency determines the price of each input variety and thus from which market the firm would purchase an input variety. Nonetheless, only the distribution of a_{ijt} matters for aggregate imports, as shown in the next section.

3.2 Firm behavior conditional on sourcing strategy

In this section, I describe the firm's decision once it has chosen the sourcing strategy, $\mathcal{J}_{it}^{m}$. Under the Frechet distribution, the share of intermediate input purchases sourced from any country j (including home country) is

$$X_{ijt} = \frac{S_{ijt}}{\Theta_{it}} \tag{6}$$

where $S_{ijt} \equiv T_j(\tau_{ijt}^{m} w_{jt})^{-\theta}$ captures the country j's sourcing potential in year t. The term $\Theta_{it}(\mathcal{J}_{it}^{m}) \equiv \sum_{k \in \mathcal{J}_{it}^{m}} S_{ikt}$ captures the sourcing capacity of firm i in year t. The marginal cost given the firm's sourcing strategy can be rewritten as

$$c_{it}(\mathcal{J}_{it}^{m}) = \frac{1}{\varphi_{it}} \Big(\gamma \Theta_{it}(\mathcal{J}_{it}^{m})\Big)^{-1/\theta} \tag{7}$$

where $\gamma = [\Gamma(\frac{\theta+1-\rho}{\theta})]^{\theta/(1-\rho)}$ and Γ is the gamma function.

The final-good market is monopolistically competitive, and thus, from the demand equation (2) the firm's optimal pricing rule is $p_{it} = \sigma/(\sigma-1)c_{it}$, and the revenue of firm i in its home market in year t is given by

$$r_{it} \equiv p_{it} q_{it} = \left[\frac{\sigma}{\sigma-1} \frac{c_{it}}{P_{ht}}\right]^{1-\sigma} Y_{ht} \tag{8}$$

Plug in equation (7) in to (8), we can rewrite the firm's revenue given its sourcing strategy as

$$r_{it}(\mathcal{J}_{it}^{m}) = \left[\frac{\sigma}{\sigma-1} \frac{1}{\varphi_{it} P_{ht}}\right]^{1-\sigma} Y_{ht} [\gamma \Theta_{it}(\mathcal{J}_{it}^{m})]^{\frac{\sigma-1}{\theta}} \tag{9}$$

As can be seen from equation (7) and the definition of Θ_{it}, adding one location increases the firm's sourcing capacity and reduces its marginal cost, which will increase the firm's revenues. The intuition is similar to Eaton and Kortum (2002): an extra location increases the competition among suppliers and accordingly creates downward pressure on the expected costs for all input varieties. Furthermore, the marginal revenue of a location depends on the sourcing potential of the incumbent import locations. The direction of this relationship relies on the term $(\sigma-1)/\theta$.

To see this point, let $r_{ijt}^{m}(\mathcal{J}_{it}^{m})$ denote the marginal revenue of a country, i.e., the change in total revenue when switching the import status of a market given firm i's sourcing strategy $\mathcal{J}_{it}^{m}$. That is, $r^m_{ijt}(\mathcal{J}^m_{it}) = r_{it}(\mathcal{J}^m_{it}) - r_{it}(\mathcal{J}^m_{it} \cup j)$ if $j \notin \mathcal{J}^m_{it}$ and $r^m_{ijt}(\mathcal{J}^m_{it}) = r_{it}(\mathcal{J}^m_{it}) - r_{it}(\mathcal{J}^m_{it} \setminus j)$ if $i \in \mathcal{J}^m_{it}$. It is straightforward to see that the gain in revenue of adding country j is increasing in the term $\Theta_{it}(\mathcal{J}^m_{it})$ if $(\sigma-1)/\theta > 1$ and decreasing in $\Theta_{it}(\mathcal{J}^m_{it})$ when $(\sigma-1)/\theta < 1$. When $(\sigma-1)/\theta > 1$, the demand is relatively responsive to price reductions and technology is relatively dispersed across markets, making sourcing from an additional source more beneficial–markets are complementary. When $(\sigma-1)/\theta < 1$, i.e., demand is inelastic and technology is similar among input sources, the marginal value of a market decreases with the number of countries and/or the sourcing potential of other countries that a firm imports from. In the knife-edge case when $(\sigma-1)/\theta = 1$, the marginal revenue of a country is unaffected by the sourcing potential of other countries and $\mathcal{J}^m_{it}$–markets are independent.

Interestingly, in the case when $(\sigma-1)/\theta > 1$, the marginal revenue of adding a new source country is larger than the marginal revenue of keeping a country that firm already imports from. That is, all else equal, if $j \in o^m_{it}$, $j' \notin o^m_{it}$, and $S_{ijt} = S_{ij't}$, then $|r^m_{ijt}(o_{it})| < |r^m_{ij't}(o_{it})|$. One the other hand, when countries are substitutes, $|r^m_{ijt}(o_{it})| > |r^m_{ij't}(o_{it})|$. Keeping an existing source has bigger revenue gain than adding a country with the same sourcing potential.

Finally, for every period for which the firm imports from country j it has to pay a fixed cost, denoted by f_{ijt}. If the firm has not imported from market j in year $t-1$, it has to pay an additional sunk cost s_{ijt}.[17] Furthermore, I assume that the fixed and sunk costs have the following structure:

$$\begin{aligned} f_{ijt} &= f^o_{ijt} + \epsilon^f_{ijt}, \\ \mathbb{E}(\epsilon^f_{ijt}|\Omega_{it}, d_{ijt}) &= 0 \end{aligned} \tag{10}$$

and

$$\begin{aligned} s_{ijt} &= s^o_{ijt} + \epsilon^s_{ijt}, \\ \mathbb{E}(\epsilon^s_{ijt}|\Omega_{it}, d_{ijt}) &= 0 \end{aligned} \tag{11}$$

where f^o_{ijt} and s^o_{ijt} are the observable part of the fixed and sunk costs.

Conditional on the firm's import history, b_{it-1}, the static firm-level profit after importing from

[17] I assume the sunk cost advantage fully depreciates after a year. This is a standard assumption in the literature of firm dynamics. However, the framework presented here can be extended to account for longer history dependence.

a set b_{it} sources in year t is

$$\pi_{it}(b_{it}, b_{it-1}) = \sigma^{-1} r_{it}(b_{it}) - f_{it}(b_{it}) - s_{it}(b_{it}, b_{it-1}) \tag{12}$$

where $\sigma^{-1} r_{it}(b_{it})$ is the firm's operating profits. The term $f_{it}(b_{it}) = \sum_{j \in b_{it}} f_{ijt}$ is the sum of fixed cost firm i pays in year t and $s_{it} = \sum_{\substack{j \in b_{it} \\ j \notin b_{it-1}}} s_{ijt}$ is the sum of sunk cost firm i pays to enter new import markets in year t.[18]

Adding an additional source country will increase the firm's sourcing capacity, lower the marginal cost, and hence increase the firm's operating profits. On the other hand, the firm has to pay an extra fixed cost for the additional source country. The trade-off between marginal cost saving and fixed cost reductions is the main tension in AFT.

My model departs from their framework by adding sunk costs, which depends on the firm's past import decisions. This simple addition of the sunk costs indeed will complicate the firm's decision, as now the firm avoids paying sunk costs if it continues importing from last year's source countries. This creates the differentiation between old sources and new sources. In other words, even in the absence of heterogeneity in fixed costs, firms face different costs of importing from different countries due to the heterogeneity in their import history.

As discussed in Section 2, the presence of sunk costs allows us to explain the persistence in import behavior and exploits the differences in firm' histories to account for the heterogeneity in the firm's import strategies. In the next section, I describe the firm's dynamic problem.

3.3 Optimal sourcing strategy

In each period t, firm i chooses a set of import sources, $b_{it} \in B_{it}$, that maximizes its discounted expected profit stream over a planning horizon L_{it}

$$\mathbb{E}[\sum_{\tau=t}^{t+L_{it}} \delta^{\tau-t} \pi_{i\tau}(b_{i\tau}, b_{i\tau-1}) | b_{it}, \Omega_{it}] \tag{13}$$

where B_{it} is the set of all import sources that firm i considers in year t, and Ω_{it} denotes the firm's information set, which includes the firm's past import set b_{it-1}. Finally, δ is the discount factor.

[18] An implicit argument in the firm's static profit is its productivity, φ_{it}, which influences the firm's revenue. I do not include it since the focus of the model is on the firm' import history. However, as in the standard Melitz-styled models, in equilibrium there would be a productivity cutoff for firms to enter each market.

Under Bellman's optimality principle, the optimal set of import sources satisfies:

$$V_{it}(\Omega_{it}) = \max_{b} \overline{\pi}_{it}(b, b_{it-1}) + \delta\mathbb{E}[V_{it+1}(\Omega_{it+1})|b, \Omega_{it}] \tag{14}$$

where $\overline{\pi}_{it}(.)$ is the expected value of equation (12). The choice-specific value function for set b is

$$V_{it}(b, \Omega_{it}) = \overline{\pi}(b, b_{it-1}) + \delta\mathbb{E}[V_{it+1}(\Omega_{it+1})|b, \Omega_{it}].$$

Given this expression, firm i will choose set b over set b' ($b' \neq b$, $b' \in B_{it}$) during period t if

$$V_{it}(b, \Omega_{it}) \geq V_{it}(b', \Omega_{it}) \tag{15}$$

Plug in the expression for the firm's static profits in equation (12). We can rewrite condition (15) in terms of differences in current profits, fixed costs, sunk costs, and future profits as follows

$$\begin{aligned}&\underbrace{\sigma^{-1}\mathbb{E}[r_{it}(b) - r_{it}(b')|\Omega_{it}]}_{(1)} + \underbrace{\{\delta\mathbb{E}[V_{it+1}(\Omega_{it+1})|b, \Omega_{it}] - \delta\mathbb{E}[V_{it+1}(\Omega_{it+1})|b', \Omega_{it}]\}}_{(2)} \\ &\geq \underbrace{\mathbb{E}[\sum_{j\in b} f_{ijt} - \sum_{j\in b'} f_{ijt}|\Omega_{it}]}_{(3)} + \underbrace{\mathbb{E}[\sum_{\substack{j\in b \\ j\notin b_{it-1}}} s_{ijt} - \sum_{\substack{j\in b' \\ j\notin b_{it-1}}} s_{ijt}|\Omega_{it}]}_{(4)}\end{aligned} \tag{16}$$

There are four factors that determine the solution to the firm's dynamic problem. The firm balances current and expected future profit gains, captured by the first, and second terms with fixed and sunk cost saving, captured by the last two terms. The addition of the country-specific sunk costs adds an inter-temporal link between last year's sourcing strategy and this year's sourcing strategy.

Whether the dynamic problem implies an increase or decrease in the value of sourcing compared to the static problem is unclear. In a static environment, when sourcing from a new market, the firm benefits from marginal cost reductions and thus increased current variable profits, but pays an additional fixed cost. In a dynamic setting, it also incurs the startup cost of importing from the new market, but at the same time reduces expected future costs. The dynamic solution may differ from a static one, depending on the size of sunk costs, discount factor, and the expected profit gains from adding a new source.

4 Estimation Approach

Estimating the firm's optimization problem described in equation (13) is challenging for a few reasons. The interdependence across input sources gives rise to a combinatorial problem since researchers have to evaluate every possible combination of countries instead of analyzing them separately. Thus, even when we restrict the analysis to a small number of countries, the number of potential choices is enormous and evaluating every choice is computationally infeasible.[19] One approach in the literature to deal with combinatorial problems applies results from lattice theory to eliminate unlikely choices (Jia, 2008; Antràs et al., 2017; Arkolakis & Eckert, 2017). The method essentially relies on the single crossing differences of the return function, i.e. the marginal value of a source country is monotone increasing/decreasing in the number of other countries the firm also sources from.

This approach, however, has only been applied to static settings and unsuitable for solving dynamic problems. In a static setting, usually there is a closed-form solution for the return function, which facilitates the verification of the single crossing differences property. It is not straightforward to prove the existence of a monotonic relationship between the value of a source and the number of sources when accounting for the dynamic implications of changing the size of a firm's import set. Furthermore, the initial stage of eliminating choices would require evaluation of two value functions for every single choice, hence undermining the method's capacity to reduce computational complexity in a dynamic problem.

Additionally, even if computational feasibility is not a constraint, point identification of the structural parameters would require strong assumptions on the firm's optimization behavior, which unavoidably reduces the credibility of inference (Manski, 2003). With the exception of MSZ 2019, most entry models in international trade settings have point identified structural parameters by specifying a planning horizon L_{it}, imposing the exact content of the information set Ω_{it}, the set of countries that a firm considers every period B_{it}, and imposing strong parametric assumptions on the unobserved components in the profit function.[20]

For these reasons, I pursue a partial identification approach that both reduces the computational

[19]Keeping the number of countries at 40 requires evaluation of 1.1×10^{12} choices.

[20]Indeed, MSZ show that misspecifications of model elements such as planning horizons, consideration sets, and information set lead to bias in their estimates.

burden and only requires mild assumptions on the firm's behavior.[21] Essentially, I assume that the firm's observed decision is optimal, given its information set. This implies that any deviation from the firm's observed path would reduce its stream of expected profits. The differences between the observed and counterfactual profits identify lower and upper bounds for the fixed and sunk cost parameters. While the total number of possible choices a firm faces in each period is 2^J with J markets, it is sufficient to consider only J deviations.[22]

Below, I describe the necessary identification assumptions and provide examples to illustrate how to identify the fixed and sunk costs.

4.1 Revealed Preferences Assumption

Assumption 1. *(Revealed preferences): Let o_{it}^m be firm i's observed import set in year t. Then o_{it}^m is the solution to*

$$\max_{b \in B_{it}} \mathbb{E}[\pi_{it}(b, b_{it-1}) + \sum_{l=1}^{L_{it}} \delta^l \pi_{it+l}(\mathcal{J}_{it+l}(b), \mathcal{J}_{it+l-1}(b)) | \Omega_{it}] \tag{17}$$

where $\mathcal{J}_{it+l}(b)$ denotes the optimal set in year $t+l$ given that it chooses set b in year t.

Essentially, Assumption 1 states a firm's observed import decision in year t is optimal given its current information set. A direct implication of the assumption is that any deviation from the observed path would decrease its expected profits.

Formally, let $\Pi_{ibt} \equiv \pi_{it}(b, o_{it-1}) + \sum_{l=1}^{L_{it}} \delta^l \pi_{it+l}(\mathcal{J}_{it+l}(b), \mathcal{J}_{it+l-1}(b))$ be the discounted sum of profits if the firm chooses b in year t. Let $\Pi_{io_{it}t} \equiv \pi_{it}(o_{it}, o_{it-1}) + \sum_{l=1}^{L_{it}} \delta^l \pi_{it+l}(\mathcal{J}_{it+l}(o_{it}), \mathcal{J}_{it+l-1}(o_{it}))$. Then, $\forall b \in B_{it}$, we should have $\mathbb{E}(\Pi_{io_{it}t}|\Omega_{it}) \geq \mathbb{E}(\Pi_{ibt}|\Omega_{it})$.[23] By definition of $\mathcal{J}_{it+l}(b)$, it follows that $\mathbb{E}(\Pi_{ibt}|\Omega_{it}) \geq \mathbb{E}(\pi_{it}(b, b_{it-1}) + \sum_{l=1}^{L_{it}} \delta^l \pi_{it+l}(\mathcal{J}_{it+l}(o_{it}), \mathcal{J}_{it+l-1}(o_{it}))|\Omega_{it})$ since the second expectation is over the profits of the firm if it would choose b in year t but in the subsequent periods act as if it

[21] One main disadvantage of this method is that it is unable to perform counterfactual experiments due to the multiplicity of admissable parameter values and unidentified distribution of the unobservables. However, Li (2019) develops a method to conduct counterfactual analysis under certain assumptions on the unobservables. In a different paper, Christensen and Connault (2019) provide sensitivity tests for counterfactual results around a neighborhood of the unobservables' distribution.

[22] Obviously, there are $2^J - 1$ possible deviations, but researchers can determine how many and which set of deviations to analyze. This creates a trade-off between efficiency and computational feasibility. A larger number of deviations gives us tighter bounds, but requires more computing power.

[23] Note that we keep the same import history on both sides of the inequality. If we also allow for the decision in year $t-1$ to be differ from the observed path, the inequality is no longer valid.

had chosen o_{it} instead. By transitivity of preferences,

$$\begin{aligned}
&\mathbb{E}(\Pi_{io_{it}t}|\Omega_{it}) \\
&= \mathbb{E}(\pi_{it}(o_{it}, o_{it-1}) + \sum_{l=1}^{L_{it}} \delta^l \pi_{it+l}(\mathcal{J}_{it+l}(o_{it}), \mathcal{J}_{it+l-1}(o_{it}))|\Omega_{it}) \\
&\geq \mathbb{E}(\pi_{it}(b, o_{it-1}) + \sum_{l=1}^{L_{it}} \delta^l \pi_{it+l}(\mathcal{J}_{it+l}(o_{it}), \mathcal{J}_{it+l-1}(o_{it}))|\Omega_{it})
\end{aligned} \tag{18}$$

Due to the one-period dependency of π_{it}, static profits for years $t+l$ where $l \geq 2$ will be the same on both sides of the inequalities. Thus, $\forall b \in B_{it}$, equation (18) is reduced to

$$\mathbb{E}(\pi_{it}(o_{it}, o_{it-1}) + \delta\pi_{it+l}(\mathcal{J}_{it+l}(o_{it}), \mathcal{J}_{it+l-1}(o_{it}))|\Omega_{it}) \geq \mathbb{E}(\pi_{it}(b, o_{it-1}) + \delta\pi_{it+l}(\mathcal{J}_{it+1}(o_{it})), b)|\Omega_{it}) \tag{19}$$

Equation (19) is important for several reasons. First, it shows how the firm's dynamic problem can be reduced to the comparison of static profits for two periods. This substantially decreases the computational burden when estimating the fixed and sunk cost parameters. Second, it does not require strict assumptions on the firm's planning horizon L_{it} or the firm's consideration set B_{it}.[24]

Note that inequality above is conditional on the information set of the firm, Ω_{it}. To bring this to the data, researchers often need to fully specify the information set and/or assume full distributions for the unobserved error terms. Furthermore, using conditional moments implies that the number of potential inequalities is generally large. Instead, I use a set of instrumental variables, Z_{it}, to construct unconditional moment inequalities from equation (19). The transformation from conditional to unconditional moments may lead to a loss of information. However, this is a trade-off between efficiency and computational feasibility that researchers have to make.

I further assume that firm has knowledge about the set of instruments, i.e., $Z_{it} \in \Omega_{it}$. To simplify notation, let

$$\pi_{idt} = [\pi_{it}(o_{it}, o_{it-1}) - \pi_{it}(b, o_{it-1})] + \delta[\pi_{it+l}(\mathcal{J}_{it+l}(o_{it}), \mathcal{J}_{it+l-1}(o_{it})) - \pi_{it+l}(\mathcal{J}_{it+1}(o_{it})), b)]$$

be the difference between the observed profits and the profits under the alternative choice b. Let

[24]The required assumptions are that $L_{it} \geq 1$ and the consideration set B_{it} includes firm i's observed choice and the one-period deviations that are used to identify the bounds for fixed and sunk costs.

$g_k(.)$ be a non-negative function. Then

$$\begin{aligned}\mathbb{E}[g_k(Z_{it})\pi_{idt}] &= \mathbb{E}[\mathbb{E}g_k(Z_{it})\pi_{idt}|Z_{it}] \\ &= \mathbb{E}[g_k(Z_{it})\mathbb{E}\pi_{idt}|Z_{it}] \\ &= \mathbb{E}[(g_k(Z_{it})\mathbb{E}[\underbrace{\mathbb{E}(\pi_{idt}|\Omega_{it})}_{\geq 0 \text{ (from eq. (19))}} |Z_{it}] \\ &\geq 0\end{aligned} \tag{20}$$

where the first and third equalities follow by applying the law of iterated expectations. The term $g_k(Z_{it})$ serves as the bridge between the conditional and unconditional moments. Except that $g_k(.)$ is required to be non-negative to preserve the sign of the conditional moment inequalities, there are few restrictions on its functional form. Different functions g_k will generate different moments.

The sample analog of the inequality (20) is

$$\bar{m}_k = \frac{1}{N}\sum_{i\in N_i}\sum_{j\in J}\sum_{t\in T} g_k(Z_{it})\pi_{idt} \geq 0 \tag{21}$$

where $N = N_t \times J \times T$.

The next section provides examples of the moment function g_k and deviations that will generate the profit difference π_{idt}.

4.2 Deriving Moment Inequalities: Intuition

Following MSZ 2019, I apply a discrete analogue of Euler's perturbation method to derive moment inequalities: I compare the stream of profits along a firm's observed sequence of import sets with the stream along alternative sequences that differ from the observed import path in just one period. More specifically, I switch the import status for each firm-country-year pair one-by-one while keeping the firm's import decisions in other years and in other markets intact. The number of deviations for each firm in a year is then equal to the number of potential import countries.

Consider a simple example illustrated by the figure below. There are four countries: A, B, C, and D. The top panel presents a firm's observed import decisions in each country for three consecutive years. In year t, this firm imports from countries A and C, but not countries B and D., i.e. $o^m_{it} = (A, B)$. The bottom panel shows how we can create four alternate paths in year t by switching the firm's import status in each country one-by-one. Its import decisions in years $t-1$ and $t+1$ are unchanged, however. This procedure is repeated for every year that I observe both the firm's past and future import decisions.

Observed import path				
Year	**A**	**B**	**C**	**D**
$t-1$	1	0	1	0
t	1	1	0	0
$t+1$	0	0	0	0
Alternate strategy in year t				
Deviation 1	0	1	0	0
Deviation 2	1	0	0	0
Deviation 3	1	1	1	0
Deviation 4	1	1	0	1

As shown in Section 4.1, the difference in the discounted sum of profits generated by the observed and alternative paths depends only on the difference in static profits in years t and $t+1$. In this example, since this firm does not import in year $t+1$, there is no change in the static profit year $t+1$.

Assume $f_{ijt} = \gamma_o^f + \epsilon_{ijt}^f$ and $s_{ijt} = \gamma_o^s + \epsilon_{ijt}^s$. The profit difference, π_{idt} under each alternative path is

$$\text{Deviation 1}: \pi_{idt} = \sigma^{-1}[r_{it}(o_{it}^m) - r_{it}(o_{it}^m \setminus j)] - \gamma^f - \epsilon_{ijt}^f$$

$$\text{Deviation 2}: \pi_{idt} = \sigma^{-1}[r_{it}(o_{it}^m) - r_{it}(o_{it}^m \setminus j)] - \gamma^f - \epsilon_{ijt}^f - \gamma^s - \epsilon_{ijt}^s$$

$$\text{Deviation 3}: \pi_{idt} = \sigma^{-1}[r_{it}(o_{it}^m) - r_{it}(o_{it}^m \cup j)] + \gamma^f + \epsilon_{ijt}^f$$

$$\text{Deviation 4}: \pi_{idt} = \sigma^{-1}[r_{it}(o_{it}^m) - r_{it}(o_{it}^m \cup j)] + \gamma^f + \epsilon_{ijt}^f + \gamma^s + \epsilon_{ijt}^s$$

Next, to create the moment inequalities in the form of equation (20), I use the following four moment functions g_1 to g_4:

$$g_1(Z_{it}) = \mathbb{1}(d_{ijt} = 1, d_{ijt-1} = 1)$$
$$g_2(Z_{it}) = \mathbb{1}(d_{ijt} = 1, d_{ijt-1} = 0)$$
$$g_3(Z_{it}) = \mathbb{1}(d_{ijt} = 0, d_{ijt-1} = 1)$$
$$g_4(Z_{it}) = \mathbb{1}(d_{ijt} = 0, d_{ijt-1} = 0)$$

where $g_1(Z_{it}) = \mathbb{1}(d_{ijt} = 1, d_{ijt-1} = 1)$ is an indicator function that takes value of one firm i continues to import from country j in year t. When $g_k(Z_{it}) = g_1(Z_{it})$, equation (20) is equal to

$$\begin{aligned} \mathbb{E}[g_1(Z_{it})\pi_{idt}] &= \mathbb{E}[g_1(Z_{it})(\sigma^{-1}r^m_{ijt} - \gamma^f - \epsilon^f_{ijt})] \\ &= \mathbb{E}[g_1(Z_{it})(\sigma^{-1}r^m_{ijt} - \gamma^f)] \\ &\geq 0 \end{aligned} \tag{22}$$

The second equality holds under the assumption that $\mathbb{E}(\epsilon^f_{ijt}|\Omega_{it}, d_{ijt}) = 0$.[25] Rearranging the terms, we can identify the upper bound for γ^f:

$$\gamma^f \leq \frac{\mathbb{E}[g_1(Z_{it})(\sigma^{-1}r^m_{ijt})]}{\mathbb{E}[g_1(Z_{it})]}$$

By similar logic, when $g_k(Z_{it}) = g_2(Z_{it}) = \mathbb{1}(d_{ijt} = 1, d_{ijt-1} = 0)$, we have

$$\begin{aligned} \mathbb{E}[g_2(Z_{it})\pi_{idt}] &= \mathbb{E}[g_2(Z_{it})(\sigma^{-1}r^m_{ijt} - \gamma^f - \epsilon^f_{ijt} - \gamma^s - \epsilon^s_{ijt})] \\ &= \mathbb{E}[g_2(Z_{it})(\sigma^{-1}r^m_{ijt} - \gamma^f - \gamma^s)] \\ &\geq 0 \end{aligned} \tag{23}$$

As before, the second equality is due to $\mathbb{E}(\epsilon^f_{ijt}|\Omega_{it}, d_{it}) = 0$ and $\mathbb{E}(\epsilon^s_{ijt}|\Omega_{it}, d_{ijt}) = 0$. Therefore,

$$\gamma^f + \gamma^s \leq \frac{\mathbb{E}[g_2(Z_{it})(\sigma^{-1}r^m_{ijt})]}{\mathbb{E}[g_2(Z_{it})]}$$

This time γ^s appears as firm i does not import to j in year $t-1$ and thus has to pay the sunk entry cost. The previous two examples provide upper bounds for γ^f and γ^s. When $d_{ijt} = 0$, we can create

[25] A detailed proof is provided in the Appendix.

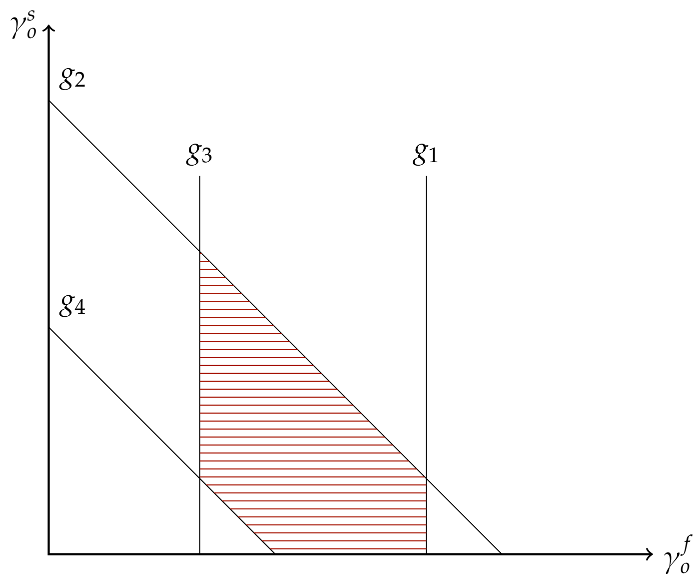


Figure 1: Identified set with nonnegativity constraints

moment inequalities that identify the lower bounds for these parameters. To be more specific,

$$\gamma^f \geq \frac{\mathbb{E}[g_3(Z_{it})(\sigma^{-1}r^m_{ijt})]}{\mathbb{E}[g_3(Z_{it})]}$$

when $g_k(Z_{it}) = g_3(Z_{it}) = \mathbb{1}(d_{ijt} = 0, d_{ijt-1} = 1)$ and

$$\gamma^f + \gamma^s \geq \frac{\mathbb{E}[g_4(Z_{it})(\sigma^{-1}r^m_{ijt})]}{\mathbb{E}[g_4(Z_{it})]}$$

when $g_k(Z_{it}) = g_4(Z_{it}) = \mathbb{1}(d_{ijt} = 0, d_{ijt-1} = 0)$.

Figure 1 illustrates the identified set from the four moments above with the additional nonnegativity restrictions on the parameters (i.e., $\gamma_o^f, \gamma_o^s \geq 0$). As each moment is linear in parameters, the identified set is an intersection of linear half-spaces, and the bounds for each parameter are defined by the extreme points of the identified set. Intuitively, the bounds for fixed costs are identified using firms that import from a country in year $t-1$ (moments 1 and 3), and the bounds for both fixed and sunk cost are identified using firms that did not import from a country in $t-1$ (moments 2 and 4). When adding a country that the firm does not presently import from (moments 3 and 4), we identify the lower bounds, and when dropping a country that the firm indeed imports from (moments 1 and 2), we identify the upper bounds.

We can think of the moment functions $g_k(Z_{it})$ as assigning weights to different observations.

With the g_k being indicator functions, each observation has a weight of either 0 or 1. However, it is reasonable to assume that bigger firms have better information (Dickstein & Morales, 2018), and thus we might want to put more weight on these observations. We can modify the functions g_1 to g_4 as

$$g_1'(Z_{it}) = \mathbb{1}(d_{ijt} = 1, d_{ijt-1} = 1)l_{i0}$$

$$g_2'(Z_{it}) = \mathbb{1}(d_{ijt} = 1, d_{ijt-1} = 0)l_{i0}$$

$$g_3'(Z_{it}) = \mathbb{1}(d_{ijt} = 0, d_{ijt-1} = 1)l_{i0}$$

$$g_4'(Z_{it}) = \mathbb{1}(d_{ijt} = 0, d_{ijt-1} = 0)l_{i0}$$

where l_{i0} is some measure of the firm's size in the initial year.

5 Estimation Procedure and Results

The estimation procedure consists of two steps. In the first step, I compute the predicted changes in operating profits when adding or dropping a sourcing location based on equation (9). In the second step, I estimate the bounds and conduct inference for the fixed and sunk cost parameters.

5.1 Step 1: Profit differences

A crucial step in estimating the bounds for the fixed and sunk costs is to identify the difference in operating profits each time we deviate from the observed import decisions. Let $r^m_{ijt}(o^m_{it})$ denote the marginal revenue of country j at firm i's observed set o^m_{it} in year t. That is, $r^m_{ijt}(o^m_{it})$ captures the change in total revenues induced by switching the status of firm i in country j at time t . The change in operating profit is simply $\sigma^{-1} r^m_{ijt}(o^m_{it})$.

To estimate r_{ijt}, note that from equation (9), we can express this quantity as

$$r^m_{ijt}(o^m_{it}) = \begin{cases} \left[1 - \left((\sum_{k \in o^m_{it}} S_{ikt} + S_{ijt}) / (\sum_{k \in o^m_{it}} S_{ikt}) \right)^{\frac{\sigma-1}{\theta}} \right] r_{iht}(o^m_{it}) & \text{if } j \notin o^m_{it} \\ \left[1 - \left((\sum_{k \in o^m_{it}} S_{ikt} - S_{ijt}) / (\sum_{k \in o^m_{it}} S_{ikt}) \right)^{\frac{\sigma-1}{\theta}} \right] r_{iht}(o^m_{it}) & \text{if } j \in o^m_{it} \end{cases}$$

This quantity depends on (1) total revenues at the observed import set, $r_{iht}(o^m_{it})$, which are directly recovered from data (2) elasticity of substitution σ (3) dispersion of technology θ (4) and firm-country-year-specific sourcing potential S_{ijt}.

First, with the CES preferences and monopolistic competition, the ratio of sales to variable input purchases (or markup) is $\sigma/(\sigma-1)$. The average mark-up is 33 percent, which implies that the elasticity of substitution, σ, is about 4.02. This value is well in the range that have been found in previous studies.[26]

Next, to estimate the dispersion of technology, θ, and firm-country-year specific sourcing potential, S_{ijt}, I follow a modified version of the estimation procedure in AFT.

Specifically, from the share of imported intermediate inputs equation (6), we get

$$X_{ijt}/X_{iht} = S_{ijt}/S_{iht}. \tag{24}$$

I assume that $S_{iht} = S_{ht}$, that is, the domestic sourcing potential is constant across firms in a year, but varies over time. Taking log on both sides of equation (24)

$$\log X_{ijt} - \log X_{iht} = \log S_{ijt} - \log S_{ht} + \epsilon^x_{ijt} \tag{25}$$

where ϵ^x_{ijt} is some unobserved firm-country-year-specific shock, assumed to be mean independent of the countries' sourcing potential. This term can also be considered as measurement error in the observed values of imported input shares. The firm-country-year sourcing potential and shocks together are the residuals after regressing the dependent variable on a set of year fixed effects, which capture the time-varying domestic sourcing potential S_{ht}.[27] To get predicted values of S_{ijt}, I face two issues. First, it is impossible to separately identify $\log S_{ijt}$ from ϵ^x_{ijt}.[28] Second, the sparsity of the import data at firm-country-year level means I cannot recover S_{ijt} for all possible pairs from equation (25).

To address these problems, I employ the definition of the firm-country-year-specific sourcing potential, i.e. $S_{ijt} = T_j(\tau^m_{ijt} w_{jt})^{-\theta}$, in combination with the information from equation (25) to recover the predicted values of the sourcing potential. Let $\hat{\lambda}_t$ denote the estimated domestic sourcing potential for each year t, and $\hat{\xi}_{ijt} = (\log X_{ijt} - \log X_{iht}) - \hat{\lambda}_t$ is the composite residual term

[26] See, for example, Simonovska and Waugh (2014) and Donaldson (2018).

[27] An implicit assumption to get unbiased estimates of $\log S_{ht}$ is that S_{ijt} is uncorrelated with S_{ht}.

[28] One can make a simplifying assumption that $S_{ijt} = S_{jt}$, meaning the sourcing potential is constant across firms. Nonetheless, under this approach we will not be able to separately identify those terms from the domestic sourcing potential S_{ht}, unless we further assume that S_{ht} is constant across time and normalize this term to unity. In addition, the ability of sourcing potential to vary at firm-country-specific level is consistent with the data patterns in Table 2.

from equation (25). I then regress that residual terms $\hat{\xi}_{ijt}$ on proxies for technology T_j, wage rates w_{jt}, and variable trade costs τ^m_{ijt}.

$$\hat{\xi}_{ijt} = \beta_0 + g(X^T_{jt}\beta^T) - \theta h(X^\tau_{ijt}\beta^\tau) - \theta \ln w_{jt} + \lambda_t + \nu_{ijt} \tag{26}$$

where X^T_{jt} is a set of technology proxies, including R&D expenditure and capital stock. X^τ_{ijt} is a set of controls to proxy for variable trade costs, which includes the firm's ownership type and size, distance, GDP, common language, contiguity, whether the country is landlocked, and GATT/WTO membership. g and h are two non-parametric functions to allow for flexible estimation of technology and trade costs. $\ln w_{jt}$ is the log of human capital-adjusted hourly wages.[29] In the final specification, I also include a set of years fixed effects, λ_t, to account for anytime time-varying factors that are common across firms that can influence the trade elasticity (θ).

By definition, the term ξ_{ijt} contains both the sourcing potential and the unobserved component, i.e., $\xi_{ijt} = \log S_{ijt} + \epsilon^x_{ijt}$. However, under the assumption that ϵ^x_{ijt} is uncorrelated with $\log S_{ijt}$, it will not bias the estimates of β^T, β^τ and θ, though it will increase standard errors.[30] As a result, I can recover the values of sourcing potential for each firm-country-year pair as the predicted values in equation (26).

The last component in the revenue change is θ, which is the coefficient on log wages in (26). Column 1 in table 5 reports the OLS results. In column 2, I follow AFT and instrument log wages with population to account for unobserved factors that are correlated with countries' productivity. The IV specification implies that θ is about 1.99. The estimated values of θ and σ confirms that input sources are complementary in production as in AFT.[31]

At this point, I have computed all components to predict the change in total revenues for each deviation from the observed import path. Results are shown in Table 6. Several noteworthy patterns emerge. First, with respect to the types of countries firms choose to import from, it seems that new import markets tend to have higher sourcing potential (3.10) compared to markets firms already have experience with (2.65), whereas firms exit markets with the lowest sourcing potential (1.43).[32] This is consistent with the sunk cost hypothesis: new importers justify incurring sunk

[29] See the Appendix for a detailed description of the construction of HC-adjusted wage rates.

[30] These terms can be interpreted as either measurement error or expectational errors. As long as firms do not observe the shocks before choosing a sourcing strategy, these terms will not bias our estimates in equation (26).

[31] $(\sigma - 1)/\theta = 1.52 > 1$.

[32] Recall that sourcing potential is a combination of technology, trade costs, and wages, and loosely captures the

Table 5: Predicting sourcing potential

	OLS	IV
	(1)	(2)
log hourly wage	-0.277***	-1.989***
	(0.0643)	(0.486)
log R&D	-0.0396	0.645***
	(0.0469)	(0.198)
log k	-0.00183***	0.00518***
	(0.000383)	(0.00201)
Landlocked	-0.574***	0.241
	(0.161)	(0.283)
GDP	0.0663***	0.255***
	(0.0145)	(0.0551)
log distance	-0.692***	-0.244*
	(0.0449)	(0.134)
Observations	9341	9341
Adjusted R^2	0.114	0.047

This table reports regression results for equation (26) in Section 5. Column 1 shows OLS coefficients while column 2 shows results when the variable log hourly wage is instrumented by log population. Other variables are listed in the main text. Sample includes the top 40 popular source countries.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

entry costs by importing from high-technology low-cost suppliers, whereas firms exit high-cost markets despite already incurring the entry costs.

Interestingly, the rate of marginal cost saving is similar for new importers and those that never import: each market saves about 2.3-2.6% of total revenues. For exiting and continuing importers, the rate of marginal cost saving is about 1.1 to 1.5%. Regardless, the absolute revenue gain is highest for a new importer: adding a new source brings about 8 mil RMB, followed by a continued source with 6.6 mil RMB. For exiting importers and firms that never import, adding a new source increases revenue by about 2.5 and 3.6 mil RMB. Here we see the interaction between the scale and substitution effects: continuing importers already have high sourcing capacity (i.e., they already import from low-cost suppliers) and thus have a lower rate of marginal cost saving (substitution effect). However, their large scale of operation leads to large absolute gain of each individual import source (scale effect). On the other hand, new importers tend to be smaller in size but the

marginal cost saving contribution. Higher sourcing potential reflects lower cost.

marginal cost saving is large, resulting in large absolute revenue gains.

Table 6: Results from Step 1

	(1) All	(2) Never	(3) Exiting	(4) New	(5) Continuing
Total revenue	239.2	179.6	344.9	387.6	504.9
	(386.4)	(298.4)	(478.3)	(520.1)	(594.5)
Rate of MC saving	0.0243	0.0262	0.0113	0.0226	0.0150
	(0.0655)	(0.0708)	(0.0221)	(0.0565)	(0.0316)
Marginal revenue	4.442	3.660	2.475	7.998	6.651
	(20.25)	(16.93)	(6.446)	(36.54)	(20.87)
Marginal profit	1.104	0.910	0.615	1.988	1.653
	(5.034)	(4.208)	(1.602)	(9.083)	(5.188)
Sourcing potential	2.682	2.627	1.439	3.106	2.650
	(7.188)	(6.669)	(3.573)	(10.05)	(7.270)
Sourcing capacity	179.6	161.7	181.2	203.7	268.5
	(76.56)	(24.52)	(42.84)	(97.96)	(161.6)
N	42994	31128	615	4612	4312

This table reports the average effects of changing sourcing strategies on firm-level total revenues and the average sourcing potential and sourcing capacity. Each firm-country-year pair is categorized into one of four types based on the firm's import status in each market. Monetary values are in million of 1998 RMB. Sample includes the top 40 popular source countries.

Standard errors in parentheses

5.2 Step 2: Fixed and Sunk Costs

To estimate the bounds for the fixed and sunk costs, I first assume that these terms have following functional forms: $f_{ijt} = \gamma_o^f + \gamma^f \cdot X_j + \epsilon_{ijt}^f$ and $s_{ijt} = \gamma_o^s + \gamma^s \cdot X_j + \epsilon_{ijt}^s$, where X_j is a vector of country characteristics. Let $\gamma = (\gamma_o^f, \gamma^f, \gamma_o^s, \gamma^s)$ collect the fixed and sunk cost parameters. As the bounds for each element in γ become larger with the dimension of γ, I choose a parsimonious specification for the fixed and sunk costs. Specifically, to capture distance between China and country j, I use a dummy variable, $Border_j$, that equals 1 if the two countries do not share a border. I also include the binary variable $Language_j$ where $Language_j = 1$ if China and country j do not share the same language.

I compute the 95% confidence set for γ using the general moment selection method developed by Andrews and Soares (2010). Specifically, I employ the modified method of moment test statistics:

$$Q_n(\gamma) = \sum_{k=1}^{K} [\bar{m}_k(\gamma)/\hat{\sigma}_k(\gamma)]_-^2$$

where $[x]_- = \min\{0, x\}$ and $m_k(\gamma)$ is the sample analoge of the moment inequalities defined in Section 4, and $\hat{\sigma}_k(\gamma)$ is the standard deviation of the observations entering moment k.

Table 7 reports the 95% confidence sets for linear combinations of the fixed and sunk cost parameters under three different specifications. In the first specification, I include a constant term for both the fixed and sunk costs. Note that this does not imply that fixed and sunk costs are homogeneous across firm-country-year triplets, as I allow for the unobserved components of fixed and sunk costs, ϵ_{ijt}^f and ϵ_{ijt}^s, to be different from zero and heterogenous across firm-year-country triplets. In the next two specifications, I include the country characteristics to proxy for distance and common language.

Table 7a shows that if a firm has import experience in country j, it pays a fixed cost of 0.52 to 1.80 mil. RMB to continue importing from the same location, equivalent of 7.81% to 27.06% of average marginal revenue. For a new importer, the total fixed and sunk costs ranges from 1.03 to 3.18 mil RMB, or 12.87% to 39.75% of average marginal revenue. This amount is consistent across specifications, between 1.13 to 3.18 mil. in the second specification and 1.51 and 3.52 mil. in the last specification. Even though zero is often the lower bound of individual parameters, jointly they are always significantly different from zero. Figure 2 shows the 95 % confidence set projections of the total costs to continuing versus new importers when they import from a market that does not share either language or border with China. The costs to a new importer are always positive, even when fixed cost is zero.

Table 7: 95% confidence sets for fixed and sunk costs

(a) Specification 1

	LB	**UB**
Constant (fixed)	0.52	1.80
Constant (sunk)	0.00	2.23
Total	1.03	3.18

(b) Specification 2

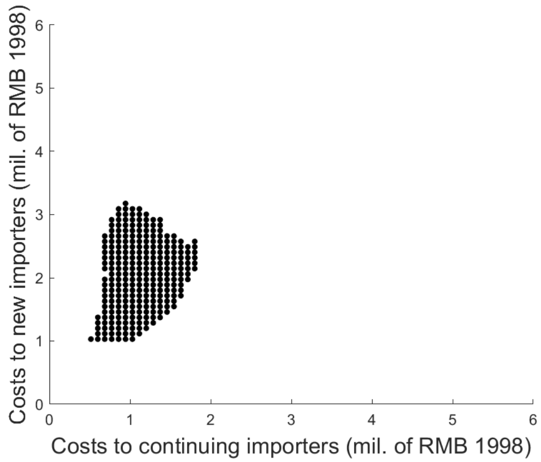
	LB	**UB**
Constant (fixed)	0.00	1.82
Language (fixed)	0.00	1.59
Constant (sunk)	0.00	3.18
Language (sunk)	0.00	2.50
Total	1.13	3.18

(c) Specification 3

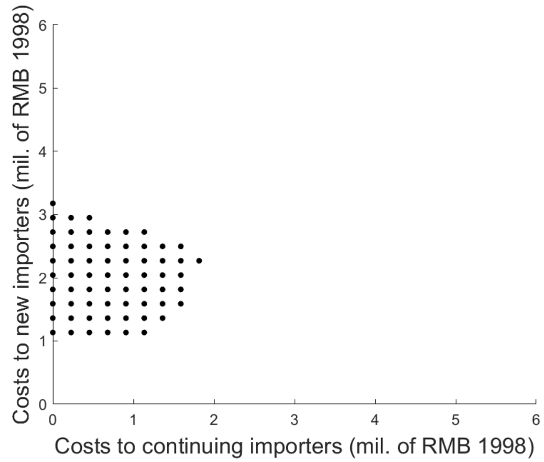
	LB	**UB**
Constant (fixed)	0.00	1.51
Language (fixed)	0.00	1.51
Border (fixed)	0.00	1.51
Constant (sunk)	0.00	3.02
Language (sunk)	0.00	3.02
Border (sunk)	0.00	2.52
Total	1.51	3.52

This table reports the projected confidence interval for each parameter using the general moment selection method in Andrews and Soares (2010). The first column reports the lower bounds and the second column reports the upper bound. For each specification, the total row presents the sum of the fixed and sunk costs. The discount factor δ is set to 0.9. Monetary values are in million of 1998 RMB.

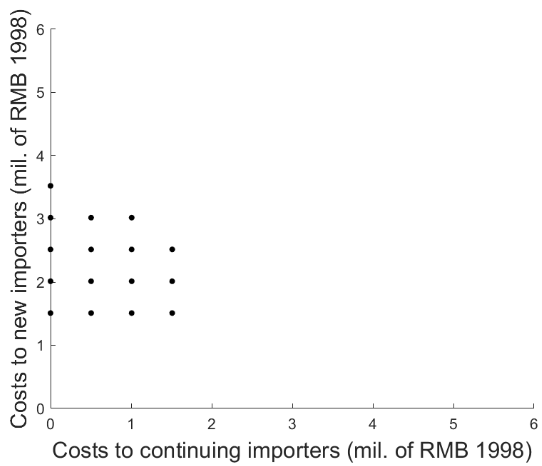
Figure 2: Importing costs for continuing versus new importers



(a) Specification 1



(b) Specification 2



(c) Specification 3

This figure illustrates the 95% confidence sets of the total costs to continuing versus new importers for three specifications. The total costs are defined as the costs firms pay if the foreign market not share the same language and/or border with the home market. Monetary values are in million of 1998 RMB.

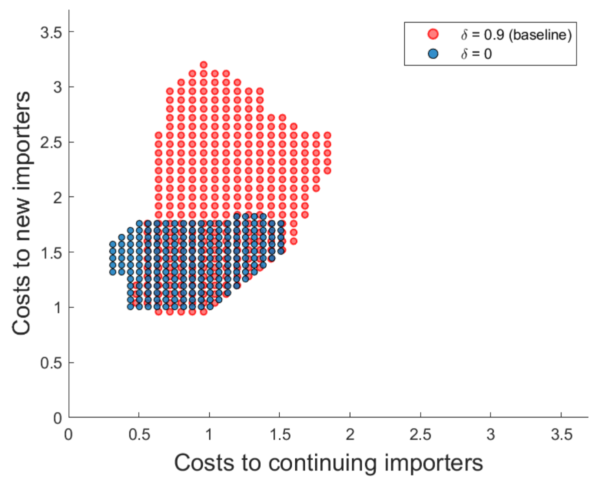


Figure 3: Comparing baseline with static model

This figure compares the 95% confidence sets in the baseline model (discount factor $\delta = 0.9$) versus a model in which firms are not forward looking (discount factor $\delta = 0$). Monetary values are in million of 1998 RMB.

5.3 Comparison with alternative model assumptions

In this section I compare the baseline results of fixed and sunk costs with those under different model assumptions. First, I estimate a model in which firms are not forward looking by setting the discount factor to zero. Figure 3 illustrates the comparison for the first specification. The results indicate that under the assumption that firms do not consider effects on future revenues, the sunk cost decreases substantially. This is consistent with the notion that when firms take into account the future profit gains of importing, they are willing to incur bigger costs to import. Not accounting for dynamic gains is thus likely to create downward bias in the sunk cost estimates.

Next, I estimate a model when countries are either independent or substitute for each other. Recall that the direction of interdependence depends on the values of the elasticity of demand σ and technology dispersion θ. Since σ affects the estimate through both the interdependence and markup, I keep σ at the baseline estimate but alter the value of θ. Specifically, to simulate an independent scenario, I set $\theta = 3.02$ so that $(\sigma - 1)/\theta = 1$. To create the substitute scenario, I fix $\theta = 6.04$ and $(\sigma - 1)/\theta = 0.5$.

Figure 4 shows that as θ increases, the estimates for both fixed and sunk costs decrease. The reason is that when there is less dispersion of technology across inputs (i.e., higher θ), the benefit of an additional draw becomes smaller since the probability firms will find a lower-cost supplier

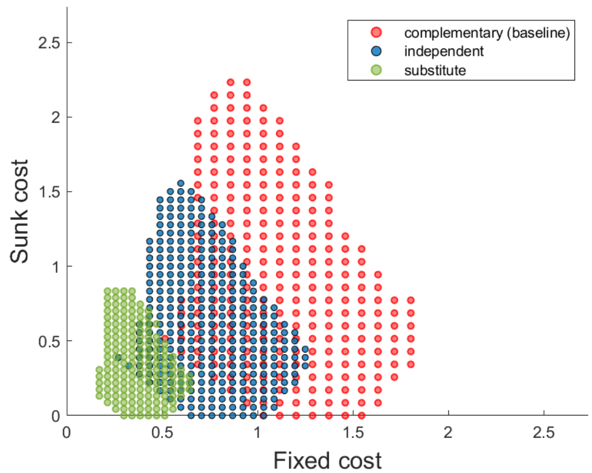


Figure 4: Independence across markets and fixed and sunk cost estimates

This figure compares the 95% confidence sets in the baseline model (countries are complementary, i.e., $(\sigma-1)/\theta = 1.52$) versus models in which countries are independent $(\sigma-1)/\theta = 1$, or substitute $(\sigma-1)/\theta = 0.5$. Monetary values are in million of 1998 RMB.

is reduced. This leads to lower marginal revenue from a given import source, thus generating smaller fixed and sunk cost estimates. We can intuitively anticipate that as countries become close to perfect substitutes, i.e. $(\sigma-1)/\theta$ converges to 0, the confidence set for fixed and sunk costs collapses. The intuition is that when countries are perfect substitutes, firms gain no additional revenue gain from sourcing from more than one market (including the domestic market). Thus, if they choose to import, it must mean that firms are indifferent between importing and not importing, and that the fixed and sunk costs should be close to zero.[33]

Nevertheless, since the the change in θ affects each of the four importer types in the same manner, the ratio of fixed and sunk costs to average marginal revenue is similar across different models, which is reflected by the similar shapes of the three confidence regions. In other words, the level of interdependence matters for the static revenue gains and thus the static decision, but does not alter the fundamental relationship between sunk and fixed costs. This exercise here also shows that the estimation of fixed and sunk costs here can accommodate different levels of

[33]When $(\sigma-1)/\theta$ converges to zero, either σ converges to one or θ becomes extremely large. In the former case, demand is inelastic to price and thus firms have little incentive to reduce costs; they can simply pass higher costs to consumers through higher prices. Firms would then become indifferent between any two sets of import sources. In the latter case, there is no variance in efficiency across inputs, meaning input prices are determined by a country's technology level T_j and should be the same across inputs within each country. Firms would purchase all of its inputs from one single source that provides that lowest price. Other countries beyond that simply provide no additional benefits.

interdependence across import sources in production.

5.4 Back-of-the-envelope calculation: Effects of a temporary US-China trade war

At this point I have provided evidence for the interdependence across import sources and sunk entry costs of importing. To demonstrate the long-run effects of a temporary trade policy in the presence of these two features, I conduct the following thought experiment. Suppose there are two periods, $t = 0, 1$. At the beginning of period $t = 0$, there is a trade war between China and the US. I assume that due to the trade war, Chinese firms exclude the US from its import set in year $t = 0$ but keep its decision in other markets unchanged. While it is likely there would be immediate effects of the trade war, this assumption allows us to focus on its long-run effects.

I investigate (1) the trade war's direct effect on firms' decisions in the US in the second period and (2) its indirect effect on firms' decisions in other countries in the second period. Intuitively, the direct effect will depend on the magnitude of the sunk cost of importing from the US whereas the indirect effect will be determined by sourcing relationships across international markets.

Since the framework provides us with an incompletely specified structural model, it is necessary to impose additional assumptions in order to estimate the effects of the trade war on firms' decisions. First, I assume that firms only plan for one period. Moreover, there is a random shock common across firms that import from the US and the shock is big enough to rationalize the import decision of the least profitable firms.[34] Under these assumptions, the firm's decision to import from the US after the trade war will solely depend on the relative size of the marginal revenue of the US and its fixed and sunk costs. If the sunk cost of importing from the US is big, the firm is likely to drop the US from its import set in the second period.

The firm's decisions in other markets are more complicated, but there are a few conclusions we can draw. First, if a firm does not change its decision in the US, it would not change its decision in other markets. The reason is that in period $t = 1$ after the trade war is over, importing from the US becomes more costly but the relative ranking among all countries other than the US remains the same. Second, when countries are substitutes, firms may replace the US with a new market.

[34] A more serious treatment of the error term is left for future research on counterfactual experiments in an incompletely specified models. The exercise here simply provides a demonstration of the long-term effect of a hypothetical temporary trade policy change in the presence of spatial interdependence and sunk entry costs. Nonetheless, imposing positive shock implies that the estimated share of firms that would stop importing from the US would fall into a conservative range of the actual effects.

When countries are complementary, however, no firms will add a new market, even if they decide to drop the US.

I focus on firms that would import from the US in $t = 0$ in the absence of a trade war.[35] Furthermore, I fix the values of the fixed and sunk costs: $\gamma^f = 1$ and γ^s at three different values—0.1, 1.1, and 2.2—which roughly correspond to the lower bound, mid-point, and upper bound of the estimate on sunk cost.

Table 8 reports the shares of incumbent importers that would switch their import status in the US after the trade war at these different values of the sunk entry cost. In general, the effect is stronger in the earlier years, which results from the fact that firms grew bigger over time during this sample period and thus would be less affected by the trade war. As expected, the bigger the sunk cost, more firms drop the US from its import set after the trade war has ended. At the lower bound ($\gamma^s = 0.1$), only 11.9% of firms that would have import from the US change their status in this country. However, this share quickly goes up to 53.8% when I increase the sunk cost to 1.1 million RMB and 62% when sunk cost is at 2.2 million RMB. The large share of firms affected even after the trade war demonstrates the long-lasting effect of temporary trade policy changes. This also confirms that the model prediction that in a static model with no sunk cost, there would be minimal long-term effect of a temporary trade war, whereas in a dynamic model with sunk entry costs, the effect of trade war could remain substantial even when the two countries normalize their trade relations.

I also explore how the firm's second period decisions in other markets are affected by the trade war in the first period. As mentioned previously, the third-market effects depend on the level of interdependence across countries. When countries are independent, the impact of the trade war will be contained to Chinese firm-level decisions in the US market while the their decisions in other markets remain intact. However, when countries are either substitute or complementary, the firm's decision in other markets might also be altered as a result of the trade war.

When countries are complementary, firms would not admit more countries even if it stops importing from the US. It is also possible that firms drop additional import sources if it decided to drop the US. This happens when the synergy between the US and other countries is large enough

[35]About 15% of the firms in my sample imported from the US at some point during 2000-2006. Since the model abstracts from general equilibrium effects, firms that would not import from the US in $t = 0$ regardless of the trade war are unaffected in this thought experiment.

Table 8: Direct effect of trade war

	(1) $\gamma^s = 0.1$	(2) $\gamma^s = 1$	(3) $\gamma^s = 2.2$
2001	14.3	62.3	68.8
2002	17.1	60.4	66.7
2003	19.2	66.4	72.8
2004	7.5	48.3	59.2
2005	10.0	49.8	56.9
2006	7.8	45.8	56.6
Average	11.9	53.8	62.0

This table reports the shares of firms that would drop the US from its import set in second year if there was a trade war in the first period. The year corresponds to the first year after the hypothetical trade war.

to cover the cost of importing from multiple countries, but without the US, it might not be worth it to importing from the remaining markets. In other words, when firms cannot find substitutes for the US, they are subject to higher marginal costs and lower scales, and thus cannot afford importing from other countries.[36]

In Table 9, I report the share of firms that would drop at least one market other than the US from its import set after the trade war in the complementary case. As expected, a fraction of firms would stop importing from other markets due to the US-China trade war. As sunk cost increases, the externality of the trade war on other markets also becomes bigger. At the lower bound of the sunk cost, only 6.9% of firms would change their decisions in third markets, whereas 47.4% of firms would alter their decisions at the upper bound of the sunk cost.

The long-term effect on third markets of the temporary trade war results from both the sunk entry costs and interdependence across import markets and cannot be obtained in previous models that do not incorporate both features in one coherent framework. A model with sunk costs alone would not generate third market effects without general equilibrium, whereas a static model that allows for interdependence would overlook the dynamic costs of temporary trade policy changes.

[36]When countries are substitutes, firms may be able to replace the US with a new country that they have not already imported from. In this case, it is unclear whether they will keep the remaining set of import sources.

Table 9: Indirect effect of China-the US trade war on third markets (complementary case)

	(1) $\gamma^s = 0.1$	(2) $\gamma^s = 1$	(3) $\gamma^s = 2.2$
2001	8.2	39.3	47.5
2002	9.1	47.5	53.5
2003	13.6	52.7	60.9
2004	4.0	35.5	46.8
2005	5.2	34.1	39.3
2006	4.2	32.4	43.0
Average	6.9	39.2	47.4

This table reports the shares of firms that would drop at least another market in addition to the US from its import set at three different values of sunk entry cost. The year corresponds to the first year after the hypothetical trade war.

6 Extensions

In the following sections, I discuss two extensions of the baseline model. First, Section 6.1 provides an estimation approach that can allow for productivity to be affected by which set of countries it purchases its intermediate goods from. In Section 6.2, I introduce exporting decisions into the model. In this setting, a firm can choose where to import intermediate goods and export final goods.

6.1 Productivity gain of importing

The baseline model assumes that marginal cost is only affected by changes by input prices when firms change their import sources. However, there is evidence that imported inputs impacts firm-level productivity (Kasahara & Rodrigue, 2008; Amiti & Konings, 2007; Halpern et al., 2015). It is possible that a firm's core productivity (φ_{it}) is also influenced by its choice of import set. For instance, if a firm imports from high-income countries, it may have exposure to more managerial know-how or technological advances embedded in the foreign inputs. While these channels may not change input prices, they may increase firm's productivity and thus lower marginal costs. Ignoring the productivity channel may lead to biased estimates of the countries' marginal revenue gains in the first stage of estimation since we attribute all of the effect on marginal costs to input price reductions. Furthermore, even if we hold all future import decisions constant, future revenues might be affected through productivity channel and thus not accounting for productivity gains will bias the estimate of import sunk costs.

Consider the case when productivity is affected by import decisions with a lag. Allowing for the productivity effect substantially complicates the firms' dynamic problem. Apart from sunk costs, productivity gains provide another channel for the inter-temporal linkages between current and future decisions.[37] While the change in future sunk costs alters future profits but has no bearing on future revenues, the change in future productivity will impact future revenues. Thus, when deviating from the firm's observed import path, we need to consider the effects on future productivity in order to predict the revenue changes.

To fix ideas, let $\varphi_{it+1} = g(\varphi_{it}, X_{it}, \xi_{it})$, where g is some unknown function, X_{it} captures import decisions in the current year, and ξ_{it} captures productivity shock. I use different measures of X_{it}, including a binary variable for importing from high income countries, import intensity, and number of import markets. Recall that the revenue function in equation (9) can be expressed as

$$r_{it} = A_t \times \varphi_{it}^{\sigma-1} \times \Theta_{it}^{\frac{\sigma-1}{\theta}}$$

where A_t captures market demand factors that are common across firms. Under the above assumption on productivity, future revenue is then a function of last period's import decision, i.e. $r_{it+1} = k(A_{t+1}, \Theta_{it+1}, \varphi_{it}, X_{it}, \xi_{it})$ for some unknown function k.

To approximate for the effect of current import decisions on future revenue, I estimate the following regression

$$\log r_{it+1} = \lambda_{t+1} + \eta X_{it} + \ln \hat{\Theta}_{it+1} + \nu_{it+1} \tag{27}$$

where $\hat{\Theta}_{it+1}$ is the firm's sourcing capacity estimated using the procedure in Section 5. Note that given the construction of the deviations in Section 4, the import decision in year $t+1$ is not changed and thus the firm's sourcing capacity Θ_{it+1} is not affected.

The coefficient of interest is η, which captures how current imports set affect future revenues. X_{it} is endogenous as it is correlated with the unobserved productivity. To address the endogeneity, I use tariffs on imported inputs in China between 2000 and 2006 as an instrumental variable for X_{it}.

[37] Nevertheless, because current import decision does not affect current productivity, the static problem remains the same.

The exclusion assumption is that input tariffs only affect firm-level revenues through their choice of input sources.

Once we obtain a reliable estimate of η, I compute the counterfactual variable X'_{it} for each deviation from the observed import set and get the predicted values for r_{it+1} given X'_{it}. The change in future revenue from the productivity channel is then the difference between $r_{it+1}(X_{it})$ and $r_{it+1}(X'_{it})$.

6.1.1 Constructing input tariffs

I construct measures of firm-level input tariffs by computing average tariffs weighted by firm-level input imports. Let Z_{it} denote firm i's total import value in year t, Z_{ipt} denote firm's i's import value of input p, and τ_{pt} is the tariffs on input p in China.[38] The firm-level input tariffs are defined as

$$\tau_{it}^{(1)} = N_p^{-1} \sum_p \mathbb{1}(Z_{it} > 0)\tau_{pt}$$

$$\tau_{it}^{(2)} = \sum_p \frac{Z_{ipt}}{Z_{it}} \tau_{pt}$$

$$\tau_{it}^{(3)} = \sum_p \frac{Z_{ipt-1}}{Z_{it-1}} \tau_{pt}$$

$$\tau_{it}^{(4)} = \sum_p \frac{Z_{ip0}}{Z_{i0}} \tau_{pt}$$

where N_p is the number of products and $\tau_{it}^{(1)-(4)}$ are average tariffs with different weights. The first one is unweighted, the second and third are weighted by current and lag import values, and the last one is weighted by initial import values.

One issue with this approach to measure firm-level input tariffs is that we only observe import values for the years that firms imported, implying using observed import values will lead to selection bias. The last measure of input tariffs, $\tau_{it}^{(4)}$, relies on the initial input import structure and thus avoids the endogeneity issue. Nevertheless, using only initial year leads to a loss of observations because not every firm imported in the first sample year. For these reasons, I replace

[38] Input tariffs are downloaded from the WITS and are average tariffs across markets.

Z_{ipt}/Z_{it}, i.e., the share of input p over total input costs for firm i in year t, with firm i's average share over the entire sample period. More specifically, for each input p, the average share for firm i is computed as

$$\overline{\frac{Z_{ip}}{Z_i}} = N_T^{-1} \sum_t \frac{Z_{ipt}}{Z_{it}}$$

The final measure of firm-level input tariffs is

$$\tau_{it} = \sum_p \overline{\frac{Z_{ip}}{Z_i}} \tau_{pt}$$

In a sense, the weight for the input tariffs is unchanging over time for each firm and hence the time-series variation comes solely from changes in input tariffs in China.

6.1.2 Results

Table 11 reports the result for equation (27) with three different measures to characterize the import set: (1) the total number of import sources, (2) the number of advanced technology countries, and (3) the number of high income countries.[39] The instrumental variable is firm-level input tariffs described in the previous section. As we can see from Columns 1, 4, and 7, the coefficients on different measures of X_{it-1} are consistently positive. The estimated coefficient ranges between 0.088 to 0.108, meaning a 10% increase in the number of productivity-enhancing sources leads to an increase in revenues by 8.8-10.8%. The remaining columns look at the effects on firms with different levels of initial revenues. The results suggest there might be heterogeneous effects of import decisions on revenue by firm size. Smaller firms tend to enjoy bigger productivity gains by importing from more (high income/advanced technology) countries.

Table 12 shows the changes in revenues by import status at the firm-country level when X_{it} is chosen as the number of high income countries. Similar to the baseline findings, new and continuing importers enjoy bigger total revenue gains than exiting importers and firms that never import. However, when breaking down the total revenue gains into the static changes due to input prices and dynamic changes due to productivity, I find that both components play equally important roles. This evidence suggests that ignoring the dynamic effect of import decision on productivity can lead to substantial bias in the fixed and sunk cost estimates.

[39] Even though the baseline model does not incorporate export decisions, I also include the number of export destinations to proxy for export revenues.

Panel (a) in Figure 5 shows the new 95% confidence set for the costs of importing when taking into account the productivity effect. As expected, as the gain from importing increases, the estimated costs to both new and continuing importers also increase. To compare costs relative to the revenue gains, in panel (b) I scale each point in the confidence sets by the corresponding average marginal revenue.[40] Even after adjusting for revenue gains, I find that new estimates are more likely to produce high estimates for fixed costs, between 19-40% of revenue gains, whereas the baseline estimates lie between 13-40%. On the other hand, the costs to continuing importers now fall into a lower range (as a percentage of revenue changes). Without the productivity effect, the costs for a new importer can be as much as 40% of marginal revenue, whereas the new upper bound lies around 32% of total revenue gains.

Table 10: Descriptive statistics

	All	Never	Exiting	New	Continuing
# advanced tech countries	2.181	1.017	2.691	5.547	6.787
	(3.460)	(1.974)	(3.105)	(4.254)	(4.597)
# high income countries	1.717	0.816	2.148	4.269	5.291
	(2.771)	(1.653)	(2.532)	(3.343)	(3.780)
# import countries	2.243	1.049	2.774	5.696	6.979
	(3.577)	(2.046)	(3.218)	(4.383)	(4.843)
Observations	42998	31128	615	4612	4312

This table reports the number of advanced technology countries, high income countries, and total number of countries from which an average firm imports. Definitions for advanced-technology countries are provided in Appendix A.
Standard errors in parentheses

6.2 Export decisions

Obviously, a firm's past experience with exporting in a market can affect import entry costs in the same market, and vice versa. Ignoring other channels through which firms participate in foreign markets may bias the estimate of sunk entry costs.[41] Though the baseline model assumes final goods are non-tradable, it can be extended to include exporting decisions.

[40]Specifically, the x-dimension values are scaled by the average revenue change for continuing importers, whereas the y-dimension values are scaled by the average revenue change for new importers.

[41]The same argument can be made about other international activities, including multinational production or offshore R&D. I focus on exporting as this is still the most common channel through which firms engage in international markets. However, the estimation framework can be adapted to account for more trade margins.

Table 11: Revenue and productivity gains

	# countries			# advanced-tech countries			# high-income countries		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.import	0.0884***	0.101***	0.188**	0.0903***	0.103***	0.190**	0.108***	0.122***	0.225**
	(0.0231)	(0.0272)	(0.0684)	(0.0235)	(0.0278)	(0.0694)	(0.0276)	(0.0329)	(0.0829)
L.import × 1(≥ med size)		-0.0228			-0.0239			-0.0269	
		(0.0177)			(0.0182)			(0.0221)	
L.import × initial size			-0.0264*			-0.0266*			-0.0311*
			(0.0139)			(0.0142)			(0.0168)
Log sourcing capacity	-0.576***	-0.527***	-0.441**	-0.577***	-0.526***	-0.439**	-0.489***	-0.449***	-0.383**
	(0.170)	(0.158)	(0.134)	(0.169)	(0.158)	(0.134)	(0.145)	(0.136)	(0.117)
# export markets	0.00369***	0.00373***	0.00371***	0.00374***	0.00377***	0.00376***	0.00400***	0.00401***	0.00397***
	(0.000536)	(0.000533)	(0.000526)	(0.000536)	(0.000533)	(0.000526)	(0.000544)	(0.000541)	(0.000533)
Foreign affiliated	-0.0415**	-0.0444**	-0.0467**	-0.0419**	-0.0449**	-0.0470**	-0.0501**	-0.0528**	-0.0551**
	(0.0155)	(0.0159)	(0.0164)	(0.0155)	(0.0159)	(0.0164)	(0.0169)	(0.0174)	(0.0179)
State owned	-0.000756	-0.00128	-0.00329	-0.00106	-0.00152	-0.00337	-0.00169	-0.00206	-0.00410
	(0.0155)	(0.0153)	(0.0153)	(0.0155)	(0.0153)	(0.0153)	(0.0155)	(0.0154)	(0.0154)
Initial size	0.963***	0.969***	0.981***	0.963***	0.969***	0.981***	0.962***	0.968***	0.980***
	(0.00779)	(0.00842)	(0.00880)	(0.00787)	(0.00846)	(0.00879)	(0.00799)	(0.00864)	(0.00879)
Constant	3.557***	3.291***	2.816***	3.563***	3.287***	2.809***	3.124***	2.902***	2.535***
	(0.862)	(0.803)	(0.676)	(0.861)	(0.800)	(0.675)	(0.738)	(0.691)	(0.590)
Observations	4943	4943	4943	4943	4943	4943	4943	4943	4943
Adjusted R^2	0.901	0.902	0.903	0.901	0.902	0.903	0.899	0.900	0.901

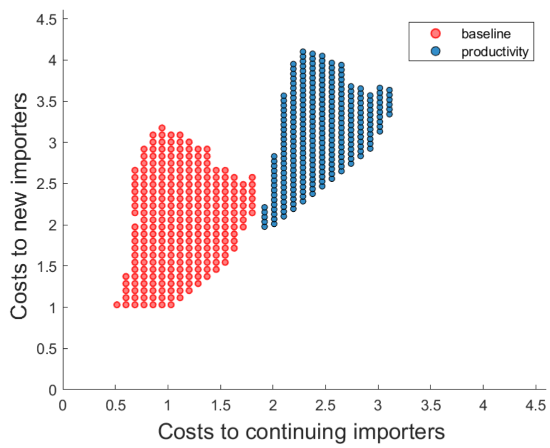
This table reports the effects of past import decisions on current revenues. Columns 1-3 use the total number of import countries as the key independent variable, columns 4-6 use the number of advanced technology countries, and columns 7-9 use the number of high-income countries. Except for columns 1, 4, and 7, I allow for heterogeneous effects of import decisions on revenue by a firm's initial revenue. 1((≥ med size) takes the value of one if the initial size is equal to or greater than the median value. A set of year dummies is included in all equations. Input tariffs (and interactions with initial size) are used as instrument variables for past import decisions. The first stage results are reported in Table A4. Monetary values are in units of million of RMB 1998.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Revenue changes - Number of high income countries

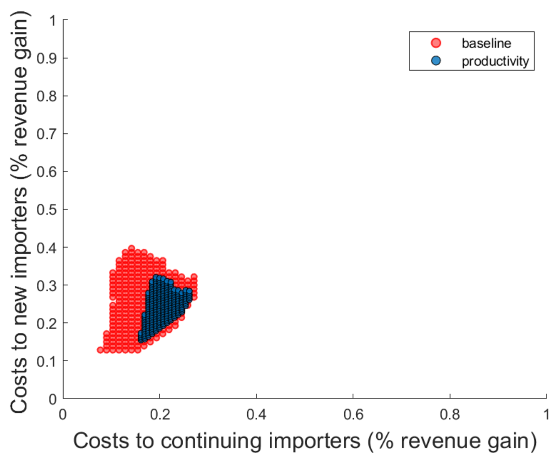
	All	Never	Exiting	New	Continuing
Current revenue changes	6.334	6.133	3.293	7.518	6.649
	(22.50)	(22.34)	(8.081)	(27.54)	(20.28)
Future revenue changes	4.152	2.324	6.006	9.091	8.158
	(11.09)	(5.535)	(6.902)	(19.99)	(16.97)
Total revenue changes	10.07	8.225	8.698	15.70	13.99
	(23.89)	(22.40)	(9.091)	(31.47)	(24.24)
Observations	25793	17325	364	3351	3181

This table reports the average revenue changes for each deviation from the observed path when accounting for productivity effect. Monetary values are in units of million of RMB 1998. The future revenue changes are discounted by a factor of 0.9.
Standard errors in parentheses

Figure 5: 95% Confidence sets



(a) Absolute values



(b) Scaled by average revenue changes

This figure illustrates the 95% confidence sets of the total costs to continuing versus new importers. The red region depicts the CI under the baseline model, whereas the blue region depicts the CI when accounting for productivity channel. Monetary values are in million of 1998 RMB.

To do so, I modify the baseline model by allowing final good producers to export to foreign markets. Firms not only choose which countries to source intermediate inputs from, but also which markets to export their outputs to. The demand and market structure of the final goods are the same as in the baseline model. However, firm i has to pay a variable trade cost τ^x_{ijt} for each unit of goods it sells in market j at time t. Conditional on the firm's sourcing strategy, $\mathcal{J}^m_{it}$, the export revenue in each market is

$$r^x_{ijt}(\mathcal{J}^m_{it}) = \left[\frac{\sigma}{\sigma-1}\frac{\tau^x_{ijt}}{\varphi_{it}P_{jt}}\right]^{1-\sigma} Y_{jt}(\gamma\Theta_{it}(\mathcal{J}^m_{it}))^{\frac{\sigma-1}{\theta}} \tag{28}$$

Equation (28) depicts the interdependence in the marginal cost between export and import decisions. The choice of input sources affects the marginal cost, which in turns affects the firm's export revenues. On the other hand, exporting to more profitable destinations increases the total revenue and thus the marginal revenue gain of an import source. Let $\mathcal{J}^x_{it}$ denote the optimal set of export destinations. Conditional on the optimal export and import decisions, the total revenue of the firm is simply the sum of its domestic revenue and export revenues

$$r_{it}(\mathcal{J}^x_{it}, \mathcal{J}^m_{it}) = r_{iht}(\mathcal{J}^m_{it}) + \sum_{j\in\mathcal{J}^x_{it}} r_{ijt}(\mathcal{J}^m_{it})$$

Similar to the import problem, firms will have to pay a fixed cost of each country it exports to, and a sunk cost if it enters the market for the first time. Denote f^m_{ijt} and s^m_{ijt} as firm i's fixed and sunk cost of importing from j in year t and f^x_{ijt} and s^x_{ijt} as firm i's fixed and sunk cost of exporting to j in year t. Furthermore, I allow for potential complementarity between export and import in the sunk costs. Simply put, the sunk entry cost of importing firm i has to pay to enter country j is reduced if it already exported to j in the previous year, i.e., $s^m_{ijt} - d^x_{ijt-1}e^m_{ijt}$, where e^m_{ijt} captures the reduction in importing sunk cost due to past export experience. And vice versa, past import experience with j also reduces the sunk entry cost of exporting to j, i.e. $s^x_{ijt} - d^m_{ijt-1}e^x_{ijt}$, where e^x_{ijt} is the reduction in exporting sunk cost.[42]

Conditional on the firm's import history, denoted by b^m_{it-1}, and export history, denoted by b^x_{it-1}, the static firm-level profit after importing from a set b^m_{it} sources and exporting to a set b^x_{it-1}

[42] It is also feasible to allow for complementarity in the fixed costs of exporting and importing. As the focus is on the sunk entry costs, I choose the more simple fixed cost structure.

destinations in year t is

$$\pi_{it}(b^m_{it}, b^m_{it-1}, b^x_{it}, b^x_{it-1}) = \sigma^{-1} r_{it}(b^m_{it}, b^x_{it}) - f^m_{it}(b_{it}) - s^m_{it}(b^m_{it}, b^m_{it-1}, b^x_{it-1}) - f^x_{it}(b_{it}) - s^x_{it}(b^x_{it}, b^x_{it-1}, b^m_{it-1}) \quad (29)$$

where $\sigma^{-1} r_{it}(b^m_{it}, b^x_{it})$ is the firm's operating profits. The term $f^m_{it}(b^m_{it}) = \sum_{j \in b^m_{it}} f^m_{ijt}$ is the sum of fixed costs of importing firm i pays in year t. Analogously, $f^x_{it}(b^x_{it}) = \sum_{j \in b^x_{it}} f^x_{ijt}$ is the sum of fixed costs of exporting firm i pays in year t. Furthermore, $s^m_{it}(b^m_{it}, b^m_{it-1}, b^x_{it-1}) = \sum_{\substack{j \in b^m_{it} \\ j \notin b^m_{it-1}}} (s^m_{ijt} - d^x_{ijt-1} e^m_{ijt})$ is the sum of sunk costs firm i pays to enter new import markets in year t and $s^x_{it}(b^x_{it}, b^x_{it-1}, b^m_{it-1}) = \sum_{\substack{j \in b^m_{it} \\ j \notin b^m_{it-1}}} (s^x_{ijt} - d^m_{ijt-1} e^x_{ijt})$ denotes the sum of sunk costs firm i pays to enter new export markets in year t.

The interdependence between exporting and importing is featured through two channels. First, importing foreign inputs reduces marginal costs, which in turn allows firms to incur costs to export to more destinations. Exporting on the other hand increases profits, meaning firms can incur importing costs from more countries. On the sunk cost side, the firm's past export experience helps reduce the sunk entry cost of importing from the same location. Likewise, past import experience helps reduce firm's sunk entry cost of exporting to the same location.

We now turn to the dynamic problem with both export and import decisions. In each period t, firm i chooses a sequence of import sources and export destinations, $\{(b^m_{i\tau}, b^x_{i\tau}) : b^m_{i\tau}, b^x_{i\tau} \in B_{it}\}_{\tau=t}^{t+L_{it}}$, that maximizes its discounted expected profit stream over a planning horizon L_{it}

$$\mathbb{E}[\sum_{\tau=t}^{t+L_{it}} \delta^{\tau-t} \pi_{i\tau}(b^m_{it}, b^m_{it-1}, b^x_{it}, b^x_{it-1}) | \Omega_{it}] \quad (30)$$

where B_{it} is the set of all import sources and export destinations that firm i considers in year t, and Ω_{it} denotes the firm's information set, which includes the firm's past import and export sets (b^m_{it-1} and b^x_{it-1}).[43]

Despite the interdependence between export and import decisions in both the marginal costs and sunk costs, under the revealed preferences assumption we can indeed estimate the export and import parameters separately. Intuitively, I assume that the observed export and import path is the optimal, and thus any deviation from the observed path will lower the firm's expected profits. The implication is that we can keep the export decision intact and deviate from the observed import

[43] Here I allow the consideration sets to be different for export destinations and import sources. We can think of B_{it} as the union of the two consideration sets, i.e., $B_{it} = B^m_{it} \cup B^x_{it}$.

path to estimate import parameters, and keep the import path fixed while changing the export path to get the bounds for the export parameters. Under the same deviation construction, the number of choices to analyze for each firm-year-country pair is $2J$. As the one-period dependency in the static profits is preserved, this method again reduces the dynamic problem to a static problem as explained in Section 4.

The same logic can be applied to a large class of multi-country models that incorporate multiple trade margins, such as multinational production as in Tintelnot (2017) or R&D as in Fan (2017). The key lies in the ability to derive closed-form solutions for the marginal value of a location with respect to one trade activity, while keeping other markets intact. The method is flexible enough to allow for interdependence across locations and/or between different trade margins.

To estimate the model, I assume the following structures on the fixed and sunk costs:

$$f^x_{ijt} = \gamma^{f,x} + \epsilon^{f,x}_{ijt}$$

$$f^m_{ijt} = \gamma^{f,m} + \epsilon^{f,m}_{ijt}$$

$$s^x_{ijt} = \gamma^{s,x} + \epsilon^{s,x}_{ijt}$$

$$s^m_{ijt} = \gamma^{s,m} + \epsilon^{s,m}_{ijt}$$

where $\mathbb{E}(\epsilon^{g,x}_{ijt}|\Omega_{it}, d^x_{ijt}, d^m_{ijt}) = 0$ and $\mathbb{E}(\epsilon^{g,m}_{ijt}|\Omega_{it}, d^x_{ijt}, d^m_{ijt}) = 0$, with $g = f, s$.

Finally, $e^x_{ijt} = \gamma^{e,x}$ and $e^m_{ijt} = \gamma^{e.m}$. Let γ collect all the parameters in the fixed and sunk costs,

$$\gamma = (\gamma^{f,m}, \gamma^{s,m}, \gamma^{f,x}, \gamma^{s,x}, \gamma^{e,m}, \gamma^{e,x})$$

Following Morales et al. (2019) to predict export revenues as a function of domestic revenues. Next, I apply the same deviation procedure in Section 4 to create the moment inequalities from both export and import decisions.

Table 13 reports the regression results for estimating export revenues. I run a PPML regression of export revenues on a set of firm and destination controls and a set of year dummies. The predicted revenues for exiting, continuing, never, and new exporters are 0.45, 2.29, 1.39, and 1.94 mil RMB, respectively.

Table 14 reports the 95% confidence intervals for individual parameters in the vector γ and Figure 6 illustrates the confidence regions of the cost that an average importer/exporter pays in the first year of importing/exporting. If a firm has neither prior export nor import experience in a market, it pays between 0.98 and 4.89 mil RMB to start importing (computed as the bounds on $\gamma^{f,m} + \gamma^{s,m}$), and between 0.39 and 0.95 mil RMB to export in the initial year ($\gamma^{f,x} + \gamma^{s,x}$). However, if the firm exported to the same country in the previous year, then it may enjoy a substantial reduction in the sunk cost of importing, up to 3.7 mil RMB. Likewise, a new exporter experiences a reduction on its sunk cost of exporting if it imported from the same market in the previous year. The results document high degree of complementarity between exporting and importing.

One interesting pattern is that the upper bounds of the confidence intervals for the γ^m parameters are much bigger than those for γ^x, indicating that importing is more costly. Note that what is captured here is the cost firms pay *per* market. Indeed, I find that the number of export destinations tends to be higher than the number of import sources. Conditional on importing, the median firm imports from two countries, whereas conditional on exporting, the median exporter sells to six markets.[44] As a result, when accounting for the number of countries that a firm imports from or exports to, I find that the total costs of importing for the median firm is indeed similar to the total costs of exporting.[45]

7 Conclusion

This paper introduces and estimates a dynamic multi-country model of imports with heterogeneous firms. The model highlights two crucial features of firm-level import decisions: (1) input sources are complementary in production and (2) a firm's current import decision is a function of its import history. These two features of the model together imply there might be complicated responses to targeted trade policies. Reducing trade barriers in one market not only affects entry in its own country, but also affects trade flows in other markets. Furthermore, temporary trade policy changes might have long-run impacts due to path dependence in the firm-level decisions.

As a result of the large dimensionality of the firm's choice set, evaluating the dynamic implication of every single choice is computationally infeasible. I overcome this problem by applying a partial identification approach to estimate the lower and upper bounds of the fixed and sunk

[44] The same pattern is observed for new exporters and importers. The median importer purchases from one new country, whereas the median exporter sells to three new destinations.

[45] This evidence explains the difference between my estimates and the results in Kasahara and Lapham (2013), in which the authors find the the costs of exporting are comparable to the costs of importing.

Table 13: Predicting export revenues

	Export revenues
log domestic revenues	0.175***
	(0.0000669)
Export to other markets	-28.89
	(608.5)
Landlocked	-0.294***
	(0.00127)
GDP	0.114***
	(0.0000340)
GATT/WTO member=1	0.293***
	(0.00121)
log distance	-0.227***
	(0.000143)
Constant	6.413***
	(0.00184)
Observations	43598
Pseudo R^2	0.148

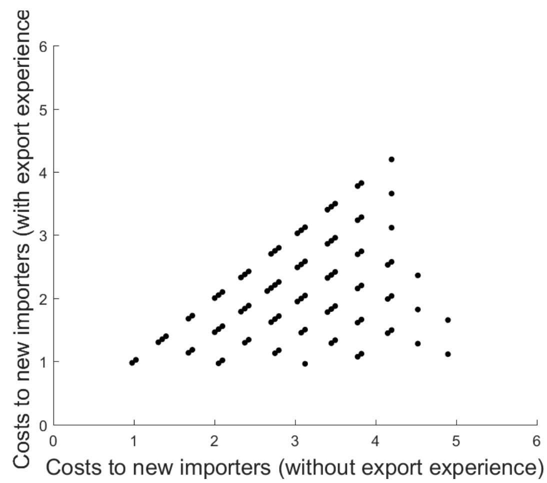
This table reports the PPML regression results of export revenues. The independent variables include log of domestic revenues, ownership types, whether firms export to other markets, destination characteristics such as distance, GDP, landlocked, and GATT/WTO membership, and a set of year dummies.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: 95% confidence set

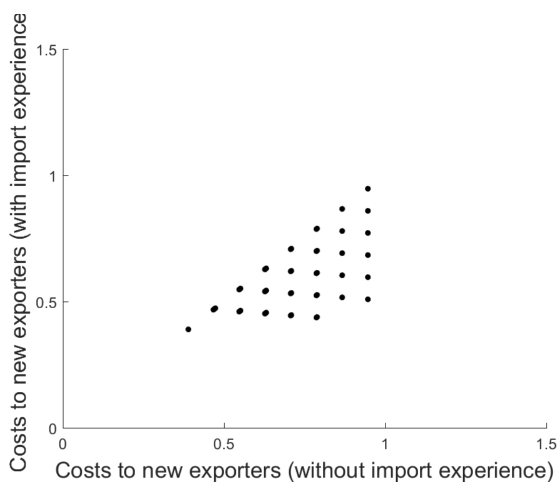
	LB	**UB**
$\gamma^{f,m}$	0.00	2.28
$\gamma^{s,m}$	0.00	4.90
$\gamma^{f,x}$	0.00	0.47
$\gamma^{s,x}$	0.00	0.95
$\gamma^{e,m}$	0.00	3.78
$\gamma^{e,x}$	0.00	0.44

This table reports the 95% confidence interval for fixed and sunk costs of exporting and importing. Monetary values are in million of 1998 RMB.

Figure 6: 95% confidence sets



(a) Import costs



(b) Export costs

This figure illustrates the 95% confidence sets of the total costs to new importers (top panel) and new exporters (bottom panel). The horizontal axis presents the costs when the new importer (exporter) does not have prior export (import) experience, whereas the vertical axis presents the costs when the firm has prior experience in the other trade margin. Monetary values are in million of 1998 RMB.

costs. The method allows for flexible assumptions on the firm's optimization behavior and avoids computing choice-specific value functions in a dynamic setting. The paper's findings indicate that countries are complementary in production and that the costs of importing for a new importer account for 12.87% to 39.75% of the import revenue gain.

There are other mechanisms that can generate similar predictions to those from the baseline model. In terms of persistence in firm-level import decisions, it is possible that firms may obtain productivity gains from importing which increase the likelihood of importing from the same set of input sources in subsequent periods. Section 6.1 proposes a modified estimation procedure that accounts for such productivity gains. In addition to the interdependence in marginal costs, the interdependence across countries might also be inherent in the sunk costs through extended gravity. As in Morales et al. (2019), firms learn about new markets from their previous experience with similar markets. The current framework can be adjusted to account for these extended gravity factors.

Finally, although the baseline model focuses on the import side, section 6.2 demonstrates an extension that incorporates the firm's export decision. The extended model preserves the interdependence across locations while introducing complementarity between importing and exporting in both the marginal costs and the fixed and sunk costs. Though adding export platforms complicates the firm's optimization problem, it does not require substantial modification to the current estimation approach due to its flexibility and mild restrictions on the firm's behavior. This is important since firms are likely to engage in the global economy through multiple channels. The next step is to expand the framework developed here in order to allow for other trade margins and provide a comprehensive picture of firm-level global supply chains.

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Appendices

A Variable construction

A.1 Wages

Data on wages for the countries in my sample are downloaded from the ILO. I use reported data on monthly wages for the manufacturing sector, divided by the total number of hours worked in a month. In a few occasions, there are multiple reported values in the same year for a single country, which come from different survey data sources. To address this, I relied on the surveys' description of reference group and methodology to ensure consistency across countries. The ILO does provide a harmonized series; however, there are many missing data that would compromise the range of countries I can include.

The ILO differentiates between employees and employed persons. In the main analysis, I use data for employees (wages data only for employees) but also conduct robustness check using total work hours for each person employed. Moreover, I converted the wages in local currency to USD using exchanges rates from the Penn World Tables. I use official instead of purchasing power exchange rates, since the goal is to capture the differences in cost of production across countries.

Finally, as in Eaton and Kortum (2002), I adjust the hourly wage for human capital by multiplying wage in country j by $\exp^{-gH_j}$ where $g = 0.06$ is the return to education and H_j is the years of schooling in country j in the initial year (2000). I set $g = 0.06$, which Bils and Klenow (2000) suggest is a conservative estimate. Data on schooling come from Barro and Lee (2013).

A.2 Country characteristics

Data on language and contiguity come from the CEPII. Countries' income bracket is based on World Bank classification and the World Development Indicator. I construct binary variables that take the value of unity if the import source does not share the corresponding characteristics with China. That is, when $language_j = 1$, Chinese is not the official language in country j. Similarly, $border_j = 1$ implies country j and China do not share the same border.

The US Census Bureau defines 10 categories of Advanced Technology Products (ATP) including (1) biotechnology (2) life science (3) opto-electronics (4) information and communication (5) electronics (6) flexible manufacturing (7) advanced materials (8) aerospace (9) weapons and (10) nuclear technology. I merge this list of products with HS code at the six-digit level and group countries into those with high share of ATP imports and those with low share of ATP imports to proxy for the level of technology embedded in goods from each country. I use both US import and Chinese import data to construct the variable. Data on ATP imports in the US are from the US Census Bureau.[46]

[46]The list of ATPs changed overtime, though the bulk of the products remained in the list. I use the list of imported ATPs in 2004.

The share of ATP imports is calculated with respect to total ATP imports and total imports. Let AT_{jt} denote the measure of advanced technology level of country j in year t. I employ different approaches to construct this variable

$$AT^{(1)}_{jt} = \frac{ImportAT_{jt}}{ImportAT_t}$$

$$AT^{(2)}_{jt} = \frac{ImportAT_{jt}}{Import_{jt}}$$

$ImportAT_{jt}$, $ImportAT_t$, and $Import_{jt}$ denote the import values of ATP, total ATP import, and total imports from country j in year t. The first measures compares the shares of ATP imports across countries, whereas the second measure compares the relative share of ATP imports versus other imports from the same country. The larger $AT^{(2)}_{jt}$ is, the higher the likelihood that firms import ATPs if they import from country j.

B Descriptive statistics

Table A1 reports the country ranking by number of importers in 2000 and 2006 for all industries. The top 10 countries remain in the exact position in both years. Correlation between 2000 and 2006 ranking for all countries is 0.94.

Table A1: Country ranking and number of importers in 2000 and 2006 - All industries

Country	Rank	2000	2006
Japan	1	12824	30204
United States	2	10999	27367
Taiwan	3	9212	21044
Germany	4	8239	20633
South Korea	5	7993	18841
Hong Kong	6	6307	13851
Italy	7	4660	11632
United Kingdom	8	4436	9946
France	9	4104	8680
Singapore	10	3682	7749

Table A2 reports the growth rates between 2000 and 2006 for the sample of Chinese chemical producers in terms of domestic revenues, import values, and number of importers. As can be seen from the table, there was tremendous growth during this period of time. Domestic sales grew by

400%, imports by 500%, and the number of importers in 2006 was more than double that in 2000.

Table A2: Growth rates between 2000 and 2006 for the chemicals sample

	(1) Domestic revenues	(2) Import values	(3) # Importers
2000	840	10	268
2006	4,239	60	618
Rate of change (%)	404.5	502.7	130.6

This table provides nominal domestic revenues, import values, and number of importers for the years 2000 and 2006. The last row reports the percentage change between the two years. Monetary values are in billions of RMB.

C Alternative procedure to predict sourcing potential S_{ijt}

Instead of predicting S_{ijt} through two steps as described in Section 5, I propose a different procedure to back out S_{ijt} directly through the imported input share X_{ijt}/X_{iht}.

I maintain the assumption that $S_{iht} = S_{ht}$, that is, the domestic sourcing potential is constant across firms but can vary across years. Additionally, S_{ht} is mean independent of S_{ijt}, i.e., $\mathbb{E}(S_{ht}|S_{ijt}) = \mathbb{E}(S_{ht})$. As before, I assume there may be a multiplicative measurement error in the share of imported input over total inputs X_{ijt}, denoted by ϵ^x_{ijt}. We can also assume there is a multiplicative measurement error in the share of domestic inputs X_{iht}. In that case ϵ^x_{ijt} is treated as the ratio of the two measurement errors.

$$\frac{X_{ijt}}{X_{iht}} = \frac{S_{ijt}}{S_{ht}}\epsilon^x_{ijt}$$

Next, suppose we run a linear regression of $\log X_{ijt} - \log X_{iht}$ on the set of independent variables in equation 26:

$$\log X_{ijt} - \log X_{iht} = \beta_0 + g(X^T_{jt}\beta^T) - \theta h(X^\tau_{ijt}\beta^\tau) - \theta \ln w_{jt} + \lambda_t \tag{31}$$

Under the new specification, the estimated values of the year dummies λ_t will be reduced by $\mathbb{E}(\log S_{ht})$, assuming $\mathbb{E}(\log \epsilon^x_{ijt}) = 0$. If we restrict S_{ht} to be constant across time, then the constant coefficient β_0 is affected. In either case, other coefficient estimates should still be consistent, though the predicted values of $\log S_{ijt}$ will be biased by $\mathbb{E}(\log S_{ht})$.

Because what we want to obtain is the predicted values for S_{ijt}, the log-linearized model may not be ideal as $\ln \mathbb{E}(S_{ijt}) \neq \mathbb{E}(\ln S_{ijt})$. For that reason, I run a Poisson regression

$$\frac{X_{ijt}}{X_{iht}} = \exp\left(\beta_0 + g(X_{jt}^T \beta^T) - \theta h(X_{ijt}^\tau \beta^\tau) - \theta \ln w_{jt} + \lambda_t\right) \tag{32}$$

In principle, the Poisson regression allows us to include zeros on the left hand side. That said, recall the definition of sourcing potential: $S_{ijt} = T_j(\tau_{ijt}^m w_{jt})^{-\theta}$. This means $S_{ijt} = 0$ if either country-level technology, variable trade costs, or wages is 0. In practice, this seems implausible that any of these terms is actually zero. For this reason, I exclude observations with zero imported inputs. Note that the Poisson regression is still subject to the previous issue with predicted value of S_{ijt} being biased, now by a scale of $\mathbb{E}(S_{ht})$.

Table A3 reports results for different methods of estimating country-level sourcing potential. The first two columns are the baseline results reported in Section 5. The next two columns report results for equation 31 under a log-linearized model. As expected, except for the year dummies and constant term, the two sets of estimates are identical.

D Additional tables

Table A3: Robustness Check - Predicting S_{ijt}

	Residuals		$\log X_j/X_h$		X_j/X_h	
	OLS	IV	OLS	IV	Poisson	IV Poisson
	(1)	(2)	(3)	(4)	(5)	(6)
log wages	-0.299***	-1.985***	-0.299***	-1.985***	0.0137	-0.596
	(0.0639)	(0.478)	(0.0639)	(0.478)	(0.0586)	(1.252)
R&D expenditure	-0.0332	0.643***	-0.0332	0.643***	-0.0505	0.262
	(0.0469)	(0.196)	(0.0469)	(0.196)	(0.0515)	(0.693)
$\log k$	-0.00168***	0.00515***	-0.00168***	0.00515***	0.000996***	0.00335
	(0.000380)	(0.00196)	(0.000380)	(0.00196)	(0.000371)	(0.00529)
landlocked	-0.576***	0.242	-0.576***	0.242	-1.070***	-0.793
	(0.161)	(0.284)	(0.161)	(0.284)	(0.274)	(0.580)
GDP	0.0692***	0.255***	0.0692***	0.255***	0.0257*	0.0967
	(0.0145)	(0.0542)	(0.0145)	(0.0542)	(0.0156)	(0.159)
log distance	-0.683***	-0.246*	-0.683***	-0.246*	-0.459***	-0.304
	(0.0448)	(0.131)	(0.0448)	(0.131)	(0.0421)	(0.346)
2001	0.0610	-0.117	0.152	-0.0263	-0.154	-0.250
	(0.142)	(0.155)	(0.142)	(0.155)	(0.143)	(0.394)
2002	0.0814	-0.200	0.0846	-0.196	0.241*	0.0733
	(0.137)	(0.162)	(0.137)	(0.162)	(0.134)	(0.411)
2003	0.259*	0.235*	0.216	0.193	-0.0937	-0.169
	(0.133)	(0.137)	(0.133)	(0.137)	(0.137)	(0.427)
2004	0.177	0.0287	0.435***	0.286**	0.545***	0.420
	(0.127)	(0.138)	(0.127)	(0.138)	(0.123)	(0.489)
2005	0.112	0.233*	0.0916	0.213	-0.604***	-0.650*
	(0.130)	(0.138)	(0.130)	(0.138)	(0.141)	(0.382)
2006	0.254*	0.449***	0.361***	0.556***	0.102	0.0605
	(0.132)	(0.148)	(0.132)	(0.148)	(0.132)	(0.411)
Constant	5.413***	4.956***	0.287	-0.170	2.169***	1.897
Observations	9341	9341	9341	9341	9341	9341
Adjusted R^2	0.114	0.047	0.115	0.049		
Pseudo R^2					0.117	

This table provides estimation results for the country-level sourcing potential equation under different specifications. Columns 1 and 2 report the baseline results. Columns 3 and 4 report results for the log-linearized model with $\log(X_{ijt}/X_{iht})$ on the left hand side. Finally, columns 5 and 6 report the estimation results for a Poisson regression with X_{ijt}/X_{iht} as the dependent variable. The independent variables are the same in all regressions. In columns 2, 4, and 6, log population is used as IV for log wages. The last equation is estimated via generalized method of moments.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Productivity gain - First stage

	# countries			# advanced-tech countries			# high-income countries		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.Input tariffs	0.0706***	-0.0290***	-0.729***	0.0691***	-0.0285***	-0.709***	0.0580***	-0.0222***	-0.591***
	(0.00918)	(0.00585)	(0.121)	(0.00883)	(0.00565)	(0.111)	(0.00695)	(0.00444)	(0.0954)
L.Input tariffs ×1(≥ med size)		0.145***			0.142***			0.116***	
		(0.0110)			(0.0107)			(0.00839)	
L.Input tariffs × initial size			0.283***			0.276***			0.231***
			(0.0428)			(0.0392)			(0.0332)
Log sourcing capacity	6.837***	5.672***	30.52***	6.710***	5.593***	30.02***	4.806***	3.966***	21.34***
	(0.338)	(0.357)	(1.612)	(0.338)	(0.357)	(1.611)	(0.271)	(0.271)	(1.259)
# export markets	-0.00313	-0.00134	-0.0103	-0.00353	-0.00157	-0.0116	-0.00539**	-0.00331*	-0.0208**
	(0.00249)	(0.00243)	(0.0114)	(0.00241)	(0.00236)	(0.0111)	(0.00209)	(0.00200)	(0.00959)
Foreign affiliated	0.383***	0.138***	1.335***	0.380***	0.136***	1.322***	0.395***	0.163***	1.412***
	(0.0455)	(0.0410)	(0.196)	(0.0444)	(0.0400)	(0.191)	(0.0381)	(0.0334)	(0.163)
State owned	0.0956*	0.0393	0.320	0.0970**	0.0435	0.332	0.0872**	0.0420	0.299
	(0.0496)	(0.0477)	(0.222)	(0.0482)	(0.0463)	(0.215)	(0.0413)	(0.0397)	(0.186)
Initial size	0.229***	0.0826**	0.00354	0.229***	0.0827**	0.0270	0.199***	0.0829***	0.0593
	(0.0241)	(0.0276)	(0.206)	(0.0236)	(0.0275)	(0.192)	(0.0209)	(0.0221)	(0.161)
year=2002	-0.562***	-0.538***	-2.623***	-0.549***	-0.526***	-2.563***	-0.405***	-0.384***	-1.885***
	(0.103)	(0.0976)	(0.454)	(0.101)	(0.0958)	(0.444)	(0.0860)	(0.0790)	(0.377)
year=2003	-0.556***	-0.598***	-2.627***	-0.552***	-0.587***	-2.605***	-0.377***	-0.417***	-1.788***
	(0.110)	(0.101)	(0.477)	(0.108)	(0.100)	(0.471)	(0.0922)	(0.0827)	(0.400)
year=2004	1.253***	0.994***	5.599***	1.228***	0.982***	5.505***	0.888***	0.694***	3.935***
	(0.103)	(0.100)	(0.469)	(0.101)	(0.0981)	(0.459)	(0.0852)	(0.0808)	(0.385)
year=2005	-0.258**	-0.284**	-1.174**	-0.261**	-0.285**	-1.190**	-0.163*	-0.189**	-0.758**
	(0.102)	(0.0954)	(0.445)	(0.100)	(0.0939)	(0.438)	(0.0841)	(0.0768)	(0.366)
year=2006	0.609***	0.393***	2.634***	0.589***	0.382***	2.555***	0.441***	0.275***	1.893***
	(0.0972)	(0.0896)	(0.428)	(0.0948)	(0.0871)	(0.417)	(0.0801)	(0.0726)	(0.353)
Constant	-35.67***	-29.10***	-155.6***	-35.01***	-28.69***	-153.1***	-25.21***	-20.42***	-109.0***
	(1.689)	(1.796)	(8.239)	(1.686)	(1.795)	(8.202)	(1.353)	(1.364)	(6.419)
Observations	4943	4943	4943	4943	4943	4943	4943	4943	4943
R-squared	0.461	0.452	0.484	0.462	0.454	0.485	0.390	0.397	0.419
F-statistic	102.8	76.81	83.15	101.5	75.98	81.95	87.33	66.28	71.95

This table provides results on the first-stage estimation in Table 11.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Productivity gain - OLS

	# countries			# advanced-tech countries			# high-income countries		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.import	0.0179***	0.0252***	0.0442**	0.0180***	0.0256***	0.0446**	0.0184***	0.0259***	0.0428**
	(0.00369)	(0.00689)	(0.0149)	(0.00375)	(0.00718)	(0.0154)	(0.00397)	(0.00749)	(0.0163)
L.import × ×1(≥ med size)		-0.00980			-0.0102			-0.0104	
		(0.00661)			(0.00686)			(0.00743)	
L.import × initial size			-0.00612**			-0.00620**			-0.00575*
			(0.00305)			(0.00315)			(0.00339)
Log sourcing capacity	-0.0829*	-0.0766*	-0.0746	-0.0811*	-0.0745	-0.0724	-0.0488	-0.0429	-0.0421
	(0.0467)	(0.0460)	(0.0459)	(0.0466)	(0.0459)	(0.0459)	(0.0423)	(0.0419)	(0.0417)
# export markets	0.00376***	0.00377***	0.00376***	0.00377***	0.00378***	0.00377***	0.00381***	0.00382***	0.00381***
	(0.000513)	(0.000513)	(0.000513)	(0.000514)	(0.000513)	(0.000513)	(0.000514)	(0.000514)	(0.000514)
Foreign affiliated	-0.00952	-0.0117	-0.0122	-0.00947	-0.0118	-0.0122	-0.00976	-0.0117	-0.0119
	(0.0103)	(0.0105)	(0.0105)	(0.0103)	(0.0105)	(0.0105)	(0.0104)	(0.0105)	(0.0105)
State owned	0.00925	0.00873	0.00820	0.00924	0.00872	0.00821	0.00949	0.00910	0.00871
	(0.0146)	(0.0146)	(0.0147)	(0.0146)	(0.0146)	(0.0147)	(0.0146)	(0.0146)	(0.0147)
Initial size	0.980***	0.982***	0.983***	0.980***	0.982***	0.983***	0.980***	0.982***	0.983***
	(0.00538)	(0.00562)	(0.00575)	(0.00539)	(0.00562)	(0.00575)	(0.00537)	(0.00562)	(0.00574)
year=2002	0.0710***	0.0699**	0.0697**	0.0707***	0.0697**	0.0695**	0.0681**	0.0672**	0.0671**
	(0.0212)	(0.0212)	(0.0212)	(0.0212)	(0.0212)	(0.0212)	(0.0212)	(0.0212)	(0.0212)
year=2003	0.183***	0.181***	0.181***	0.183***	0.181***	0.181***	0.180***	0.178***	0.178***
	(0.0203)	(0.0202)	(0.0202)	(0.0203)	(0.0202)	(0.0202)	(0.0202)	(0.0201)	(0.0201)
year=2004	0.217***	0.218***	0.218***	0.217***	0.218***	0.219***	0.222***	0.223***	0.223***
	(0.0207)	(0.0207)	(0.0207)	(0.0207)	(0.0207)	(0.0207)	(0.0204)	(0.0204)	(0.0204)
year=2005	0.425***	0.424***	0.424***	0.425***	0.424***	0.424***	0.423***	0.422***	0.422***
	(0.0192)	(0.0192)	(0.0192)	(0.0192)	(0.0192)	(0.0192)	(0.0192)	(0.0192)	(0.0192)
year=2006	0.578***	0.577***	0.577***	0.578***	0.577***	0.578***	0.580***	0.580***	0.580***
	(0.0208)	(0.0208)	(0.0208)	(0.0208)	(0.0208)	(0.0208)	(0.0208)	(0.0207)	(0.0208)
Constant	0.470**	0.430*	0.416*	0.461*	0.419*	0.405*	0.296	0.259	0.252
	(0.238)	(0.235)	(0.234)	(0.238)	(0.234)	(0.234)	(0.215)	(0.214)	(0.213)
Observations	4943	4943	4943	4943	4943	4943	4943	4943	4943
Adjusted R^2	0.910	0.910	0.910	0.910	0.910	0.910	0.910	0.910	0.910

This table provides OLS estimates on the effect of past import decisions on current revenues. See Table 11 for IV estimates.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$