ESSAYS ON FIRM-LEVEL DYNAMICS IN THE GLOBAL ECONOMY

By

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Dissertation

Submitted to the Faculty of the

Graduate School of Vanderbilt University

in partial fulfillment of the requirements

for the degree of

DOCTOR OF PHILOSOPHY

in

Economics

June 30, 2021

Nashville, Tennessee

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Acknowledgments

I am indebted to my advisor, Joel Rodrigue, for his guidance and his belief in my work. Joel provided me with all the resources and support that I needed to make this happen. His impact on my intellectual growth at Vanderbilt is unparalleled and his dedication unquestionable.

I am grateful for the advice from Eric Bond. His vast knowledge of the trade literature and critical comments have made me a better trade economist. Pedro Sant'Anna and Jeffrey Wooldridge have also been extremely generous with their time to explain to me various econometric issues.

I also want to thank John Weymark for being a great mentor, and, Tam Bui, my formal TA and roommate, for always being there regardless of the distance between us. I am lucky to be in the best cohort with Jun, Ebehi, Chris, Nick, Kristine, and Teyanna, Matthew, and Mathew. I am grateful to have Thu, Elijah, Oscar, and Zizhang accompany me for hours of Pokemon Go and board games. I would like to thank Andrea Moro for organizing the book club, which has kept me sane during the pandemic.

My last ten years away from home would have been much more difficult without the support from my family in Vietnam. My parents have been incredibly understanding and provided the safety net whenever I felt like giving up. My lifelong friends, Giang Le and Mai Nguyen, while we have taken vastly different career paths, still inspire me to become a better person.

My journey at Vanderbilt University started with an end to my time at Cornell College, where I took my first economic classes. The professors and classmates in those classes have become great friends, whose conversations with me have moved beyond economic discussion (thankfully!). Finally, I want to thank my late advisor at Cornell College, Jerry Savitsky, who continued to provide his support even after my graduation. While I can no longer send him a draft of my dissertation as he requested, knowing Jerry I am sure he would think most of it is gibberish anyway. Rest in peace, Jerry.

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CHAPTER 1

The Dynamics of Global Sourcing

1.1 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 et al., 2009) and long-run changes in aggregate trade flows (Eaton et al., 2008). There is also strong evidence for the impact of foreign inputs on firm-level productivity, varieties of final goods, and product quality (Amiti and Konings, 2007; Kasahara and Rodrigue, 2008; Goldberg et al., 2010; Gopinath and Neiman, 2014), and aggregate welfare gains from trade (Caliendo and Parro, 2015; Blaum et al., 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 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

[1] The early theoretical work by Baldwin (1988), 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 et al. (2007) structurally estimate the sunk export costs and find them to be substantial.

data patterns presented in Section 1.2 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 et al. (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.

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 et al. (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

[2] In Section 1.6.1, 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.

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 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]

[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.

[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 et al., 2016; Erbahar and Zi, 2017; Bown et al., 2020). In my baseline model, the effect takes place across producers at the same stage of production. Nevertheless, Section 1.6 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.

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 et al., 2015; Antràs et al., 2017), and therefore unable to address the path dependence of import decisions.[5] Kasahara and Lapham (2013) study 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 et al. (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

[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.

[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 et al. (2020).

et al., 2019). Furthermore, as firms have been increasingly engaged in the global markets through many channels as reported in Bernard et al. (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 1.6, 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 1.2 provides a description of the data sources and several data patterns. Section 1.3 presents a model that is consistent with the data patterns. Section 1.4 discusses the identifying assumptions. In Section 1.5, I provide a detailed description of the estimation procedures and results. Section 1.6 presents two extensions of the baseline model. Section 1.7 concludes.

1.2 Data and Stylized Facts

1.2.1 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.

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

Since the two data sets do not have a common firm identifier, I follow the procedure in Feng et al. (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 et al. (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 misclassified 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 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 et al. (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 and focus on ordinary trade.[11] Finally, I choose the chemicals industry to study 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

[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.

[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]For a detailed discussion on sample selection, see Section 1.5.4.

[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).

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.

1.2.2 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 1.1. 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 1.2 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 3, I include a set of year dummies to control for macroeconometric trends that might influence the likelihood of importing in a particular year. Yet, this variable may pick up effect that

[13] Descriptive statistics are provided in Appendix 1.8.1.2.

comes from time-varying characteristics that are correlated with firm's import history (e.g.: firm's past productivity affects both its past import decision and its current productivity), which leads to omitted variable bias. In column 4, I include domestic sales to proxy for productivity growth that is due to the firm's past import decisions.[14]

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 .212 and 0.544, meaning that if a firm imported from country j in the previous period, it is at least 21 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 1.3, 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 1.2, 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.[15] Hence, I focus on the country-specific sunk costs in the main analysis of the paper.

Table 1.1: 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*

[14]Section 1.6.1 provides an extension of the model that accounts for productivity gain of importing.

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

Table 1.2: Persistence in import status

	(1)	(2)	(3)	(4)	(5)
Import to j in $t-1$	0.524***	0.343***	0.344***	0.212***	0.212***
	(0.00505)	(0.0121)	(0.0120)	(0.0194)	(0.0193)
Import in $t-1$					0.00831*
					(0.00502)
Observations	1934730	1612275	1612275	426018	426018
Country Dummies	Yes	Yes	Yes	Yes	Yes
Firm-Country FE		Yes	Yes	Yes	Yes
Year Dummies			Yes	Yes	Yes
Domestic sales				Yes	Yes

This table reports results on regressing current import status on past import status at the firm-country level. Columns 2-5 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. Results using OLS estimation and under a modified random effects probit model proposed by Wooldridge (2005) are qualitatively similar. Columns 4 and 5 include domestic sales, thus restricting the sample to firms that appear in both the customs and the NBS data.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 1.3 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 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.[16]

In Table 1.4, I follow Eaton et al. (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 1.3. 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.

[16]Country rankings using all industries are reported in Table 1.13.

Table 1.3: 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 1.4: 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 1.3.

1.3 Model

To explain the empirical patterns documented in Section 1.2, 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.

1.3.1 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.

1.3.1.1 Demand

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

$$U_{jt} = \left(\int_{\psi \in \Psi_{jt}} q_{jt}(\psi)^{\sigma/(\sigma-1)} d\psi \right)^{\sigma/(\sigma-1)}, \sigma > 1, \tag{1.1}$$

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

$$q_{jt}(\psi) = p_{jt}(\psi)^{-\sigma} P_{jt}^{\sigma-1} Y_{jt} \tag{1.2}$$

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.

1.3.1.2 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.[17]

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

[17] In Section 1.6, 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.

paid by firm i in year t is then

$$z_{it}(v;\mathcal{J}_{it}^m) = \min_{k\in\mathcal{J}_{it}^m}\{\tau_{ikt}^m a_{ikt}(v)w_{kt}\} \tag{1.3}$$

where $\mathcal{J}_{it}^m$ 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

$$c_{it} = \frac{1}{\varphi_{it}}\Big(\int_0^1 z_{it}(v;\mathcal{J}_{it}^m)^{1-\rho}dv\Big)^{1/(1-\rho)} \tag{1.4}$$

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

$$P(a_{ikt}(v) \geq a) = e^{-T_k a^\theta}, \qquad \text{with } T_k > 0 \tag{1.5}$$

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 1.2, 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_{ijt}^m 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.

1.3.2 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

$$X_{ijt} = \frac{S_{ijt}}{\Theta_{it}} \tag{1.6}$$

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

$$c_{it}(\mathcal{J}^m_{it}) = \frac{1}{\varphi_{it}} \Big(\gamma \Theta_{it}(\mathcal{J}^m_{it}) \Big)^{-1/\theta} \tag{1.7}$$

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 (1.2) 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

$$r_{it} \equiv p_{it} q_{it} = \left[\frac{\sigma}{\sigma - 1} \frac{c_{it}}{P_{ht}} \right]^{1-\sigma} Y_{ht} \tag{1.8}$$

Plug in equation (1.7) in to (1.8), we can rewrite the firm's revenue given its sourcing strategy as

$$r_{it}(\mathcal{J}^m_{it}) = \left[\frac{\sigma}{\sigma - 1} \frac{1}{\varphi_{it} P_{ht}} \right]^{1-\sigma} Y_{ht} [\gamma \Theta_{it}(\mathcal{J}^m_{it})]^{\frac{\sigma-1}{\theta}} \tag{1.9}$$

As can be seen from equation (1.7) 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 $r^m_{ijt}(\mathcal{J}^m_{it})$ 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 $\mathcal{J}^m_{it}$. 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 $j \in o_{it}^m$, $j' \notin o_{it}^m$, and $S_{ijt} = S_{ij't}$, then $|r_{ijt}^m(o_{it})| < |r_{ij't}^m(o_{it})|$. One the other hand, when countries are substitutes, $|r_{ijt}^m(o_{it})| > |r_{ij't}^m(o_{it})|$. 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}.[18] Furthermore, I assume that the fixed and sunk costs have the following structure:

$$\begin{aligned} f_{ijt} &= f_{ijt}^o + \epsilon_{ijt}^f, \\ \mathbb{E}(\epsilon_{ijt}^f | \Omega_{it}, d_{ijt}) &= 0 \end{aligned} \tag{1.10}$$

and

$$\begin{aligned} s_{ijt} &= s_{ijt}^o + \epsilon_{ijt}^s, \\ \mathbb{E}(\epsilon_{ijt}^s | \Omega_{it}, d_{ijt}) &= 0 \end{aligned} \tag{1.11}$$

where f_{ijt}^o and s_{ijt}^o 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 a set b_{it} sources in year t is

$$\pi_{it}(b_{it}, b_{it-1}) = \sigma^{-1} r_{it}(b_{it}) - f_{it}(b_{it}) - s_{it}(b_{it}, b_{it-1}) \tag{1.12}$$

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.[19]

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

[18] 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.

[19] 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.

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 1.2, 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.

1.3.3 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}

$$\mathbb{E}[\sum_{\tau=t}^{t+L_{it}} \delta^{\tau-t}\pi_{i\tau}(b_{i\tau}, b_{i\tau-1})|b_{it}, \Omega_{it}] \tag{1.13}$$

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.

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

$$V_{it}(\Omega_{it}) = \max_{b} \overline{\pi}_{it}(b, b_{it-1}) + \delta\mathbb{E}[V_{it+1}(\Omega_{it+1})|b, \Omega_{it}] \tag{1.14}$$

where $\overline{\pi}_{it}(.)$ is the expected value of equation (1.12). 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

$$V_{it}(b, \Omega_{it}) \geq V_{it}(b', \Omega_{it}) \tag{1.15}$$

Plug in the expression for the firm's static profits in equation (1.12). We can rewrite condition (1.15) in terms of differences in current profits, fixed costs, sunk costs, and future profits as follows

$$
\underbrace{\sigma^{-1}\mathbb{E}[r_{it}(b) - r_{it}(b')|\Omega_{it}]}_{(1)} + \underbrace{\{\delta\mathbb{E}[V_{it+1}(\Omega_{it+1})|b, \Omega_{it}] - \delta\mathbb{E}[V_{it+1}(\Omega_{it+1})|b', \Omega_{it}]\}}_{(2)}
$$

$$
\geq \underbrace{\mathbb{E}[\sum_{j\in b} f_{ijt} - \sum_{j\in b'} f_{ijt}|\Omega_{it}]}_{(3)} + \underbrace{\mathbb{E}[\sum_{\substack{j\in b\\ j\notin b_{it-1}}} s_{ijt} - \sum_{\substack{j\in b'\\ j\notin b_{it-1}}} s_{ijt}|\Omega_{it}]}_{(4)} \tag{1.16}
$$

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.

1.4 Estimation Approach

Estimating the firm's optimization problem described in equation (1.13) 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.[20] 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 and 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,

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

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.[21]

For these reasons, I pursue a partial identification approach that both reduces the computational burden and only requires mild assumptions on the firm's behavior.[22] 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.[23]

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

1.4.1 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*

$$\max_{b \in B_{it}} \mathbb{E}[\pi_{it}(b, b_{it-1}) + \sum_{l=1}^{L_{it}} \delta^l \pi_{it+l}(\mathcal{J}_{it+l}(b), \mathcal{J}_{it+l-1}(b)) | \Omega_{it}] \tag{1.17}$$

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

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

[22] 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.

[23] 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.

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 $\mathbb{E}(\Pi_{io_{it}t}|\Omega_{it}) \geq \mathbb{E}(\Pi_{ibt}|\Omega_{it})$.[24] 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 had chosen o_{it} instead. By transitivity of preferences,

$$\begin{aligned}
&\mathbb{E}(\Pi_{io_{it}t}|\Omega_{it}) \\
&= \mathbb{E}(\pi_{it}(o_{it}, o_{it-1}) + \sum_{l=1}^{L_{it}} \delta^l \pi_{it+l}(\mathcal{J}_{it+l}(o_{it}), \mathcal{J}_{it+l-1}(o_{it}))|\Omega_{it}) \\
&\geq \mathbb{E}(\pi_{it}(b, o_{it-1}) + \sum_{l=1}^{L_{it}} \delta^l \pi_{it+l}(\mathcal{J}_{it+l}(o_{it}), \mathcal{J}_{it+l-1}(o_{it}))|\Omega_{it})
\end{aligned} \tag{1.18}$$

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 (1.18) is reduced to

$$\mathbb{E}(\pi_{it}(o_{it}, o_{it-1}) + \delta\pi_{it+l}(\mathcal{J}_{it+l}(o_{it}), \mathcal{J}_{it+l-1}(o_{it}))|\Omega_{it}) \geq \mathbb{E}(\pi_{it}(b, o_{it-1}) + \delta\pi_{it+l}(\mathcal{J}_{it+1}(o_{it})), b)|\Omega_{it}) \tag{1.19}$$

Equation (1.19) 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}.[25]

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 (1.19). 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.

[24] 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.

[25] 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.

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

$$\begin{aligned}
\mathbb{E}[g_k(Z_{it})\pi_{idt}] &= \mathbb{E}[\mathbb{E}g_k(Z_{it})\pi_{idt}|Z_{it}] \\
&= \mathbb{E}[g_k(Z_{it})\mathbb{E}\pi_{idt}|Z_{it}] \\
&= \mathbb{E}[(g_k(Z_{it})\mathbb{E}[\underbrace{\mathbb{E}(\pi_{idt}|\Omega_{it})}_{\geq 0 \text{ (from eq. (1.19))}}|Z_{it}] \qquad (1.20) \\
&\geq 0
\end{aligned}$$

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 (1.20) is

$$\bar{m}_k = \frac{1}{N} \sum_{i \in N_i} \sum_{j \in J} \sum_{t \in T} g_k(Z_{it})\pi_{idt} \geq 0 \qquad (1.21)$$

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}.

1.4.2 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. $o_{it}^{m} = (A, B)$. 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 1.4.1, 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

$$\begin{aligned}
\text{Deviation 1}: \pi_{idt} &= \sigma^{-1}[r_{it}(o_{it}^m) - r_{it}(o_{it}^m \setminus j)] - \gamma^f - \epsilon_{ijt}^f \\
\text{Deviation 2}: \pi_{idt} &= \sigma^{-1}[r_{it}(o_{it}^m) - r_{it}(o_{it}^m \setminus j)] - \gamma^f - \epsilon_{ijt}^f - \gamma^s - \epsilon_{ijt}^s \\
\text{Deviation 3}: \pi_{idt} &= \sigma^{-1}[r_{it}(o_{it}^m) - r_{it}(o_{it}^m \cup j)] + \gamma^f + \epsilon_{ijt}^f \\
\text{Deviation 4}: \pi_{idt} &= \sigma^{-1}[r_{it}(o_{it}^m) - r_{it}(o_{it}^m \cup j)] + \gamma^f + \epsilon_{ijt}^f + \gamma^s + \epsilon_{ijt}^s
\end{aligned}$$

Next, to create the moment inequalities in the form of equation (1.20), 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 (1.20) is equal to

$$\begin{aligned}\mathbb{E}[g_1(Z_{it})\pi_{idt}] &= \mathbb{E}[g_1(Z_{it})(\sigma^{-1}r^m_{ijt} - \gamma^f - \epsilon^f_{ijt})] \\ &= \mathbb{E}[g_1(Z_{it})(\sigma^{-1}r^m_{ijt} - \gamma^f)] \\ &\geq 0\end{aligned} \tag{1.22}$$

The second equality holds under the assumption that $\mathbb{E}(\epsilon^f_{ijt}|\Omega_{it}, d_{ijt}) = 0$.[26] 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

$$\begin{aligned}\mathbb{E}[g_2(Z_{it})\pi_{idt}] &= \mathbb{E}[g_2(Z_{it})(\sigma^{-1}r^m_{ijt} - \gamma^f - \epsilon^f_{ijt} - \gamma^s - \epsilon^s_{ijt})] \\ &= \mathbb{E}[g_2(Z_{it})(\sigma^{-1}r^m_{ijt} - \gamma^f - \gamma^s)] \\ &\geq 0\end{aligned} \tag{1.23}$$

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

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

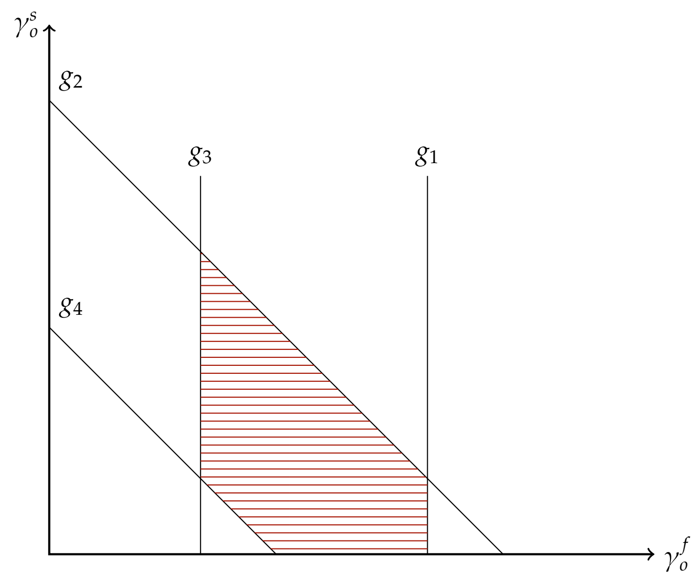


Figure 1.1: Identified set with nonnegativity constraints

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

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

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

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

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

Figure 1.1 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 and 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.

1.5 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 (1.9). In the second step, I estimate the bounds and conduct inference for the fixed and sunk cost parameters.

1.5.1 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 (1.9), 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.[27]

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 (1.6), we get

$$X_{ijt}/X_{iht} = S_{ijt}/S_{iht}. \tag{1.24}$$

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 (1.24)

$$\log X_{ijt} - \log X_{iht} = \log S_{ijt} - \log S_{ht} + \epsilon^x_{ijt} \tag{1.25}$$

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}.[28] 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}.[29] Second, the sparsity of the import data at firm-country-year level means I cannot recover S_{ijt} for all possible pairs from equation (1.25).

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 (1.25) 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 from equation (1.25). 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}.

$$\hat{\xi}_{ijt} = \beta_0 + g(X^T_{jt}\beta^T) - \theta h(X^\tau_{ijt}\beta^\tau) - \theta \ln w_{jt} + \lambda_t + \nu_{ijt} \tag{1.26}$$

where X^T_{jt} is a set of technology proxies, including R&D expenditure and capital stock. X^τ_{ijt} is a set

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

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

[29]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 1.2.

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.[30] 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.[31] As a result, I can recover the values of sourcing potential for each firm-country-year pair as the predicted values in equation (1.26).

The last component in the revenue change is θ, which is the coefficient on log wages in (1.26). Column 1 in table 1.5 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.[32]

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 1.6. 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).[33] This is consistent with the sunk cost hypothesis: new importers justify incurring sunk 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

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

[31] 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 (1.26).

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

[33] Recall that sourcing potential is a combination of technology, trade costs, and wages, and loosely captures the marginal cost saving contribution. Higher sourcing potential reflects lower cost.

Table 1.5: 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 (1.26) in Section 1.5. 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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 is large, resulting in large absolute revenue gains.

1.5.2 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.

Table 1.6: 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

By construction, a continuing importer incurs only the fixed cost f_{ijt} and a new importer pays both the fixed and sunk costs, $f_{ijt}+s_{ijt}$. For the estimation, I will report the cost to a continue importer and the cost to a new importer. Define $\tilde{\gamma}^s = \gamma^f + \gamma^s$. The vector of parameters is $\gamma = (\gamma_o^f, \gamma^f, \tilde{\gamma}_o^s, \tilde{\gamma}^s)$

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 1.4, and $\hat{\sigma}_k(\gamma)$ is the standard deviation of the observations entering moment k.

Table 1.7 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 1.7a 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 1.2 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 1.7: 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

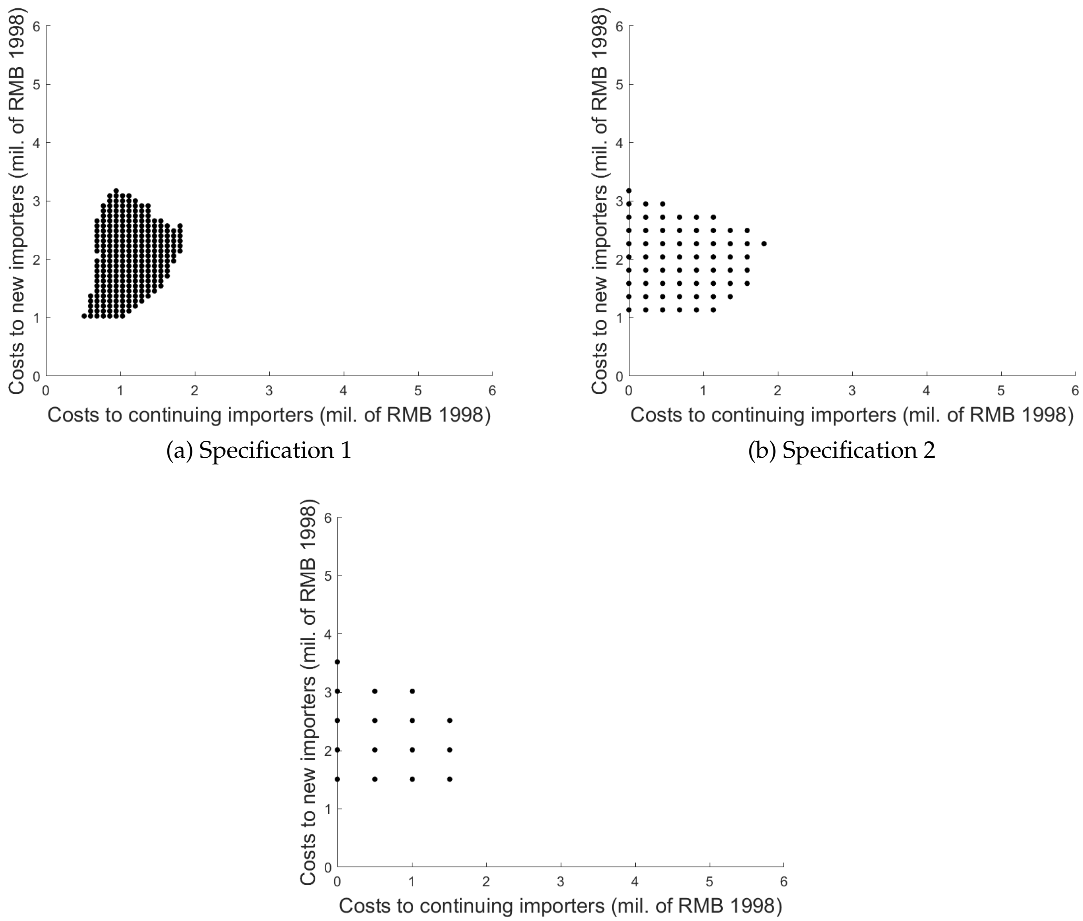
	LB	**UB**
Constant (fixed)	0.00	1.82
Language (fixed)	0.00	1.59
Constant (sunk)	0.00	3.18
Language (sunk)	0.00	2.50
Total	1.13	3.18

(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 1.2: 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.

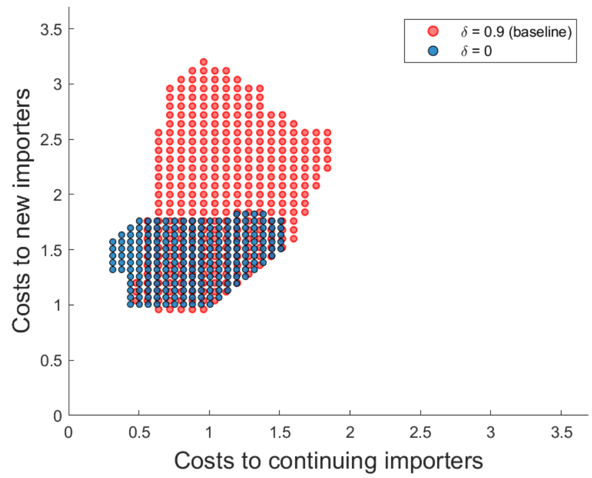


Figure 1.3: Comparing baseline with static model

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.

1.5.3 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 1.3 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 1.4 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 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

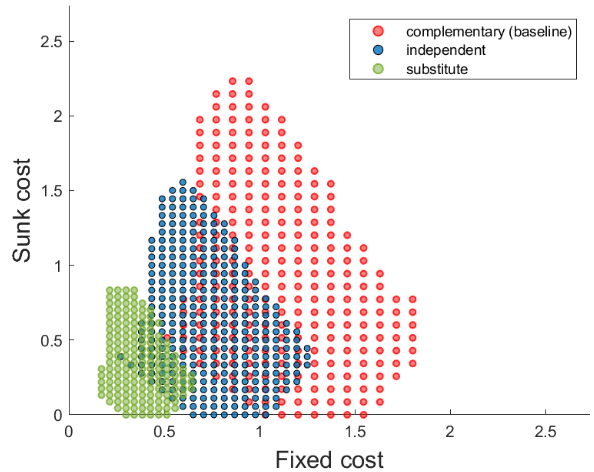


Figure 1.4: Independence across markets and fixed and sunk cost estimates

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.

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.[34]

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 interdependence across import sources in production.

1.5.4 Sample Selection and Potential Data Issues

Country list: Table 1.16 presents the list of all 40 countries that are included in the data. Though there are 96 countries from which the firms in my sample imported, more than half of the countries

[34]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.

had fewer than 20 importers during the sample period. To avoid those with few observations, I only included the top 40 countries ranked by the number of importers. The main results are not affected by choosing a different cutoff point (see Figure 1.5).

Processing firms: In China there is a dual trade regime: ordinary trade and processing trade.[35] Existing studies have documented that Chinese firms selecting into processing trade make different sourcing choices from those engaged in ordinary trade (Koopman et al., 2012; Manova and Yu, 2012; Jarreau and Poncet, 2012; Wang and Yu, 2012). There are several reasons that can explain the difference in sourcing behaviors. First, the latter regime exempts from import duties foreign inputs used for further processing and assembling and re-exporting. Processing firms are not allowed to sell in the domestic market. Apart from the import duty exemptions, there are other policies favoring pure exporters, such as the attraction of Foreign-Invested Enterprises, the promotion of Processing Trade Enterprises and the establishments of Free-Trade Zones (Defever and Riaño, 2012). There are potentially differences in foreign contracts, capacity and credit constraints, and lack of input flexibility in the assembling process between processing and other firms. Furthermore, the lack of import duties incurred by these firms is problematic since variation in input tariffs is used as an IV for the analysis in Section 1.6.1 For these reasons, I exclude firms that engage in processing trade from the sample.

Trade intermediaries: Since I am matching firms in the NBS data with the customs data, I exclude transactions conducted by intermediaries.[36] However, some firms which are classified as non-importers in the data might import indirectly through trade intermediaries. Since the NBS data set does not report domestic firm-level transactions and import values, I cannot differentiate between non-importers and indirect importers.[37]

This misclassification can affect the sunk cost estimates in several ways. First, firms that use intermediaries may have more information about the foreign sourcing countries and thus pay a lower sunk cost to directly import in subsequent periods. On the other hands, firms that have access to foreign inputs may enjoy higher future productivity. Both channels increase the likelihood of importing in subsequent periods conditional on using intermediaries.[38] Nonetheless, while the first one introduces an attenuation bias, the second channel creates an upward bias in the sunk cost

[35] For more institutional background about trading regimes in China, see Manova and Yu (2012); Jarreau and Poncet (2012); Morrow and Brandt (2013); Manova and Yu (2016).

[36] About 19.7% of firms in the customs data that exported chemical products between 2000 and 2006 are intermediaries. Those firms accounted for 24.7% of total import values.

[37] Bai et al. (2017) are able to identify direct and indirect exporters based on the total export values reported in the NBS data, i.e., if a firm reports export values but does not appear in the customs data, it is classified as an indirect exporter. Since import values are not reported, I cannot use the same method to identify indirect importers.

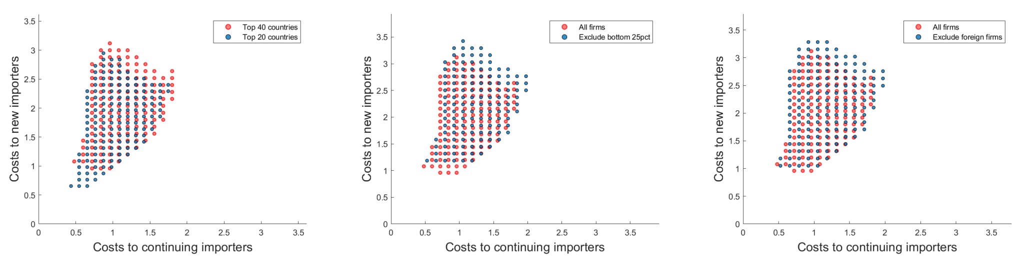
[38] Ahn et al. (2011) find suggestive evidence that once small firms export indirectly by using intermediary services, they could switch to exporting directly.

estimate. It is, therefore, unclear which direction of the bias would be.

However, there are several reasons why this might not be a concern for my study. First, since I focus on country-specific sunk costs, the bias might not be severe if the countries from which firms indirectly import are not the same as those they directly trade with. Second, I limit the sample to those that imported at least once, meaning that the sample does not contain firms that only indirectly imported during 2000-2006. Yet, some firms might indirectly import in the earlier years and then switch to direct importing later. To address this problem, I exploit the fact that intermediation is used mostly by small firms. For example, Ahn et al. (2011), Akerman (2018) and Blum et al. (2010) show that smaller firms matched with intermediaries to avoid the cost of direct exporting. Thus, I conduct a robustness check that excludes firms with average sales in the bottom 25 percentiles. The new sunk cost estimate is slightly bigger, indicating that firms that use intermediaries may incur small costs of directly importing later. However, the difference in the two estimates is negligible.

Intra-firm trade: Foreign firms in China might import from their parent countries and thus do not pay the full sunk cost of importing. Though I do not observe the foreign suppliers and cannot identify whether a firm is purchasing from its parent company, I conduct a robustness check that excludes foreign firms from the main analysis. As expected, the sunk cost estimate is bigger, but not by a large extent.

Figure 1.5: Robustness checks - Sample selection



(a) Top 20 countries (b) Exclude small firms (c) Exclude foreign firms

This figure illustrates the 95% confidence sets of the total costs to continuing versus new importers for different samples. The baseline result is presented by the red region. Panel (a) reports estimates for the top 20 countries, panel (b) reports estimates when small firms are excluded from the sample, and panel (c) reports results when foreign firms are excluded. Monetary values are in million of 1998 RMB.

1.6 Extensions

In the following sections, I discuss two extensions of the baseline model. First, Section 1.6.1 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 1.6.2, I introduce exporting decisions into the model. In this setting, a firm can choose where to import intermediate goods and export final goods.

1.6.1 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 and Rodrigue, 2008; Amiti and 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.[39] 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 (1.9) 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.

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

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

$$\log r_{it+1} = \lambda_{t+1} + \eta X_{it} + \ln \hat{\Theta}_{it+1} + \nu_{it+1} \tag{1.27}$$

where $\hat{\Theta}_{it+1}$ is the firm's sourcing capacity estimated using the procedure in Section 1.5. Note that given the construction of the deviations in Section 1.4, 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}. 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 $r_{it+1}(X'_{it})$.

1.6.1.1 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.[40] 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

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

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 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.

1.6.1.2 Results

Table 1.9 reports the result for equation (1.27) 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.[41] 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 1.10 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

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

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.

Panel (a) in Figure 1.6 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.[42] 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 1.8: 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 1.8.1.1.
Standard errors in parentheses

1.6.2 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.[43] Though the baseline model assumes final goods are non-tradable, it can be extended to include exporting decisions.

[42]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.

[43]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 1.9: 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

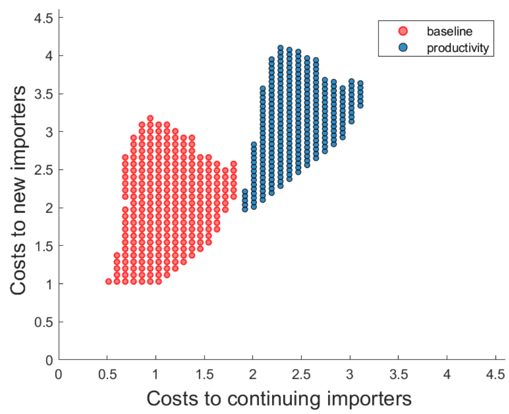
This table reports the effects of past import decisions on current revenues. Columns 1-3 use the total number of import countries as the key independent variable, columns 4-6 use the number of advanced technology countries, and columns 7-9 use the number of high-income countries. Except for columns 1, 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 1.18. Monetary values are in units of million of RMB 1998.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.10: Revenue changes - Number of high income countries

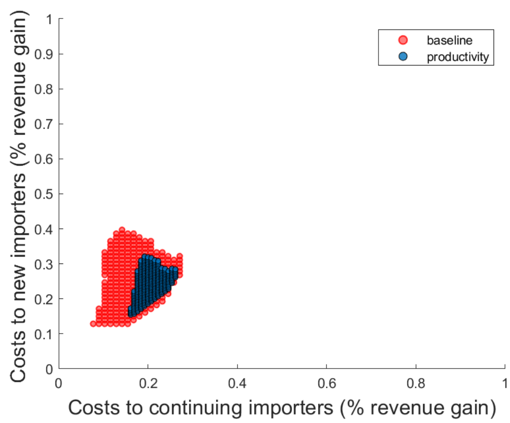
	All	Never	Exiting	New	Continuing
Current revenue changes	6.334	6.133	3.293	7.518	6.649
	(22.50)	(22.34)	(8.081)	(27.54)	(20.28)
Future revenue changes	4.152	2.324	6.006	9.091	8.158
	(11.09)	(5.535)	(6.902)	(19.99)	(16.97)
Total revenue changes	10.07	8.225	8.698	15.70	13.99
	(23.89)	(22.40)	(9.091)	(31.47)	(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 1.6: 95% confidence sets - Baseline results



(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

$$r^x_{ijt}(\mathcal{J}^m_{it}) = \left[\frac{\sigma}{\sigma-1}\frac{\tau^x_{ijt}}{\varphi_{it}P_{jt}}\right]^{1-\sigma} Y_{jt}(\gamma\Theta_{it}(\mathcal{J}^m_{it}))^{\frac{\sigma-1}{\theta}} \tag{1.28}$$

Equation (1.28) 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.[44]

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} destinations in year t is

$$\pi_{it}(b^m_{it}, b^m_{it-1}, b^x_{it}, b^x_{it-1}) = \sigma^{-1}r_{it}(b^m_{it}, b^x_{it}) - f^m_{it}(b_{it}) - s^m_{it}(b^m_{it}, b^m_{it-1}, b^x_{it-1}) - f^x_{it}(b_{it}) - s^x_{it}(b^x_{it}, b^x_{it-1}, b^m_{it-1}) \tag{1.29}$$

[44]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.

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}

$$\mathbb{E}[\sum_{\tau=t}^{t+L_{it}} \delta^{\tau-t} \pi_{i\tau}(b^m_{it}, b^m_{it-1}, b^x_{it}, b^x_{it-1}) | \Omega_{it}] \tag{1.30}$$

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}).[45]

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 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 1.4.

[45] 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., $B_{it} = B^m_{it} \cup B^x_{it}$.

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:

$$f_{ijt}^{x} = \gamma^{f,x} + \epsilon_{ijt}^{f,x}$$

$$f_{ijt}^{m} = \gamma^{f,m} + \epsilon_{ijt}^{f,m}$$

$$s_{ijt}^{x} = \gamma^{s,x} + \epsilon_{ijt}^{s,x}$$

$$s_{ijt}^{m} = \gamma^{s,m} + \epsilon_{ijt}^{s,m}$$

where $\mathbb{E}(\epsilon_{ijt}^{g,x}|\Omega_{it}, d_{ijt}^{x}, d_{ijt}^{m}) = 0$ and $\mathbb{E}(\epsilon_{ijt}^{g,m}|\Omega_{it}, d_{ijt}^{x}, d_{ijt}^{m}) = 0$, with $g = f, s$.

Finally, $e_{ijt}^{x} = \gamma^{e,x}$ and $e_{ijt}^{m} = \gamma^{e.m}$. 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 1.4 to create the moment inequalities from both export and import decisions.

Table 1.11 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 1.12 reports the 95% confidence intervals for individual parameters in the vector γ and Figure 1.7 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

Table 1.11: 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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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.[46] 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.[47]

1.7 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

[46]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.

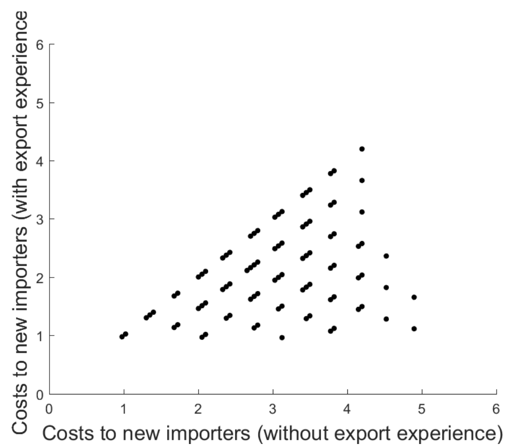
[47]This evidence explains the difference between my estimates and the results in Kasahara and Lapham (2013), in which the authors find the the costs of exporting are comparable to the costs of importing.

Table 1.12: 95% confidence set for export and importing costs

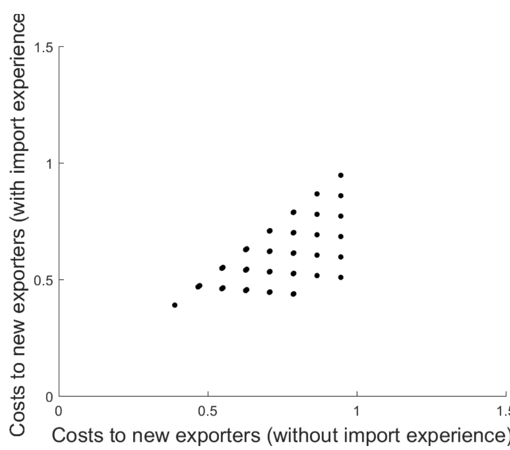
	LB	**UB**
$\gamma^{f,m}$	0.00	2.28
$\gamma^{s,m}$	0.00	4.90
$\gamma^{f,x}$	0.00	0.47
$\gamma^{s,x}$	0.00	0.95
$\gamma^{e,m}$	0.00	3.78
$\gamma^{e,x}$	0.00	0.44

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 1.7: 95% Confidence Sets for Exporting and Importing Costs



(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.

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 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 1.6.1 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 morales2019extended, 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 1.6.2 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.

1.8 Appendix

1.8.1 Data

1.8.1.1 Variable construction

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).

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.[48]

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

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.

1.8.1.2 Descriptive Statistics

Table 1.13 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 1.13: 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 1.14 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.

in 2004.

Table 1.14: 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.

Table 1.15 provides descriptive statistics for the sample of chemical producers in the main analysis.

Table 1.15: Firm-level summary statistics

	Mean	Std. Dev.	Min	Max
Log domestic revenues	10.534	1.734	-0.169	16.341
Log import values	7.627	3.284	-4.794	15.201
Log export values	8.223	2.199	-4.110	13.722
Import status	0.173	0.378	0	1
Export status	0.312	0.463	0	1
Number of import markets	0.582	1.873	0	23
Number of export markets	2.764	6.523	0	71
State-owned	0.164	0.370	0	1
Private	0.327	0.469	0	1
Foreign	0.115	0.319	0	1
Joint venture	0.205	0.404	0	1

This table provides the firm-year-level descriptive statistics for the main sample. Import values capture the average total values that a firm imports in a year. A firm's import status takes the value of one if a firms imports in that year from any country. The export variables are defined in the same way.

1.8.2 Alternative Procedure to Predict Sourcing Potential S_{ijt}

Instead of predicting S_{ijt} through two steps as described in Section 1.5, 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

Table 1.16: Country list

Australia	Germany	Malaysia	South Africa
Austria	Hong Kong	Mexico	South Korea
Belgium	Hungary	Netherlands	Spain
Brazil	India	New Zealand	Sweden
Canada	Indonesia	Norway	Switzerland
Chile	Iran	Philippines	Taiwan
Czech Republic	Ireland	Poland	Thailand
Denmark	Israel	Russia	Turkey
Finland	Italy	Saudi Arabia	Ukraine
France	Japan	Singapore	United Kingdom
			United States

This table lists the source countries used in my analysis. Countries are ranked by the total number of importers during 2000-2006 and the top 40 are included (there are 41 countries in the list due to a tie).

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 1.26:

$$\log X_{ijt} - \log X_{iht} = \beta_0 + g(X^T_{jt}\beta^T) - \theta h(X^\tau_{ijt}\beta^\tau) - \theta \ln w_{jt} + \lambda_t \tag{1.31}$$

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

$$\frac{X_{ijt}}{X_{iht}} = \exp\left(\beta_0 + g(X^T_{jt}\beta^T) - \theta h(X^\tau_{ijt}\beta^\tau) - \theta \ln w_{jt} + \lambda_t\right) \tag{1.32}$$

In principle, the Poisson regression allows us to include zeros on the left hand side. That said, recall the definition of sourcing potential: $S_{ijt} = T_j(\tau^m_{ijt} w_{jt})^{-\theta}$. 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 1.17 reports results for different methods of estimating country-level sourcing potential.

The first two columns are the baseline results reported in Section 1.5. The next two columns report results for equation 1.31 under a log-linearized model. As expected, except for the year dummies and constant term, the two sets of estimates are identical.

1.8.3 Additional Tables

Table 1.17: 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 1.18: 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 1.9.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.19: 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 1.9 for IV estimates.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

CHAPTER 2

Anticipation Effects of the TPP on Vietnamese Manufacturing Firms

2.1 Introduction

There is a well established literature that studies the effect of trade reforms and free trade agreements (FTAs) on productivity. Existing findings indicate that reductions in trade costs have implications for both firm-level and aggregate productivity.[1] At the same time, even though in most real world settings there is usually a time lag between the announcement of the new policy and its implementation, the majority of current studies have focused on the actual implementation of trade policy changes but overlook potential effects of policy announcements.[2]

This paper fills in the gap by providing a deliberate analysis of the anticipation effect of FTAs or trade policies in general–that is, how firms respond to the announcement of future policy changes. While most trade models are static under a stable aggregate environment, trade liberalization or trade agreements oftentimes requires analysis of transition dynamics, especially in the setting of developing countries. Firms' expectation about future policies and future profits is a key factor in generating aggregate transition dynamics (Costantini and Melitz, 2007; Ruhl et al., 2008; Burstein and Melitz, 2013; Alessandria and Choi, 2014). Therefore, it matters whether firms anticipate trade policy changes.

Identifying anticipation effects constitutes an empirically challenging task. A natural approach is to look at the evolution of firm-level productivity between a new policy's announcement and implementation. Unfortunately, this strategy is potentially flawed since researchers do not directly observe the firms' expectations about the timing of policy implementation. In the case of an FTA, a signed agreement will not enter into force until the national delegations obtain approval of the agreement by their states. The ratification process is bound by each state's internal procedure and the entire process can take from a few months to years, creating much uncertainty about the time lag between an agreement's announcement and its actual implementation. Without strong assumptions on the firms' expectations, it is thus infeasible to separately identify the effect of actual policy implementation from that of policy anticipation.

The ideal setting is one when firms anticipate future policy changes which do not happen, so that most changes in firm outcomes are a direct effect of the anticipation. This is tricky in the setting

[1] See Wagner (2012), Goldberg and Pavcnik (2016), and Shu and Steinwender (2019) for comprehensive reviews of the literature.

[2] For instance, NAFTA was signed in December 1992 and did not take effect until January 1994.

of trade liberalization because not carrying out promised reforms may cast doubts on the credibility of the government and whether firms actually expect reforms in the first place. In other words, we need the failure to carry out new policies to be unexpected. Furthermore, we need firms to have sufficient information about the new policy in order to make appropriate investments and have sufficient time to carry out the investments before the new policy is abolished.

Although not many trade reforms and FTAs satisfy these requirements, one stands out: the Trans-Pacific Partnership (TPP). Its timeline provides a unique setting in which there was anticipation and not actual implementation of trade policy changes. The TPP negotiations were concluded in October 2015, and during the following year, it was highly anticipated until Donald Trump became the US president in November 2016 and withdrew the US shortly afterwards.

I choose the Vietnamese manufacturing firms as the subject of this study for two reasons. The TPP was predicted to have a significant impact on the Vietnamese economy, and thus would induce strong responses from Vietnamese firms. There is anecdotal evidence that Vietnamese producers believed the TPP would have a large impact on their future profits and planned to make adjustments accordingly. Second, from the viewpoint of Vietnamese firms, the signing of the US in the trade deal was credible and thus its withdrawal was not predicted.[3] Section 2.2 provides detailed background on the TPP timeline and Vietnamese economy and explains why the context provides a natural experiment suitable to study the anticipation effects.

Section 2.3 discusses the theoretical motivation underlying the effect of anticipated trade liberalization on aggregate and firm-level productivity. Existing studies provide two potential channels through which *actual* tariff reductions affect productivity: (1) reallocation of resources from least productivity to most productive firms and (2) within-firm changes that come from either endogenous productivity improvement or spillovers from exposure to trade and/or competition. When it comes to *expected* tariff reductions, it is unclear all channels are relevant. Nevertheless, it is safe to assume that in the absence of actual policy changes, any effect on aggregate productivity is likely to come from changes in firm expectations. Studying the effects of trade agreement announcements, we can thus infer how firms interpret different policies and react accordingly.

This paper focuses on the impact of output tariff liberalization under the TPP agreement.[4] Two key policy variables are expected reductions in tariffs on final good export from Vietnam to other

[3] Vietnamese pundits expected delay in the ratification process, but there was hardly any prediction about its withdrawal.

[4] Due to the lack of data on firm inputs, this work abstracts from the impact of input tariff liberalization. Several studies have found that access to imported inputs can improve productivity, for example, Amiti and Konings (2007). Nevertheless, given that input tariff reductions were never implemented during my sample period, I rule out this possibility. Another potential effect is that firms might start to purchase foreign inputs in order to improve product quality and/or physical efficiency. In this case, the change in input purchases should not respond directly to expected changes in input tariffs.

TPP counties (export tariffs for short) and in tariffs on imports from these countries to Vietnam (import tariffs). The use of expected tariff reductions resembles that in Handley and Limão (2017), in which the authors exploit the differences between MFN tariffs (current rates) and Column 2 tariffs (expected rates) to explore the effect of expected tariff changes on Chinese firms' investments during 2000-2005. In my setting, because almost every tariff would eventually be reduced to zero under the TPP, the heterogeneity of tariff reductions comes from two sources: baseline tariff levels in 2015 and the phase out length. Here it matters how forward-looking firms would be: two products with the same base rates might generate different responses from firms if one is subject to an immediate cut while the other is reduced more gradually. For this reason, I construct different measures of expected tariff reductions under different discount factors and planning horizons. Details on construction of expected tariff cuts are presented in Section 2.4.

The empirical strategy follows a two-step approach. In the first step, I compute firm productivity using the control function method introduced by Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg et al. (2015), and Wooldridge (2009). In the second step, I apply a method similar to difference-in-differences estimation and exploit the variation in expected tariff reductions across 4-digit industries and compare the differential changes in TFP before and after the signing of the TPP between firms in industries with high expected tariff reductions versus those with low expected tariff reductions. Two assumptions are required under this identification strategy: (1) in the absence of treatment, the difference between firms with higher tariff reductions and those with low tariff reductions should stay constant over time (parallel trends), and (2) firms do not exit and enter certain industries because of the TPP announcement (stability of industry matching). Section 2.6.3 discusses the validity of these assumptions.[5]

The baseline results indicate that Vietnamese firms respond positively to future export tariff reductions: a one percentage point decrease in export tariffs imposed on Vietnamese goods by other TPP countries leads to 0.34-0.45% increase in productivity. On the other hand, a one point decrease in import tariffs lowers productivity by 0.29-0.32%. Productivity only responds to future tariff changes in 2016 but not 2017, suggesting that from the firms' viewpoint, it was unlikely that the TPP was going to be implemented in 2017.[6] In contrast, there is not much evidence on the effect of TPP announcement on reallocation, exit, or entry in Vietnam. Quantifying the impact on aggregate productivity due to firm-level changes, I find that though the net effect on the entire

[5]This method allows for selection on non-treatment level, that is, industries with high tariff reductions and those with low tariff reductions can be inherently different from each other. Nevertheless, I control for important initial four-digit industry characteristics and include two-digit industry fixed effects in the main specification.

[6]This results are robust to different measurements of the future tariff changes.

manufacturing sector is minimal, there is much heterogeneity across two-digit industries.

Related Literature

My study relates to several strands of literature. There is first the literature on firms' joint decisions to enter foreign markets and to invest or innovate (López, 2009; Lileeva and Trefler, 2010; Bustos, 2011; Aw et al., 2011). The common assumption among these papers is that there is a sunk cost of investing and/or upgrading; trade agreements increase the profitability of investment and innovation and thus induce the marginal firms to engage in such activities in order to export. These papers use actual policy changes as exogenous shocks, but do not look into the anticipatory effects of trade agreements.[7] Two exceptions are Costantini and Melitz (2007) and Burstein and Melitz (2013), in which the authors introduce theoretical models that characterize the dynamics of firm adjustments according to the timing and pace of trade liberalization. Their simulated results show that when trade liberalization is anticipated by firms, they innovate ahead of the export market participation, thus amplifying the productivity difference between exporters and non-exporters. My paper provides empirical evidence for their theoretical predictions that firms indeed make adjustments to their productivity in anticipation of the trade policy changes, but departs from the existing studies by examining the anticipation effect of both greater market access and increased foreign competition on firm-level productivity.[8]

This work is also related to the literature which studies the impact of trade policy uncertainty on exporting and innovation (Handley, 2014; Handley and Limão, 2015, 2017; Feng et al., 2017; Liu and Ma, 2016). A common feature among these papers is Chinese accession into the WTO in 2001, which reduced the probability of China facing higher tariffs the US. Building on their results, I argue that firms delay incurring costs to raise productivity until the member countries reached a final agreement in 2015 and the uncertainty about the TPP was reduced. To my knowledge, this paper is to first to look at the effect of the *unrealized* trade agreements.

Finally, this paper contributes to the studies on trade policies in Vietnam. Since the 1986 economic reform, the Vietnamese economy has become increasingly integrated into international markets. The country joined the WTO in 2007 and has signed 17 preferential trade agreements. Between 2010 and 2017, the ration of Vietnam's total trade values to GDP rose from 134% to 200%. In 2016, manufactured products accounted for 83% of total Vietnamese exported goods and 80% of

[7] López (2009) and Van Beveren and Vandenbussche (2010) show that firms invest in productivity in advance prior to their export entry decisions, but do not analyze the impact of trade policy changes.

[8] Bergin and Lin (2012) provide empirical evidence that firms' expectations about the future aggregate environment induces changes in firms' current export market entry decisions. Moreover, Das et al. (2007) find effects of anticipated changes in exchanges rates in some Colombian sectors. These papers, nevertheless, abstract from the decision to innovate or invest in productivity.

imported goods. The TPP is a natural next step that would add steam to Vietnam's manufacturing-based, export-led growth path. The existing studies on the impact of trade policies at firm level have mostly focused on the agriculture and/or the informal sector (Brambilla et al., 2012; Fukase, 2013; McCaig and Pavcnik, 2015, 2018). Even though the informal sector continues to account for a significant fraction of Vietnamese economy, the formal manufacturing sector is the main drive for trade and growth. Thus, the findings in this paper also have implications for other developing countries, particularly in Asia, that have been growing by expanding manufacturing.

The remaining paper is organized as follows. Section 2.2 provides a background on the Trans-Pacific Partnership and its potential impacts on the Vietnamese economy. Section 2.3 discusses the conceptual framework underlying the effect of anticipated trade policy changes on productivity. Section 2.4 describes the principle data set and construction of key variables. In Section 2.5, I provide an overview of trends in aggregate productivity during 2010-2017. Sections 2.6 presents the empirical strategy and the results for firm-level productivity. Section 2.7 documents the heterogeneous effects of TPP anticipations across different firm types and potential industry growth levels. Section 2.8 concludes.

2.2 Background Information

2.2.1 The Trans-Pacific Partnership

Originally, the TPP was a proposed trade agreement among 12 countries that border the Pacific Ocean. In the Americas, it included the NAFTA signatories (United States, Canada, and Mexico) plus Peru and Chile. The TPP's largest economy in Asia is Japan, followed by Malaysia, Singapore, Vietnam, and Brunei. The TPP economies together account for 40% of world GDP and 26% of global trade. The final agreement cuts over 18,000 tariffs, lowers various non-tariff barriers, and harmonizes a wide range of regulations.

Beginning as the Trans-Pacific Strategic Economic Partnership signed by 4 member countries, in 2008 the TPP expanded to include other countries, such as the US and Vietnam. Between this period and 2015, there were 19 formal rounds of negotiation and a number of subsequent meetings. Details of those negotiations were kept secret and access to the working drafts of the agreement were restricted even to government officials. However, in December 2013, WikiLeaks released two documents that included excerpts from internal government commentary on the state of the Salt Lake City round and country-by-country positions on remaining issues. These documents indicate deep divisions between the US and other members on several contentious points, including intellectual property rights, limited support for state-owned enterprises, and the investor-state dispute settlement mechanism. There were also tensions between the US and Japan, the two largest economies among TPP members, regarding agricultural and auto tariffs. It seemed that little progress had been made toward a final agreement by the end of 2014.

During 2015, however, there were a sequence of events that brought about a more positive outlook for the TPP. Arguably, the most influential of all was the passage of the Trade Promotion Authority (TPA), which permits the US President to negotiate international trade deals without interference and reduces the Congress' responsibility to a yes or no vote on the final version. Whereas the TPA had been pushed by the Obama administration since 2012, its passage was unlikely due to opposition from the President's own party. The November 2014 midterm election led to a new Republican majority in the Senate and an enlarged majority in the House of Representatives, which increased Congressional support for trade liberalization. This was critical for completing the TPP agreement, as it guaranteed other negotiating countries that the deals they make with the US would not be amended by the US Congress.[9] Another key event leading to the final TPP agreement is the bilateral accord between the US and Japan in which Japan agreed to open its market for several politically sensitive agricultural products and accept US vehicle safety standards for US cars sold in Japan. In return, the US, Canada, and Mexico would lower the threshold of how much of an automobile would have to come from Trans-Pacific signatory countries to avoid hefty tariffs. Eventually in October 2015, twelve countries reached a final agreement and signed the deal in February 2016.

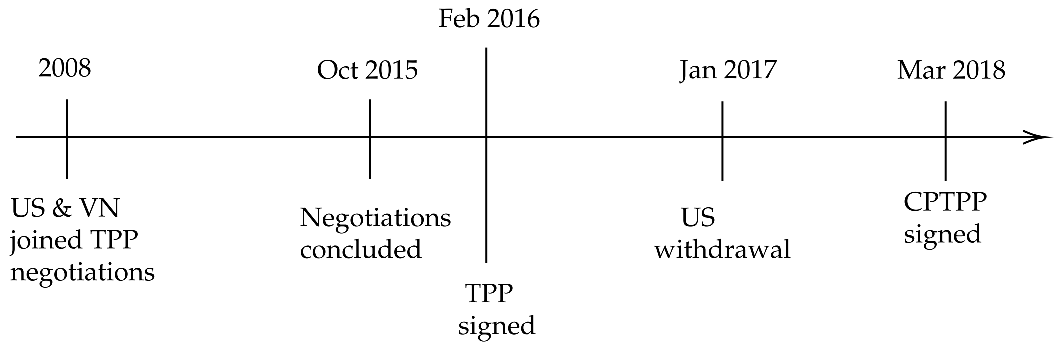
The end of 2016 witnessed an unexpected turn in the US presidential election. The anti-free trade Republican candidate won and quickly withdrew the US out of the TPP. From the prospective of remaining members, including Vietnam, the US was a crucial key player in the negotiation which shaped much of the content of the final agreement. Without the US participation, countries were unwilling to proceed with the current final agreement. Since 2016, the future of the TPP has remained uncertain.

In January 2018, the remaining 11 countries reached a new agreement, which is called the Comprehensive and Progressive Agreement for Trans-Pacific Partnership, or the CPTPP. The new deal resembles much of the 2015 agreement, but suspended 22 provisions that the United States favored but other countries opposed. However, my main analysis focuses on the original trade agreement and the period prior to 2018.

In Vietnam, public attention and knowledge of the TPP was low between 2008 and 2014, but

[9] Celik et al. (2018) provide a theoretical explanation for why the fast-track authority is critical for small countries when bargaining with large economies such as the US.

Figure 2.1: Timeline of the Trans-Pacific Partnership



grew quickly around the month of October 2015, as demonstrated in Figure 2.2. The top panel shows the cumulative number of online articles by major Vietnamese newspapers that contained the keyword TPP between 2008 and 2018.[10] While there was hardly any mention of the trade agreement in the news, even during the 2013-14 Wikileaks, the number of articles on the topic sharply increased in the first quarter of 2015 and steadily rose thereafter. Indeed, while there were only 300 new articles written about the TPP during the fourth quarter of 2014, the number grew to 2,500 within one year.

Figure 2.2b reports the frequency of searches for TPP-related keywords in Vietnam. The number of searches for the TPP spiked during October 2015, when the final agreement was reached. The two graphs together indicate that (1) there was little knowledge of the TPP in Vietnam prior to 2015 and (2) there was a large degree of public information and public awareness of the trade agreement after the TPP negotiations were concluded.

2.2.2 Potential Impacts on the Vietnamese Economy

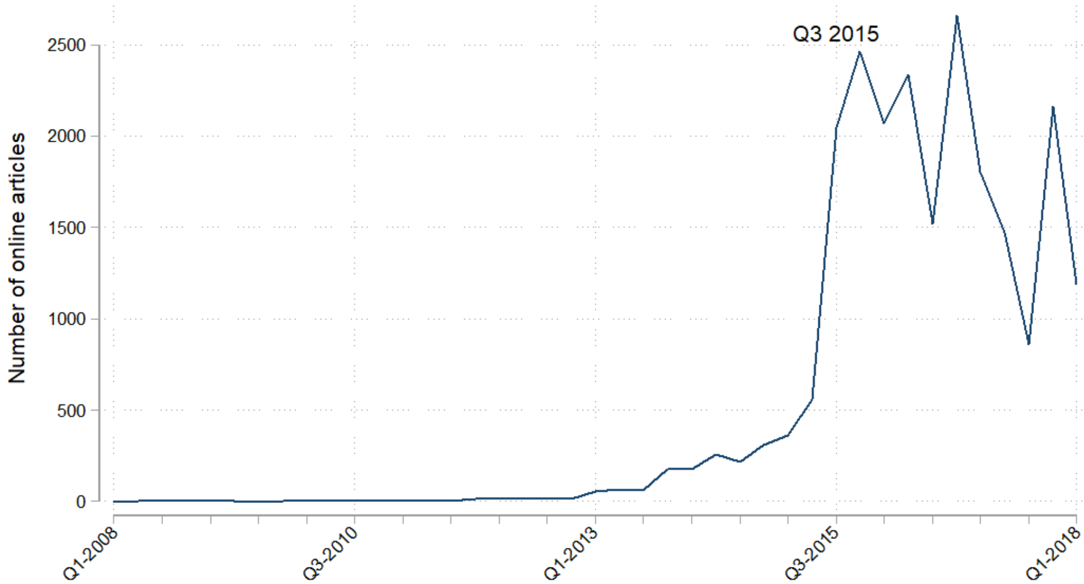
The signing of the TPP was one of Vietnam's most anticipated economic events during recent years. Several studies concluded the trade agreement would generate significant macroeconomic benefits for the Vietnamese economy. Vietnam's GDP was expected to grow between 6 and 8% and export values was anticipated to grow between 20 and 30% by 2030.[11] Prior to 2015, however, Vietnam had already signed trade agreements with seven TPP countries.[12] Hence, most of the changes in tariffs would come from the US, Canada, Mexico, and Peru, which are currently applying MFN tariff rates on Vietnamese exports. The US–which has consistently been Vietnam's top export destination (20%

[10] The sites are chosen based on their popularity (web traffic ranking reported by Alexa.com) and legitimacy. There are 10 general newspapers and 5 business-oriented sites. The complete list can be found in the Appendix.

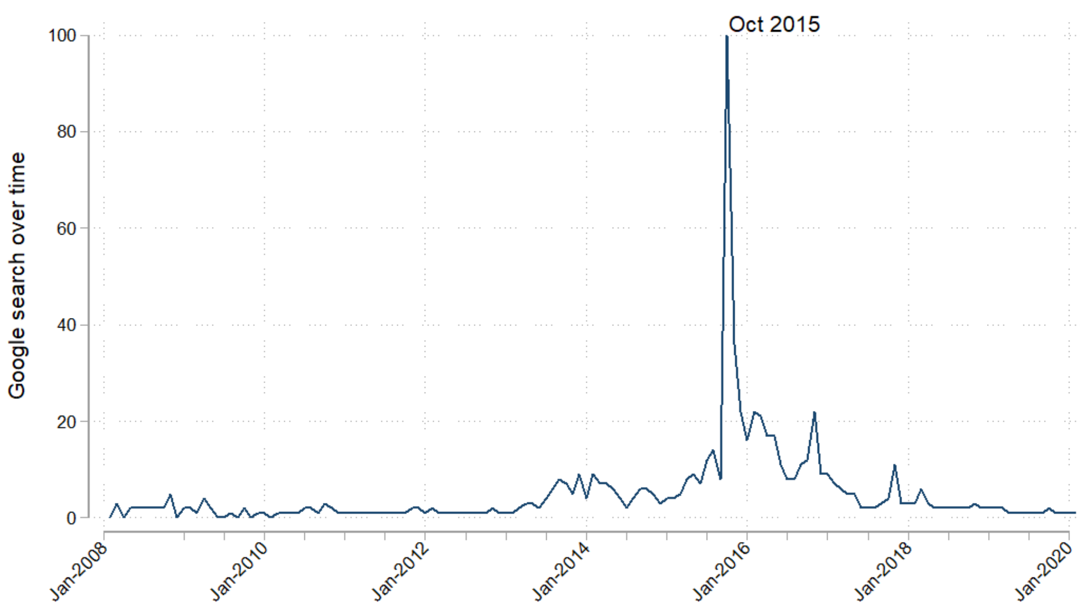
[11] See Petri and Plummer (2012); Petri et al. (2017); Kikuchi et al. (2018); Lakatos et al. (2016); Maliszewska et al. (2018).

[12] The elimination phase has finished for five of them, with the exception of the FTAs with Japan and Chile.

Figure 2.2: Public interest about the TPP in Vietnam



(a) Online articles in Vietnamese about the TPP (quarterly)



(b) Frequency of Google searchers on TPP-related key words (monthly)

The top panel present the number of articles about the trade agreement in 15 major online newspapers in Vietnam. The bottom panel shows the trend in Google searches in Vietnam related to the Trans-Pacific Partnership from 2008 to 2020. The vertical axis represents search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term.
Source: Google Trends

of export as of 2016)–contributes a significant part of Vietnam's economic benefits from the TPP. It was estimated that the US would double its share of Vietnam's exports, reaching 37% in 2030. Without US participation, the estimated gains from the trade agreement for Vietnam were reduced substantially (Petri et al., 2017; Maliszewska et al., 2018).

The TPP was also expected to serve as soft balancing against the rising Chinese dominance in the region. Vietnamese manufacturers, even export-eccentric ones, are becoming more reliant on Chinese inputs. Imported goods from China encompass various essential materials for export-specific production, including raw materials, machinery and equipment, steel, chemicals. The TPP, if came into force, would compensate for its trade deficit with China through a surplus with TPP members. Furthermore, the South China sea conflict and anti-China sentiment in the country motivates the Vietnamese government to strengthen its ties with the United States.

All in all, the importance of the TPP and its potential economic and geopolitical impacts made it likely that Vietnamese firms would keep a close watch on its course of events and respond accordingly. Indeed, a government survey conducted between December 2015 and April 2016 reported that about 88.6% of firms knew about the TPP agreement, 70% planned to expand production, and 31% would improve their executives' management skills and workers' vocational skills.[13]

2.3 Theoretical Motivation

In this section, I provide a conceptual framework to understand how anticipation of trade policy changes can affect productivity. In particular, I focus on two output-oriented trade policies: a reduction in export tariffs, which leads to greater foreign market access, and a reduction in import tariffs, which creates higher competition in the domestic market. The existing literature emphasizes two channels through which these policy changes affect aggregate productivity: (1) within-firm changes and (2) the reallocation of resources. The first channel occurs when firms are induced to make productivity-enhancing investments or there are spillovers from exposure to foreign firms and foreign products (Lileeva and Trefler, 2010; Bustos, 2011; Aw et al., 2011; Liu et al., 2015; Van Biesebroeck, 2005). However, aggregate productivity might still change without any effect at the firm level if there is reshuffling of resources from least productive to most productive firms (Pavcnik, 2002; Melitz, 2003).

Nevertheless, in the absence of actual policy changes, changes in productivity must come from changes in firm' expectations. When forward-looking firms learn about future policies, they make adjustments in advance to respond to the trade policy announcements, especially if there is a time

[13] The survey was part of the 2015 Vietnam Enterprise Survey described in Section 2.4.

lag between investment and productivity adjustments. A decrease in export variable costs will increase the expected profits of (potential) exporters, thus increasing the firm' incentive to improve productivity. One might ask why firms were willing to leave money on the table prior to trade reforms. A potential explanation is that raising productivity is costly, and firms only engage in such activity only if the profit gain outweighs the cost associated with improving productivity.[14]

The effect of an expected reduction in import tariffs, however, is less straightforward to predict. While export tariffs enter directly into the firm's profit function through the variable costs of exporting, import tariffs affect firms' expected profits indirectly through their expectations about future market demand (or future competition). If firms predict that future market demand will shrink due to the entry of foreign firms, they may reduce investment on productivity. On the other hand, firms may increase productivity-enhancing investments in order to escape competition.[15]

The changes from firms' investment in productivity can potentially lead to the reallocation of resources to firms with the most productivity improvement. The mechanism underlying reallocation here is different from that in Hsieh and Klenow (2009), in which the authors argue that economic reforms, such as trade liberalization, reduce distortions in both the output and input markets and lead to a more efficient allocation of resources across firms. Here, reallocation is an indirect effect of within-firm productivity changes.

A related effect of anticipated trade policy changes is that firms may enter and exit the market in response to future profit changes. For example, increased competition might reduce the value of staying for low-productivity incumbents and thus induce these firms to exit early. Analogously, it may also deter low-productivity firms from entering. Increased access to foreign markets might also change the values of exiting and entering, though it is unclear whether the marginal entrants and exiters are also exporters.

Finally, the theoretical literature has mostly abstracted from the redistribution effect across industries.[16] Since there is heterogeneity in the level of tariff reductions across industries, we should expect some industries may enjoy bigger increases in aggregate productivity than other. Another effect of industry heterogeneity in exposure to trade agreements is that there might be reallocation of resources from one industry to another, either because exit and entry behavior changes, or because entrants switch industries. This will also have implications for industry-level

[14]This argument is central to the models of joint exporting and investing in Bustos (2011) and Aw et al. (2011).

[15]Which effect dominates depends on the firms' initial level of productivity. Aghion et al. (2005) show that competition discourages laggard firms from innovating, but when competing firms are neck-to-neck in their levels of technological advancement, competition may increase innovation.

[16]One notable exception is Bernard et al. (2007), in which the authors argue that trade openness induce reallocation of resources both within and across industries.

productivity.

In a nutshell, we should expect that the announcement of a trade agreement, which would alter firm' expectations, will affect aggregate productivity in three ways: (1) within-firm changes due to changes in firm-level incentives to invest or innovate (2) reallocation of resources, which can occur within an industry or across industries (3) exit and entry. In the empirical analysis, I explore all of these channels.

2.4 Data and Variable Construction

2.4.1 Vietnam Enterprise Surveys

The principal data set come from the Vietnam Enterprise Surveys 2010-2017. Conducted annually by the General Statistics Office (GSO) of Vietnam, the survey contains a wide range of information, including firm identification, ownership types, industry classification, sales, employment, and capital stock. The sampling unit is registered enteprises with independent business accounts. Thus, different branches which are under the same company but file taxes separately are treated as unique business entities. Throughout this study, I use the term "firm" the same way as defined in the survey. A panel data set can be constructed by linking firms across years using both tax IDs and an ID series generated by the GSO. My baseline sample includes manufacturing firms with ten workers or more and are active for at least two consecutive years.[17]

Each year the surveys comprise of a main questionnaire that every firm answers and supplementary modules for specific industries. For my purposes I only use information from the main questionnaire. Firm-level values are deflated using producer price indices. Though Vietnam joined the TPP negotiations in 2008, I excluded the years 2008 and 2009 to avoid the macroeconomic impact of the financial crisis. I provide more details on the construction of the final sample in Appendix 2.9.1.[18]

Even though all firms are surveyed they do not respond to the same questionnaire. There are two versions of the main questionnaire: a complete and a reduced version (which are called questionnaires 1A and 1B). Each year with the exception of 2011 and 2016, the General Statistics Office (GSO) of Vietnam chooses about 25% of all firms to answer the complete questionnaire. The remaining firms respond to a shorter version, which only contains basic information, and the missing information is imputed based on the sample that answer the full questionnaire. This data set is then combined with the non-imputed sample to create a final data that researchers receive.

[17] An establishment under 10 workers can register as either a household business or a formal firm. For this reason I choose the 10-worker cutoff to avoid the choice problem of microenterprises.

[18] Firm-level descriptive statistics are presented in Table 2.26.

Unfortunately, this data set cannot be used directly as the imputation rates are uneven across years. More importantly, the imputation procedure reduces the variability in the true data since the imputed data rely solely on the non-missing part of the sample. I apply a multiple imputation procedure to tackle these problems. Details of the procedure are provided in Appendix 2.9.2.

2.4.2 Tariff Data

To construct future tariffs, I use the tariff elimination schedules between 2016 and 2030 for Vietnam under the ASEAN, VN-Chile, VN-Japan, and ANZ-ASEAN trade agreements. For the TPP schedule, I use the original agreement published in November 2016. I use MFN tariff rates between Vietnam and the United States, Canada, Mexico, and Peru in 2016 to proxy for future tariffs without the TPP. MFN tariff rates are sourced from the World Bank's World Integrated Trade Solution (WITS). The original data is at the tariff line level, which I average to create tariff rates at 6-digit HS level. Since there is no available concordance between HS codes and the Vietnam Standard Industry Classification (VSIC), I first convert 6-digit HS to four-digit ISIC and then manually match ISIC with VSIC.[19] The matching process is described in more detail in the appendix. Trade data between Vietnam and the US, Canada, Mexico, and Peru were obtained from the UN COMTRADE database. This information is aggregated at the four-digit ISIC industry level.

Table 2.1: Country-level tariffs and current FTAs, 2016

		Export tariffs				Import tariffs			
Country	**FTA**	**mean**	**sd**	**min**	**max**	**mean**	**sd**	**min**	**max**
Brunei		0.003	0.301	0	30	0.573	3.942	0	135
Malaysia	ASEAN FTA	0.045	0.728	0	20	0.573	3.942	0	135
Singapore		0		0	0	0.573	3.942	0	135
Chile	VN-CL FTA	0.532	1.318	0	6	8.172	9.870	0	135
Japan	VN-JP FTA	1.874	5.865	0	50	4.864	8.254	0	135
Australia	AANZ FTA	0.264	1.534	0	10	3.669	6.530	0	100
New Zealand		0.681	2.297	0	10	3.669	6.530	0	100
Canada		2.651	7.087	0	238	9.792	11.058	0	135
Mexico		5.423	8.727	0	100	9.792	11.058	0	135
Peru		2.245	3.662	0	11	9.792	11.058	0	135
United States	VN-US FTA	3.875	10.552	0	350	9.792	11.058	0	135
Total		1.913	6.057	0	350	5.414	8.939	0	135

Notes: Ad-valorem tariffs are computed at HS 6-digit level. All traded products are included.

Table 2.1 presents average tariff rates between Vietnam and other TPP members in 2016. Since 2015 Vietnam has enjoyed near zero tariffs with the Southeast Asian countries (Malaysia, Singapore, and Brunei) as a member of the Association of Southeast Asian Nations (ASEAN), with Australia

[19] I use HS 2012, ISIC Rev. 4, and VSIC 2007.

and New Zealand through an FTA between these two countries and ASEAN. A bilateral trade agreement between Vietnam and Japan was enforced in 2010, and the Vietnam-Chile FTA in 2015. In short, the biggest tariff changes would come from reduction of MNF tariff with the remaining countries, i.e., the US, Canada, Mexico, and Peru.[20]

2.4.3 Measuring Expected Tariff Cuts

The main treatment variable measures how tariffs would have changed if the TPP had been implemented. Formally, the expected tariff change for product h under the TPP is defined as

$$\Delta\tau_h = \sum_{t=t_o}^{T} \delta^{t-t_o} \mathbf{1}\{\tau_0^C > 0\}(\tau_{ht}^C - \tau_{ht}^T)$$

where t_o is the earliest year the TPP was supposed to enter into force (assumed to be 2016), T determines firms' planning horizon, δ denotes the discount factor, τ_{ht}^C is the tariff rate in year t under the current tariff schedule, and τ_{ht}^{TPP} is the tariff rate in year t under the TPP schedule. The effective rates under the TPP, τ_{ht}^T, is defined as $\tau_{ht}^T \equiv \min\{\tau_{ht}^C, \tau_{ht}^{TPP}\}$.[21] I exclude tariffs that are already at zero prior to 2016 from the baseline measures as firms would not expect any changes in these tariff lines. The final tariff changes are simple averages at the four-digit industry level, denoted by $\Delta\tau_j$.[22] I compute $\Delta\tau_j$ for both export and import tariffs.

The firms' planning horizon and discount factor affects the value of (see Table 2.2). The larger T and δ, the more weight a firm puts on tariff cuts in later years, and hence, if firms are very patient, the rate of tariff reduction over years matters. I fix $T = 15$ years and construct for three different values of the discount factor: $\delta = 0$ (i.e., firms only plan one-period ahead), $\delta = 0.5$, and $\delta = 0.9$.[23] When accounting for changes in tariffs in the initial year only ($\delta = 0$), export tariffs are reduced by 4.35% and import tariffs by 4.82%, on average. Expanding the horizon to 15 years, the accumulative reduction goes up to 41.8% and 53.7% for export and import tariffs, respectively.

Figure 2.3 illustrates how the values of δ affect under different staging categories. The left panel shows two products with immediate reductions in the first year when TPP is implemented, and

[20] Vietnam and the US signed a bilateral trade agreement in 2001, which moved Vietnam from Column 2 to MFN tariff schedule. Furthermore, as can be seen from Table 2.1, even though the average exporters faced modest tariffs to export the US, the large standard deviation implies there is much variability across products. Indeed, some exporters faced exceptionally large tariff rates.

[21] Since the base rates in the TPP tariff schedule are set to the 2010 MFN rates, there are a number of products for which TPP's tariff rates are higher than the current rates.

[22] Because the firm surveys lack information on firms' products and the countries that they export or import from, I cannot construct tariff changes at product and/or country level. Using variations across industries, however, is a common strategy among previous studies on effects of trade policies on firm outcomes.

[23] Even though T and δ capture different aspects of a firm' expectation, technically they have similar effects on . I pick $T = 15$ since this is the upper bound of the tariff phaseout length for most countries, except the US.

Table 2.2: Average tariff cuts at ISIC4 level

	Export tariffs	Import tariffs
$\Delta\tau(\beta = 0)$	0.0435	0.0482
	(0.0330)	(0.0377)
$\Delta\tau(\beta = 0.5)$	0.0907	0.111
	(0.0674)	(0.0668)
$\Delta\tau(\beta = 0.9)$	0.418	0.537
	(0.297)	(0.338)

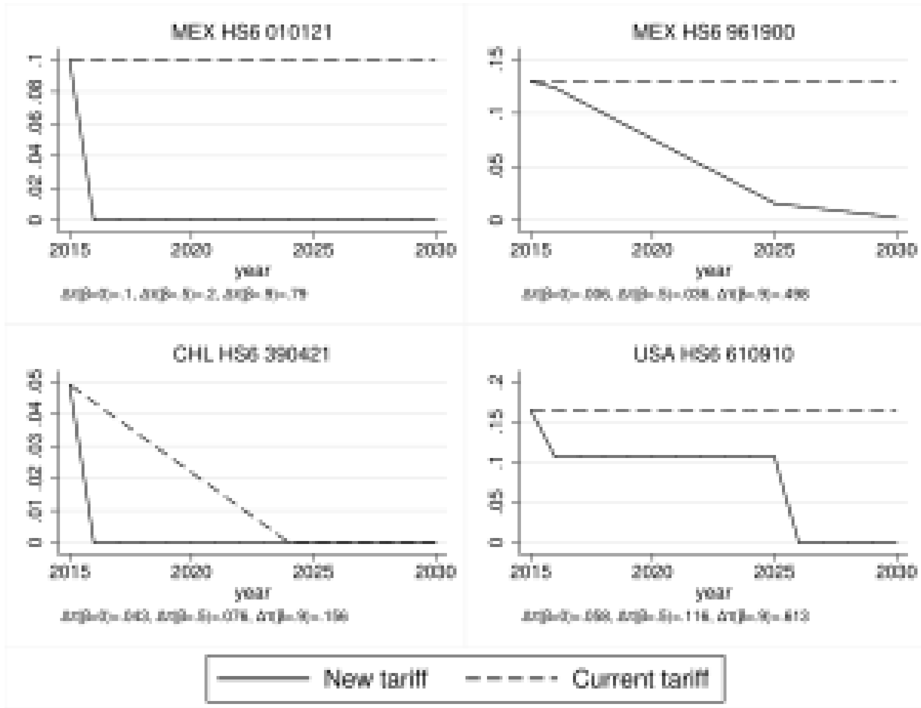
This table presents average export and import tariff reductions at 4-digit ISIC industry level. Only manufacturing industries (ISIC2 code 10-33) are included.
Standard errors are in parentheses.

the right panel provides examples of phase-out tariffs. For the bottom left panel, the current tariff schedule has not been completed by 2016 and therefore, the difference between the two tariff rates depends on the phase-out length of both the TPP and the current tariff schedule. We can intuitively anticipate that the value of δ (and T) matters more for products with longer phase-out periods under either tariff schedules.

As can be seen from Figure 2.4, all three measurements of changes in export rates are highly correlated with each other and with the base rates. This is not surprising given that about 67% of non-zero tariffs would be removed immediately once the TPP enters into force and 15% within five years. On the other hand, import tariffs have longer phase-out periods–about 50% remain non-zero for at 5 years after the first effective date–and therefore there is more variation across different measurements of . Furthermore, higher values of δ imply greater correlation of with the base rate.

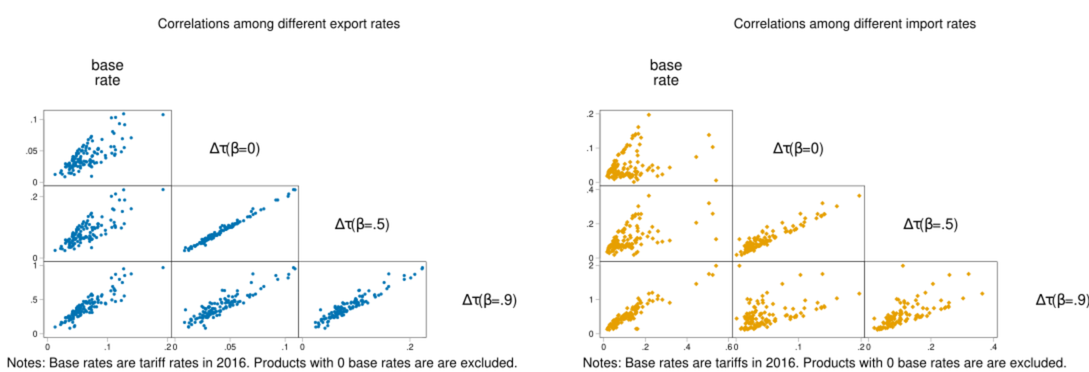
Finally, excluding zero tariffs might cause a problem if the share of products with zero base tariffs are heterogeneous across industries. In this case, an industry with many zero tariffs but a few large tariffs might seemingly face larger tariff reductions than an industry with many non-zero but low tariffs. As can be seen from Table 2.3, there seems to be heterogeneity across industries in terms of the shares of products in each industry with zero base tariffs, immediate elimination, elimination within 5 years, elimination within 10 years, and elimination after 10 years. Nevertheless, the correlation between measures of $\Delta\tau$ with and without zero tariffs is very quite high. Figure 2.5 presents the correlations between tariff cut measures when including and excluding zero tariff lines at different discount factors. Overall, import tariff cuts are highly correlated ($\rho = 0.919 - 0.959$). Correlations between export tariff cuts are somewhat lower ($\rho = 0.756 - 0.763$), but remain reasonably high. In Appendix 2.9.4, I provide additional results using zero-included tariff measures, which show

Figure 2.3: Examples of products with different phase-out



This figure illustrates four six-digit HS products with different staging categories. The solid line presents the current tariff schedule and the dashed line presents the TPP schedule. The first year of the TPP schedule is assumed to be 2016.

Figure 2.4: Correlations among tariff changes (at four-digit ISIC level) with different values of discount factor



This figure presents the correlations between the base rate in 2015 and three different measures of tariff reductions (discount rate equals 0, 0.5, and 0.9, respectively). The left panel shows the export tariff rates and the right panel reports import tariff rates.

Table 2.3: Share of HS6 products in each staging category

	Export tariffs			
	mean	sd	min	max
0 base tariff	0.77	0.13	0.33	1.00
Immediate	0.13	0.08	0.00	0.43
Within 5 years	0.04	0.04	0.00	0.22
Within 10 years	0.04	0.05	0.00	0.23
After 10 years	0.01	0.02	0.00	0.13
Number of industries	125			

	Import tariffs			
	mean	sd	min	max
0 base tariff	0.48	0.29	0.00	1.00
Immediate	0.21	0.26	0.00	0.91
Within 5 years	0.22	0.27	0.00	0.89
Within 10 years	0.07	0.19	0.00	1.00
After 10 years	0.01	0.10	0.00	1.00
Number of industries	125			

This table presents the share of 6-digit HS codes in each industry that belong to one of the five staging categories: tariffs that are already zero, tariffs eliminated immediately, within 5 years, within 10 years, and after 10 years.

similar effects for the expected tariff cuts on the average industry.

2.4.4 Measuring Productivity

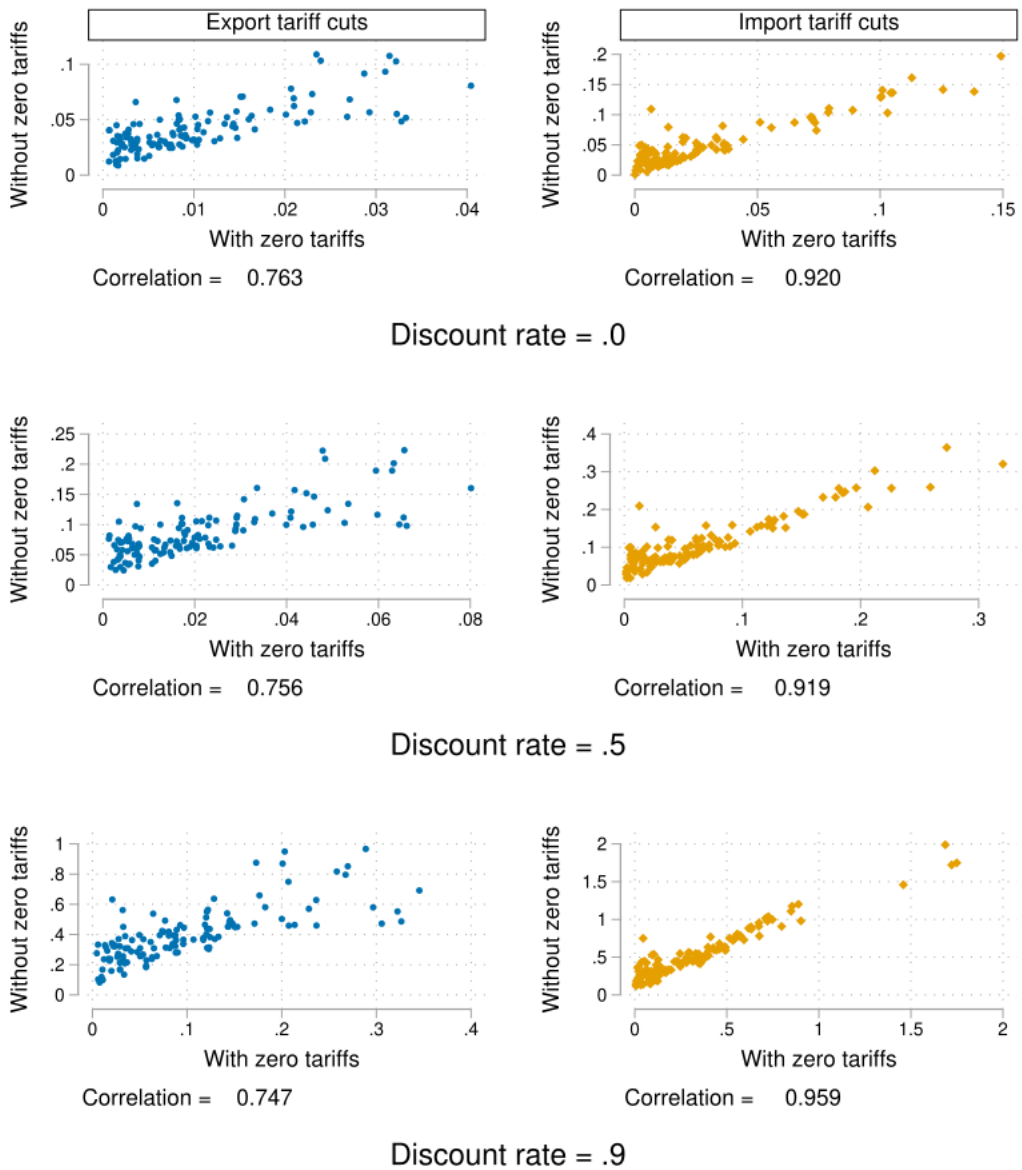
My main dependent variable is revenue productivity, obtained as the residual from a gross output production function. Nominal revenues, capital, and material inputs are deflated using sector-level price indices. Employment is measured by the number of workers. I assume a Cobb-Doughlas functional form and estimate the following equation (in logs) for firm i at time t:

$$q_{it} = \alpha_k k_{it} + \alpha_l l_{it} + \alpha_m m_{it} + \omega_{it} + u_{it} \tag{2.1}$$

where q, k, l, m denote the log of output, capital, labor, and materials, and u is a random error term. I distinguish between a persistent productivity term ω_{it} and a standard i.i.d. error term u_{it} that captures contemporaneous production shock and measurement error. As input choices are determined by ω_{it}, estimation of (2.1) is subject to omitted productivity bias. I follow Ackerberg et al. (2015) and invert the material input demand equation to obtain a proxy for productivity.

Note that this method is based on the assumptions that researchers observe quantities of the main variables. Since my data only contain output revenues and input expenditures, I use a modified

Figure 2.5: Correlations between measures of $\delta\tau$ (at ISIC4 level) with and without zero tariffs



This figure shows the correlations between industry-level tariff reduction measures with and without zero tariffs. The top panel shows tariff cuts in the first year under TPP (discount rate = 0), the middle panel presents the discounted sum of tariff cuts within 15 years with discount rate of 0.5, and the bottom panel shows the discounted sum of tariff cuts with discount rate of 0.9.

version of equation (2.1):

$$r_{it}^* = \alpha_k k_{it}^* + \alpha_l l_{it}^* + \alpha_m m_{it}^* + \underbrace{\omega_{it} + (p_{yit}^* - \alpha_m p_{mit}^*)}_{\pi_{it}} + u_{it} \tag{2.2}$$

where the asterisk denote deflated revenue and expenditures, p_y^* denotes deviation between firm i's output price and the output price deflator, and p_m^* denotes deviation between firm i's material price and the input price deflator.

The unobserved prices create an endogeneity problem as they are correlated with the choice of inputs. There have been a few attempts to address this issue by either assuming a market demand structure or a relationship between input and output quality (De Loecker and Goldberg, 2014; De Loecker et al., 2016). De Loecker et al. (2016) note that if the price variations is monotonic in productivity, the control function method will be sufficient to take care of the endogeneity issue due to unobserved prices. For now, I assume that we can estimate the α's consistently and ignore the endogeneity problem. The new residual term does not only contains physical efficiency, but also output and input prices. Throughout this paper, I will refer to this composite term as "productivity". The mechanisms for how expected tariff reduction influences π_{it} is therefore not confined to technology upgrading or innovation, but also to changes in input choices and/or markups. Nevertheless, the key takeaway of this paper remains: changes in π_{it} should come mainly from firms' active response to future tariff changes.

Another potential issue with the estimation procedure is that productivity is assumed to evolve exogeneously, which can be inconsistent with theoretical predictions. I modify the procedure in ACF by allowing the productivity evolution to be endogenous. Under the assumption that firms share the same beliefs I impose the following law of motion

$$= g(\omega_{it-1}, E_t\Delta(\tau_j)) + \xi_{it} \tag{2.3}$$

where $E_t(\Delta\tau_j)$ is the expected tariff changes in industry j in year t, ξ_{it} is i.i.d and independent of ω_{it-1} and $E_t(\Delta\tau_j)$. More details are provided in Appendix 2.9.3.1.

2.5 Overview of Aggregate Productivity

In this section, I provide an overview of aggregate productivity in the Vietnamese manufacturing sector between 2010 and 2017. Specifically, I follow Olley and Pakes (1996) (hereafter OP) to decompose aggregate productivity as follows (suppressing subscript t for now):

$$W \equiv \sum_i s_i w_i = N^{-1} \sum_i w_i + \sum_i (s_i - \bar{s})(w_i - \overline{w})$$

where N is the total number of firms, s_i is the market share of firm i, $\sum_i s_i = 1$ and w_i is firm i's productivity. This quantity is decomposed into the unweighted average productivity and the covariance between firm-level productivity and market share. Positive covariance means that more output is produced by more productive firms. Changes in the unweighted productivity reflects changes within firms, whereas changes in the covariance captures the reallocation of resources across firms.

This decomposition, however, has two drawbacks. First, it does not separately quantify two different channels of reallocation: within industries and between industries. In section 2.5.1, I propose a modified version of OP to account for both channels. Second, the OP decomposition does not account for exit and entry. Both components in the OP aggregate productivity, unweighted productivity and covariance, can be simultaneously affected by the exit and entry of firms. To address this, I apply the method in Melitz and Polanec (2015). This is the focus of section 2.5.2.

2.5.1 Static Decomposition

Though the common aggregate productivity decomposition mainly focuses on reallocation across firms, this reshuffling of market share may come from either reallocation of firms within the same industry or from reallocation across industries. In this section I extend the Olley-Pakes decomposition in order to explicitly account for both channels. Let $S_j = \sum_{i \in j} s_i$ be the market share of industry j and $W_j = \sum_{i \in j}(s_i/S_j)w_i$ be industry j's productivity. We can rewrite the aggregate productivity as $W = \sum_j S_j W_j$. Applying the Olley-Pakes decomposition we get

$$\begin{aligned}
W &= \frac{1}{J}\sum_j W_j + \sum_j (S_j - \overline{S_j})(W_j - \overline{W_j}) \\
&= \frac{1}{J}\sum_j \Big(\frac{1}{N_j}\sum_{i\in j} w_i + \sum_{i\in j}(\frac{s_i}{S_j} - \overline{s_j})(w_i - \overline{w_j})\Big) + \sum_j (S_j - \overline{S_j})(W_j - \overline{W_j}) \\
&= \frac{1}{J}\sum_j \overline{w_j} + \frac{1}{J}\sum_j\sum_{i\in j}(\frac{s_i}{S_j} - \overline{s_j})(w_i - \overline{w_j}) + \sum_j (S_j - \overline{S_j})(W_j - \overline{W_j}) \\
&= \frac{1}{N}\sum_i w_i + \frac{1}{J}\sum_j\sum_{i\in j}(\frac{s_i}{S_j} - \overline{s_j})(w_i - \overline{w_j}) + \sum_j (S_j - \overline{S_j})(W_j - \overline{W_j}) - \sum_j (\frac{N_j}{N} - \frac{1}{J})(\overline{w_j} - \frac{1}{J}\sum_j \overline{w_j}) \\
&= \underbrace{\frac{1}{N}\sum_i w_i}_{\substack{\text{unweighted}\\ \text{productivity}}} + \underbrace{\mathbf{cov}(\frac{s_i}{S_j}, w_i)}_{\substack{\text{within-industry}\\ \text{covariance}}} + \underbrace{\mathbf{cov}(S_j, W_j) - \mathbf{cov}(\frac{N_j}{N}, \overline{w_j})}_{\substack{\text{between-industry}\\ \text{covariance}}}
\end{aligned} \tag{2.4}$$

where J is the number of industries, N_j is the number of firms in industry j, the uppercase letters denote industry level quantities, and the lowercase letters denote firm-level quantities. The first equality ensues from a direction application of the OP decomposition, and the second equality follows by applying the decomposition to each industry productivity, W_j. The last equality follows by treating the unweighted productivity as the average of industry productivity weighted by industry firm shares.

As we can see from equation 2.5, there are three channels contributing to the aggregate productivity. The first term is average productivity, analogous to the unweighted productivity in the original OP decomposition. The second term is the average covariance between firm productivity and firm market share within the same industry and thus represents the contribution to the aggregate weighted productivity resulting from the reallocation of resources among firms within the same industry. The last term is the covariance between industry market share and industry productivity, which captures the reallocation of resources across industries.[24] In a sense, the original OP covariance is approximately the sum of the within-industry and between-industry covariance. Nevertheless, it is a common practice to apply the OP decomposition to each industry separately, in which case the third channel is entirely ignored.

Table 2.4 reports the static decomposition of aggregate productivity for each sample year using both the OP and the augmented OP methods described above.[25] The results show that aggregate

[24] This last term is adjusted to account for the covariance of industries' firm share and unweighted industry productivity. Figure 2.13 demonstrates the trend for each component in the between-industry covariance.

[25] I use employment shares as the weights to reduce the number of missing observations. Nevertheless, the decomposition

productivity can be explained almost entirely by unweighted productivity. During the period of 2010-2017, aggregate productivity grew by 14%, almost all coming from growth in unweighted productivity. As we can see from figure 2.6a, the two terms also followed very similar trends, suggesting that within-firm changes play an important role in explaining aggregate productivity. Interestingly, while there was a big increase in 2016, aggregate productivity seemed to slightly decrease in 2017. The movement of productivity coincides with the timeline of the TPP, supporting the hypothesis that productivity responded to the anticipation of the TPP.

Another notable feature of aggregate productivity during this period is that the original OP covariance term is largely driven by the between-industry covariance (Table 2.4) as opposed to the within-industry covariance, suggesting the importance of reallocation across industries in explaining aggregate productivity movements. The two covariance terms nonetheless followed similar trends. As can be seen from Figure 2.6b, they were largely flat in the initial years, decreased slightly in 2014 and 2015, and then increased between 2016 and 2017.

In a nutshell, the results so far show us that the unweighted productivity contributes to the majority of aggregate productivity growth between 2010 and 2017, whereas resource reallocation plays a somewhat minor but increasingly important role, especially during the last two years. Nevertheless, the static decomposition here is unable to tell us the contribution of exit and entry to aggregate productivity changes, which leads to the next section which provides a on dynamic decomposition of aggregate productivity.

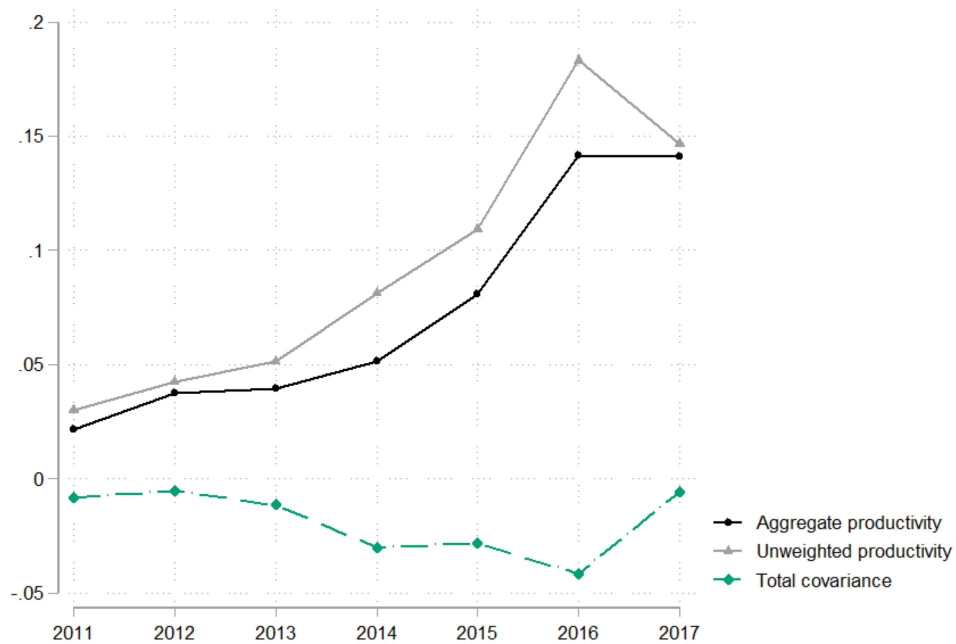
Table 2.4: Static decomposition of aggregate productivity

		OP		Augmented OP	
	Aggregate	Unweighted	Total	Covariance	
Year	Productivity	Productivity	Covariance	Within industry	Between industry
2010	1.810	1.925	-0.115	-0.020	-0.095
2011	1.832	1.955	-0.123	-0.001	-0.122
2012	1.848	1.968	-0.120	0.003	-0.122
2013	1.850	1.976	-0.126	0.002	-0.128
2014	1.862	2.006	-0.145	-0.005	-0.140
2015	1.891	2.034	-0.143	-0.003	-0.140
2016	1.952	2.108	-0.156	-0.011	-0.145
2017	1.951	2.072	-0.120	0.014	-0.134

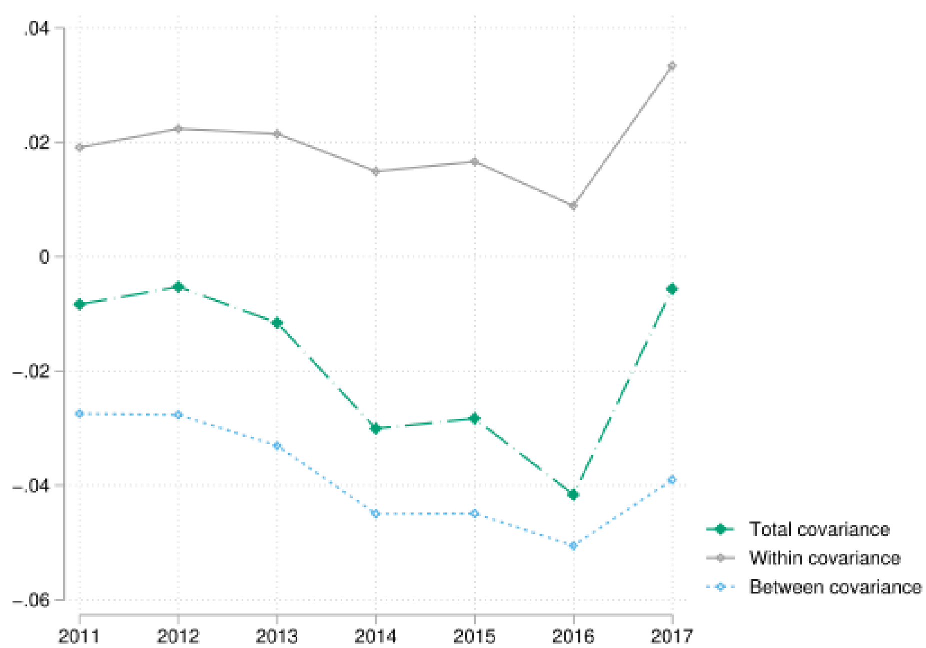
This table reports the static decomposition of aggregate weighted productivity for the manufacturing sector during 2010-2017 using the OP and the augmented OP methods. The last two columns show the covariance within industries and between industries' market share and productivity. See equation 2.5 for formal description of the augmented OP decomposition.

results are robust to other choices of weights, such as market shares.

Figure 2.6: Static decomposition of aggregate productivity (reference year = 2010)



(a) Olley-Pakes decomposition



(b) A breakdown of the total covariance

This figure reports the changes in aggregate productivity and its components with respect to 2010. The top panel shows the the aggregate and unweighted productivity from the OP decomposition. The bottom panel compares the total (OP) covariance, within-industry and between-industry covariance.

2.5.2 Dynamic Decomposition with Exit and Entry

In this section I apply the dynamic Olley-Pakes decomposition method (DOPD) proposed by Melitz and Polanec (2015). This method allows me to decompose yearly changes in aggregate productivity into changes from surviving firms, entrants, and exiters. Following the notation in their paper, I denote S, E and X as the surviving, entering, and exiting groups, respective. Let $s_{Gt} = \sum_{i \in G} s_{it}$ be the aggregate market share of group G and $W_{Gt} = \sum_{i \in G}(s_{it}/s_{Gt})w_{it}$ as the group's aggregate productivity. Let $\Delta W_t = W_t - W_{t-1}$ be the change in aggregate productivity between year t and $t-1$. Melitz and Polanec (2015) show that this term can be decomposed as

$$\Delta W_t = \underbrace{(W_{St} - W_{St-1})}_{\text{survivors}} + \underbrace{s_{Et}(W_{Et} - W_{St})}_{\text{entrants}} + \underbrace{s_{Xt-1}(W_{St-1} - W_{Xt-1})}_{\text{exiters}} \tag{2.5}$$

The first term represents the contribution of survivors to aggregate productivity growth, the second term captures the difference between new entrants and survivors, and the last term compares the productivity of exiters and survivors in the last period. Each of these terms can be further decomposed into the unweighted productivity and covariance between market share and productivity of firms in each group using the static decomposition. I do not show the further decompositions in order to maintain the focus on exit and entry.

As we can see from table 2.5 (and also Figure 2.7), most of the growth in aggregate productivity can be attributed to changes in surviving firms. This group accounted for 84% of aggregate productivity growth during this period. The remaining proportion came from greater productivity among new entrants, especially between 2015-2017, whereas the exiting firms' aggregate productivity remained constant during this period. The relative contribution of survivors, entrants, and exits is stable across years.

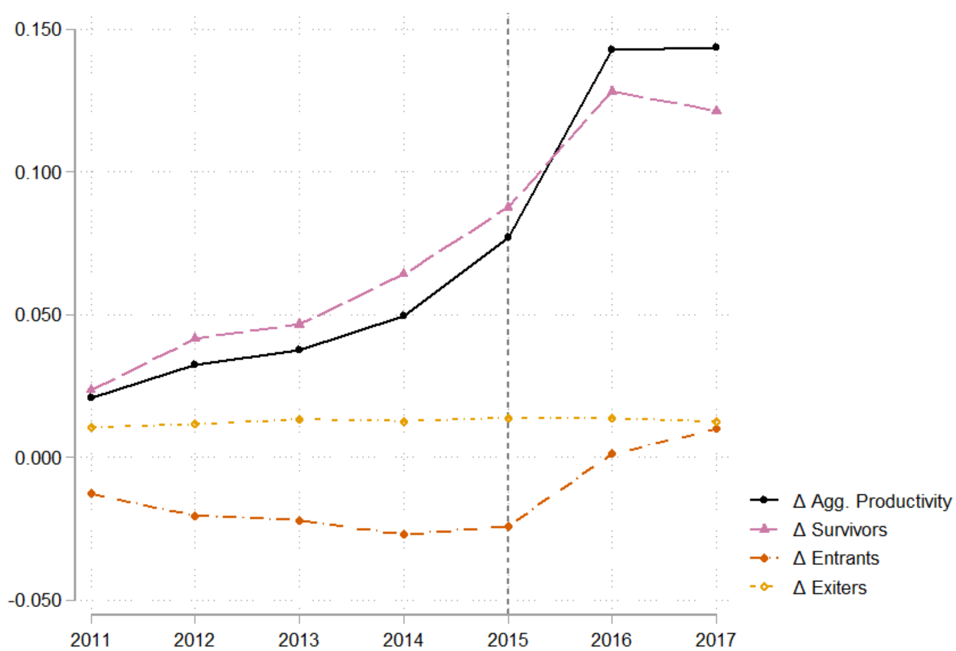
To summarize, the patterns we see from both the static and dynamic decomposition exercise suggest that in order to understand aggregate productivity growth, it is important to investigate changes within firms, especially firms that remain in the market. Furthermore, the movement in aggregate productivity coincides with the TPP announcement at the end of 2015 and the US withdrawal in 2017. In the next few sections, I provide an in-depth analysis of firm-level productivity and establish a causal link between TPP anticipation and productivity growth.

Table 2.5: Dynamic decomposition of aggregate productivity growth (reference year = 2010)

Year	Aggregte Productivity	Survivors	Entrants	Exiters
2010	0.000	0.000	0.000	0.000
2011	0.021	0.023	-0.013	0.010
2012	0.032	0.042	-0.021	0.011
2013	0.037	0.046	-0.022	0.013
2014	0.049	0.064	-0.027	0.013
2015	0.077	0.088	-0.024	0.014
2016	0.143	0.128	0.001	0.014
2017	0.144	0.121	0.010	0.012

This table reports the decomposition of aggregate productivity growth that accounts for firm exit and entry with the method proposed in (Melitz and Polanec, 2015). 2010 is the reference year.

Figure 2.7: Dynamic decomposition of aggregate productivity growth



This figure reports the dynamic decomposition of aggregate productivity to account for exit and entry. The reference year is 2010.

2.6 Firm-level Analysis: Empirical Strategy and Results

2.6.1 Empirical Strategy

My identification of the effect of anticipated tariff changes on firm productivity comes from two sources. First, I rely on variation across four-digit ISIC industries in the expected reduction of export and import tariffs that would occur after the TPP entered into force. I predict that bigger expected changes in tariffs lead to stronger responses from firms. As previously discussed, the direction of the effect depends on how firms believe the reduction of tariffs will affect their future profits.

Second, I assume there was no anticipation of the TPP before it was signed at the beginning of 2016.[26] Under this assumption, a natural approach to estimate the effect of anticipating the TPP is to use a framework akin to difference-in-differences that compares the differential changes in firm productivity before and after 2015 between firms that are subject to small versus large expected tariff reduction. If firms respond to the signing of the TPP, we should see significant changes in productivity after 2015 for firms with large expected tariff declines.

However, the task at hand is complicated by the fact that the US withdrew from the trade deal in January 2017. That means for the majority of this year firms might have different expectation of the TPP compared to 2016. Instead we can reasonably assume that anticipation of the TPP after US withdrawal in 2017 was low and allow the effect of to vary between 2016 and 2017.[27] The main specification is

$$\begin{aligned}\log(TFP)_{it} = \sum_{t=2016}^{2017} \beta_{t\,j}^{xx} + \sum_{t=2016}^{2017} \beta_{t\,j}^{mm} + \eta^{xx}_{j} + \eta^{mm}_{j} + \\ \delta X_{it} + \theta Z_j + \lambda_t \times \lambda_p + \lambda_t \times \lambda_s + \lambda_s \times \lambda_p + \epsilon_{it}\end{aligned} \tag{2.6}$$

where i, j, s, t, p denote firm, four-digit ISIC industry, two-digit ISIC industry, year, and province, respectively. The main outcome variable, $\log(TFP)_{it}$, captures firm i's productivity at time t. I use $\Delta\tau_j^x$ and $\Delta\tau_j^m$ to denote the expected changes in industry-level export and import tariffs, respectively. X_{it} is firm ownership types and Z_j includes four-digit ISIC industry level skill and labor intensities in 2011. I also include λ_t, λ_s, and λ_p, which are year, sector, and province dummies, and their interactions.[28]

[26] Some may argue that firms might have started to anticipate the TPP since the negotiations were concluded in October 2015 and the final draft was published in November 2015. Even if that is the case, there was not enough time for firms to adjust productivity before 2016 and thus my estimation strategy would still be valid. At the same time, if firms did adjust productivity early, it would attenuate any effect that I would find.

[27] The expected tariffs cut in 2016 and 2017 are slightly different since the base rates change (due to changes in Japan's and Chile's tariff rates). However, the correlation between the two is nearly perfect, and thus I remain using one measure of expected tariff cuts for both years.

[28] Beside tariff cuts, the TPP agreement covers a wide range of regulations compared to previous regional agreements. That's why I control for industry characteristics and several sets of fixed effects. As long as firms within the same sector are

Table 2.6: When we should see productivity responds to TPP

When firms think TPP is enforced	(1) Firms can adjust within a year	(2) Investment is time-consuming
(a) 2016	2016	2017
(b) 2017		2017
(c) After 2017 (or no anticipation at all)		

Shaded cells mean neither year would have significant effects.

The coefficients of interest are β^x_{16}, β^m_{16}, β^x_{17} and β^m_{17}. It is not obvious when we should see productivity responds to future tariff changes without further assumptions on firm-level expectations of TPP timing–whether firms expect the first year of TPP to be 2016 or 2017–and the time lag between investment and productivity improvement.

Table 2.6 presents different combinations of firms' expectations and investment dynamics and when we should expect to see an effect of anticipated tariff changes on productivity. Under case (1a) when firms expect the TPP to start to take effect in 2016 and can adjust productivity quickly enough, a productivity response will appear in 2016, meaning that β_{16} would pick up the effect of . However, if the adjustment takes longer than a year, firms have to make investment decisions prior to the US withdrawal in 2017. Productivity would increase in 2017 even if by then firms no longer believed the trade agreement would be enforced. Nevertheless, if productivity responds to in either 2016 or 2017, it is evidence that an anticipation effect exists.

If firms can adjust productivity quickly and respond to TPP events, we should see that β_{16} is significant while β_{17} is not significantly different from zero, since in 2017 there was not much anticipation of the TPP. As discussed above, it is possible that β_{17} is significant while β_{16} is not, if firms make investment prior to the US withdrawal and there is a delay in productivity improvement.

Due to the fact that my sample period ends in 2017, one issue is that if I do not observe a significant effect in either 2016 or 2017, I cannot differentiate between two possible situations: (1) firms do not anticipate the TPP to happen during my sample period (cases 1c and 2c) and (2) firms learned about the US withdrawal before making their investment decision (case 1b).

2.6.2 Baseline results

Table 2.7 presents the baseline results (discount factor $\beta = 0$ and an endogeneous productivity evolution). I run variations of equation (2.6) by including different sets of controls. The estimated

affected by the regulations in the same way, we should expect these controls to absorb the effects from non-tariff regulations.

coefficients and standard errors are adjusted for variation across multiple imputations. A cursory look tells us that the point estimates are fairly consistent across five specifications, and that controlling for firm, industry characteristics, two-digit industry dummies, and province dummies negligibly varies the results. The main results, however, are based on the last specification with the most complete set of controls.

Three observations stand out with respect to the effect on firm-level productivity. First, the coefficients β^x_{16} and β^m_{16} are both statistically significant at 1% level across all specifications. The evidence presented here supports the hypothesis that when the TPP was signed in early 2016, firms anticipated the trade agreement to be implemented and had sufficient time to make adjustments according to the future tariff changes.

Second, the coefficient β^x_{16} is positive while β^m_{16} is negative. Each percentage point decrease in export tariffs leads to a 0.34-0.4% increase in productivity, whereas a one percentage point decrease in import tariffs leads to a 0.29-0.32% decrease in productivity. The direction of the effects imply that Vietnamese firms believe that reducing export costs increases their future profits and thus are induced to raise productivity. On the other hand, reducing import costs seems unfavorable from firms' viewpoint. Even though ^{m} does not enter firms' profit directly, it still causes negative productivity responses, implying that firms anticipate their domestic market share to shrink due to higher competition from foreign products.

Third, the effect of tariff reductions on productivity in 2017 is consistent with those estimated for the year 2016. Nevertheless, the coefficient β^m_{17} is not statistically significant, indicating that the productivity effect may be fading after one year. Further checking this claim, I compare the coefficients β^x_{16} and β^x_{17} and cannot reject the null hypothesis that $\beta^x_{16} = \beta^x_{17}$. Similarly, β^m_{16} is not statistically significant from β^m_{17}. This is mainly due to the large standard errors for the 2017 parameters. The fact the there are changes in TFP in 2016 but no further change in 2017 coincides with the timeline of the US announcement to withdraw from the TPP. The US withdrawal–which had a large negative impact on the prospect of the trade agreement–occurred in January 2017, meaning that for the majority of the year Vietnamese firms did not anticipate the TPP to take effect. This evidence again confirms that the impact of on firms' productivity is driven by their anticipation of the trade agreement.

Table 2.7: Baseline Results–Effect of Anticipating TPP on Productivity

Depvar log TFP	(1)	(2)	(3)	(4)	(5)
β^x_{16}	0.449	0.397	0.404	0.396	0.341
	(0.213)**	(0.186)**	(0.184)**	(0.189)**	(0.187)*
β^m_{16}	-0.312	-0.307	-0.319	-0.288	-0.309
	(0.072)***	(0.069)***	(0.069)***	(0.074)***	(0.071)***
β^x_{17}	0.706	0.601	0.635	0.505	0.488
	(0.339)**	(0.327)*	(0.327)*	(0.357)	(0.359)
β^m_{17}	-0.246	-0.223	-0.239	-0.174	-0.208
	(0.154)	(0.166)	(0.167)	(0.181)	(0.177)
Observations	293,633	293,633	293,610	292,184	292,183
Adjusted R^2	0.171	0.194	0.225	0.218	0.244
Year#ISIC2	Yes	Yes	Yes	Yes	Yes
Year#Province	No	Yes	Yes	Yes	Yes
ISIC2#Province	No	No	Yes	Yes	Yes
Year#ISIC2#Province	No	No	No	Yes	Yes
ISIC4	No	No	No	No	Yes

This table reports the results on firm-level productivity. Firm controls include firm size and ownership types, and 4-digit ISIC industry controls include capital intensity and share of skilled workers. Industry FEs are at 2-digit ISIC industry level. The sample consists of active manufacturing firms with at least 10 workers. Standard errors are clustered at 4-digit ISIC level. Estimated coefficients, standard errors, and the additional hypothesis test statistics are adjusted for multiple imputations using the procedure in Appendix 2.9.2.
Standard error are in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.6.3 Potential Identification Threats

2.6.3.1 Parallel Trend Assumption

One assumption required for the validity of my empirical strategy is that in the absence of treatment, the difference between firms with high TPP exposure and those with low TPP exposure should stay constant over time.[29] This assumption is not directly testable since the counterfactual outcomes are unobserved. Instead, I present evidence that firms in an industry with higher tariff reductions did not behave differently from those in an industries with low tariff reductions prior to the signing of the TPP.

Specifically, I conduct an exercise akin to an event study but with continuous treatment variables by interacting the level of tariff reductions ^x_j and ^m_j with a vector of year dummies:

$$\begin{aligned}\log(TFP)_{it} =& \alpha + \sum_{t=2010}^{2017} \beta_t^{xx}{}_j + \sum_{t=2010}^{2017} \beta_t^{mm}{}_j + \eta^{xx}{}_j + \eta^{mm}{}_j + \\ & \delta X_{it} + \theta Z_j + \lambda_t + \lambda_s + \lambda_p + \epsilon_{it}\end{aligned} \tag{2.7}$$

[29] Note that this assumption allows for selection on non-treatment levels, that is, in the absence of treatment, the outcomes for each group can be different, and selection on gains, i.e. the benefits of getting larger tariff reductions are different for different firms.

By convention, I choose the one period before the event (i.e. TPP announcement) as the reference year. Otherwise, the equation here is similar to the specification in equation 2.6.

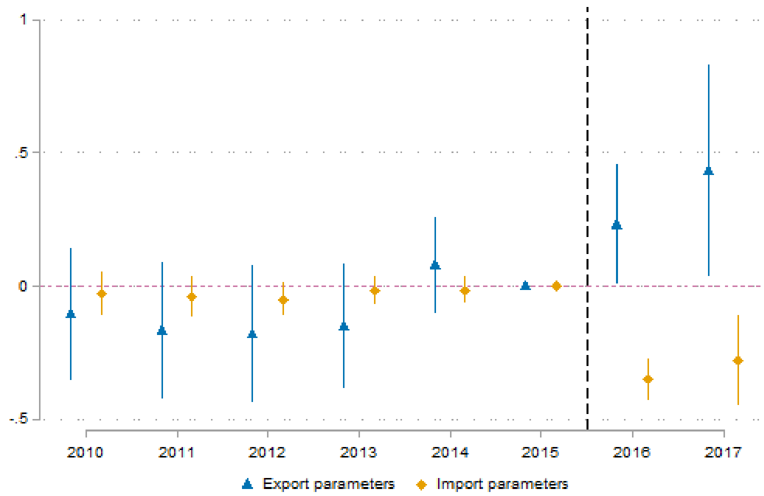
Figure 2.8a reports the estimated coefficients for the vector of β_t^x and β_t^m. Nearly all of the coefficients prior to 2016 are small and not statistically different from zero. This implies that there is little evidence of differential trends among firms facing different levels of tariff reductions prior to 2016. Nevertheless, it is somewhat difficult to compare different groups in the presence of a continuous treatment variable. Figure 2.8b reports the results when I discretize the two main independent variables. Namely, I defined an event by $event_j = \mathbf{1}(\Delta\tau_j \geq \text{industry median})$, that is, a firm experiences an event if it is in an industry with tariff reduction at least as large as the median expected change across industries. Each β_t now represents the difference between the group of firms with expected tariff reductions below the median versus the group with expected tariff reductions above the median in year t. The pattern prior to 2016 displays a similar trend as that depicted in Figure 2.8a.

Because the effect of TPP tariff reductions on productivity does not differ between 2015 (the reference period) and the previous years, it is also evidence that there was not much anticipation of the TPP prior to 2016. Another possible explanation for the lack of differential trends during 2010-2015 is that firms could have anticipated the trade agreement as early as 2010. However, as explained in Section 2.2, there was virtually no information on the TPP negotiations available to the public except for the two WikiLeak documents in 2013 and 2014 (still, there were no details on tariff elimination schedule in these documents). Thus, it is unlikely that Vietnamese firms could have expected the TPP to be implemented before the final agreement in October 2015.

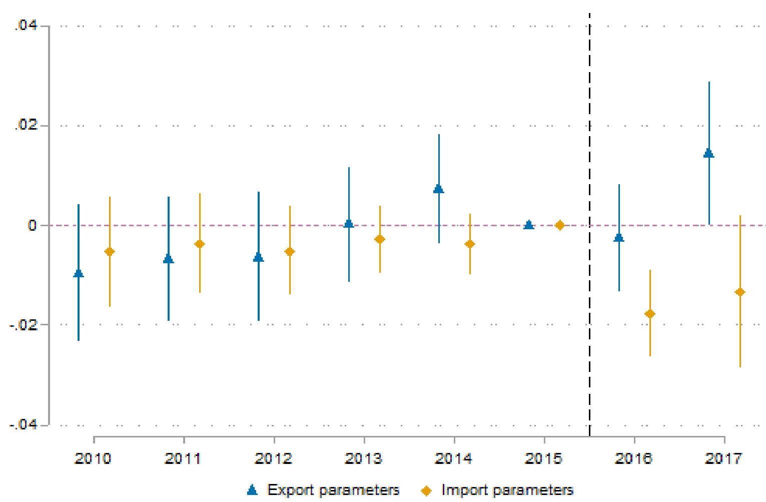
2.6.3.2 Endogeneous Exit and Entry

Another threat to my identification strategy is that the announcement of the TPP might also affect firm-level exit and entry. Two separate issues arise. First, incumbent firms may choose to exit the market altogether if they think future profits are low, and new firms may enter the market if they believe future profits are high. The marginal firm that opts out of the market due to higher competition and those that enter due to greater market access are likely to be low productivity relative to incumbent firms. Thus, we should see that the average productivity in industries with lower protection increases whereas average productivity in industries with greater market access becomes lower. Nevertheless, this is the opposite of what we see in the main results. If there exist firms that exit and enter the market due to the TPP, the coefficients β^x and β^m are indeed underestimated. To investigate this issue further, I conduction a regression under the main

Figure 2.8: Event study with continuous and discrete treatment variables



(a) Event study coefficients - Continuous treatment variable



(b) Event study coefficients - Discrete treatment variable

This figure presents the vector of event study parameters and 95% confidence intervals with the year 2015 omitted as the reference period. The top panel shows results with continuous tariff reductions, and the bottom panel shows results with discrete treatment variables, which take a value of unity if the expected tariff change is equal or larger than the median expected change.

specification using a sample of manufacturing firms that did not change their operation status before and after the TPP agreement announcement.[30] Results are reported in Table 2.8. The signs of the coefficients remain the same, whereas their magnitude is somewhat bigger, especially for the 2016 coefficients. This suggests that the baseline findings are not driven by firm exit and entry in response to anticipation of the TPP.

Second, even if firms stay in the market, they may switch industries due to heterogeneous tariff reductions. For example, high productivity firms may be able to incur costs to switch to relatively more profitable industries whereas low productivity firms are unable to make such adjustments. If this is the case, the results might be driven by firms reallocating across industries instead of within-firm changes.

I argue that this is not a concern. First, evidence from Section 2.5 shows that reallocation across industries was minimal during this period. Furthermore, the percentage firms that reported being in a different industry after the TPP announcement is low. Among those that switched industries, a fraction reported being in a non-manufacturing industry such as wholesale and retail. As firms are required to report the most important industry, it is unclear whether this means firms actually exit the manufacturing sector altogether. Nevertheless, I include a robustness check in Table 2.23 in which I include firms that consistently report being in manufacturing.

2.6.4 Implications for Aggregate Productivity

In the last few sections, I have shown evidence of a causal link between the TPP announcement and firm-level productivity changes. Next, I quantify the effect on industry (weighted) productivity. Specifically, the aggregate productivity change due to the TPP for each two-digit industry in year 2016 is computed as

$$\Delta W_s^k = \sum_{i \in s} (s_i / S_s)(\Delta \tau_j^k \beta_{16}^k), \qquad k = \{x, m\}$$

where s denotes two-digit industries, j denotes four-digit industries and i denotes firms. ΔW_s^x represents the aggregate productivity changes caused by expected reduction in export tariffs. Analogously, ΔW_s^m represents the aggregate productivity changes caused by expected reduction in import tariffs. s_i is firm i's market share and S_s is the total market share of industry s, and $(\Delta \tau_j^k \beta_{16}^k)$ captures the change in firm i's productivity due to the TPP in the year 2016. The net productivity gain is then defined as $\Delta W_s = \Delta W_s^x + \Delta W_s^m$.

[30] Restricting the sample to a balanced panel of firms that were consistently active during the entire sample period leads to a substantial loss of observations. Thus, I exclude firms if they changed their status during 2015-2017. Firms that entered and/or exited the market during other periods can still be included in the sample.

Table 2.8: Productivity - Balanced Panel

Dependent var log TFP	(1)	(2)	(3)	(4)	(5)
β^x_{16}	0.600	0.598	0.581	0.502	0.454
	(0.312)*	(0.300)**	(0.301)*	(0.279)*	(0.317)
β^m_{16}	-0.370	-0.395	-0.418	-0.403	-0.378
	(0.114)***	(0.117)***	(0.120)***	(0.108)***	(0.118)***
β^x_{17}	0.704	0.635	0.619	0.724	0.646
	(0.597)	(0.618)	(0.621)	(0.715)	(0.723)
β^m_{17}	-0.300	-0.329	-0.354	-0.406	-0.377
	(0.220)	(0.230)	(0.233)	(0.220)*	(0.232)
Observations	219,902	219,901	219,870	218,358	218,443
Adjusted R^2	0.107	0.123	0.146	0.397	0.152
Year#ISIC2	Yes	Yes	Yes	Yes	Yes
Year#Province	No	Yes	Yes	Yes	Yes
ISIC2#Province	No	No	Yes	Yes	Yes
Year#ISIC2#Province	No	No	No	Yes	Yes
ISIC4	No	No	No	No	Yes

This table reports the results for firm-level productivity. Firm controls include firm size and ownership types, and 4-digit ISIC industry controls include capital intensity and share of skilled workers. Industry FEs are at 2-digit ISIC industry level. The sample consists of a balanced panel of active manufacturing firms with at least 10 workers. Standard errors are clustered at 4-digit ISIC level. Estimated coefficients, standard errors, and the additional hypothesis test statistics are adjusted for multiple imputations using the procedure in Appendix 2.9.2.
Standard error are in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

On average, reduction in export tariffs leads to 1.5% increase while reduction in import tariffs decreases aggregate productivity by 2.7%, leaving the average net gain at roughly -1.3%.[31] However, there is much heterogeneity across industries, as can be seen from Figure 2.9, which presents the effect of the TPP on (weighted) aggregate productivity, respectively. The biggest net beneficiaries are Tobacco (code 12) and Beverages (code 11) with productivity gains of 8% and 2.5% , whereas Textiles (code 13), Apparel (code 14), and Leather products (code 15) suffer net productivity declines of up to 3.8%.[32]

The choice of weights depends on the implicit assumption of the effect of the TPP on market share reallocation. I use 2016 market share as weights under the assumption that market share is minimally influenced by the announcement of the TPP, and thus the changes in aggregate productivity comes from within-firm changes. Using 2016 as market share might lead to bias if market shares are also affected (which it does not as I will show below). However, to check the validity of this assumption, I compute the aggregate productivity changes in 2016 using 2010 market shares as weights (see Figure 2.15). The results are very similar.

[31] To compute the aggregate gains, I use the most conservative estimates for TPP effects provided in the last column of Table 2.7. Under a more generous estimate (e.g., Column 1), I find the net productivity gain is about -0.8%.

[32] A complete report of aggregate effect at the two-digit industry level is provided in Table 2.9.

Figure 2.9: Effect of TPP on two-digit industry productivity (weighted by 2016 market share)

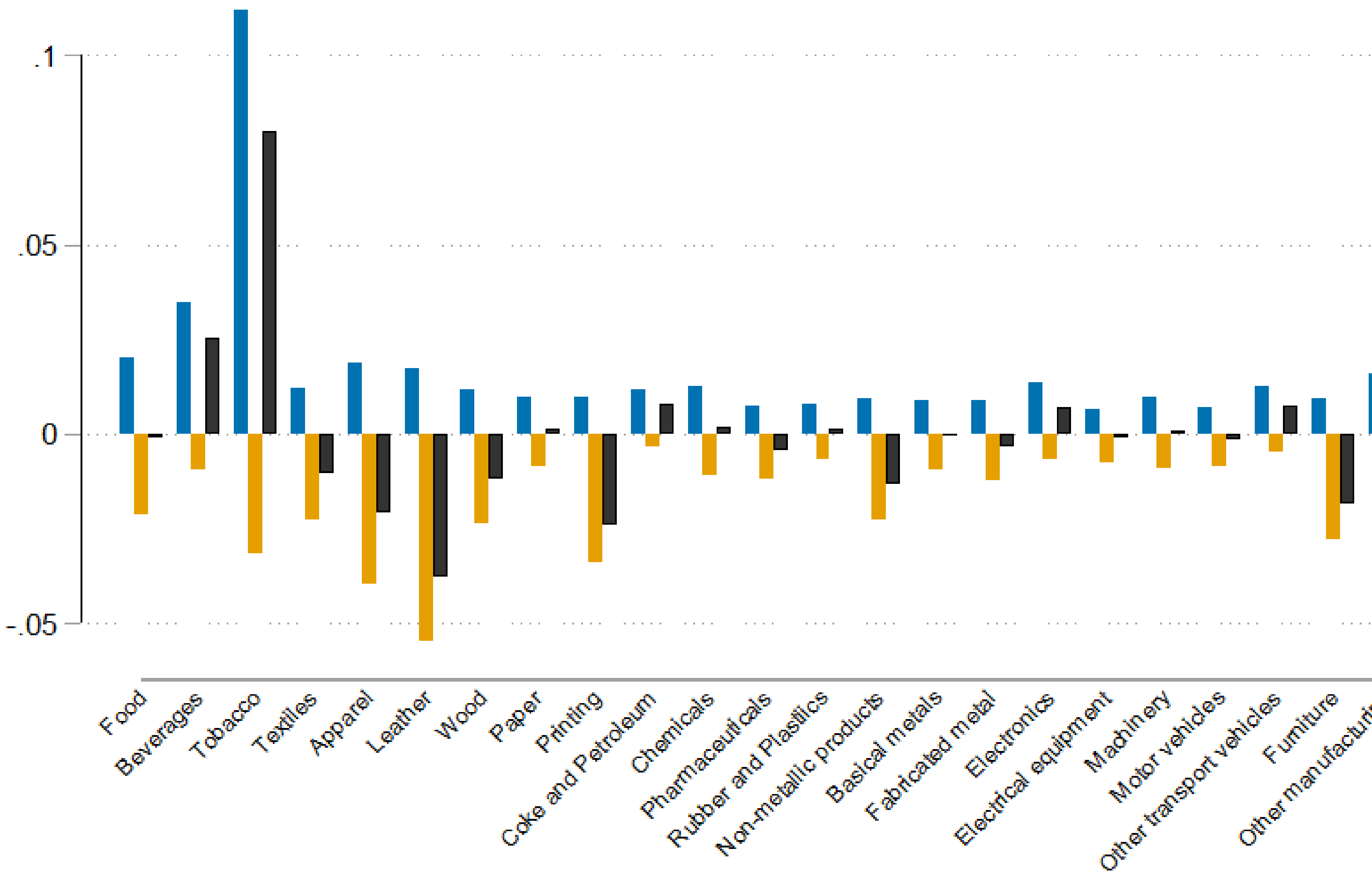


Table 2.9: Weighted vs. unweighted productivity gain at two-digit industry level (weighted by 2016 market share)

	Weighted			Unweighted		
ISIC2	Export	Import	Net	Export	Import	Net
Food	0.020	-0.021	-0.001	0.023	-0.017	0.006
Beverages	0.035	-0.010	0.025	0.035	-0.009	0.026
Tobacco	0.112	-0.032	0.080	0.112	-0.032	0.080
Textiles	0.012	-0.023	-0.010	0.013	-0.024	-0.011
Apparel	0.019	-0.040	-0.021	0.019	-0.039	-0.021
Leather	0.017	-0.055	-0.038	0.017	-0.040	-0.023
Wood	0.012	-0.024	-0.012	0.012	-0.022	-0.009
Paper	0.010	-0.008	0.001	0.010	-0.009	0.001
Printing	0.010	-0.034	-0.024	0.010	-0.035	-0.025
Coke and Petroleum	0.011	-0.003	0.008	0.011	-0.004	0.008
Chemicals	0.013	-0.011	0.002	0.013	-0.011	0.002
Pharmaceuticals	0.007	-0.012	-0.004	0.007	-0.012	-0.004
Rubber and Plastiics	0.008	-0.007	0.001	0.008	-0.007	0.001
Non-metallic products	0.009	-0.023	-0.013	0.010	-0.024	-0.014
Basical metals	0.009	-0.009	-0.001	0.009	-0.010	-0.001
Fabricated metal	0.009	-0.012	-0.003	0.008	-0.011	-0.003
Electronics	0.014	-0.007	0.007	0.012	-0.007	0.006
Electrical equipment	0.007	-0.008	-0.001	0.008	-0.008	-0.000
Machinery	0.010	-0.009	0.001	0.009	-0.010	-0.001
Motor vehicles	0.007	-0.008	-0.001	0.008	-0.008	-0.000
Other transport vehicles	0.013	-0.005	0.008	0.015	-0.005	0.010
Furniture	0.009	-0.028	-0.019	0.010	-0.027	-0.018
Other manufacturing	0.016	-0.015	0.001	0.016	-0.018	-0.002

This table reports the aggregate effect of TPP anticipation on two-digit industry productivity using $\beta^x_{16} = 0.341$ and $\beta^m_{16} = -0.312$.
Standard error are in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.7 Heterogeneous Effects and Mechanisms

In this section, I provide further evidence that firm-level expectations, not actual tariff changes, is the key driver for the productivity responses we see in the previous section. To do so, I explore the heterogeneous effects of the TPP agreement across different groups of firms and industries with differential potential exposure to the TPP. Section 2.7.1 documents the difference between foreign and domestic firms and section 2.7.2 explores productivity responses within industries with high potential growth and those with low potential growth.

2.7.1 Foreign versus Domestic Firms

There has been strong evidence that foreign firms respond to trade agreements and trade liberalization differently from domestic firms. For example, Feenstra et al. (2014) and Manova et al. (2015) find that foreign firms face fewer financial frictions and thus have better export performance and these resutlts are stronger for destinations with higher trade costs. Rho and Rodrigue (2015) document differences between foreign and domestic firms in terms of physical investments, consistent with the credit constraint explanation. If improving productivity is costly, we should expect that credit constrained firms are less responsive to expected reductions in tariffs.

In my setting, it is also plausible that foreign and domestic firms might hold different expectations about the likelihood of TPP implementation and/or the potential impact of TPP on their future profits. For example, foreign firms might have different information sets from domestic firms and thus the same tariff change could induce dissimilar responses. They may also face different market demands and demand elasticities for their products. For these reasons, I investigate whether there are differential productivity responses to TPP anticipation between foreign and domestic firms in Vietnam after the TPP agreement was announced. Furthermore, I divide foreign firms into TPP and non-TPP originated firms as the might not have the same expectations about how the TPP would affect their future profits.[33]

Results are reported in Table 2.10 for a triple-differences specification and Figure 2.10 plots the estimated coefficients for three groups of firms. Three notable patterns emerge. First, I find a there is a lack of response among foreign firms to expected tariff reductions in 2016. This does not necessarily reflect a lack of response but simply that we may not observe its performance in the parent countries. Another explanation is that many foreign firms already have market access to TPP countries and thus the added benefits VN having access to market may not be big enough to induce investment.

Interestingly, expected import tariff reduction induced stronger response from foreign firms compared to domestic firms, indicating that for firms that are already entered the Vietnamese market, increased foreign competition would generate larger disincentive to invest. The differences between domestic and foreign firms are not driven by state-owned enterprises (Column 2). This can be explained by the fact that foreign firms already in Vietnam would face more direct competition from future foreign entrants compared to domestic firms. It might also reflect production shifting from Vietnam to other markets.

Third, there is some weak evidence that non-TPP firms are affected more negatively by the expected import tariffs compared to TPP firms. This pattern may imply that non-TPP foreign

[33]Since there is no direct information about the parent countries, I use each firm's CEO nationality as a proxy for its origin country. Though this is not an exact match, there is some evidence that CEO nationality can reflect the source country of capital. The majority of foreign companies have foreign CEOs. A quarter of foreign CEOs are from TPP countries (excluding Vietnam). About 40% of non-TPP foreign firms have South Korean CEOs, 30% of foreign CEOs are Taiwanese and 15% are Chinese. Among CEOs from TPP countries, 71% are Japanese. This matches reasonably well with the common perception of foreign firm composition in Vietnam.

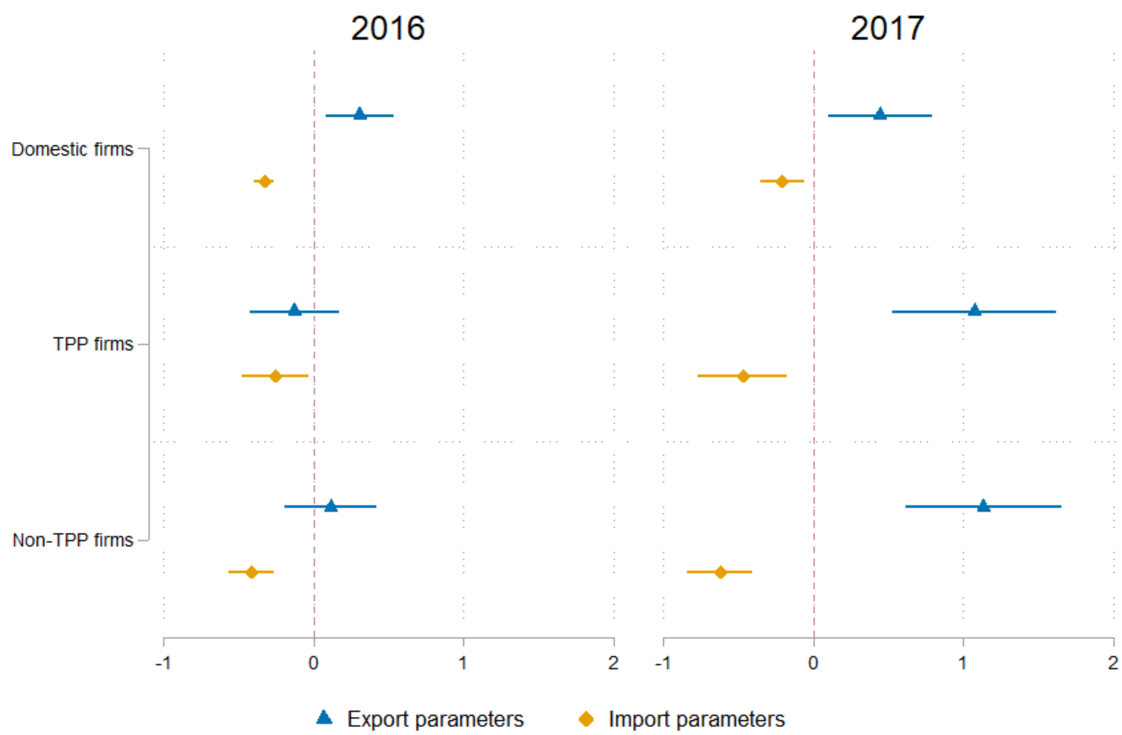


Figure 2.10: Heterogeneous effects among different groups of firms by CEO nationality

firms anticipated stiffer competition if the TPP agreement takes effect. Nonetheless, the difference between the two coefficients is not statistically significant.

2.7.2 Potential Growth

This section examines whether the effect is heterogeneous across industries with different levels of potential growth. Firms in industries subject to similar tariff reductions might experience different growth rates depending on the potential demand once tariffs are removed. To capture the potential demand growth for Vietnamese goods once the TPP is implemented, I use exports from China to TPP countries prior to 2016. Similarly, I use the import values from TPP countries to China to measure the potential domestic demand for foreign goods in Vietnam. There are a number of reasons to believe that this is a reasonable measure. First, China and Vietnam share similar market structure and are in close proximity (Kerkvliet et al., 1998). The current growth trajectory of Vietnam has been repeatedly compared to that of China for more than a decade (Chaponnière et al., 2010).[34] Second, there is anecdotal evidence that the TPP was a strategic instrument the US

[34]Evidence from media: https://www.forbes.com/sites/salvatorebabones/2017/11/09/vietnam-is-following-in-chinas-footsteps-in-gdp-growth-at-least/"Vietnam's GDP Is Just 11 Years Behind China, And Growing Rapidly" (Forbes Nov 9,

Table 2.10: Foreign versus Domestic Firms

Dependent var log TFP		(1)	(2)	(3)	(4)
$2016 \times \Delta\tau^x$		0.414	0.410	0.309	0.486
		(0.185)**	(0.188)**	(0.171)*	(0.251)*
	$\times foreign$	-0.292	-0.312		
		(0.163)*	(0.177)*		
	×TPP			-0.442	-0.168
				(0.222)**	(0.211)
	×non-TPP			-0.182	
				(0.188)	
$2016 \times \Delta\tau^m$		-0.299	-0.302	-0.327	-0.490
		(0.068)***	(0.069)***	(0.063)***	(0.099)***
	$\times foreign$	-0.082	-0.073		
		(0.094)	(0.098)		
	×TPP			0.079	0.178
				(0.157)	(0.115)
	×non-TPP			-0.090	
				(0.103)	
$2017 \times \Delta\tau^x$		0.528	0.510	0.444	0.399
		(0.343)	(0.351)	(0.343)	(0.388)
	$\times foreign$	0.548	0.585		
		(0.306)*	(0.309)*		
	×TPP			0.621	-0.111
				(0.368)*	(0.272)
	×non-TPP			0.694	
				(0.368)*	
$2017 \times \Delta\tau^m$		-0.174	-0.172	-0.209	-0.289
		(0.175)	(0.175)	(0.187)	(0.219)
	$\times foreign$	-0.405	-0.416		
		(0.157)**	(0.158)***		
	×TPP			-0.260	0.079
				(0.210)	(0.139)
	×non-TPP			-0.416	
				(0.163)**	

This table compares the effects on productivity between foreign and domestic firms. Columns 1&3 include the baseline sample while Column 2 excludes state-owned enterprises. The last column only includes foreign firms. Firm controls include firm size and ownership types, and 4-digit ISIC industry controls include capital intensity and share of skilled workers. A full set of year, sector, and province dummies is included in each specification. Standard errors are clustered at 4-digit ISIC level. Estimated coefficients, standard errors, and the additional hypothesis test statistics are adjusted for multiple imputations using the procedure in Appendix 2.9.2.
Standard error are in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

sought to isolate or contain China. Meanwhile, Vietnam and other Southeast Asian nations in the trade deal have continued to provide cheap labor and export manufactured goods. Vietnam also has a large population (93 mil. in 2016) with a growing middle class, thus increasing demand for high-quality imported goods. It is plausible that other TPP countries, especially the US, look to Vietnam as a potential alternative to China for both import demand and manufactured exports.[35]

To this end, I construct a variable that measures the difference in export/import structure between China and Vietnam in the base year. Since the Chinese economy is much bigger in size than its Vietnamese counterpart, it is unreasonable to compare the level of trade values between the two countries. Instead, I construct a measure of the *relative* trade intensity at the four-digit industry level. Specifically, let $X_{j,VN}$ denote the trade value of goods in four-digit industry j between Vietnam and TPP countries (excluding Vietnam) in the base year and X_{VN} the total trade values between Vietnam and TPP countries. Define the trade intensity for industry j in Vietnam, $\chi_{j,VN} \equiv X_{j,VN}/X_{VN}$ as the industry j's share of trade values between Vietnam and TPP countries. Similarly, let $\chi_{j,CH}$ denote the trade intensity of industry j in China. The difference in trade intensity for industry j between the two countries is $\Delta\chi_j \equiv \chi_{j,VN} - \chi_{j,CH}$. Finally, I calculate this quantity for exports and imports separately, denoted as $\Delta\chi_j^x$ and $\Delta\chi_j^m$.[36]

Intuitively, if $\Delta\chi_j^x < 0$, it means in 2010 Vietnam exported relatively less of goods j to TPP markets compared to China. In other words, if Vietnam is in fact a replacement for Chinese markets and/or Chinese manufacturers, then a negative value might be indicative of bigger potential growth and thus should amplify the positive effect of tariff reductions on productivity as firms may expect bigger demand growth. On the other hand, when $\Delta\chi_j^m < 0$, Vietnam imported relatively less goods j from TPP countries compared to China in the base year. This implies that there would potentially be more import competition in these markets, further reducing the gain of improving productivity for firms in those industries.

Table 2.11 report the results. As we can see, lower relative trade intensity indeed amplifies the effect of the TPP anticipation. Firms in industries with low relative export intensity (and thus high potential export growth) have bigger productivity increases in response to expected export tariff reductions. Similarly, expected import tariff reductions generate deeper decreases in productivity for firms in industries with less import intensity. This is consistent with the hypothesis that Vietnam

2017)

[35]For discussion of US policies toward TPP and China in the media, see https://www.brookings.edu/blog/up-front/2013/05/24/the-containment-fallacy-china-and-the-tpp/Link 1, https://www.scmp.com/news/china/diplomacy-defence/article/2048319/whats-tpp-has-been-omitted-china-led-free-trade-optionLink 2, https://fortune.com/2015/10/19/china-exclusion-tpp-economic-growth/Link 3

[36]About 15% of firms are in industries with $\Delta\chi_j^m < 0$ and 34% with $\Delta\chi_j^x < 0$.

Table 2.11: Potential Growth across Industries

Dependent var log TFP		(1)	(2)	(3)	(4)	(5)
$2016 \times \Delta\tau^x$		0.280	0.211	0.241	0.155	0.137
		(0.188)	(0.157)	(0.154)	(0.158)	(0.154)
	$\times(\chi^x < 0)$	0.076	0.135	0.099	0.231	0.248
		(0.257)	(0.177)	(0.167)	(0.146)	(0.138)*
$2016 \times \Delta\tau^m$		-0.192	-0.205	-0.219	-0.169	-0.170
		(0.075)**	(0.068)***	(0.065)***	(0.067)**	(0.063)***
	$\times(\chi^m < 0)$	-0.201	-0.169	-0.167	-0.197	-0.204
		(0.061)***	(0.055)***	(0.053)***	(0.055)***	(0.051)***
$2017 \times \Delta\tau^x$		0.378	0.340	0.377	0.265	0.277
		(0.208)*	(0.192)*	(0.195)*	(0.223)	(0.229)
	$\times(\chi^x < 0)$	0.508	0.432	0.427	0.388	0.414
		(0.181)***	(0.155)***	(0.156)***	(0.192)**	(0.188)**
$2017 \times \Delta\tau^m$		-0.186	-0.209	-0.217	-0.153	-0.166
		(0.095)*	(0.086)**	(0.087)**	(0.083)*	(0.084)**
	$\times(\chi^m < 0)$	-0.058	-0.006	-0.012	-0.027	-0.031
		(0.094)	(0.099)	(0.098)	(0.094)	(0.092)
Observations		291,404	291,404	291,381	289,952	289,951
Adjusted R^2		0.175	0.199	0.230	0.222	0.246
Year#ISIC2		Yes	Yes	Yes	Yes	Yes
Year#Province		No	Yes	Yes	Yes	Yes
ISIC2#Province		No	No	Yes	Yes	Yes
Year#ISIC2#Province		No	No	No	Yes	Yes
ISIC4		No	No	No	No	Yes

This table reports the results on firm-level productivity. Firm controls include firm size and ownership types, and 4-digit ISIC industry controls include capital intensity and share of skilled workers. Industry FEs are at 2-digit ISIC industry level. The sample consists of active manufacturing firms with at least 10 workers. Standard errors are clustered at 4-digit ISIC level. Estimated coefficients, standard errors, and the additional hypothesis test statistics are adjusted for multiple imputations using the procedure in Appendix 2.9.2.
Standard error are in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

is considered a substitute for Chinese goods and thus an industry in Vietnam with less trade intensity compared to its counterpart in China would enjoy bigger expected growth.

2.7.3 Capacity Utilization

Tariff change expectations can affect demand and thus capacity utilization. If this is the case, we should expect that industries with high adjustment costs do not change capacity utilization that much whereas industries with low adjustment costs should show stronger response to tariff-induced demand volatility.[37]

To explore this story, I estimate the effect of anticipated tariff changes on capacity utilization for low and high adjustment cost industries. Capacity utilization is measured as the ratio of material

[37] Butters (2020) provides evidence for this story by showing that differences in annual demand volatility can explain a large share of the variation in capacity utilization in a high adjustment cost industry but not in a low adjustment cost industry.

inputs to physical capital.[38] Estimates from Hall (2004) and Mizobata (2016) imply that capital intensive industries tend to have higher adjustment costs.[39] Thus, I classify an industry as high adjustment cost industry if its level of capital intensiveness is above the median. In Table **??**, I regress the anticipated tariff changes on capacity utilization and differentiate between low and high adjustment cost industries.

I find that on average, there is no significant effect of expected tariff changes on capacity utilization. There is weak evidence that capacity utilization industries with high adjustment costs tend to respond more to anticipated changes in tariffs. It is unlikely that firms adjust their capacity utilization in response to demand changes due to the TPP signing.

Table 2.12: Capacity utilization

Dependent var Capacity utilization		(1)	(2)	(3)	(4)	(5)
$2016 \times \Delta\tau^x$		1.660	1.575	1.643	0.984	0.575
		(1.418)	(1.412)	(1.417)	(1.404)	(1.424)
	$\times$ high adj. cost	1.597	1.726	1.421	1.745	2.184
		(1.293)	(1.395)	(1.385)	(1.302)	(1.285)*
$2016 \times \Delta\tau^m$		-0.785	-0.412	-0.566	-0.097	-0.187
		(1.039)	(1.009)	(1.017)	(0.911)	(0.928)
	$\times$high adj. cost	0.621	0.319	0.467	0.210	0.112
		(1.019)	(1.006)	(1.013)	(0.903)	(0.913)
$2017 \times \Delta\tau^x$		2.315	2.237	2.399	1.473	1.220
		(1.518)	(1.516)	(1.508)	(1.534)	(1.552)
	$\times$ high adj. cost	-0.009	-0.389	-0.718	-0.580	-0.308
		(1.413)	(1.402)	(1.411)	(1.385)	(1.386)
$2017 \times \Delta\tau^m$		-1.161	-1.221	-1.471	-0.803	-0.943
		(1.484)	(1.411)	(1.424)	(1.439)	(1.441)
	$\times$ high adj. cost	0.979	1.199	1.415	1.032	0.977
		(1.541)	(1.469)	(1.492)	(1.518)	(1.520)
Observations		293,644	293,644	293,621	292,195	292,194
Adjusted R^2		0.037	0.054	0.072	0.067	0.076
Year#ISIC2		Yes	Yes	Yes	Yes	Yes
Year#Province		No	Yes	Yes	Yes	Yes
ISIC2#Province		No	No	Yes	Yes	Yes
Year#ISIC2#Province		No	No	No	Yes	Yes
ISIC4		No	No	No	No	Yes

This table reports results when the expected tariff reductions are constructed with a discount factor of 0.5. The sample consists of active manufacturing firms with at least 10 workers. Standard errors are clustered at 4-digit ISIC level and adjusted for multiple imputations using the procedure in Appendix 2.9.2.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[38] This is under the assumption that capital is fixed in the short term and material is flexible.

[39] In the context of Japan, Mizobata (2016) finds that steel, machinery, and transportation equipment are industries with the highest capital adjustment costs. For the US, the industries are transportation equipment, instruments and related products, and water transportation based on the calculations in Hall (2004).

2.8 Conclusion

In this paper, I exploit the unique timeline of the Trans-Pacific Partnership to study the anticipation effect of trade agreements on firm-level productivity. The identification comes from variation across industries in expected export and import tariff changes if the TPP had been implemented. Essentially, I compare the differential trends between firms in industries with high expected tariff cuts versus those in industries with low expected tariff cuts before and after the TPP announcement in October 2015. As there was no actual policy changes, it can be concluded that any productivity responses should be a result of changes in firm-level expectations.

Using a sample of Vietnamese manufacturing firms between 2010 and 2017, I find that an expected decrease in tariffs on Vietnamese exports, which would bring about greater access to foreign markets, leads to an increase in productivity in 2016–the year the TPP was expected to take effect. On the other hand, an expected decrease in tariffs on Vietnamese imports, which would increase foreign competition, leads to a decrease in productivity. I find that most of the effect comes from within-firm changes, whereas there is little reallocation across industries. Furthermore, I do not find any further effects beyond 2016, indicating that as firms might have adjusted their expectation of the TPP implementation due to the US withdrawal at the beginning of 2017 and thus made no further changes in their productivity. Finally, though net effect on aggregate productivity in the manufacturing sector is small, there are heterogeneous effects on productivity at the two-digit industry level.

My empirical findings indicate that even without any policy implementation, an announcement of trade policy changes can alter firm' expectations and thus induce productivity responses at the firm level. This response in turn has ramifications for aggregate productivity and welfare gains from trade. Future work could focus on different factors that can affect firms' expectations about future policy implementation, including access to reliable information and/or validity of government announcement. In addition, incorporating other firm-level outcomes is also a potential venue of research and will add to our understanding of firms' strategy shifting in the anticipation of future trade reforms and free trade agreements.

2.9 Appendix

2.9.1 Details on Construction of Final Sample

2.9.1.1 Linking firms across years

There is no consistent way to identify firms across years. Round 2016 reports a 13-digit tax ID, which is a unique legal number assigned to each registered enterprise. Prior to 2016, however, only the first nine or ten digits of the tax ID numbers are recorded. The GSO created its own identification series, which I will refer to as firm ID numbers, to keep track of firms over time, but this information is not without issues. The use of this series is discontinued starting in 2016. Furthermore, there are occasions when multiple tax numbers attached to the same firm ID number. The GSO advises researchers to use information on location along with firm IDs to identify unique firms, which helps alleviate the second problem under the assumption that firms do not move between sample years. To deal with missing firm IDs in 2016 and 2017, I link firms between 2016-2017 and the period of 2010-2015 using 10-digit tax ID numbers and province. When there is more than one firm ID number matched, I link 2016-2017 firms to those with the same industry and/or similar labor and capital structure in the previous year. This procedure matches about 80% of the firms in 2016, leaving about 100,000 firms unmatched. These are likely to be new entrants; in 2016 there are 510,000 firms in total while this number is 430,000 in 2015. At this point I have about 630,000 firms and 2.6 millions observations. I keep firms which report being in the manufacturing sector (ISIC codes 10-33) for at least one of the sample years, which is about 20% of the original sample.

2.9.1.2 Defining A Firm's Main Industry

Firms change their main industry over years even though they might produce the same product. About 40% of firms also report being in a non-manufacturing industry, among which the most frequent ones are wholesale (ISIC 46) and retail (ISIC 47). Information at more refined industry level reveals that these firms manufacture and sell the same products, but choose to report different industries in different years. For example, a manufacturer of textiles (ISIC 1311-1399) may report being in the wholesale of textiles, clothing, and footwear (ISIC 4641) in some other year. A problem arises when converting between HS codes and ISIC codes, as manufacture of textiles (ISIC 1311-1399) and wholesale of textiles, clothing, and footwear (ISIC 4641) are associated with different HS products and thus different tariff levels even though the firm may produce the same product. To avoid this reporting issue, I assign each firm to its respective manufacturing industry as its only industry through the 2010-2017 period. In the robustness checks, I report results using a sample of firms who consistently report being in the manufacturing sector (see Table 2.23).

2.9.1.3 Deflators

I deflate revenue variables using a producer price index at the two-digit industry level. Material expenditures are deflated by input producer price indices. To deflate capital values, I follow two approaches (1) there are four types of capital: buildings, machine/equipment, vehicles, and others. In principle, I can construct a deflator for capital and average the individual deflators weighted by their share of capital values. Price indices for machinery and vehicles are available. For types 2 and 3, I deflate using PPI in machinery (ISIC 27 and 28) and vehicles (ISIC 29 and 30). Then I construct an average of the price deflators weighted by the share of investment in each type of capital. Since I don't have a deflator for the others category, I assume its weight is close to zero.

It is not straightforward to construct a deflator for the first category. Though it is natural to use construction price indices, there is no consistent construction price index in Vietnam. In 2010 and 2011, the Ministry of Construction reported indices for the entire country; however, after 2011 each province and central city would report their own index. The lack of availability in some years for some provinces prevents me from constructing a general index every year. Furthermore, before 2016 the provincial level reports did not include a price index for the construction of plants and warehouses. Given the lack of availability for capital price deflator, I use PPI to deflate capital stock in the main analysis.

2.9.2 Imputation

The original data set from the GSO combines both raw and imputed data for firms that respond to questionnaire 1B. There are several problems with this data set. First, the criteria to select which observations to impute changed over time. In 2015 two important variables are not imputed: fixed assets and the costs of goods sold. Imputing only these two variables will lead to inconsistency because I do not know the imputation procedure used by the GSO for the rest of the missing variables. In 2017, the GSO only imputed data for firms with fewer than 99 workers, whereas in previous years they imputed data for all firms answering the short questionnaire.

A potential approach is to use only firms that answer the complete questionnaire and discard all imputed observations, then control for factors that determine missingness in the regression estimation. To identify these firms, I match the combined data with the reduced survey data and find that these two cannot be matched entirely. This means there is a number of firms that are falsely classified as non-imputed observations.

To tackle the issues with both the original data and the non-imputed data, I follow the multiple imputation method introduced by rubin1987multiple, using information from all years in my

Table 2.13: Number of non-missing observations across years and samples

Year	Baseline	Original	No Imp.
2010	32,472	26,055	18,443
2011	36,624	27,804	27,804
2012	36,257	31,216	23,634
2013	36,631	31,768	20,614
2014	38,014	32,776	19,839
2015	37,980	16,433	16,433
2016	38,106	30,274	30,274
2017	35,506	28,546	18,281
All years	291,590	224,872	175,322

This table reports the number of non-missing observations in each year. The first column shows the observations for the multiply imputed sample used in the baseline analysis. The second column shows the observations in the singly imputed sample. The last column shows the number of non-imputed observations.

sample. This method guarantees consistency in the imputation process across years and thus changes in variable values over time are less likely to be affected by the imputation. The method potentially reduces bias from the falsely identified non-imputed observations if this group only contributes a small fraction of my sample.

Most importantly, as imputed data should not be treated as true data, I need to account for the uncertainty from imputation. Single imputation also reduces the variability in the true data as the imputed rely solely on the non-missing part of the sample. Stochastic imputation reintroduces random error to the data but the standard errors produced during the regression estimation will still be attenuated. Applying multiple imputations will provide a more accurate set of estimates as each imputed value includes a component that cannot be predicted by other variables in the imputation model Johnson and Young (2011); White et al. (2011). Furthermore, I need to impute several variables that are potentially correlated with each other. This cannot be done with either single imputation or stochastic imputation, which replaces missing variables with predicted values from separate regression estimations.

2.9.2.1 Procedure

I conduct multiple imputations for the log of sales, capital, and materials using the log of labor as the key predictor. I assume a multivariate normal distribution and impute the missing variables using MCMC methods. There are non-parametric methods that avoid making assumptions about the distribution, including matching and classification and regression trees (CART). The disadvantages are that these methods are more computationally intensive and the control-function TFP is sensitive to imputed data White et al. (2018). Below is the imputation procedure:

1. Impute the missing data for M times (in this paper I use $M = 10$). For each imputation $m = 1, ..., M$,
2. Compute productivity
3. Conduct the regression analysis in section 4 and 5
4. The final estimate is simply the mean of estimates from each imputation m

$$\hat{\beta} = \frac{1}{M}\sum_{m=1}^{M}\hat{\beta}_m$$

and the variance is

$$V = W + (1 + \frac{1}{M})B$$

where $W = \frac{1}{M}\sum_{m=1}^{M} s_m^2$ is the within-imputation variance and $B = \frac{1}{M-1}\sum_{m=1}^{M}(\hat{\beta}_m - \hat{\beta})^2$ is the between-imputation variance. The additional term $(1/M) \times B$ accounts for sampling variance with a small number of imputations M White et al. (2011).

2.9.2.2 Inference

Inference for each parameter is based on the approximation

$$V^{-1/2}(\beta - \hat{\beta}) \sim t_\nu$$

where t_ν is a Student's t distribution with ν degrees of freedom, which depends on the number of imputations, M, and the increase in variance of estimates due to missing data. The degree of freedom, ν, is computed based on the large-sample assumption

$$\nu = (M - 1)(1 + \frac{1}{r})^2$$

where

$$r = \frac{1 + M^{-1}B}{W}$$

is the relative variance increase due to missing data. For derivations of ν, please refer to barnard1999miscellanea.

Inference when β is a vector of parameters is not simple. As the number of imputations M is small, the between-variance B cannot be reliably estimated. Furthermore, when M is smaller than the number of parameters, B does not have full rank. One way to circumvent this problem is to assume that the between and within-imputation variance-covariance matrices are proportional to each other. This assumption is equivalent to assuming that the fractions of missing data for all components of β are equal.

Under this assumption, the estimate for the total variance is

$$V = (1 + r)W$$

where now $r = (1 + M^{-1})tr(BW^{-1})/k$ and k is the number of dimensions in β. Intuitively, r is the average relative increase in variance due to missing information across the parameters of β. Though this procedure relies on the assumption that the fraction of missing data is similar across k parameters in β, li1991large show that the proposed procedure is robust to violations of this assumption. The test statistics

$$(\beta - \hat{\beta})V^{-1}(\beta - \hat{\beta})'/k \sim F(k, v)$$

follow an F-distribution with k and ν degrees of freedom. The formula for ν I use in the paper applies to the case when $k(M - 1) > 4$:

$$\nu = 4 + [k(M - 1) - 4][1 + (1 - \frac{2}{k(M - 1)})r^{-1}]^2$$

See li1991large for further details. Note that the equation above is derived under the assumption that the error degrees of freedom would be set at infinity (i.e. large sample size).

2.9.3 Estimating Productivity

2.9.3.1 Endogenous Productivity Evolution

I impose three different laws of motion for productivity:

$$\begin{aligned}
\text{MODEL 1: } &= \sum_{j=0}^{3} \rho_j \omega_{it-1}^j + \xi_{it} \\
&+ \rho_6 Post2015 \times \Delta\tau_j^x + \rho_7 Post2015 \times \Delta\tau_j^m + \rho_8 \Delta\tau_j^x + \rho_9 \Delta\tau_j^m + \xi_{it} \\
\text{MODEL 2: } &= \sum_{j=0}^{3} \rho_j \omega_{it-1}^j + \sum_{k=2016,2017} \rho_4^k (year = k) \times \Delta\tau_j^x + \sum_{k=2016,2017} \rho_5^k (year = k) \times \Delta\tau_j^m \\
&+ \rho_6 \Delta\tau_j^x + \rho_7 \Delta\tau_j^m + \xi_{it} \\
\text{MODEL 3: } &= \sum_{j=0}^{3} \rho_j \omega_{it-1}^j + \sum_{k=2016,2017} \rho_4^k (year = k) \times \Delta\tau_j^x + \sum_{k=2016,2017} \rho_5^k (year = k) \times \Delta\tau_j^m \\
&+ \rho_6 \Delta\tau_j^x + \rho_7 \Delta\tau_j^m + \rho_8 OWNERSHIP_i + \xi_{it}
\end{aligned}$$

Table 2.14: Production function estimates (average)

	Model 1	Model 2	Model 3
α_l	0.403	0.414	0.405
α_k	0.0500	0.0493	0.0467
α_m	0.611	0.607	0.617

This table reports the average results across ten imputations for the production function estimation. The first column presents result when productivity follows an exogenous evolution process (baseline result), while the second and third columns allow for endogenous growth as described in the text. See Table 2.15 for the full list of estimates for each imputation.

Table 2.15: Production function estimates - ACF approach

	Model 1			Model 2			Model 3		
Imputation	α_l	α_k	α_m	α_l	α_k	α_m	α_l	α_k	α_m
1	0.402	0.051	0.610	0.411	0.050	0.607	0.412	0.050	0.608
2	0.404	0.051	0.609	0.414	0.050	0.605	0.417	0.050	0.603
3	0.402	0.050	0.611	0.412	0.049	0.608	0.384	0.041	0.643
4	0.401	0.050	0.612	0.414	0.050	0.606	0.412	0.049	0.608
5	0.400	0.050	0.613	0.412	0.049	0.607	0.412	0.049	0.608
6	0.402	0.049	0.613	0.412	0.048	0.609	0.413	0.048	0.609
7	0.403	0.050	0.610	0.416	0.050	0.603	0.417	0.050	0.603
8	0.403	0.049	0.612	0.415	0.049	0.606	0.388	0.041	0.641
9	0.405	0.050	0.609	0.412	0.048	0.609	0.376	0.039	0.646
10	0.405	0.050	0.610	0.417	0.049	0.605	0.419	0.050	0.603

This table reports the production function estimation results for all ten imputations.

Model 1 imposes an exogenous productivity evolution. Models 2 and 3 allow for productivity to be function of expected tariff changes. Model 3 allows productivity growth to depend on firm ownership types. Table 2.14 presents the average point estimates for each coefficient in the production function, and Table 2.15 reports the point estimates for each imputation. The point estimates for labor, material, and capital coefficients are surprisingly similar across different assumptions. The baseline results rely on the second assumption on productivity evolution.

2.9.3.2 First-Order Condition Approach

In the main analysis, the firm-level productivity is computed using the approach developed by levinsohn2003estimating and ackerberg2015identification. One assumption for this method to work is that the lagged values of variable inputs need to have enough power to predict current inputs. This requirement may not be reasonable for freely chosen inputs such as materials, meaning we might face a weak IV problem when using past materials expenditure to instrument for current materials

Table 2.16: Productivity function estimates - GNR approach

		Model 1		Model 2		Model 3	
Imputation	α_m	α_l	α_k	α_l	α_k	α_l	α_k
1	0.559	0.444	0.071	0.455	0.068	0.430	0.066
2	0.558	0.448	0.075	0.458	0.068	0.428	0.067
3	0.558	0.446	0.072	0.442	0.071	0.429	0.064
4	0.557	0.445	0.074	0.449	0.071	0.430	0.064
5	0.558	0.449	0.075	0.456	0.070	0.432	0.067
6	0.559	0.438	0.074	0.453	0.069	0.431	0.065
7	0.558	0.444	0.075	0.457	0.069	0.426	0.067
8	0.558	0.442	0.075	0.450	0.071	0.432	0.064
9	0.559	0.443	0.072	0.450	0.071	0.421	0.067
10	0.559	0.441	0.074	0.456	0.069	0.429	0.063

This table reports the average elasticities of materials, labor, and capital for all ten imputations using the GNR approach. The estimation of material elasticity is the same across three models.

expenditures. To check the robustness of this requirement, I re-estimate firm-level productivity using the approach in gandhi2020identification (hereafter GNR). The authors rely on a first order condition to derive the elasticity of materials in the first stage. In the second stage, the labor and capital elasticities are estimated in a similar fashion to the LP/ACF approach.

To ensure comparability between two sets of results, I estimate GNR version of productivity with Cobb-Douglas production function and endogenous productivity evolution in the second stage. Under the Cobb-Douglas production assumption, materials expenditure share of total revenue, denoted by s_{it}, is

$$s_{it} = \ln \xi + \ln \alpha_m + \epsilon_{it}$$

where and $\xi = \mathbb{E}[\exp(\epsilon_{it})]$. Assuming $\mathbb{E}(\epsilon_{it}) = 0$, I can identify $(\ln \xi + \ln \alpha_m)$ and $\xi = \mathbb{E}[\exp(\ln \xi + \ln \alpha_m) - s_{it})]$. Thus, α_m is identified. In the second stage I use the same assumption for the productivity evolution as in the main analysis.

Table 2.16 reports the production function estimates and Table 2.17 reports the effect of TPP anticipation on productivity. In general, the directions of the effects are consistent with the baseline results: expected export tariff reduction leads to an increase in productivity while expected import tariff reduction leads to a decrease in productivity.

2.9.4 Other Robustness Checks

In this section, I check how robust the results in Section 1.5 are with respect to measurement of the expected tariff reductions, imputation procedures, and sample selection.

Table 2.17: Productivity Effect - GNR approach

log *TFP*	(1)	(2)	(3)	(4)	(5)	(6)
β^x_{16}	0.625	0.607	0.624	0.452	0.688	0.611
	(0.252)**	(0.243)**	(0.244)**	(0.206)**	(0.256)***	(0.249)**
β^m_{16}	-0.385	-0.409	-0.428	-0.427	-0.359	-0.397
	(0.117)***	(0.119)***	(0.124)***	(0.108)***	(0.133)***	(0.123)***
β^x_{17}	0.708	0.674	0.688	0.577	0.662	0.618
	(0.492)	(0.507)	(0.510)	(0.471)	(0.589)	(0.591)
β^m_{17}	-0.238	-0.285	-0.308	-0.352	-0.256	-0.303
	(0.233)	(0.239)	(0.239)	(0.205)*	(0.239)	(0.229)
Observations	293,633	293,633	293,610	293,513	292,184	292,183
Adjusted R^2	0.094	0.109	0.130	0.375	0.130	0.137
Year#ISIC2	Yes	Yes	Yes	Yes	Yes	Yes
Year#Province	No	Yes	Yes	Yes	Yes	Yes
ISIC2#Province	No	No	Yes	Yes	Yes	Yes
Initial TFP	No	No	No	Yes	No	No
Year#ISIC2#Province	No	No	No	No	Yes	Yes
ISIC4	No	No	No	No	No	Yes

This table re-estimates Table 2.7 using the GNR approach to compute firm productivity. Firm controls include firm size and ownership types, and 4-digit ISIC industry controls include capital intensity and share of skilled workers. Industry FEs are at 2-digit ISIC industry level. The sample consists of active manufacturing firms with at least 10 workers. Standard errors are clustered at 4-digit ISIC level. Estimated coefficients, standard errors, and the additional hypothesis test statistics are adjusted for multiple imputations using the procedure in Appendix 2.9.2.
Standard error are in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.9.4.1 Expected tariff reduction measure

I also check the robustness of the baseline findings with respect to different measurements of tariff reductions. In the main analysis, I assume firms only plan one period ahead and thus consider the changes in tariffs in 2016 only. In this section I check four other measures of tariff reduction (1) discount rate = 0.5 (2) discount rate = 0.9 (3) including zero tariffs, and (4) trade-weighted tariffs.

The first two measures impose that firms place more weight on future tariff cuts but increasing the discount factor.[40] Results are reported in Tables 2.18 and 2.19. Under a discount rate of 0.5, the effect of tariff changes on productivity remains largely unchanged. However, when I set a high value of discount rate, the coefficient on export tariff reductions is no longer significant, but the signs of the coefficients are the same. One potential explanation is that most tariffs are reduced to zero in the final years of the TPP schedule and as we put more weight on future years, there is less variation in tariff reductions across industries.

In Table 2.20, I include tariffs that were already zero in 2015. In the baseline analysis, I exclude zero tariffs to focus on tariffs where firms would expect changes. The drawback is that an industry with many products at zero tariffs but big changes in a small number of tariffs will have larger

[40] The planning horizon is fixed at 15 years. As most of tariff elimination schedules would be complete by 2030, expanding the planning horizon beyond 15 years does not change the levels of tariff cuts.

average cut than industries with many tariffs cut at smaller rates. Interestingly, the sign of each coefficient remains unchanged, but the magnitude becomes much bigger. One possible reason for the larger magnitude in Table 2.20 is that the treatment variables are scaled down as we include zero tariffs, which means one percent changes in the new tariff measure will require much bigger change in the baseline measure, leading to bigger point estimates. Another plausible explanation is that we now add more weight to industries with many products at non-zero initial tariffs. In a sense, we give more weight to industries where a higher fraction of firms experience an expected tariff cut. To further explore this story, I also account for the share of zero tariffs within each industry but do not find evidence that industries with more non-zero tariffs experienced bigger changes in productivity.

Finally, in Table 2.21, I compute the industry-level tariff reductions weighted by the trade share of each product in an industry.[41] The results are also consistent with the baseline findings.

Table 2.18: Robustness Check–Discount factor = 0.5

Dependent var log TFP	(1)	(2)	(3)	(4)	(5)
β^x_{16}	0.248	0.219	0.223	0.228	0.194
	(0.115)**	(0.100)**	(0.100)**	(0.102)**	(0.101)*
β^m_{16}	-0.187	-0.182	-0.191	-0.175	-0.186
	(0.040)***	(0.037)***	(0.038)***	(0.040)***	(0.038)***
β^x_{17}	0.403	0.335	0.354	0.288	0.274
	(0.173)**	(0.161)**	(0.161)**	(0.180)	(0.181)
β^m_{17}	-0.125	-0.100	-0.111	-0.075	-0.091
	(0.091)	(0.097)	(0.097)	(0.106)	(0.105)
Observations	293,633	293,633	293,610	292,184	292,183
Adjusted R^2	0.171	0.194	0.225	0.218	0.244
Year#ISIC2	Yes	Yes	Yes	Yes	Yes
Year#Province	No	Yes	Yes	Yes	Yes
ISIC2#Province	No	No	Yes	Yes	Yes
Year#ISIC2#Province	No	No	No	Yes	Yes
ISIC4	No	No	No	No	Yes

This table reports results when the expected tariff reductions are constructed with a discount factor of 0.5. The sample consists of active manufacturing firms with at least 10 workers. Standard errors are clustered at 4-digit ISIC level and adjusted for multiple imputations using the procedure in Appendix 2.9.2.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[41] To calculate the weights, I use total exports/imports between Vietnam and TPP country between 2010 and 2016.

Table 2.19: Robustness Check–Discount factor = 0.9

Dependent var log TFP	(1)	(2)	(3)	(4)	(5)
β^x_{16}	0.030	0.024	0.025	0.031	0.021
	(0.026)	(0.022)	(0.023)	(0.024)	(0.023)
β^m_{16}	-0.031	-0.030	-0.033	-0.031	-0.033
	(0.011)***	(0.011)***	(0.011)***	(0.011)***	(0.011)***
β^x_{17}	0.075	0.059	0.063	0.055	0.047
	(0.040)*	(0.038)	(0.038)	(0.045)	(0.045)
β^m_{17}	-0.007	0.001	-0.001	0.002	-0.001
	(0.022)	(0.021)	(0.021)	(0.024)	(0.024)
Observations	293,633	293,633	293,610	292,184	292,183
Adjusted R^2	0.171	0.195	0.225	0.218	0.244
Year#ISIC2	Yes	Yes	Yes	Yes	Yes
Year#Province	No	Yes	Yes	Yes	Yes
ISIC2#Province	No	No	Yes	Yes	Yes
Year#ISIC2#Province	No	No	No	Yes	Yes
ISIC4	No	No	No	No	Yes

This table reports results when the expected tariff reductions are constructed with a discount factor of 0.9. The sample consists of active manufacturing firms with at least 10 workers. Standard errors are clustered at 4-digit ISIC level and adjusted for multiple imputations using the procedure in Appendix 2.9.2.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.20: Robustness Check–Including zero tariffs

No	(1)	(2)	(3)	(4)	(5)	(6)
β^x_{16}	3.106	3.109	3.082	1.307	1.310	1.307
	(0.512)***	(0.511)***	(0.515)***	(0.253)***	(0.248)***	(0.245)***
β^m_{16}	-0.182	-0.182	-0.177	-0.705	-0.709	-0.713
	(0.132)	(0.132)	(0.131)	(0.076)***	(0.075)***	(0.075)***
β^x_{17}	2.254	2.257	2.248	0.350	0.349	0.322
	(0.858)**	(0.856)**	(0.857)**	(0.748)	(0.739)	(0.745)
β^m_{17}	-0.136	-0.137	-0.132	-0.691	-0.698	-0.700
	(0.225)	(0.224)	(0.224)	(0.229)***	(0.229)***	(0.230)***
Observations	291,405	291,405	291,404	291,404	291,404	291,404
Adjusted R^2	0.057	0.058	0.073	0.091	0.112	0.126
Firm controls	No	Yes	Yes	Yes	Yes	Yes
ISIC4 controls	No	No	Yes	Yes	Yes	Yes
Year FEs	No	No	No	Yes	Yes	Yes
ISIC2 FEs	No	No	No	No	Yes	Yes
Province FEs	No	No	No	No	No	Yes

This table reports results when zero tariffs are included in the construction of industry-level tariff reduction. The sample consists of active manufacturing firms with at least 10 workers. Standard errors are clustered at 4-digit ISIC level and adjusted for multiple imputations using the procedure in Appendix 2.9.2.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.21: Robustness Check–Trade-weighted tariffs

Dependent var log TFP	(1)	(2)	(3)	(4)	(5)
β^{x}_{16}	0.166	0.162	0.175	0.211	0.171
	(0.099)*	(0.089)*	(0.088)*	(0.101)**	(0.101)*
β^{m}_{16}	-0.121	-0.122	-0.128	-0.128	-0.123
	(0.023)***	(0.022)***	(0.022)***	(0.028)***	(0.028)***
β^{x}_{17}	0.097	0.094	0.096	0.048	0.015
	(0.240)	(0.218)	(0.217)	(0.243)	(0.245)
β^{m}_{17}	-0.058	-0.059	-0.062	-0.045	-0.040
	(0.078)	(0.073)	(0.073)	(0.098)	(0.098)
Observations	293,633	293,633	293,610	292,184	292,183
Adjusted R^2	0.171	0.194	0.225	0.218	0.244
Year#ISIC2	Yes	Yes	Yes	Yes	Yes
Year#Province	No	Yes	Yes	Yes	Yes
ISIC2#Province	No	No	Yes	Yes	Yes
Year#ISIC2#Province	No	No	No	Yes	Yes
ISIC4	No	No	No	No	Yes

This table reports results when zero tariffs are included in the construction of industry-level tariff reduction. The sample consists of active manufacturing firms with at least 10 workers. Standard errors are clustered at 4-digit ISIC level and adjusted for multiple imputations using the procedure in Appendix 2.9.2.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.9.4.2 Imputation

I check whether the baseline results are driven by the imputed data by constructing productivity series using only the census years, 2011 and 2016. Then I conduct the following regression:

$$\log(TFP)_{it} = \beta_o + \beta^{e}_{16}{}^{e}_{j} \times year2016 + \beta^{m}_{16}{}^{m}_{j} \times year2016 + \eta^{xe}_{j} + \eta^{mm}_{j} + X_{it} + \theta Z_{jt} + \lambda_s + \lambda_p + \lambda_t + \epsilon_{it}$$

The set of firm controls X_{it} contains ownership types and initial productivity. Z_{it} contains 2-digit ISIC level capital intensity and share of skilled workers. The coefficients β^{x}_{16} and β^{m}_{16} now capture the relative change in productivity between 2011 and 2016.

Table 2.22 reports the results. As can be seen from Column 1, both β^{x}_{16} and β^{m}_{16} are statistically significant and showing the same signs as in Table 2.7, thought the magnitude of β^{x}_{16} is somewhat smaller. Consistent with the baseline results, in 2016 firm-level productivity increases for firms with larger reductions in export tariffs and decreases for those with larger reductions in import tariffs.

In the appendix, I repeat the exercise in Section 2.6 using the singly imputed data and non-imputed samples. Results are reported in Columns 2 and 3. The single imputation sample produces fairly similar results, although the estimated coefficient for β^{x}_{16} is smaller and no longer statistically significant, whereas β^{x}_{17} has positive sign (but remains insignificant). As noted in Appendix 2.9.2, in 2015 a few key variables were not imputed by the GSO. This leads to a loss of sample and might explain the difference in results between the singly imputed and multiply imputed samples. Nevertheless, the import parameters are very similar to the baseline findings. Results using non-imputed data also show a similar pattern.

Table 2.22: Robustness Check–Imputation

	(1) 2011&2016	(2) Singly imputed	(3) Non-imputed
β^x_{16}	1.522*	0.0638	0.565
	(0.788)	(0.483)	(0.707)
β^m_{16}	-0.395	-0.465**	-0.524**
	(0.245)	(0.186)	(0.218)
β^x_{17}		-0.141	-0.0184
		(0.548)	(0.696)
β^m_{17}		-0.307*	0.130
		(0.178)	(0.240)
Observations	58137	225743	175791
Adjusted R^2	0.189	0.249	0.215

This table reports the robustness of the baseline results to imputation procedure. The first column reports results using singly imputed data provided by the GSO. The second column uses non-imputed data. In the last column, I restrict the sample period to the two census years, 2011 and 2016. Firm-level TFP is estimated using these two years only. A full set of year, industry, and province dummies are included in all regressions. The sample consists of active manufacturing firms with at least 10 workers. Standard errors are clustered at 4-digit ISIC level.
Standard error are in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.9.4.3 Sample Selection

I repeat the last column in Table 2.7 using different samples. Table 2.23 reports the results. In columns (1) and (2), I select the sample based on initial productivity instead of firm size as in the main analysis by excluding the top and bottom one and five percentile of the initial productivity, respectively. Column (3) includes firms that reported being in the manufacturing sector for all available years. Next, I restrict the sample to small and medium firms (i.e., firms between 10 and 300 employees) to avoid the possibility that big firms might have been able to obtain private information about the negotiations. In the last column I exclude 2010-2013 from the sample years to avoid the effect of the Vietnam-Chile FTA tariff phase-out. All results are consistent with the baseline results.

Table 2.23: Robustness Check–Sample Selection

Dependent var	TFP 1-99	TFP 5-95	Manuf. code	size 10-300	2014-2017
log TFP	(1)	(2)	(3)	(4)	(5)
β^x_{16}	0.398	0.272	0.474	0.374	0.203
	(0.189)**	(0.175)	(0.198)**	(0.191)*	(0.179)
β^m_{16}	-0.340	-0.326	-0.340	-0.317	-0.347
	(0.073)***	(0.074)***	(0.063)***	(0.069)***	(0.070)***
β^x_{17}	0.515	0.402	0.616	0.715	0.428
	(0.335)	(0.337)	(0.395)	(0.373)*	(0.343)
β^m_{17}	-0.262	-0.243	-0.296	-0.261	-0.267
	(0.162)	(0.165)	(0.179)	(0.183)	(0.182)
Observations	279,643	257,657	205,107	265,746	149,415
Adjusted R^2	0.225	0.200	0.277	0.206	0.203

This table reports the robustness of the baseline results to sample selection. The first column recreates the baseline results. Columns 1 and 2 show the results when excluding the top and bottom one and five percentile of initial TFP, respectively. Column 3 provides results for firms that consistently reported being in the manufacturing sector in all years. Column 4 restricts the sample to firms with initial number of employees between 10 and 300. Column 5 excludes 2017 from the sample period. All regressions replicate the specification in the last column of Table 2.7. The sample consists of active manufacturing firms with at least 10 workers. Standard errors are clustered at 4-digit ISIC level and adjusted for multiple imputations using the procedure in Appendix 2.9.2.
Standard error are in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.9.5 Additional Tables and Figures

2.9.5.1 Worldwide Interest about the TPP

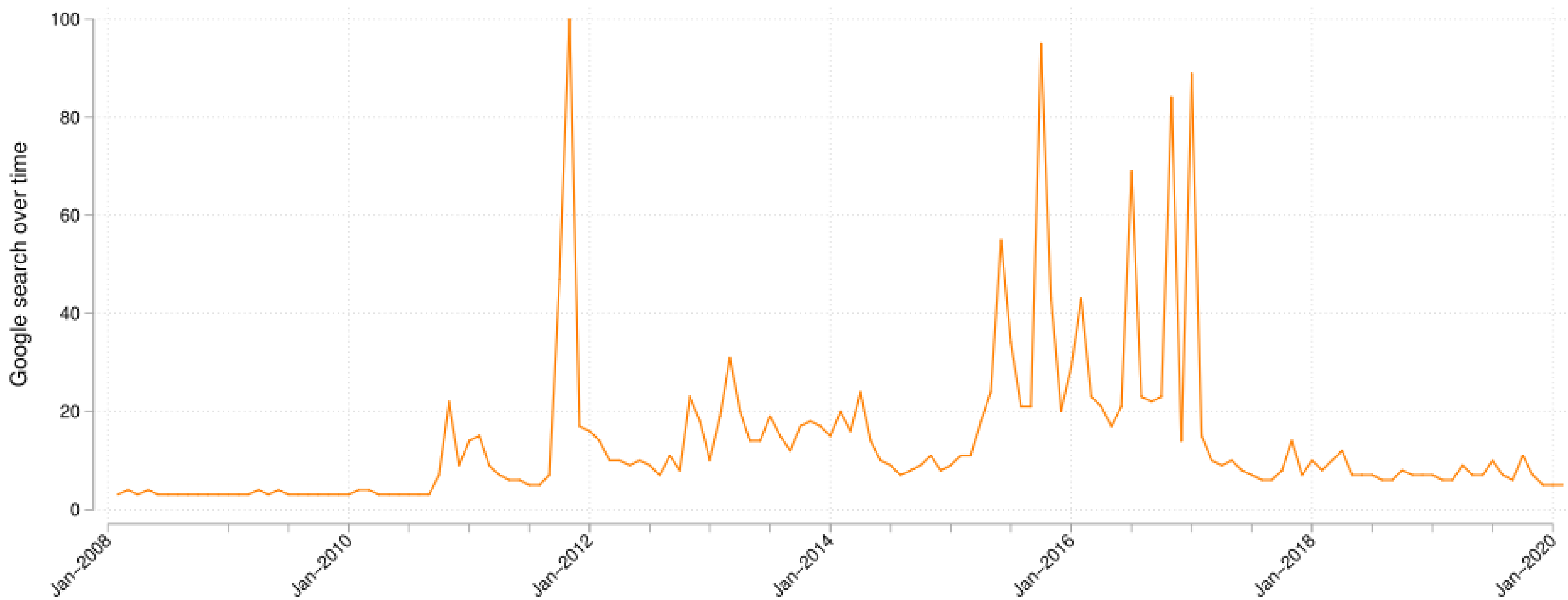


Figure 2.11: Worldwide Interest about the TPP

This figure shows the trend in Google searches worldwide related to the Trans-Pacific Partnership from 2008 to 2020. The vertical axis represents search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term.
Source: Google Trends

2.9.5.2 Trade and Tariffs

Table 2.24 presents the trade values and trade share by TPP countries in 2007 and 2014. I provide average tariffs at two-digit ISIC level in Table 2.25.

Table 2.24: Export and import values by partners

	Export values (mil USD)		Share		Import values (mil USD)		Share	
Partner	2007	2014	2007	2014	2007	2014	2007	2014
All	48561	150186	1.000	1.000	62765	148049	1.000	1.000
TPP	24816	58407	0.511	0.389	19603	33985	0.312	0.230
AUS	3802	3990	0.078	0.027	1059	2058	0.017	0.014
CAN	539	2081	0.011	0.014	287	387	0.005	0.003
MYS	1555	3931	0.032	0.026	2290	4193	0.036	0.028
USA	10105	28656	0.208	0.191	1701	6284	0.027	0.042
JPN	6090	14704	0.125	0.098	6189	12909	0.099	0.087
SGP	2234	2933	0.046	0.020	7614	6827	0.121	0.046
CHL	47	522	0.001	0.003	110	368	0.002	0.002
PER	17	187	0.000	0.001	48	98	0.001	0.001
MEX	360	1037	0.007	0.007	59	265	0.001	0.002
NZL	68	316	0.001	0.002	246	478	0.004	0.003
BRU		50		0.000		118		0.001

This table reports trade values and share of trade between Vietnam and other TPP countries in 2007 and 2014. Source: General Statistics Office of Vietnam

2.9.5.3 Firm-level Statistics

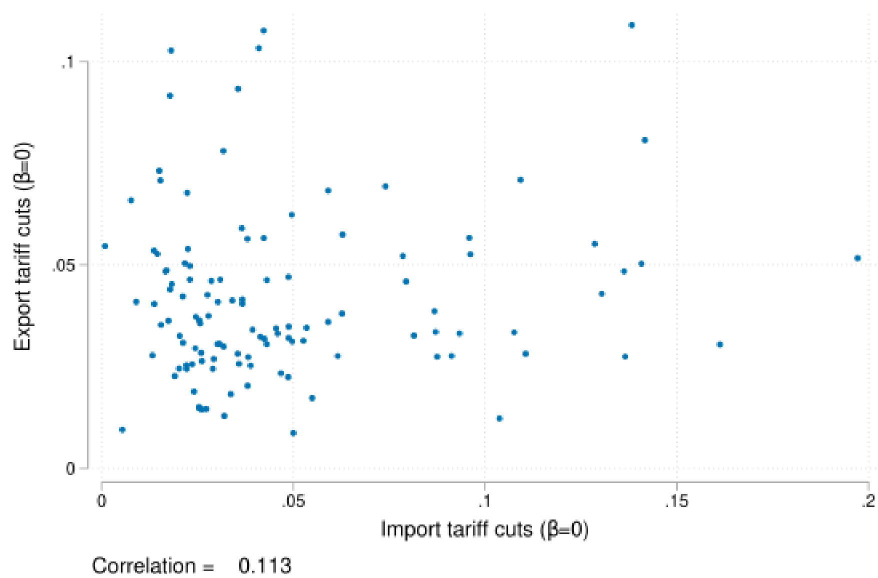
2.9.5.4 Aggregate Productivity

Table 2.25: Two-digit ISIC industry tariffs - Manufacturing sector

Two-digit ISIC	Description	Export tariffs	Import tariffs
10	Food	1.503912	10.81611
11	Beverages	1.168938	28.93975
12	Tobacco	17.60015	67.69318
13	Textiles	1.897007	5.775532
14	Apparel	5.106792	10.43742
15	Leather	2.674415	9.092511
16	Wood	.7414408	4.498477
17	Paper	.3227524	6.166025
18	Printing	.52	5.579545
19	Coke and petroleum	.2314411	3.880731
20	Chemicals	.5299887	1.467476
21	Pharmaceuticals	.1412959	.4230114
22	Rubber and plastic	.9399525	6.938764
23	Non-metallic products	.7737832	9.082087
24	Basic metals	.2762192	1.516076
25	Fabricated metal	.7836393	6.606757
26	Electronics	.4037012	3.221211
27	Electrical equipment	.7110584	5.903378
28	Machinery	.193543	1.412961
29	Motor vehicles	.8098514	15.77651
30	Other transport vehicles	.9211596	7.915242
31	Furniture	1.376087	12.48123
32	Other manufacturing	.9714892	7.066741

This table reports the average tariffs in 2015 for each two-digit industry. Ad-valorem tariffs are computed at HS 6-digit level. All traded products are included.

Figure 2.12: Correlation between export and import tariff cuts



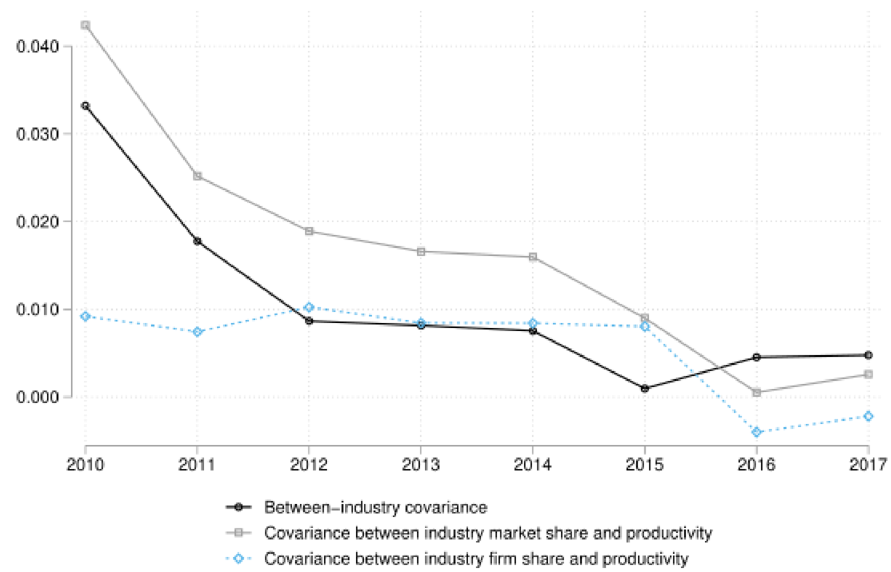
This figure presents the correlation between expected export and import tariff cuts when the discount factor is set at zero. Tariff cuts are measured at four-digit ISIC level.

Table 2.26: Descriptive statistics at firm level

	2010	2011	2012	2013	2014	2015	2016	2017	Total
log revenue	8.885	8.967	9.027	9.085	9.174	9.252	9.500	9.403	9.167
	(2.121)	(2.034)	(2.043)	(2.029)	(2.024)	(2.021)	(1.924)	(1.908)	(2.022)
log capital	7.522	7.441	7.725	7.768	7.841	7.889	7.934	8.062	7.777
	(1.861)	(2.104)	(1.942)	(1.945)	(1.903)	(1.836)	(2.094)	(1.923)	(1.964)
log materials	8.309	8.420	8.478	8.545	8.636	8.713	8.967	8.853	8.621
	(2.434)	(2.358)	(2.343)	(2.307)	(2.299)	(2.280)	(2.205)	(2.097)	(2.300)
log employment	3.735	3.696	3.690	3.705	3.707	3.706	3.746	3.768	3.719
	(1.272)	(1.250)	(1.256)	(1.272)	(1.278)	(1.281)	(1.300)	(1.318)	(1.279)

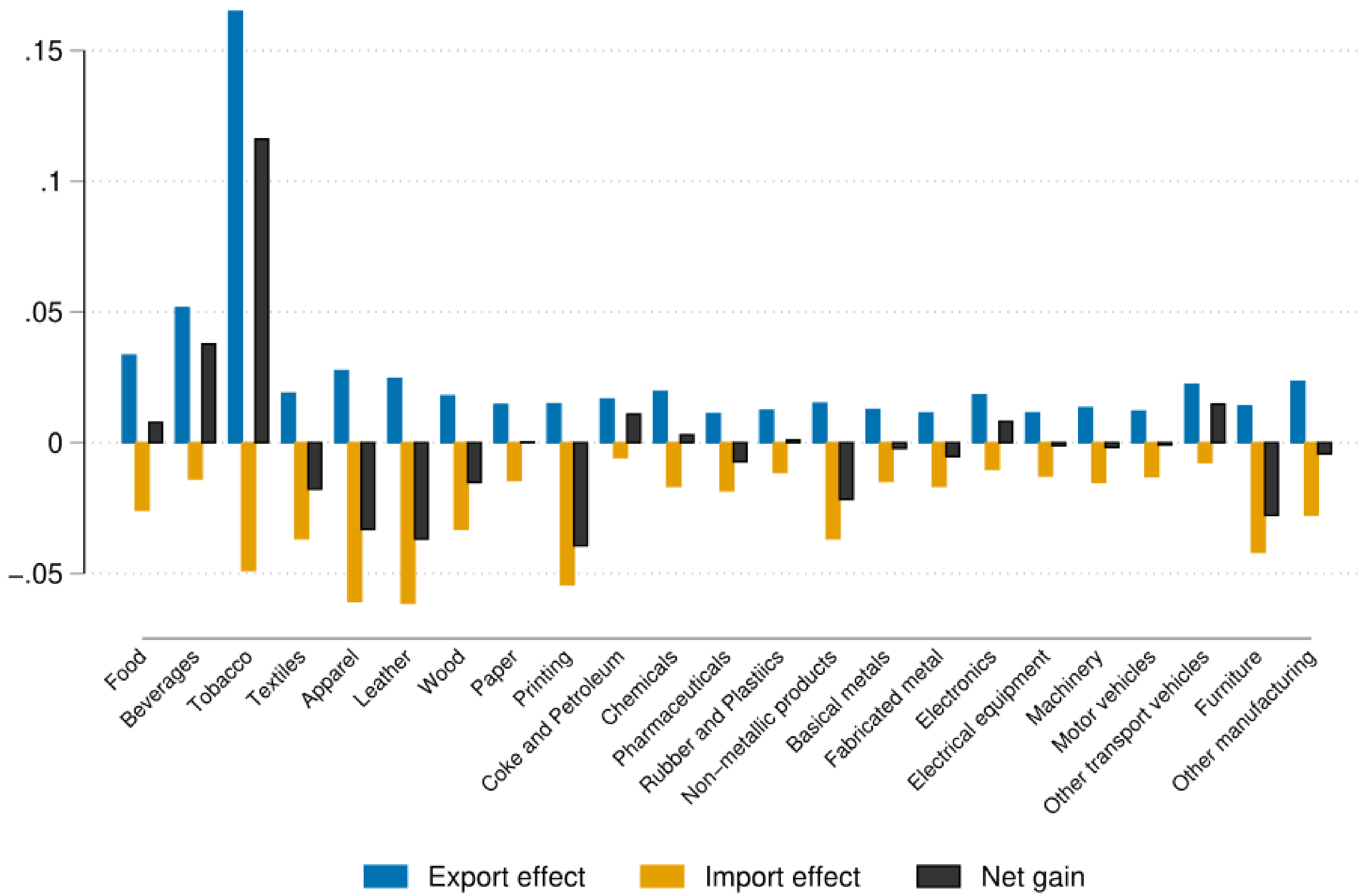
This table reports mean and standard deviations of productivity and key variables used to construct productivity. Standard deviations are in parentheses.

Figure 2.13: Between-industry covariance



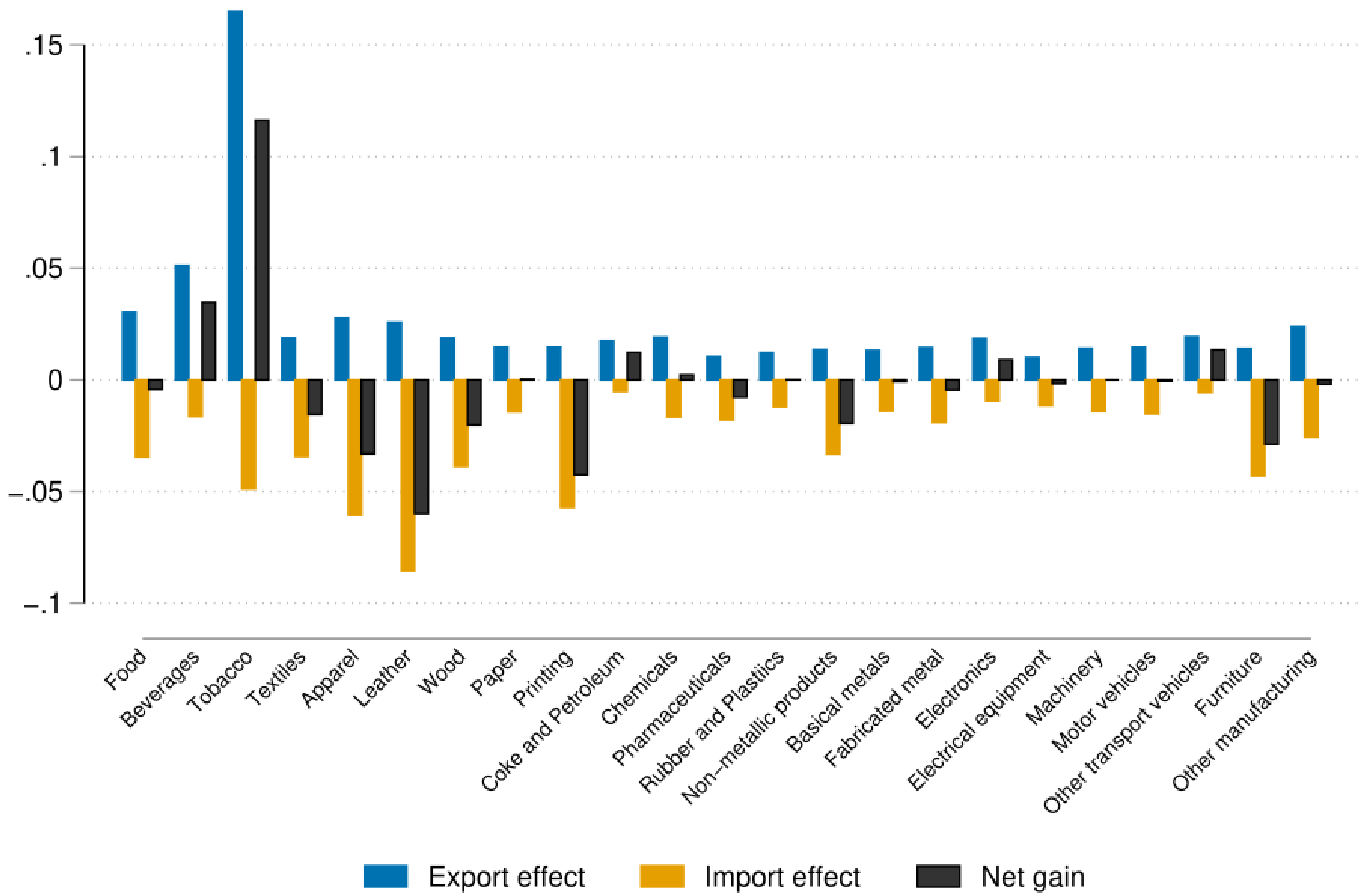
This figure presents different components in the between-industry covariance. See Section 2.5 for more details.

Figure 2.14: Effect of TPP on two-digit industry productivity (unweighted)



This table reports the change in unweighted productivity at the two-digit industry level due to change in firm-level productivity in 2016.

Figure 2.15: Effect of TPP on two-digit industry productivity (weighted by 2010 market share)



This table reports the change in aggregate (weighted) productivity at two-digit industry level. I use market shares in 2010 as weights.

CHAPTER 3

Global Costs and Benefits of Export Promotion

3.1 Introduction

Recent studies indicate that many export promotion programs are highly effective; existing causal evidence demonstrates that promotion substantially increases firm-entry and growth (Munch and Schaur, 2018), that promotion-driven firm growth is mediated by expansions in firm-specific demand and expansions of export promotion programs are potentially a highly effective mechanism to grow industry-level exports in target markets (Buus et al., 2020a). While the benefits of export promotion are widely reported, the costs associated with export promotion, and thus the dynamic long-run gains are less well understood. For example, in Denmark, our country of interest, the Trade Council has budget of DKK 400 million (USD 65 million) and a primary mandate of growing Danish export sales by offering promotion services at highly subsidized rates. Do expensive export promotion agencies justify their costs? Given that government-subsidized trade councils, export development agencies and trade facilitation services exist in nearly every country of the world, answering this question is of particular policy relevance.

Unfortunately, identifying the costs and benefits of export promotion poses a number of serious quantitative challenges. Investments in export promotion occur in the present, but the benefits largely accure over time as new entrants grow into fertile export markets. Buus et al. (2020b) document that the benefits to export promotion are long-lasting within individual export markets, but the private costs of securing promotion services and entering export markets are also large. Although this analysis provides some intertemporal evidence of the net gains from export promotion, it does so under two strong assumptions: (1) all firms are perfectly informed about export markets and (2) the decision to export in one destination is completely unrelated to the decision to enter another.[1] Our paper departs from this crucial, and nearly univeral assumption, to argue that there is significant evidence of that entry into a given export market depends on the firm's past decisions *in the same export market* and *other export markets*.

We demonstrate that the nature export market entry and selection varies systematically at the firm and destination-level. For instance, like other papers, we demonstrate that among Danish

[1] These conditions either implicitly or explicitly assumed in large majority of studies characterizing firm-level entry into export markets. See Das, Roberts and Tybout (2007), Aw, Roberts and Xu (2011), Rodrigue and Soumonni (2014), Rodrigue and Tan (2019), Fitzgerald et al. (2019), or Piveteau (2020) for examples. An important exception is Morales, Sheu and Zahler (2019).

manufacturers, past export experience is a strong predictor of future export market participation. Disaggregating the data to study destination-specific entry decisions, firm-level export market persistence remains present, but is somewhat dampened. In constrast, while a similar degree of persistance appears when we examine promotion at the firm-level, it all but disappears at the firm-destination-level. This difference has fundamental consequences for trade policy and export promotion programmes in particular. Once a firm has employed export promotion to enter particular market, they are more likely to use it again - but in other export markets. In this sense, policies that support entry into a particular export destination are likely spillovers to other non-targeted markets.

We further establish that past export or promotion experience has large and statistically significant impacts on the entry decisions in new export markets. One explanation for this result is the notion of extended gravity in exporting pioneered in Morales, Sheu and Zahler (2019): entry into one export market allows the firm to learn about similar markets and reduces the cost of future entry into markets which share characteristics with their existing export bundle. While intuitive, we do not pursue this line of inquiry for three reasons. First, while extended gravity can address the sequential, and interdependent, nature of export entry decisions, it is unlikely to be able to provide a similar argument for the firm's promotion decisions. Indeed, we observe very little evidence of extended gravity effects in the promotion decisions of Danish manufacturers. Second, even after flexibly controlling for the presence of extended gravity in either the firm's export or promotion decisions, past export or promotion experience continue to have a large impact on entry and promotion decisions in new export markets.

Our evidence is consistent with the notion that new and prospective exporters must incur costs that are general or global in nature - that is, they apply to all export markets - and those which are destination market-specific. Evaluating the tradeoffs associated with trade policy, and targeted trade policy in particular, requires understanding the costs and benefits both targeted and untargeted markets. Yet, there are no existing studies which verify the presence of global export or promotion entry costs, distinguish them from destination-specific costs, or quantify their magnitude.

These characteristics pose two significant challenges for empirical research on trade policy. The first hurdle is the computational burden associated with evaluating the firm's optimal decisions over time. Market interdependence, through promotion or firm-level export histories, inherently tie all of the firm's current and future export and promotion decisions together. Characterizing the evolution of firm entry decisions thereby requires evaluating the optimal dynamic path of the firm over all possible export markets, promotion markets and years. With even a small number of potential export destinations, our problem is characterized by trillions of potential firm choices.

We pursue a partial identification approach in the spirit of Morales et al. (2019) and Hoang (2020) to address the combinatorial problem engendered by policy interdependence. Our approach allows us to efficiently identify bounds on structural fixed and sunk cost parmeters for both exporting and promotion and quantify the magnitude of these firm-level frictions in reaching, and succeeding, in export markets.

Our paper complements three active areas of research. First, we contribute to a large extant literature documenting the impact of export promotion on firm-level outcomes. While aggregate or industry-level studies of export promotion have found weakly positive evidence favoring the impact of promotion ability on export sales (Rose 2007; Head and Ries 2010; Cassey 2014; Bernard and Jensen 2004; Lederman, Olarreaga, and Payton 2010), a growing body of robust firm-level evidence finds significant support for the claim that promotion improves firm-performance on a host of dimensions. For example, recent studies find that export promotion encourages firms enter target markets, increases the probability of survival and the rate of export growth (Martincus and Carballo 2008, 2010a, 2010b, 2012; Van Biesebroeck, Yu, and Chen 2015; Cadot et al. 2015, Buus et al, 2020b), grows firm-level employment, sales, and value added (Munch and Schaur, 2018), and improves product quality or brand appeal (Atkin, Khandelwal, and Osman 2017; Buus et al. 2020a).

This paper also adds to studies of firm entry and growth in export markets. Although early papers focussed on the nature of entry and growth in a single market (Das et al., 2007; Rho and Rodrigue, 2016; Ruhl and Willis, 2017) or separable export markets (Rodrigue and Tan 2019; Fitzgerald et al, 2020; Buus et al, 2020b; Piveteau, 2020), there has been more recent emphasis on entry and growth within and across export markets. Few papers characterize export growth across markets and time. For instance, Albornoz et al (2012) develop a model of sequential exporting across destination markets. Similarly, Eaton et al (2011) posit and quantify a static model in which there is a pecking order of export markets. In each case, markets are individually separable and firm-history plays no role in determining firm outcomes.

In a paper most closely related to ours, Morales et al. (2019) consider a dynamic model of firm-entry and growth with entry spillovers across markets. We extend their contribution to consider a setting where firm endogenously choose not just which markets to export to, but also in which markets they want to purchase promotion services to aid entry and growth. Moreover, our work highlights market interdependencies which do not depend on the gravity of trade flows; we highlight the fact that becoming an exporter to any country is an irreversible investment which inherently changes the outward orientation of the firm into international markets. This does not imply that the mechanisms emphasized in Morales et al (2019) are not similarly important. Rather, they jointly indicate that there are numerous margins which link export entry decisions across time and space that have yet to be explored in trade research.

In this sense, our work bridges the nascent literature studying export growth through interdependent markets with the extant body of research focussed on export and investment complementarity. Indeed, there is substantial evidence that exporting is complementary to a host of supply-side firm-level investments: productivity improvement (Aw et al, 2011; Bustos, 2011; Lileeva and Trefler, 2010), quality-upgrading (Verhoogen, 2008; Fieler et al, 2018), or changes in product scope (Bernard et al, 2011; Mayer et al, 2014; Arkolakis and Muendler, 2020). Few papers consider the impact of demand and the complementarity with demand-driven investments (Rodrigue and Soumonni, 2014; Fitzgerald and Priolo, 2018; Rodrigue and Tan, 2019; Piveteau, 2020) and even more rare are papers which study the complementarity with policy-driven, firm-level investments aimed at improving demand in target markets (Buus et al, 2020b). None of these papers address the nature of firm-level investments that direct the firm's export path through heterogeneous destination markets and time.

This paper proceeds as follows. The next two sections respectively document three salient facts regarding export promotion and develop an empirical model of export entry and growth. Section 4 describes the Danish manufacturing sector, its relationship with the Danish Trade Council and presents the data used to estimate model, while Section 5 documents our partial identification approach to quantifying the model's key parameters. The sixth section presents the empirical results and the seventh concludes.

3.2 Stylized Facts

This section documents two sets of stylized facts regarding exporting and export promotion among Danish manufacturers. The first set documents features of our sample which are broadly consistent with existing evidence.

1. Established Exporting and Promotion Facts.

    (a) Past entry in a given export market is a strong predictor of future entry in the same market.

    (b) Firms which purchase promotion services for a given target country are more likely to export to that market in the future.

    (c) Firms which purchase promotion services sell a greater number of units in export markets, conditional on entry.

The first set of facts are routinely documented in the literatures studying the nature export entry, export promotion, and the mechanisms underlying the impact of promotion services on firm performance. In contrast, the second set of facts are new to this study.

2. New Exporting and Promotion Facts.

   Conditional on a firm's export and promotion histories, along with a vector of control variables, we observe the following two robust empirical patterns.

   (a) Past entry in *any* export market increases the probability of entry into *new* export markets.

   (b) Past purchases of promotion services for *any* export market increases the probability of future promotion purchases for *new* export markets.

The new facts suggest a notion of market interdependencies in the export entry and promotion purchasing decisions of individual firms. In particular, these facts capture the idea that firm attributes which lower the cost of entering export markets or effectively using export promotion in any market, can reinforce and encourage future participation in new markets through past experience. In this sense, first time exporters are at a particular disadvantage: not only do they need to incur destination-specific expenses, but also *general* or *global sunk costs* to enter export markets. Moreover, this relationship may occur on either the promotion or export margins, creating a very rich set of policy-dependent market interdepencies.

To fix ideas, we begin by presenting the transition matrices across exporting and promotion for a subset of Danish manufacturers in the machinery and transportation equipment industry. While these are common to the literature on exporting and investment, rarely are they presented at the firm-destination level.[2] As common to the existing literature, Panel (a) of Table 3.1 documents the high degree of persistence in non-exporting and export status. It also highlights a meaningful degree of persistance in export promotion. Among firms that purchased promotion services, a non-trivial fraction choose to promote again in the subsequent year. Indeed, in the fourth row of panel (a), where nearly all current promoting firms can be found, over 53 percent choose to promote again in the subsequent year.

While these patterns are of interest and have common been used to motivate the potential existance of sunk entry costs (see Das, Roberts and Tybout (2007) or Aw, Roberts and Xu (2011) for

[2] See for example Aw et al. (2011), Kasahara and Lapham (2013), Rodrigue and Soumonni (2014), Buus. et al (2020b) for examples firm-level transition matrices, while Eaton et al. (2011) document sorting across markets in a single period and Albornoz et al (2012) highlights the sequential nature of export market entry. We further document very similar patterns to those presented in Section 2 for all Danish manufacturers in the appendix, but concentrate on a single industry here to keep our working sample consistent throughout the manuscript.

example), our primary interest is the relative degree of persistence in each of these categories when compared to the firm-destination-year transition matrix.

In panel (b), where we consider firm-destination-year transitions, we observe some striking, but expected, differences. Firms that are not currently engaged in a particular foreign market are highly unlikey to enter in the subsequent year. Likewise, persistance in export status at the firm-destination level is nearly as persistant as that at the firm-level. This suggests that much of the persistence in export markets is destination specific. As such, we might anticipate that if there are sunk entry costs in export markets, much of these expenses are unique to the particular countries the firm has entered.

Table 3.1: Transition matrices (%)

Panel (a): Firm-year transition matrix					
	Status in year t+1				Total
Status in year t	Neither	Only exp.	Only prom.	Both	
Neither	79.9	17.7	1.9	0.5	100.0
Only exp.	3.9	85.8	0.1	10.2	100.0
Only prom.	37.9	27.6	29.3	5.2	100.0
Both	0.4	46.5	0.4	52.8	100.0
Total	17.5	66.9	0.7	14.9	100.0

Panel (b): Firm-destination-year transition matrix					
	Status in year t+1				Total
Status in year t	Neither	Only exp.	Only prom.	Both	
Neither	97.7	2.2	0.1	0.0	100.0
Only exp.	15.9	83.0	0.1	1.0	100.0
Only prom.	67.6	15.6	12.2	4.7	100.0
Both	6.9	64.4	1.7	27.1	100.0
Total	88.9	10.8	0.1	0.2	100.0

Notes: The transition matrix above is based on 41,079 firm-year observations (3,647 unique firms) for the period 2002-2015. Export destinations are limited to those 76 destinations in which some firm purchased promotion at some point.

In contrast, the opposite occurs for promotion services. While there is significant persistance at the firm-level, there is little evidence of significant persistance once we disaggregate the data to the firm-destination level. This pattern suggests that while there may be sunk costs associated with adopting export promotion as part of the firm's strategy to expand into international markets, it is not clear that the incurred costs are tied to particular export destinations.

To investigate the patterns in export promotion further we create an additional transition matrix that examines whether firms tend to promote to new destinations - markets for which they did not purchase promotion services in the previous year - or whether they simply continue purchasing promotion services for the same set of markets they did in the previous year. More specifically, Table 3.2 considers transitions between 5 possible states in the subsequent year: (1) no promotion to any market, (2) promotion to a single existing target market, (3) promotion to a single new target market, (4) promotion to multiple markets, but no new markets and (5) promotion to multiple markets, but at least one new target market.

Table 3.2: Promotion transition matrix (%)

	Status in year t+1					Total
Status in year t	Nowhere	One dest., old	One dest., new	Mult. dest., old	Mult. dest., new	
Nowhere	91.4	0.0	6.7	0.0	1.8	100.0
One dest.	57.5	13.2	16.0	0.0	13.3	100.0
Mult. dest.	28.7	16.4	13.5	6.0	35.4	100.0
Total	84.5	2.3	8.1	0.3	4.9	100.0

Notes: For "Mult. dest.", "old" means all the destination the firm promoted to in $t+1$ were also destinations the firm promoted to in t, "new" means at least one destination was not promoted in t.

For any existing (year t) promotion-status it is clear that firms which purchase promotion services are most likely to be looking to add *new* promotion target markets. This is most clearly presented in the second row of Table 3.2: among firms that purchased promotion services to a single destination last year, they are more than twice as likely to purchase promotion services for at least one new market in the subsequent year relative to sticking with the previous year's purchasing decisions.

Although the above transitions are compelling, they need not necessarily reflect differences in the structure of entry costs, provide evidence of global entry costs or suggest relevant disparities in the promotion and export decisions. Rather, these differences are plausibly the differential impact of firm heterogeneity, differences in firm histories, or unobserved heterogeneity. As such, we reexamine the nature of promotion and export market selection and their impact on firm performance, conditional of firm characteristics through a series of regression exercises.

Specifically, let $D_{dft} = 1$ and $E_{dft} = 1$ if firm f respectively purchases promotion services or exports to destination d in year t and 0 otherwise, while r_{dft} is the current revenue firm f generates exporting to market d. We then consider the collection of linear regressions:

$$\begin{aligned}
D_{fdt} &= \alpha_0 D_{fd,t-1} + \alpha_1 D_{f,t-1} + \alpha_2 E_{fd,t-1} + \alpha_3 E_{f,t-1} + \mathbf{X}'_{fdt}\gamma + \lambda^D_{dt} + \epsilon^D_{fdt} \\
E_{fdt} &= \alpha_0 D_{fd,t-1} + \alpha_1 D_{f,t-1} + \alpha_2 E_{fd,t-1} + \alpha_3 E_{f,t-1} + \mathbf{X}'_{fdt}\gamma + \lambda^E_{dt} + \epsilon^E_{fdt} \\
\ln r_{fdt} &= \alpha_0 D_{fd,t-1} + \alpha_1 D_{f,t-1} + \alpha_2 E_{fd,t-1} + \alpha_3 E_{f,t-1} + \mathbf{X}'_{fdt}\gamma + \lambda^r_{dt} + \epsilon^r_{fdt}
\end{aligned} \tag{3.1}$$

The binary variables $D_{ft} \equiv \max_d\{D_{fdt}\}$ and $E_{ft} \equiv \max_d\{E_{fdt}\}$ indicate whether the firm purchased promotion services for any potential destination market or exported to any country in year t. These firm characteristics are useful for distinguishing between *global* and *market specific* sunk costs in either exporting or promotion behavior. The matrix $\mathbf{X}_{fdt}$ includes the controls for firm performance (e.g. productivity differences) and firm export and promotion histories (e.g. extended gravity).[3] In each regression, we also condition our results on destination-year specific fixed effects to capture differential trends across markets and time.

Table 3.3: Promotion and Exporting

	(1) D_{fdt}	(2) D_{fdt}	(3) D_{fdt}	(4) E_{fdt}	(5) E_{fdt}	(6) E_{fdt}	(7) r_{fdt}	(8) r_{fdt}
$D_{fd,t-1}$	0.217***	0.214***	0.214***	0.0827***	0.0806***	0.0584***	0.381***	0.281***
	(0.00905)	(0.00906)	(0.00906)	(0.00775)	(0.00772)	(0.00773)	(0.0570)	(0.0577)
$D_{f,t-1}$		0.00485***	0.00479***			0.0325***		0.163***
		(0.000314)	(0.000315)			(0.00109)		(0.0141)
$E_{fd,t-1}$	0.00504***	0.00440***	0.00429***	0.738***	0.726***	0.723***	1.452***	1.453***
	(0.000321)	(0.000318)	(0.000322)	(0.00143)	(0.00146)	(0.00147)	(0.0178)	(0.0181)
$E_{f,t-1}$			0.000492***		0.0478***	0.0447***		-0.252***
			(0.000115)		(0.000468)	(0.000469)		(0.0881)
N	577,524	577,524	577,524	577,524	577,524	577,524	109,683	109,683
FE	dt	dt	dt	dt	dt	dt	dt	dt
R-squared	0.0650	0.0658	0.0658	0.643	0.645	0.646	0.333	0.333

Standard errors in parentheses

Controlling for 4th order polynomial of lagged total sales.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3 documents the regression estimates for each exercise.[4] Columns (1)-(3) consider the decision to purchase promotion services for target market d in year t conditional on past promotion

[3] Following Morales et al. (2019) we create firm performance/productivity controls are generated by predicting export sales in each market. Likewise, we restrict attention to three measures of extended gravity capturing whether the firm has experience exporting to countries with the same language, on the same continent, or in the same income bracket. Definitions of extended gravity variables along with a description of their measurement can be found in the appendix. We abstract from reporting the coefficients on these variables here since they are not central to our stylized facts, but address potential bias arising from these endogenous productivity evolution or extended gravity later in our empirical work.

[4] An analogous table for all of Danish manufacturing can be found in the appendix.

and export decisions. Column (1) includes lagged, market-specific promotion and export status co-variates, D_{fdt-1} and E_{fdt-1}, column (2) adds the global promotion indicator, D_{ft-1}, while column (3) all of the preceding co-variates and the global export status variable. We observe that past promotion and exporting in market d are strong predictors of current promotion decisions, even after we flexibly condition on firm fundamentals. Adding the binary global promotion or export variables in subsequent that these two are significant determinants of firm promotion decisions.

While the inclusion of the global entry variables reduces the lagged destination-specific indicators by a small amount, their estimated coefficients are also individually important. For example, given that the probability of purchasing promotion for any given destination is 0.3 percent, past promotion experience is any other country is estimated the probability of purchasing promotion to country d by roughly two percent. While this may not strike the reader as a large number offhand, back-of-the-envelope calculation imply that it could represent nearly a forty percent increase in the probability of purchasing export promotion services to some country.[5]

A similar pattern presents itself in columns (4)-(6) where we examine the firm's decision to export to specific destination markets. As expected, past export experience is a large and strong determinant of future exporting, while past promotion purchases also encourage future entry into target export markets. Of particular interest to our research, we observe that, even after conditioning on the firm's history in a specific export market, any foreign market experience, either via promotion or exporting, likewise encourage future entry to that destination country.

Global entry costs are one possible interpretation for the findings in columns (4)-(6), but not the only potential explanation. Indeed, Table 3.3 abstracts from firm-specific export histories (or extended gravity). In the appendix we repeat these exercises after conditioning on a full vector of extended gravity variables. Our estimates are nearly unchanged and suggesting that while extended gravity may be an important determinants of export market entry decisions, they are not the only source of export market interdependencies (see Table 3.5).

The last columns of Table 3.3 highlight that past export and promotion experience drives export growth in target export markets. The estimates coefficients for the destination-specific co-variates are in line with those found elsewhere: new entrants grow rapidly into export markets conditional on survival and purchasing promotion services can substantially the firm's first foray into a foreign country. We highlight the global export and promotion coefficients in column (8). Previous promotion experience improves export outcomes in non-target countries. Consistent with previous

[5] We admit that these figures require strong assumptions on the error terms across countries. We relax these assumptions in our subsequent empirical work.

studies (Buus et al, 2020a), this effect is conditional on firm fundamentals. Export promotion is not expected to inherently change firm performance, pricing strategy or product quality. Rather, it acts primarily as a shifter of firm-specific demand.

In contrast, to the global promotion indicator, the coefficient for global export status is negative. This coefficient inherently captures two different mechanisms. On one hand, to the extent that exporting improves firm performance (e.g. learning-from-exporting), we would expect that the coefficient on the lagged export status variable is positive. On the other hand, previous research suggests that firms enter the most profitable export markets first. Selection and market sorting suggest that subsequent entry into secondary markets is likely to be less profitable than initial entry into the most profitable destinations. Given that our firm-performance co-variates should ideally control the first mechanism (e.g. learning), but not the second, the negative coefficient on lagged export status is intuitive.

The estimates above highlight the significant role that past experience has future firm-level success in export. They also, however, hint at the challenges associated with credibly quantifying models of firm growth across diverse markets and time. Even though we restrict attention to roughly 80 markets for which at least one Danish firm purchased promotion over our period, addressing the scope of the firm's problem is gigantic. Understanding the nature of market selection and firm growth requires characterizes optimal firm decisions through trillions of potential export paths across countries and time when each decision is jointly determined with all other decisions in all other markets and years. Below we develop a model and estimation strategy to flexibly characterize the firm's problem and conduct counterfactual analysis despite the large dimensionality of the firm's problem.

3.3 Data

3.3.1 Export Promotion in Denmark

In Denmark, the Trade Council (TC) organizes all governmental export-promotion activities, and offers tailored export-promotion services to Danish firms. These services are provided by caseworkers employed by the TC at Danish embassies and consulates abroad, and thus naturally destination-specific. Firms are charged for these services, but prices are heavily subsidized (at around half the costs). In practice, firms pay a fixed rate per caseworker hour.

The TC offers a variety of services. The largest portion of these, partner search and matchmaking, helps firms find new trade partners such as distributors in foreign markets. Other services include intelligence and analysis on political and economic conditions, advertising, fairs, exhibitions, public relations activities, and communication with customs authorities and diplomacy. The TC's services are intended for firms interested in engaging in new export activities as well as firms interested in expanding existing exporting activities.

3.3.2 Data Sources

To construct our principal data, we combine three different data sets: (1) export-promotion data from the TC, (2) export data and (3) register data. We describe these data sets in more details below.

The information on export-promotion services are collected from the TC's Customer Relationship Management database. We obtain the full list of firms that purchased promotion services by country for which the services were directed the for years 2002-2015. In the raw trade-promotion data, we have more than 86,000 observations accounting for a total revenue of DKK 905 million.

Our export data comes from the statistics for International Trade in Goods. For each firm and year we have exports disaggregated by product and destination country. Trade flows are recorded according to the eight-digit Combined Nomenclature (CN8). To account for changes in product categories over time, we apply the algorithm proposed by Van Beveren et al. (2012), aggregating categories to the so-called CN8+ level. For each trade flow we observe its f.o.b. value in Danish Kroner (DKK) and its quantity. The trade data consists of two sub-systems, Intrastat (trade with EU countries) and Extrasta (trade with non-EU countries). Intrastat does not have complete coverage as firms are only obliged to report intra-EU trade if the annual export value exceeds a threshold (5 million DKK in 2015). Extrastat has close-to-complete coverage. However, extra-EU transactions of less than 7,500 DKK are not required to be categorized as separate products. To ensure comparability across intra- and extra-EU exports, we exclude all trade flows with a value lower than this threshold.

Finally, we obtain firm-level characteristics, e.g. industry codes, domestic sales, number of employees and etc., from the Firm Statistics Register and Firm Accounts Statistics, covering the universe of private sector Danish firms.

Estimation sample: Access to data on export promotion services restricts the sample period to 2002-2015. Export destinations are limited to those 76 destinations in which some firm (not necessarily belonging to this sub-sample) purchased promotion at some point. The final sample includes 7,599 firm-years (729 unique firms) that belong to ”manufacturing of machinery and transportation”.

3.4 Empirical Model

This section develops a empirical model which guides our estimation approach. Conditional on entering an export market, exporters compete in monopolistically competitive markets. The revenue earned by firm f if it exports to destination d at period t is

$$r_{fdt} \equiv p_{fdt}q_{fdt} = \left[\frac{\eta}{\eta-1}\frac{\tau_{fdt}w_{ft}}{P_{dt}}\right]^{1-\eta} Q_{dt}. \tag{3.2}$$

Following Morales et al. (2019) and Hoang (2020) we model the impact of variable trade costs on revenues as

$$\tau_{fdt}^{1-\eta} = \exp(\xi_{dft} + (X_{fdt}^{\tau})'\xi^{\tau}) + \varepsilon_{fdt}^{\tau} \tag{3.3}$$

where ξ_{fdt} is a collection of fixed effects and X_{fdt}^{τ} is a vector of co-variates that determine export revenues. In our benchmark setting ξ_{fdt} only includes a firm-year fixed effect and a destination-year fixed effect. The firm-year fixed effects account for firm and year specific characteristsics, such as firm productivity, which are unobservable to the researcher, but do not vary across locations. Destination-year fixed effects control for the direct impact of gravity on trade costs. The vector of observable trade cost determinants, X_{dft}, includes the firm's lagged export status in market d, E_{dft-1} and the firm's lagged promotion status in market d, D_{dft-1}, and the firm's lagged *global* export and promotion status, E_{ft-1} and D_{ft-1}, respectively.

The variable ε_{fdt}^{τ} accounts for all other determinants of variable trade costs, and we assume that

$$\mathbb{E}[\varepsilon_{fdt}^{\tau}|X_{fdt}^{\tau}, D_{fdt}, E_{fdt}, \mathcal{I}_{ft}] = 0 \tag{3.4}$$

where $\mathbb{E}_{dt}[\cdot]$ denotes an expectation conditional on a destination-period pair dt, and $\mathcal{I}_{ft}$ is firm f's information set when deciding whether to purchase promotion services and where to export in period t. Combining equations (3.2) and (3.3) and rewriting the firm's marginal production costs, w_{ft}, as a function of its domestic sales, yields

$$r_{fdt} = \exp(\alpha_{dt} + \alpha_{ft} + (X_{fdt}^{r})'\alpha^{r}) + \varepsilon_{fdt}^{r}, \tag{3.5}$$

where α_{dt} is a country and year-specific term, α_f is a firm-specific term, and X_{fdt}^{r} is a vector of co-variates that includes the firm's domestic revenues, past promotion status (D_{dft-1} and D_{ft-1}), along with all of the trade cost determinants, X_{fdt}. The variable ε_{fdt}^{r} is a function of the trade costs term ε^{τ}_{fdt}, and the mean independence restriction in equation (3.4) implies

$$\mathbb{E}[\varepsilon^{r}_{fdt}|X^{r}_{fdt}, D_{fdt}, E_{fdt}, \mathcal{I}_{ft}] = 0 \tag{3.6}$$

We use equations (3.5) and (3.6) to build a proxy for the potential export revenues for every firm, country, year and export promotion decision. Importantly, residual variation in export revenues, ε^{r}_{fdt}, does not affect firm f's decision to export to market d at time t or its decision to purchase promotion services.

3.4.1 Fixed and Sunk Export Costs

Exporters face fixed costs that are independent of how much they sell to a destination:

$$f^{x}_{fdt} = f^{x}_{d} + \varepsilon^{xf}_{fdt} \tag{3.7}$$

where f^{x}_{d} is the observable part of fixed export costs for all firms, and we assume that the observed fixed cost shock, ε^{xf}_{fdt}, has a mean-zero expectation conditional on the firm's export and promotion decisions and its information set

$$\mathbb{E}[\varepsilon^{xf}_{fdt}|D_{fdt}, E_{ft}] = 0. \tag{3.8}$$

New exporters to destination d also face global and destination-specific sunk entry costs. These are independent of the quantity exported and take the form

$$s^{x}_{fdt} = s^{x}_{g} - s^{xp}_{gt} + \varepsilon^{xs}_{fdt}. \tag{3.9}$$

$$s^{x}_{ft} = s^{x}_{d} - s^{xp}_{dt} \tag{3.10}$$

The term s^{x}_{ft} captures *global* sunk entry costs, while s^{x}_{fdt} represents the sunk costs that are specific to export destination d. Sunk costs depend on past promotion decisions through s^{xp}_{gt} and s^{xp}_{dt} which reduce the entry barrier to exporting through the purchase of promotion services. A firm only incurs the global sunk cost once, regardless of the number of countries that it exports to in period t. We assume that the observed sunk cost shock, ε^{xs}_{fdt}, has a mean-zero expectation conditional on the firm's export and promotion decisions and its information set

$$\mathbb{E}[\varepsilon^{xs}_{fdt}|D_{fdt}, E_{ft}] = 0. \tag{3.11}$$

3.4.2 Fixed and Sunk Promotion Costs

Firms that purchase promotion services also incur fixed costs

$$f^p_{fdt} = f^p_d + \varepsilon^{pf}_{fdt} \tag{3.12}$$

where f^p_d is the observable part of fixed export costs for all firms and the unobserved fixed cost shock, ε^{pf}_{fdt}, has a mean-zero expectation conditional on the firm's export and promotion decisions and its information set

$$\mathbb{E}[\varepsilon^{pf}_{fdt}|D_{fdt}, E_{ft}] = 0. \tag{3.13}$$

Firms that purchase promotion services for the first time also face a *global* sunk promotion cost, s^p_{dt}, and *destination-specific* sunk promotion cost, $s^p_{ft} = s^p_g + \varepsilon^{ps}_{ft}$. As with export sunk costs, we assume the unobserved sunk cost shock, ε^{ps}_{ft}, has a mean-zero expectation conditional on the firm's export and promotion decisions and its information set

$$\mathbb{E}[\varepsilon^{ps}_{ft}|D_{fdt}, E_{ft}] = 0. \tag{3.14}$$

Because global and export promotion costs are independent of export destinations, the incurred expenses create interdependencies across export destinations. That is, without any other link between countries, the presence of a global entry cost or promotion cost imply the firm's decision to enter any given market is made jointly with their decision to enter all other markets in their consideration set this year and over time.

3.4.3 Profits

Firm profits in any year depend on its current export and promotion decisions and its export and promotion history. To conserve on notation we let b^p and b^x denote a generic bundle of promotion and export destinations, while J^p and J^x represent the optimal bundles and o^p and o^x are the observed bundles.

The potential static profits of exporting to a country d can be written as

$$\begin{aligned} \pi_{fdt}(b^p_{ft}, b^x_{ft}, b^p_{ft-1}, b^x_{ft-1}) &= \eta^{-1} r_{fdt}(b^p_{ft}, b^x_{ft}, b^p_{ft-1}, b^x_{ft-1}) - f^p_{fdt}(b^p_{ft}) - f^x_{fdt}(b^p_{ft}, b^x_{ft}) \\ &\quad - s^p_{fdt}(b^p_{ft}, b^p_{ft-1}) - s^x_{fdt}(b^p_{ft}, b^x_{ft}, b^p_{ft-1}, b^x_{ft-1}). \end{aligned} \tag{3.15}$$

The total potential static profits of exporting to a bundle b^x of destinations are

$$\pi_{ft}(b^p_{ft}, b^x_{ft}, b^p_{ft-1}, b^x_{ft-1}) = \sum_{d \in b^x} \pi_{fdt}(b^p_{ft}, b^x_{ft}, b^p_{ft-1}, b^x_{ft-1}) \tag{3.16}$$

3.4.4 Optimal Export and Promotion Decisions

In each period t, firm f chooses a sequence of export and promotion destinations, $\{b^p_{ft}, b^x_{ft} \in B_{ft}\}$, that maximizes its discounted expected profit stream over a planning horizon L_{ft}

$$\mathbb{E}\left[\sum_{\tau=t}^{t+L_{ft}} \delta^{\tau-t} \pi_{ft}(b^p_{f\tau}, b^x_{f\tau}, b^p_{f,\tau-1}, b^x_{f,\tau-1} | I_{ft})\right]$$

where B_{ft} is the set of all destination that firm f considers in year t, I_{ft} denotes the firm's information set, and δ is the discount factor.

The choice-specific value function for bundle $b \equiv (b^p, b^x)$ satisfies:

$$V_{ft}(b^p_{ft}, b^x_{ft}, I_{ft}) = \pi_{ft}(b^p_{f\tau}, b^x_{f\tau}, b^p_{f,\tau-1}, b^x_{f,\tau-1}) + \delta \mathbb{E}[V_{f,t+1}(I_{f,t+1}) | b^p_{f\tau}, b^x_{f\tau}]$$

Firm f will choose bundle b over bundle b' ($b' \neq b, b' \in B_{ft}$) during period t if

$$\begin{aligned}
V_f t(b^p_{ft}, b^x_{ft}, I_{ft}) \quad &\geq \quad V(b^{p\prime}_{ft}, b^x_{ft}, I_{ft}) \\
&\text{or} && (3.17) \\
V_f t(b^p_{ft}, b^x_{ft}, I_{ft}) \quad &\geq \quad V(b^p_{ft}, b^{x\prime}_{ft}, I_{ft}) \\
&\text{or} && (3.18) \\
V_f t(b^p_{ft}, b^x_{ft}, I_{ft}) \quad &\geq \quad V(b^{p\prime}_{ft}, b^{x\prime}_{ft}, I_{ft}) && (3.19)
\end{aligned}$$

Employing the first inequality in (3.19) and the definition of static profits, we can rewrite the above relationships in terms of revenues, export costs, promotion costs and the future value of the firm:

$$
\underbrace{\eta^{-1}\Big[r_{ft}(b^p_{ft}, b^x_{f\tau}, b^p_{f,t-1}, b^x_{f,t-1}) - r_{ft}(b^{p\prime}_{f\tau}, b^x_{ft}, b^p_{f,t-1}, b^x_{f,t-1})\Big]}_{\text{current revenue gains}}
$$

$$
+\underbrace{\delta\Big\{\mathbb{E}[V_{f,t+1}(I_{f,t+1})|b^p_{ft}, b^x_{ft}, I_{ft}] - \mathbb{E}[V_{f,t+1}(I_{f,t+1})|b^{p\prime}_{ft}, b^x_{ft}, I_{ft}]\Big\}}_{\text{expected future profit gains}}
$$

$$
\geq \underbrace{\Big(\sum_{d\in b^p_{ft}} f^p_{fdt} - \sum_{d\in b^{p\prime}_{ft}} f^p_{fdt}\Big)}_{\text{fixed promotion costs}} + \underbrace{\Big\{(1-\max_d\{D_{fdt}\})s^p_{fdt}\Big\}}_{\text{sunk promotion costs}}
$$

where we note that this expression is independent of the firm's export decisions since we are only perturbing current, rather than past, promotion decisions.

When determining the optimal export and promotion paths, the firm balances current revenue and expected future profit gains with additional fixed and sunk costs. Country-specific sunk costs link the firm's previous export and promotion decisions to its future choices, while global sunk costs connect the firm's present engagement in current markets to entry into *new* export markets in future periods.

3.5 Estimation

Estimation is complicated for a number of reasons:

1. A large number of export and promotion choices create a combinatorial problem.

2. Many firms only export or purchase promotion for a small number of destinations.

3. Current choices greatly affect future decisions (e.g. persistance in export status).

4. The presence of global sunk costs create multiple, overlapping, dynamic interdependencies across destination markets.

For these reason we pursue a partial identification approach which imposes mild assumptions on firm behaviour.

3.5.1 Revealed Preferences Assumption

Assumption 2 *(Revealed Preferences) For every firm f and year t, let o^p_{ft}, o^x_{ft}, $\mathcal{I}_{ft}$ and $\mathcal{B}_{ft}$ denote the observed bundle of promotion destinations, the observed bundle of export destinations, the information set,* *and the consideration set, respectively. Then*

$$o_{ft} = \underset{b^p, b^x \in \mathcal{B}_{ft}}{argmax}\, \mathbb{E}[\pi_{ft}(b^p, b^x, b^p_{f,t-1}, b^x_{f,t-1}) + \sum_{l=1}^{L_{ft}} \delta^l \pi_{ft+l}(J^p_{f,t+l}(b), J^x_{f,t+l}(b), J^p_{f,t+l-1}(b), J^x_{f,t+l-1}(b)|I_{ft})]$$

where $b_{ft} = \{b^p_{ft}, b^x_{ft}\}$, $\mathbb{E}[\cdot]$ denotes the expectation consistent with the data generating process, δ is the discount factor, $J^p_{ft+l}(b)$ and $J^x_{ft+l}(b)$ denote the optimal export and promotion bundles that firm f would choose at period $t+l$ if it had exported to the countries in bundle b^x while hiring promotion services for bundle b^p in year t.

The above assumption characterizes the firm's observed export and promotion choices as the outcome of an optimization problem with three elements:

1. The L_{ft}-periods-ahead discounted sum of profits;
2. The consideration set $\mathcal{B}_{ft}$ among which the firm selects its preferred export destination and preferred target country for promotion services;
3. The information set $\mathcal{I}_{ft}$ the firm uses to predict its potential export profits in each of the bundles included in $\mathcal{B}_{ft}$ conditiononal on the bundle of promotion services purchased by the firm.

Identifying the impact of global sunk costs requires imposing restrictions on these three elements of the optimization problem as described below.

Formally, let

$$\Pi^{b^p,b^x}_{ft} = \pi_{ft}(b^p, b^x, o^p_{f,t-1}, o^x_{f,t-1}) + \sum_{l=1}^{L_{ft}} \delta^l \pi_{f,t+l}(J^p_{f,t+l}(b), J^x_{f,t+l}(b))$$

be the discounted sum of profits if the firm chooses $b = (b^D, b^E)$ in year t. Then, let the discounted sum of profits from the observed choices be

$$\Pi^{o^p,o^x}_{ft} = \pi_{ft}(o^p_{ft}, o^x_{ft}, o^p_{f,t-1}, o^x_{f,t-1}) + \sum_{l=1}^{L_{ft}} \delta^l \pi_{f,t+l}(J^p_{f,t+l}(o_{ft}), J^x_{f,t+l}(o_{ft}))$$

It follows that for all $b^p, b^x \in B_{ft}$ we should have $\mathbb{E}[\Pi^{o^p,o^x}_{ft}|I_{ft}] \geq \mathbb{E}[\Pi^{b^p,b^x}_{ft}|I_{ft}]$. The definitions of $J^p(\cdot)$ and $J^x(\cdot)$ then imply

$$\mathbb{E}[\Pi^{o^p,o^x}_{ft}|I_{ft}] \geq \mathbb{E}[\pi(b^p, b^x, b^p_{f,t-1}, b^x_{f,t-1}) + \sum_{l=1}^{L_{ft}} \delta^l \pi_{f,t+l}(J^p_{f,t+l}(o_{ft}), J^x_{f,t+l}(o_{ft})|I_{ft})]$$

since the expectation is over firm profits if the firm chooses (b^p_{ft}, b^x_{ft}) in year t but in subsequent periods act as if it had chosen o_{ft} instead.

By transitivity of preferences we have

$$\begin{aligned}
\mathbb{E}[\Pi^{o^p,o^e}_{ft}] &= \mathbb{E}[\pi_{ft}(o^p_{ft}, o^x_{ft}, o^p_{f,t-1}, o^x_{f,t-1}) \\
&\quad + \sum_{l=1}^{L_{ft}} \delta^l \pi_{f,t+l}(J^p_{f,t+l}(o_{ft}), J^x_{f,t+l}(o_{ft}), J^p_{f,t+l-1}(o_{ft}), J^x_{f,t+l-1}(o_{ft})|I_{ft})] \\
&\geq \mathbb{E}[\pi_{ft}(b^p, b^x, o^p_{f,t-1}, o^x_{f,t-1}) \\
&\quad + \sum_{l=1}^{L_{ft}} \delta^l \pi_{f,t+l}(J^p_{f,t+l}(o_{ft}), J^x_{f,t+l}(o_{ft}), J^p_{f,t+l-1}(o_{ft}), J^x_{f,t+l-1}(o_{ft})|I_{ft})]
\end{aligned}$$

Due to the one-period dependency of π_{ft}, static profits for $t+l$ where $l \geq 2$ will be the same on both sides of the inequality. We can then reduce the above relationship to

$$\mathbb{E}[\pi_{ft}(o^p_{ft}, o^x_{ft}, o^p_{f,t-1}, o^x_{f,t-1}) + \delta\pi_{ft+1}(J^p_{f,t+1}(o_{ft}), J^x_{f,t+1}(o_{ft}), J^p_{ft}(o_{ft}), J^x_{ft}(o_{ft})|I_{ft})]$$
$$\geq$$
$$\mathbb{E}[\pi_{ft}(b^p, b^x, o^p_{f,t-1}, o^x_{f,t-1}) + \delta\pi_{ft+1}(J^p_{f,t+1}(o_{ft}), J^x_{f,t+1}(o_{ft}), b^p_{ft}, b^x_{ft}|I_{ft})]$$

We further assume that firms have knowledge of a vector of instruments.

Assumption 3 *(IV) $Z_{ft} \subset \mathcal{I}_{ft}$, where Z_{ft} is a vector of observed covariates.*

When specifying the variables which compose Z_{ft} there is an important trade-off to consider. The more variables included in Z_{ft}, the more likely it is that some of the variables we include in Z_{ft} do not belong to the true information set $\mathcal{I}_{ft}$. At the same time, the larger the content of Z_{ft}, the more information we can use in estimation. A minimal, and conservative, vector Z_{ft} would include

$$Z_{ft} = (Z_{fdt}, d = 1, ..., \mathcal{D}) \text{ where } Z_{fdt} = (f^x_d, f^p_d, s^x_d, s^{xp}_{dt}, s^x_g, s^{xp}_{gt}, s^p_g, s^p_{dt}, D_{fdt-1}, E_{fdt-1}). \tag{3.20}$$

There is not any restriction on the firm's information sets or their consideration sets $\mathcal{B}_{ft}$. The potential choice set among which firms may choose their optimal export and promotion bundles include all combinations of foreign countries. Given the large number of countries, it is unrealistic to assume that firms evaluate the trade-offs for all possible combinations of countries. Thus, although the consideration set is likely smaller than the firm's choice set, we have little information from which to characterize the firm's consideration set.

To conserve on notation, let $\Delta^p\pi_{ft}$, $\Delta^x\pi_{ft}$ and $\Delta^{px}\pi_{ft}$ denote the difference in profits between the firms observed path and a one-period deviation when we respectively perturb the current promotion purchase, export decision or both. That is,

$$\begin{aligned}
\Delta^p\pi_{ft} \quad \equiv \quad & [\pi_{ft}(o^p_{ft}, o^x_{ft}, o^p_{ft-1}, o^x_{ft-1}) - \pi_{ft}(b^p_{ft}, o^x_{ft}, o^p_{ft-1}, o^x_{ft-1})] \\
& \delta[\pi_{f,t+1}(J^p_{f,t+1}(o_{ft}), J^x_{f,t+1}(o_{ft}), J^p_{ft}(o_{ft}), J^x_{ft}(o_{ft})|I_{ft}) \\
& -\pi_{f,t+1}(J^p_{f,t+1}(o_{ft}), J^x_{f,t+1}(o_{ft}), J^p_{ft}(b^D_{ft}, o^x_{ft}), J^x_{ft}(b^p_{ft}, o^x_{ft})|I_{ft})]
\end{aligned}$$

where $\Delta^x\pi_{ft}$ and $\Delta^{px}\pi_{ft}$ are defined analogously. Letting $g_k(\cdot)$ represent a non-negative function we have

$$\begin{aligned}
\mathbb{E}[g_k(Z_{ft})\Delta^p\pi_{ft}] &= \mathbb{E}[_k(Z_{ft})\Delta^p\pi_{ft}|Z_{ft}] \\
&= \mathbb{E}[g_k(Z_{ft})\mathbb{E}\Delta^p\pi_{ft}|Z_{ft}] \\
&= \mathbb{E}[g_k(Z_{ft})\mathbb{E}[\mathbb{E}(\Delta^p\pi_{ft}|I_{ft})|Z_{ft}]]
\end{aligned}$$

and likewise

$$\begin{aligned}
\mathbb{E}[g_k(Z_{ft})\Delta^x\pi_{ft}] &= \mathbb{E}[g_k(Z_{ft})\mathbb{E}[\mathbb{E}(\Delta^x\pi_{ft}|I_{ft})|Z_{ft}]] \\
\mathbb{E}[g_k(Z_{ft})\Delta^{px}\pi_{ft}] &= \mathbb{E}[g_k(Z_{ft})\mathbb{E}[\mathbb{E}(\Delta^{px}\pi_{ft}|I_{ft})|Z_{ft}]]
\end{aligned}$$

Sample analogs of the above inequalities are

$$\begin{aligned}
m^p_k &= \frac{1}{N}\sum_{f\in\mathcal{N}_f}\sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}} g_k(Z_{ft})\Delta^p\pi_{ft} \geq 0 \\
m^x_k &= \frac{1}{N}\sum_{f\in\mathcal{N}_f}\sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}} g_k(Z_{ft})\Delta^x\pi_{ft} \geq 0 \\
m^{px}_k &= \frac{1}{N}\sum_{f\in\mathcal{N}_f}\sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}} g_k(Z_{ft})\Delta^{px}\pi_{ft} \geq 0
\end{aligned}$$

where $N = \mathcal{N}_f \times \mathcal{D} \times \mathcal{T}$.

3.5.2 Deriving Moment Inequalities: Some Examples

This section provides examples of the moment function g_k and deviations that will generate the profit differences $\Delta^p\pi_{ft}$, $\Delta^x\pi_{ft}$, and $\Delta^{px}\pi_{ft}$. Following Morales et al. (2019), we apply a discrete analogue of Euler's perturbation method to derive moment inequalities: we compare the stream of

Observed export path

Year	Firm 1 A	Firm 1 B	Firm 2 A	Firm 2 B	Firm 3 A	Firm 3 B	Firm 4 A	Firm 4 B
$t-1$	0	0	0	0	0	1	1	1
t	0	0	0	1	0	1	0	1
$t+1$	0	0	1	1	1	1	1	1

Observed promo path

Year	Firm 1 A	Firm 1 B	Firm 2 A	Firm 2 B	Firm 3 A	Firm 3 B	Firm 4 A	Firm 4 B
$t-1$	0	0	0	0	0	0	0	0
t	0	0	0	0	0	0	0	0
$t+1$	0	0	0	0	0	0	0	0

Alt. export path in t

	Firm 1		Firm 2		Firm 3		Firm 4	
Deviation 1	1	0	0	0	0	0	0	0
Deviation 2	na	na	na	na	1	1	1	1

Alt. promo path in t

	Firm 1		Firm 2		Firm 3		Firm 4	
Deviation 1	0	0	0	0	0	0	0	0
Deviation 2	0	0	0	0	0	0	0	0

profits along a firm's observed sequence of export and promotion decisions with the stream along alternative sequences that differ from the observed path in just one period. In particular, we switch the export or promotion status for each firm-country-year pair one by one while keeping the firm's decisions in other years and in other markets intact.

We will begin by illustrating how we can identify export fixed and sunk costs, net of promotion costs, in a simple example. Consider four firms (1, 2, 3, 4) and two countries (A and B). The top left panel presents a firm's observed export decisions in each country for three consecutive years. In year t, firm 1 does not export to either country, while firms 2, 3 and 4 export to country B, but not to country A, i.e. $o^x_{ft} = (B)$. The top right panel similarly documents the firm's observed promotion decisions and, in this case, we focus on firms which never purchases export promotion services.

The bottom panel shows how we can create alternate paths in year t by switching a firm's export status in each country one by one. The export decisions in years $t-1$ and $t+1$ are unchanged, however. Likewise, to isolate export costs alone we purposely consider firms which never purchase promotion in the bottom right panel and leave their promotion path unchanged. The identification of these terms follows a very similar intuition. Then, the profit difference, $\Delta^x \pi_{ft}$, under each alternative path is

$$
\begin{aligned}
\text{Firm 1, Deviation 1: } \Delta^x \pi_{ft} &= \eta^{-1}[r_{ft}(o^p_{ft}, o^x_{ft}, o^p_{f,t-1}, o^x_{f,t-1}) - r_{ft}(o^p_{ft}, o^x_{ft} \setminus d, o^p_{f,t-1}, o^x_{f,t-1})] \\
&+ s^x_g + s^x_d + f^x_d + \varepsilon^{xs}_{fdt} + \varepsilon^{xf}_{fdt} \\
\text{Firm 2, Deviation 1: } \Delta^x \pi_{ft} &= \eta^{-1}[r_{ft}(o^p_{ft}, o^x_{ft}, o^p_{f,t-1}, o^x_{f,t-1}) - r_{ft}(o^p_{ft}, o^x_{ft} \setminus d, o^p_{f,t-1}, o^x_{f,t-1})] \\
&- s^x_g - s^x_d - f^x_d - \varepsilon^{xs}_{fdt} - \varepsilon^{xf}_{fdt} \\
\text{Firm 3, Deviation 1: } \Delta^x \pi_{ft} &= \eta^{-1}[r_{ft}(o^p_{ft}, o^x_{ft}, o^p_{f,t-1}, o^x_{f,t-1}) - r_{ft}(o^p_{ft}, o^x_{ft} \setminus d, o^p_{f,t-1}, o^x_{f,t-1})] \\
&- f^x_d - \varepsilon^{xf}_{fdt} \\
\text{Firm 3, Deviation 2: } \Delta^x \pi_{ft} &= \eta^{-1}[r_{ft}(o^p_{ft}, o^x_{ft}, o^p_{f,t-1}, o^x_{f,t-1}) - r_{ft}(o^p_{ft}, o^x_{ft} \cup d, o^p_{f,t-1}, o^x_{f,t-1})] \\
&+ s^x_d + f^x_d + \varepsilon^{xs}_{fdt} + \varepsilon^{xf}_{fdt} \\
\text{Firm 4, Deviation 1: } \Delta^x \pi_{ft} &= \eta^{-1}[r_{ft}(o^p_{ft}, o^x_{ft}, o^p_{f,t-1}, o^x_{f,t-1}) - r_{ft}(o^p_{ft}, o^x_{ft} \setminus d, o^p_{f,t-1}, o^x_{f,t-1})] \\
&- s^x_d - f^x_d - \varepsilon^{xs}_{fdt} - \varepsilon^{xf}_{fdt} \\
\text{Firm 4, Deviation 2: } \Delta^x \pi_{ft} &= \eta^{-1}[r_{ft}(o^p_{ft}, o^x_{ft}, o^p_{f,t-1}, o^x_{f,t-1}) - r_{ft}(o^p_{ft}, o^x_{ft} \cup d, o^p_{f,t-1}, o^x_{f,t-1})] \\
&+ f^x_d + \varepsilon^{xf}_{fdt}
\end{aligned}
$$

To create corresponding moment inequalities we can employ the following moment functions g_1 to g_6:

$$
\begin{aligned}
g_1(Z_{ft}) &= \mathbb{1}(\tilde{D}_{ft} = 0, \tilde{D}_{f,t-1} = 0, \tilde{E}_{ft} = 0, \tilde{E}_{f,t-1} = 0) \\
g_2(Z_{ft}) &= \mathbb{1}(\tilde{D}_{ft} = 0, \tilde{D}_{f,t-1} = 0, E_{ft} = 1, \tilde{E}_{f,t-1} = 0) \\
g_3(Z_{ft}) &= \mathbb{1}(\tilde{D}_{ft} = 0, \tilde{D}_{f,t-1} = 0, E_{fdt} = 0, E_{fd,t-1} = 0, \tilde{E}_{f,t-1} = 1) \\
g_4(Z_{ft}) &= \mathbb{1}(\tilde{D}_{ft} = 0, \tilde{D}_{f,t-1} = 0, E_{fdt} = 1, E_{fd,t-1} = 0, \tilde{E}_{f,t-1} = 1) \\
g_5(Z_{ft}) &= \mathbb{1}(\tilde{D}_{ft} = 0, \tilde{D}_{f,t-1} = 0, E_{fdt} = 0, E_{fd,t-1} = 1) \\
g_6(Z_{ft}) &= \mathbb{1}(\tilde{D}_{ft} = 0, \tilde{D}_{f,t-1} = 0, E_{fdt} = 1, E_{fd,t-1} = 1)
\end{aligned}
$$

where $\tilde{Y}_{ft} = \max_d\{Y_{fdt}\}$, $Y_{ft} \in \{D_{ft}, E_{ft}\}$ and $g_1(Z_{ft}) = \mathbb{1}(\tilde{D}_{ft} = 0, \tilde{D}_{f,t-1} = 0, \tilde{E}_{ft} = 0, \tilde{E}_{f,t-1} = 0)$ is an indicator function that takes value of one if the firm is a non-exporter and non-promoter in both year $t-1$ and t. When $g_k(Z_{ft}) = g_1(Z_{ft})$, $\mathbb{E}[g_k(Z_{ft})\Delta^E \pi_{ft}]$ is equal to

$$\begin{aligned}
\mathbb{E}[g_1(Z_{ft})\Delta^x \pi_{ft}] &= \mathbb{E}[g_1(Z_{ft})(\eta^{-1}\Delta^x r_{fdt} + s_g^x + s_d^x + f_d^x + \varepsilon_{fdt}^{xs} + \varepsilon_{fdt}^{xf})] \\
&= \mathbb{E}[g_1(Z_{ft})(\eta^{-1}\Delta^x r_{fdt} + s_g^x + s_d^x + f_d^x)] \\
&\geq 0
\end{aligned}$$

where $\Delta^x r_{fdt}$ denotes the difference in firm revenues (gross profits before accounting for fixed or sunk costs) and the second equality holds under the assumption that $\mathbb{E}[\varepsilon_{fdt}^{xf} | I_{ft}, D_{ft}, E_{fdt}] = 0$. Rearranging terms, we identify the lower bound for the sum $s_g^x + s_d^x + f_d^x$ as

$$s_g^x + s_d^x + f_d^x \geq \frac{\mathbb{E}[g_1(Z_{ft})(\eta^{-1}\Delta^x r_{fdt})]}{\mathbb{E}[g_1(Z_{ft})]}$$

Similarly when $g_k(Z_{ft}) = g_2(Z_{ft})$ we have

$$\begin{aligned}
\mathbb{E}[g_2(Z_{ft})\Delta^x \pi_{ft}] &= \mathbb{E}[g_2(Z_{ft})(\eta^{-1}\Delta^x r_{fdt} - s_g^x - s_d^x - f_d^x - \varepsilon_{fdt}^{xs} - \varepsilon_{fdt}^{xf})] \\
&= \mathbb{E}[g_1(Z_{ft})(\eta^{-1}\Delta^x r_{fdt} - s_g^x - s_d^x - f_d^x)] \\
&\geq 0
\end{aligned}$$

and we identify the upper bound for $s_g^x + s_d^x + f_d^x$ as

$$s_g^x + s_d^x + f_d^x \leq \frac{\mathbb{E}[g_2(Z_{ft})(\eta^{-1}\Delta^x r_{fdt})]}{\mathbb{E}[g_2(Z_{ft})]}$$

Analogous arguments using moments $g_3(Z_{ft})$, $g_4(Z_{ft})$, $g_5(Z_{ft})$, and $g_6(Z_{ft})$ allow us to recover bounds for the destination fixed and sunk export cost parameters net of global sunk export costs. Similar arguments can be developed to identify the fixed and sunk promotion costs, while perturbing both export histories among promoting firms allow us recover the parameters governing the effect of promotion on export sunk costs. Moment conditions can then be developed analogously to the export sunk and fixed costs.[6]

3.5.3 Preliminary Results

In the following section, we present some preliminary results for the export parameters.

[6]Less obviously, the above deviations exploit a key timing assumption: the investment in promotion in year t does not affect export fixed and sunk costs until year $t+1$. In the absence of this assumption, the fixed and sunk export costs would also change in the current period among exporting firms which adjust their contemporaneous promotion status. While identification under this alternative assumption is possible, data characteristics suggest that it will be challenging to separately identify the promotion fixed and sunk costs.

Table 3.4 presents the export revenue based on equation (3.5). To get predicted revenue gain from promotion services, we use the estimated coefficients on D_{dft-1} and D_{ft-1}. To be more specific, we assign the specific gain in promotion for firm f in destination d in year t to the difference in predicted export values when $D_{dft-1} = 1$ versus when $D_{dft-1} = 0$. However, if firm f does not export to d in year t, we assign this value to 0.

To obtain the global revenue gain of promotion for each firm-year pair, we follow this procedure: (1) estimate the difference in revenues for each firm-destination-year pair between $D_{ft-1} = 0$ and $D_{ft-1} = 0$, (2) set this value to zero if (a) firm f does not export to d in year t or (b) firm f purchases promotion services to any country $d' \neq d$ in year $t-1$, and (3) take the sum of the revenue differences across all destinations.

Using the predicted export revenues and revenue gains of promotion services, we proceed to estimate the bounds for the fixed and sunk costs of exporting and promotion. The fixed cost of exporting is between 230.2 and 237.1 thousand DKK. The country-specific sunk cost of exporting is much smaller, ranging between 0 and 8.6 thousand DKK. The global sunk cost of exporting is between 0 and 94.1 thousand DKK.

Nonetheless, we cannot obtain an estimated set for the promotion parameters with the current sample. One issue is that we observe some firms that purchased promotion services in one year and then stopped actually have higher total revenues compared to firms that purchased promotion services for the first time. There are several possible explanations for this pattern. First, the 2008 financial crisis might have affected firms' decision to export and purchase promotion services. Second, the return to promotion services might differ across firm size. For example, big firms might already have information about foreign markets and thus gain less from these services, whereas small firms might find them highly beneficial.

3.6 Conclusion

Though government-subsidized trade councils, export development agencies, and trade facilitation services exist in nearly every countries, no study has quantified at the micro level the costs and benefits of export promotion services. We aim to fill in this gap in the literature by developing a dynamic, multi-country model of joint export and export promotion, in which a firm pays a lower cost of exporting and higher export revenues in the subsequent period if it incurs a fixed cost to purchase promotion service in the current period. We then pursue a partial identification approach to estimate the bounds for the costs of exporting and purchasing services. This approach requires mild assumptions on the firm's information set, planning horizon, and consideration sets, while

Table 3.4: Predicting export revenues

	Export revenues
log domestic revenues	0.073***
	(0.008)
log capital	0.701***
	(0.007)
Past destination-specific promotion (D_{dft-1})	0.156***
	(0.056)
Past global promotion (D_{ft-1})	0.178***
	(0.019)
Constant	-0.605***
	(0.094)
Observations	452,144
Pseudo R^2	0.596
Year dummies	Yes

This table reports results for the export prediction regression. Monetary values are in units of 1000 DKK.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

allowing for interdependence across destinations and complementarity between export decisions and promotion service purchases.

We find evidence for the effects of export promotion on export along both the extensive and intensive margins. Furthermore, a firm's current decision in a market depends not only on its past status in the same market but also its prior experience in other markets. We obtain preliminary results on the specific and global sunk costs of exporting. The next step is to investigate the potential heterogeneity in promotion costs across different groups of firms and destinations.

3.7 Appendix

Table 3.5: Promotion and Exporting (with Extended Gravity Variables)

	(1) D_{fdt}	(2) D_{fdt}	(3) D_{fdt}	(4) E_{fdt}	(5) E_{fdt}	(6) E_{fdt}	(7) r_{fdt}	(8) r_{fdt}
$D_{fd,t-1}$	0.214***	0.213***	0.213***	0.0647***	0.0647***	0.0588***	0.322***	0.275***
	(0.00906)	(0.00906)	(0.00906)	(0.00763)	(0.00762)	(0.00763)	(0.0570)	(0.0574)
$D_{f,t-1}$		0.00206***	0.00207***			0.0160***		0.131***
		(0.000432)	(0.000432)			(0.00133)		(0.0178)
$E_{fd,t-1}$	0.00392***	0.00385***	0.00385***	0.695***	0.695***	0.695***	1.375***	1.387***
	(0.000332)	(0.000331)	(0.000331)	(0.00154)	(0.00154)	(0.00155)	(0.0183)	(0.0184)
$E_{f,t-1}$			-0.000122		-0.00975***	-0.00996***		-0.683***
			(0.000135)		(0.000544)	(0.000544)		(0.0959)
N	577,524	577,524	577,524	577,524	577,524	577,524	109,683	109,683
FE	dt	dt	dt	dt	dt	dt	dt	dt
R-squared	0.0662	0.0663	0.0663	0.652	0.652	0.652	0.336	0.337

Standard errors in parentheses

Controlling for 4th order polynomial of lagged total sales.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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