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To my father who taught his children to be lifelong learners

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Introduction

In this dissertation, I investigate firm dynamics and the obstacles that they face in international trade. The first is financial frictions, which limit the amount of financing that a firm can access. The second obstacle is uncertainty about market demand: firms do not know the true demand for a product in a destination market. I analyze how these obstacles affect the firm decisions and firm dynamics, particularly in the context of developing countries.

The first chapter examines the effect of firm level financial constraints on exporters' decisions and the role of trade intermediaries in facilitating trade and alleviating financial frictions. These intermediaries provide an alternative channel for the financially constrained firms to participate in the global markets. Therefore, understanding their role in global trade is important, particularly in developing countries where access to finance is limited. In this chapter, I use a dataset on Vietnamese firms from 2005 to 2015 to study how financial frictions affect firm's export mode choice. I calibrate the model to match key empirical moments from the data. The findings in this paper have some important policy implications. In one of the policy experiments, I evaluate the effects of a financial reform that increases the financial development of Vietnam. This reform raises the total sales and exports in the first year, but the effect fades over time. Moreover, a financial reform has the biggest impact on small firms in increasing their export participation rates. The effects of the policy on small firms are even larger in a model without indirect exporting, indicating that indirect exporting already acts as a platform to mitigate the effects of financial frictions.

The second and third chapters analyze how firms resolve demand uncertainty in trade. In these chapters, I build a model of learning where the demand for a product in a market is uncertain and analyze different channels that firms use to overcome this uncertainty. The models yield testable predictions that I then test using the Chinese customs data at the HS-6 product code level.

In the second chapter, I investigate how firms respond to demand uncertainty and make decisions to add or drop a product. Due to this uncertainty, firms form a belief of the appeal of a product in a destination. Conditional on entry into a market, firms learn about the demand by observing signals available to them, update their beliefs and respond by adjusting their product mix accordingly. When they decide whether to add a new product to a market, they observe signals revealed to them by other firms that export the same product to a destination.

The third chapter extends the model in the second chapter to allow for cross market learning about demand at the firm level. Similar to the second chapter, firms do not have perfect knowledge of the demand of a product in a destination. Markets in the model are assumed to have imperfectly correlated demand for a product to reflect the similarity in tastes between pairs of countries. Before entering a market, firms form a prior belief about the distribution of this demand shock and update their beliefs from observing demand signals from their own experience serving the same products in other markets. The correlation of preferences between markets implies that firms are able to form an expectation of how well they will do in a potential market based on their past experience in previous destinations.

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CHAPTER 1

Financial constraints and trade intermediation

1.1 Introduction

Trade intermediaries such as wholesalers, retailers and trading companies play an important role in facilitating international trade. Ahn et al. (2011) estimate that about 20% of Chinese exports are carried by these intermediaries. In Turkey and the U.S., about 17% and 10% of total exports are carried indirectly respectively (Abel-Koch, 2013; Bernard et al., 2010a). The role of trade intermediaries is particularly important in countries with poor financial development as finance can be a major barrier to international trade for firms due to the large upfront costs associated with exporting (Manova, 2012; Chaney, 2016; Engemann et al., 2014). If a firm is not able to export directly due to the large upfront costs, exporting indirectly through a trade intermediary can be a viable alternative to participate in trade. In this paper, I investigate how a firm's financial constraints affect their export decisions and the role of indirect exporting in alleviating such constraints.

Using a firm-level dataset on Vietnamese firms from 2005 to 2015, I document that firms are financially constrained and rely heavily on external finance for their working capital needs. I classify firms in the sample into three types based on their reported sales: non-exporters, indirect and direct exporters. The data suggest that non-exporters and direct exporters have high persistence in their status: most of them maintain the same status between periods. On the other hand, indirect exporting seems less persistent and acts more as a temporary platform. When compared to domestic producers, firms with indirect exporting experience have twice the likelihood of becoming a direct exporter in the next period.

To explain these observations from the data, I extend the standard dynamic Melitz (2003) model by including financial frictions in the form of a borrowing limit and trade intermediation. In order to finance their working capital and the fixed costs of operating, firms have to borrow money but can only borrow up to a multiple of their assets due to financial frictions. Under a borrowing constraint, there is a minimum asset threshold along with the productivity cutoff into exporting (directly/indirectly): not only do firms have to be productive enough to enter exporting, they also need to have enough assets to finance their production. Financing constraints also imply that some firms will not be able to operate at their optimal level as they would in the frictionless economy because they do not have enough assets. Some firms with limited assets do not find it profitable to export directly but they may still have enough assets to export indirectly. Without indirect exporting, these low asset firms would only serve the $Home$ market.

The existence of a financial constraint implies that firms must accumulate assets to overcome the borrowing limit. This allows the model to explain the observation from the data that indirect exporters are more likely to become direct exporters than their domestic peers. The additional income from indirect exporting helps a firm finance their transition into direct exporting. The option to export indirectly allows them to earn higher profits and to accumulate more assets than they would as a non-exporter. This relaxes the borrowing constraint and raises the firm's likelihood of transitioning into direct exporting in the future. As a result, a firm is likely to start small and have few assets, so they are less likely to be a direct exporter. But as they grow and accumulate more wealth from their retained earnings, they are able to expand production and eventually become direct exporters. Similar to the data, indirect exporting in the model is transitory and acts as a stepping stone to transition into direct exporting.

Using the quantitative model, I analyze the effects of financial frictions and the role of indirect exporting. The calibrated model shows that as the degree of financial frictions increases, the role of indirect exporting becomes more important. More firms choose to be indirect exporters and consequently, a larger share of the total industry exports is carried indirectly. Additionally, indirect exporting mitigates the severity of financial frictions by reducing the need for assets.

In the first policy experiment, I examine the effects of a trade liberalization, represented by a 5% reduction in the trade costs for both direct and indirect exporting. As a result of trade liberalization, the impact on total sales gradually increases over time: from a 17.27% increase in the first year to a 23.75% increase by year 10. Half of the changes in the total export sales come from producers switching their export modes due to the policy.

The second policy experiment investigates the impact of a policy that promotes indirect exporting. Since indirect exporting is an alternative channel to accumulate assets, a 25% reduction in the fixed costs of indirect exporting (a subsidy) reduces the amount of assets that a firm must save by 3.61% in the first year.

In the last policy experiment, I examine the effect of a financial reform that brings the level of financial development of Vietnam to that of the U.S. Total sales and exports increase by 1.97% and 2.89% after 10 years. The reform increases the export participation rate for small firms by 1.45 percentage points in the first year. This effect diminishes over time as these firms accumulate assets, overcome the financial constraint and become less dependent on external borrowing. I find that the reform has higher impact on individual firms when indirect exporting is not available. This suggests that the existence of indirect exporting acts as a tool to alleviate the effects of financial frictions.

The paper is organized as follows. Section 1.2 briefly outlines the related literature. Section 1.3 is an overview of the dataset and some motivating evidence. Section 1.4 presents the theoretical framework. Sections 1.5 and 1.6 present the model calibration and results. Section 1.7 conducts three policy experiments from the model. Section 1.8 concludes.

1.2 Related Literature

This paper contributes to the growing literature on a firm's export decision and access to financing. Other empirical and theoretical works such as Manova (2012) and Chaney (2016) incorporate credit constraints into the Melitz (2003) model and find that access to credit is an important determinant of a firm's export decision. Using a survey of Italian firms, Minetti and Zhu (2011) show that credit constrained firms have a lower chance of becoming exporters. They also find that a lack of access to credit lowers both domestic and foreign sales. Besedeš et al. (2014) show that the role of financial constraints diminishes as export duration increases.

Other quantitative studies such as Caggese and Cuñat (2013) and Brooks and Dovis (2020) analyze the aggregate impact of financial constraints and find that financial frictions lower the aggregate gains from trade. In particular, Caggese and Cuñat (2013) find that financial frictions reduce the aggregate productivity gains from trade liberalization by 25%. In Brooks and Dovis (2020), financial frictions act as barriers to trade, but the gains from trade liberalization depends on the structure of the borrowing constraint. Kohn et al. (2016) study how a borrowing constraint impacts new exporter dynamics and show that financial frictions are an important barrier to trade. Financial constraints in my paper are modelled similar to the symmetric case in Kohn et al. (2016) and the backward-looking case in Brooks and Dovis (2020). My paper contributes to this quantitative literature but adds the dimension of indirect exporting as a channel for firms to overcome existing financial frictions.

This paper also contributes to the literature on trade intermediation. Ahn et al. (2011) extend the

Melitz (2003) framework in a static model to incorporate the intermediary sector and allow firms to choose their modes of export: directly or indirectly through an intermediary at a lower fixed cost. When traded through an intermediary, despite paying a lower cost, firms are charged a per-unit cost as a service fee. Therefore, to access the foreign market, firms face a trade off between high fixed cost and low variable costs for direct exports versus lower fixed cost but higher variable costs if they trade through an intermediary. The model predicts that the most productive firms export directly, smaller and less productive firms export indirectly. Grazzi and Tomasi (2016) also find similar sorting patterns among exporters. Abel-Koch (2013) use the World Bank Enterprise dataset for Turkey to find that the share of indirect exporters declines with firm size: as firms grow, indirect exporting becomes less attractive. My work is closely related to Bai et al. (2017), who develop a dynamic model with trade intermediaries and learning by exporting to show that direct exporters are able to learn about how to produce faster than indirect exporters. In contrast to their work, I focus on the effects of financial frictions on firms' choice of export modes.

1.3 Data

This project focuses on Vietnamese firms, utilizing The World Bank Enterprise Dataset. Bai et al. (2017) study Chinese firms' behaviors when Chinese firms could only export if they could obtain a trading license. Unlike China, Vietnam did not impose restrictions on exporting. Firms are not required to have a license to trade and are allowed to trade freely by law. Any firm with a business license is allowed to be an intermediary. Many Vietnamese firms exist solely as trade intermediaries, advertising themselves as service providers for those that wish to import or export but do not have the means or the expertise.[1] This could be because they do not have experience in trading or because they wish to participate in the world market without having to pay the high cost associated with direct trading.

In this section, I document a set of facts from the data on a firm's export decision and their financial status. These facts provide motivation for the theoretical model.

Table 1.1: Summary of firms (WBE Survey)

	Non-exporters	Indirect Exporters	Direct exporters	Total exporters
2005	56.90%	8.62%	34.48%	43.10%
2009	50.00%	10.34%	39.66%	50.00%
2015	51.72%	9.48%	38.79%	48.27%
Average	52.87%	9.48%	37.64%	47.13%

Note: Non-exporters report 100% of their annual sales as domestic sales. Indirect exporters report positive shares of annual sales in indirect exporting but none in direct exporting. The remaining firms are direct exporters. Note that some direct exporters report sales through both indirect and direct exporting. Total exporters refers to the sum of indirect and direct exporters.

1.3.1 Data overview

The survey used in this paper is the World Bank Enterprise (WBE) Dataset, conducted on a set of registered firms[2] in Vietnam in 2005, 2009 and 2015, containing information on firms' finance, sales, employment, borrowing and business environment. Firms are asked about general characteristics of their operations such as financial vulnerability, barriers to enter exporting, employment (skilled and unskilled, temporary and full-time), types of ownership, capital utilization, collateral value etc. While the survey includes firms in both manufacturing and the services sectors, only manufacturing firms are included.

The common practice in the trade intermediary literature is to infer export mode from firms' names (Ahn et al., 2011) or to match balance sheets data with export transactions data (Bai et al., 2017). These imputations could be prone to systematic errors and thus bias inferences about trade growth and intermediation. In contrast, the World Bank Survey directly identifies firms' export modes as they are asked about the shares of their sales that are from domestic, indirect or direct exporting. Specifically, the survey asks firms the percentage of their annual sales that were from: (1) national sales, (2) indirect exports (sold domestically to a third party that exports products) and (3) direct exports.[3] I divide firms in the sample into three groups based on their responses. I

[1] These firms usually have both Export and Import or Trading in their registered names.

[2] The sample for Vietnam was selected using stratified random sampling. Firms are identified by a unique code in all years of the sample.

[3] I cannot observe carry-along trade in the dataset.

Table 1.2: Export status and firm size

	Export status			
Firm size	Non-exporters	Indirect exporters	Direct exporters	All exporters
Average number of workers	116.66	212.60	720.65	570.65
Small firms	77.06	9.18	13.77	22.94
Medium firms	53.50	12.61	33.89	46.50
Large firms	26.32	7.02	66.67	73.69

Note: Firms are sorted into size bins based on the number of workers that they report. Each entry in the table reports the shares of the size bin that belongs to each export status.

characterize a firm as a non-exporter if they report 100% of their sales as domestic sales. Firms are labeled as indirect exporters if they report positive percentage of sales in indirect exporting but zero in direct export sales. In the data, some firms report positive shares of annual sales for both indirect and direct exporting. I classify those firms as direct exporters.[4] Table 1.1 provides a summary of these three firm types in the WBE data. The shares of each type of firms remain steady over the years observed in the data. The share of firms as indirect exporters is small but not insignificant, about 9% each year.[5]

Table 1.2 documents firm-size differences across three groups of firms: non-exporters, indirect and direct exporters. On average, direct exporters are the biggest firms and employ the most number of workers, followed by indirect exporters and non-exporters.[6] The average number of workers employed by direct exporters is about 3.40 and 6.18 times the average employment by indirect exporters and non-exporters respectively. Based on the number of workers, I divide firms into three size bins: small, medium and large. Among small firms in the bottom third of the distribution, most of them are non-exporters (77.06%). The share of non-exporters among the large firms is significantly smaller (only 26.32%). The reverse is true for exporters (including direct and indirect

[4]The results in the paper remain qualitatively similar when I choose different definitions for exporters so that direct exporters have 0% of sales from indirect exporting.

[5]Bai et al. (2017) and Abel-Koch (2013) find similar statistics: between 7 and 9% of firms in China and Turkey are indirect exporters each year.

[6]Permanent and temporary workers.

exporters). While the share of exporters among small firms is only 22.94%, this number increases to 73.68% among large firms. As firms become larger, direct exporting is more prevalent. This observation follows the empirical evidence in international trade that exporters tend to be larger and more productive since they have to be big enough to cover the fixed and sunk costs of exporting (Abel-Koch, 2013; Bernard and Jensen, 2007).

1.3.2 Transition probability of export modes

Next, I compare the dynamic exporting behavior of the three groups. Table 1.3 shows the transition probability across export modes among all firms in the sample. Firms that have had exposure to exporting through intermediaries in the previous period are more than twice as likely to switch to direct exporting than firms without the experience (probability of 0.2771 versus 0.1371). This table shows that there exists some persistence in export mode choice: firms tend to stay in the same exporting category between t and $t+1$. Direct exporters are likely to remain in direct exporting with a probability of 0.7907. The persistence of non-exporting is similar at 0.7823. The persistence in indirect exporting is lower (probability of 0.4091). This suggests that indirect exporting is possibly a transitory platform to facilitate access to foreign markets.

Table 1.3: Transition probability of export modes

Export status in period t	Export status in period $t+1$		
	Home	Indirect exporting	Direct exporting
Home	0.7823	0.0806	0.1371
Indirect Exporting	0.3182	0.4091	0.2727
Direct Exporting	0.1628	0.0465	0.7907

Note: Each row shows the probability of a firm's switching from each exporting status between t and $t+1$ (WBE data). Home producers are firms that have 100% of annual sales as domestic sales. Indirect exporters report positive values in indirect exporting but none in direct exporting. Firms that report positive sales in direct exporting are classified as direct exporters.

1.3.3 Financial constraint

This project is also motivated by how financial constraints may affect firm decisions in international trade. Table 1.4 provides an overview of firms' financial needs using the World Bank Enterprise

Table 1.4: Financing needs among firms (WBE Survey)

	All	Home	Indirect exporters	Direct exporters
Shares of firms as constrained	21.47%	23.64%	23.79%	17.06%
Fraction of working capital financed externally	49.66%	47.88%	51.30%	58.12%

Note: Firms are classified as "constrained" if they answer "major obstacle" or "very severe obstacle". External finance includes loans from banks, non-bank institutions and other informal sources (friends, relatives, customers etc.) other than a firm's retained earnings.

Survey. I took the average across all years in the sample. Firms in the survey are asked how difficult it is to access finance (collateral requirements, costs, availability of loans etc). Answers include: no obstacle, minor obstacle, moderate obstacle, major obstacle and very severe obstacle. I identify firms as having major financial constraint if their answer is either "major obstacle" or "very severe obstacle". Around a fifth of firms in the survey (21.47%) consider finance as a major constraint in their operations. The second row in the table shows how firms finance their working capital. On average, they rely heavily on external finance for their working capital needs. About half of a firm's working capital is financed by external sources. This includes loans from banks, non-bank institutions and other informal financial sources (friends, relatives etc).[7]

As expected, direct exporters require the most financing from external sources (58.12%), followed by indirect exporters and non-exporters. There is about a 10 percentage point difference between non-exporters and direct exporters in their working capital needs. Exporting either as an indirect or a direct exporter is costly because of the high requirement for working capital. Note that direct exporters use more external finance for their working capital needs but are less likely to identify access to finance as a "major constraint". This reflects the fact that exporters tend to be bigger and more productive, hence, they require more financing for their production needs. At the same time, as these firms tend to be bigger, they may be perceived as more reputable and less risky. Therefore, they are more likely to secure more loans from banks and other financial institutions.

[7] Among external sources for lending, bank loans are the main source, followed by loans from money-lenders, friends and relatives. Direct exporters have the highest shares of external finance from banks, followed by indirect exporters and non-exporters.

1.4 Model

To explain the empirical observations documented in section 1.3, I develop an extension of the standard Melitz (2003) model to include financial frictions and intermediated trade in a partial equilibrium setting. Financial frictions arise in the form of a borrowing limit for working capital.

1.4.1 Model overview

Since the paper focuses on firms' export decisions, all firms in my model always serve the Home market. Additionally, I do not consider firm entry and exit. Each firm enters the period with a firm-specific productivity z and assets a. Given these state variables, firms choose their export modes: non-exporting, indirect exporting or direct exporting. The problem of the firm can be split into two problems:

1. The static problem: firm chooses their optimal prices and export modes to maximize their profits in the Home and the Foreign markets subject to a borrowing constraint. Without sunk costs, the firm's export mode decision is a part of the static problem.

2. The dynamic problem: The firm chooses the dividend distribution and assets for the next period.

1.4.2 Consumers

Individuals in a country supply labor inelastically. Preferences have a constant elasticity of substitution between varieties $\sigma > 1$:

$$U = \left(\int_{\Omega_t} q_t(\omega)^{\sigma/(\sigma-1)} d\omega \right)^{\sigma/(\sigma-1)}, \quad \sigma > 1 \tag{1.1}$$

where Ω_t is the set of varieties available, $q_t(\omega)$ is the demand for variety $\omega \in \Omega_t$.

1.4.3 Static problem

Each firm hires only labor as input and produces a single variety according to the production function: $y_i = z_i L_i$. For a firm i that exports, their production function can be written as the sum of production for the Home market and production for exporting:

$$y_i = y_H + y_F = z_i L^H + z_i L^{\{I,D\}} = z_i L_i$$

where L^H is labor for Home production, $L^{\{I,D\}}$ is the labor input for export production and depends on the firm's choice of export mode. Each firm faces the following demand schedules:

$$q_H = \left(\frac{p_H^{-\sigma}}{P_H^{1-\sigma}} \right) Q_H \qquad q_X = \left(\frac{p_F^{-\sigma}}{P_F^{1-\sigma}} \right) Q_F$$

where σ is the elasticity of substitution, (Q_H, Q_F, P_H, P_F) are aggregate quantities and price indices for the industry; q_H is the quantity sold in the Home market, and q_X is the quantity sold in the foreign market where $X \in \{I, D\}$ depends on the firm's export mode decisions. Note that a direct exporter and an indirect exporter face a similar demand schedule. However, their pricing decisions will differ due to the the specific variable trade costs associated with each exporting technology.

In each period, a firm has to pay in advance their product costs, which include the total wage bill and any fixed costs if they choose to export. However, each firm faces a borrowing constraint and can only borrow up to a multiple of their current assets, similar to the case of symmetric working capital needs in Kohn et al. (2016).[8]

The domestic firm solves the following profit maximization problem by choosing the optimal price p_H subject to the demand schedule in the Home market and the borrowing constraint for the total wage bill:

$$\pi_H = \max_{p_H} \; p_H q_H - wL^H \tag{1.2a}$$

$$s.t. \; q_H = \left(\frac{p_H^{-\sigma}}{P_H^{1-\sigma}} \right) Q_H \tag{1.2b}$$

$$L^H = \frac{q_H}{z} \tag{1.2c}$$

$$wL^H \leq \lambda a \tag{1.2d}$$

In the Foreign market, a firm that chooses to be an indirect exporter pays a fixed cost F_I that can be interpreted as a search cost for a trade intermediary in each period. Additionally, they have a to pay a per unit variable cost $\tau^I > 1$ that represents an intermediary commission fee. Their profit

[8] Another way to model financial frictions is to include borrowing for capital such as in Brooks and Dovis (2020) and Buera and Shin (2013). The choice to model financial constraint as a limit on working capital payment in this paper is due to data availability. The data has explicit information on how much a firm borrows for their working capital for the calibration of the parameters. See Bergin et al. (2021) for a model with financial frictions and long-term financing.

maximization problem is:

$$\pi_I = \max_{p_I} \ p_I q_I - wL^I - \frac{w}{z}\tau^I q^I - wF_I \tag{1.3a}$$

$$s.t. \ q_I = \left(\frac{p_F{}^{-\sigma}}{P_F^{1-\sigma}}\right) Q_F \tag{1.3b}$$

$$wL^I + wF_I \leq \lambda a \tag{1.3c}$$

$$L^I = \frac{\tau^I q_I}{z} \tag{1.3d}$$

Similarly, a direct exporter chooses the optimal price to maximize their period profits subject to the demand schedule and the borrowing constraint:

$$\pi_D = \max_{p_D} \ p_D q_D - wL^D - \frac{w}{z}\tau^D q^D - wF_D \tag{1.4a}$$

$$s.t. \ q_D = \left(\frac{p_F{}^{-\sigma}}{P_F^{1-\sigma}}\right) Q_F \tag{1.4b}$$

$$wL^D + wF_D \leq \lambda a \tag{1.4c}$$

$$L^D = \frac{\tau^D q_D}{z} \tag{1.4d}$$

where F_D is the per period fixed costs, $\tau_d > 1$ is the unit variable cost.

In order to sort firms into different bins of export modes, the model requires a trade-off between the costs to export for direct and indirect exporting. The fixed cost for direct exporting F^D is higher than the fixed cost for indirect exporting F^I. On the other hand, an indirect exporter incurs a higher variable cost τ^I than a direct exporter.[9] Intuitively, a direct exporter has to pay a higher cost each period to set up their own stores abroad but does not have to pay a commission fee besides the shipping cost for each unit. Therefore, they face a higher fixed cost F^D and a lower variable cost τ^D.

In each period, a firm makes the export decision of whether to export and the mode of export

[9] If the fixed cost of direct exporting is lower $F^D < F^I$, then the variable cost τ^D must be higher than τ^I. Otherwise, one option is always cheaper and no firms select into that mode of export.

(direct versus indirect exporting). The export mode decision (X_t) can be written as:

$$X_t = \begin{cases} \text{Indirect, if } \pi^I = \max\{\pi^H, \pi^I, \pi^D\} \text{ and } \pi^I \geq 0 \\ \text{Direct, if } \pi^D = \max\{\pi^H, \pi^I, \pi^D\} \text{ and } \pi^D \geq 0 \\ \text{Home, otherwise} \end{cases}$$

where $X_t \in \{I, D\}$ is the export mode choice.

1.4.4 Dynamic problem

A firm's productivity is modelled as an AR(1) process with persistence ρ:

$$\ln(z_t) = \rho \ln(z_{t-1}) + \varepsilon_t, \qquad \varepsilon \sim N(0, \sigma_z^2) \tag{1.5}$$

Given firm specific state variables (z, a), other aggregate state variables for prices and quantity demanded (P_H, Q_H, P_F, Q_F), a firm chooses the dividend distribution d and asset saving a' for the next period to solve:

$$V(z, a; X) = \max_{d, a'} \left\{ d + \beta E_z V(z', a'; X') \right\} \tag{1.6}$$

$$s.t. \qquad d + a' = (1 + r)a + \pi^X(a, z) \tag{1.7}$$

where $X \in \{I, D, H\}$ is the export status decision of the firm. The per period profit $\pi^x(a, z)$ is characterized in the static problem given their export status choice. If a firm decides to only operate in the Home market and not to export ($X = H$), they earn a profit $\pi(a, z) = \pi^H$. If a firm is an indirect exporter ($X = I$), their profit is the sum of the profits in the Home and Foreign markets: $\pi = \pi^H + \pi^I$. Similarly, a direct exporter's profit is $\pi = \pi^H + \pi^D$. These cases are summarized in the following manner:

$$\pi^X(a, z) = \begin{cases} \pi^H, \text{ if } X_t = H \\ \pi^H + \pi^I, \text{ if } X_t = I \\ \pi^H + \pi^D, \text{ if } X_t = D \end{cases}$$

1.5 Calibration

In this section, I discuss the model estimation and the model's fit to the data. The model is calibrated to match key firm-level moments related to export participation and external finance dependence as documented in section 1.3. Parameters in the model are split into two groups: one set consists of parameters' values taken from the literature, another set is estimated within the model using Simulated Method of Moments (SMM). I show that the model is able to match broadly the features in the data. For comparison, I calibrate a version of the model without financial frictions.

1.5.1 Externally calibrated parameters

Table 1.5: Parameters determined outside of the model

Parameters		Value	Source
Discount factor	β	0.967	Average annual real interest rates 2005-2015
Elasticity of substitution	σ	5	Brooks and Dovis (2020)

Table 1.5 lists the parameters and their values that are taken from the literature or the data. I set the discount factor β equal to 0.967 to match the annual real interest rates in Vietnam between 2005 and 2015.[10] This value is within the range of common values in the literature. I follow the standard practice in the literature and set the elasticity of substitution σ equal to 5.[11]

1.5.2 Internally calibrated parameters

The remaining parameters in the model are: $\{F_D, F_I, \lambda, \tau^I, \tau^D, \sigma_z, \rho\}$. They are jointly estimated to match moments from the data that describe the export participation, the size difference, export intensity and the external finance dependence. Specifically, these moments are: (1) the share of firms that are direct exporters, (2) the share of firms that are indirect exporters, (3) the median size difference (labor usage) between direct exporters and *Home* firms, (4) the median size difference between direct and indirect exporters, (5) the average export intensity of direct exporters, (6) the average export intensity of indirect exporters and (7) the average external finance ratio. All of these

[10]I use the World Bank Data on real interest rates in Vietnam to calculate this value.

[11]See Brooks and Dovis (2020), Ruhl and Willis (2017), Melitz and Redding (2015), and Broda and Weinstein (2006).

moments from the data are calculated using the WBE dataset. For comparison, I also calibrate a version of the model without financial frictions ($\lambda = \infty$). In this version, I only have 6 parameters to estimate $\{F_D, F_I, \tau^I, \tau^D, \sigma_z, \rho\}$ and I match the first six moments.

To find the parameters of interest, I use the Simulated Method of Moments (SMM) and search over the parameter space to minimize the following objective function:

$$L(\phi) = \min_{\phi}(M_{model} - M_{data})' W (M_{model} - M_{data})$$

where $\phi = \{F_D, F_I, \lambda, \tau^I, \tau^D, \sigma_z, \rho\}$ is the vector of model parameters to be estimated, M_{model} is the vector of moments computed from the simulated data in the model and M_{data} is the vector of moments computed from the data. The weighting matrix W is the inverse of the variance-covariance matrix of the data moments.[12] I simulate a panel of 2000 firms for 1000 periods. I then drop the initial periods and save only the last 11 periods (the same as the data) to calculate the moments the same way as I have done in the WBE dataset.

Table 1.6: Calibrated parameters

		Model	
Calibrated parameters		(a)	(b)
Fixed cost of direct exporting	F_D	6.55	6.92
Fixed cost of indirect exporting	F_I	4.56	4.56
Variable cost of indirect exporting	τ^I	1.21	1.24
Variable cost of direct exporting	τ^D	1.12	1.13
Persistence productivity process	ρ	0.93	0.85
Std. productivity process	σ_z	0.05	0.07
Borrowing parameter	λ	3.45	—

(a): Calibration for economy with financial frictions.

(b): Calibration for economy without financial frictions.

The per period fixed costs of direct and indirect exporting (F_D, F_I) affect the firm's decision

[12] The moments are calculated by bootstrapping the sample 1000 times. Each bootstrapped sample is drawn with replacement.

whether to export and which export mode. Therefore, these parameters affect the shares of direct and indirect exporters in the sample.

The parameters for the productivity process govern the distribution of productivity in the model. This allows me to match the size difference in the calibration.

The iceberg trade cost for direct exporting τ^D and the intermediary cost for indirect exporting τ^I affect the export values relative to total sales since they reflect how costly exporting production is relative to Home production.

Firms that export also have higher financing needs due to the per period fixed costs. In the model, in order to produce, these exporting firms seek external finance conditional on their assets. Therefore, the borrowing parameter λ also affects the size difference between exporters and Home producers. This parameter also affects the external finance ratio since it reflects the access to finance for a firm.[13]

Table 1.7: Moments in the data and in the model

Moments	Data	Model	
		(a)	(b)
Share of direct exporters	0.38	0.39	0.35
Share of indirect exporters	0.09	0.11	0.08
Export intensity (direct exporters)	0.63	0.61	0.60
Export intensity (indirect exporters)	0.56	0.53	0.52
Median size difference(D/H)	5.31	5.67	5.40
Median size difference(D/I)	3.53	1.78	1.71
External finance ratio	0.50	0.50	—

Note: Data moments are calculated using the WBE dataset.

(a): Calibration for financial friction model.

(b): Calibration for frictionless model.

Table 1.6 reports the estimates for the internally calibrated parameters. The calibration in both models (a) and (b) yields higher fixed costs for direct exporting compared to the fixed costs for

[13] External finance ratio is calculated in the data as the percentage of working capital that is financed not by a firm's internal retained earnings. In the model, this corresponds to the additional payment for working capital and fixed costs of exporting besides the firm's existing assets.

indirect exporting. On average, fixed costs are about 10% and 8% of indirect and direct exporters' revenues. On the other hand, the variable cost of direct exporting is lower than indirect exporting. This reflects the trade-off between paying lower fixed costs but higher variable costs for indirect exporting as discussed in the previous section. The calibration for a frictionless model yields lower persistence in the productivity process and higher fixed cost of direct exporting to match the export participation rates.

1.5.3 Model fit

Table 1.7 reports the model performance in matching the key empirical moments. The model broadly matches the data.[14] Specifically, the models matched almost exactly the shares of firms as exporters, the average export intensity, the median size difference between direct exporters and Home producers and the external finance ratio. In both models (a) and (b), the moments for size differences between direct and indirect exporters in the sample are underestimated. The models require a smaller fixed cost of direct exporting in order to match the share of firms as direct exporters. In the model, some of the indirect exporters would have chosen to be *constrained* direct exporters without indirect exporting. As a result, they are on average larger and closer in size to direct exporters than in the data.

In section 1.3, I show that there is persistence in export modes: firms are likely to maintain the same export status between periods. In the data, indirect exporters have twice the likelihood of becoming direct exporters compared to non-exporters. Having calibrated the model, I use the simulated data from the model to predict the transition probability for different modes of exporting. The results from the simulated data are in table 1.8.

The calibrated model is able to replicate the observation in the data that indirect exporters in period t are much more likely than Home firms to transition into direct exporting in period $t+1$. Indirect exporters have a probability of 0.4320 of switching to direct exporting in the frictions model compared to Home firms' probability of 0.1559. The model without financial frictions has a similar prediction: indirect exporters' probability of becoming a direct exporter is higher than $Home$ producers (0.3918 versus 0.2406). However, model (a) matches more closely the persistence

[14] While the external finance ratio is not targeted in the calibration for the frictionless model, this moment is about 0.98 in the model.

Table 1.8: Transition probabilities of export status (simulated data)

		Export status in period $t+1$		
Period t		Home	Indirect exporting	Direct exporting
Home	Data	0.7823	0.0806	0.1371
	Model a	0.7333	0.1108	0.1559
	Model b	0.6814	0.0780	0.2406
Indirect exporting	Data	0.3182	0.4091	0.2727
	Model a	0.4511	0.1169	0.4320
	Model b	0.5016	0.1066	0.3918
Direct exporting	Data	0.1628	0.0465	0.7907
	Model a	0.2128	0.0929	0.6942
	Model b	0.3804	0.0871	0.5325

Note: Simulated data come from the calibrated model. These moments are not targeted in the calibration. Model (a): calibration with financial frictions; Model (b): calibration without financial frictions.

of export statuses than model (b) without financial frictions.

1.6 Results

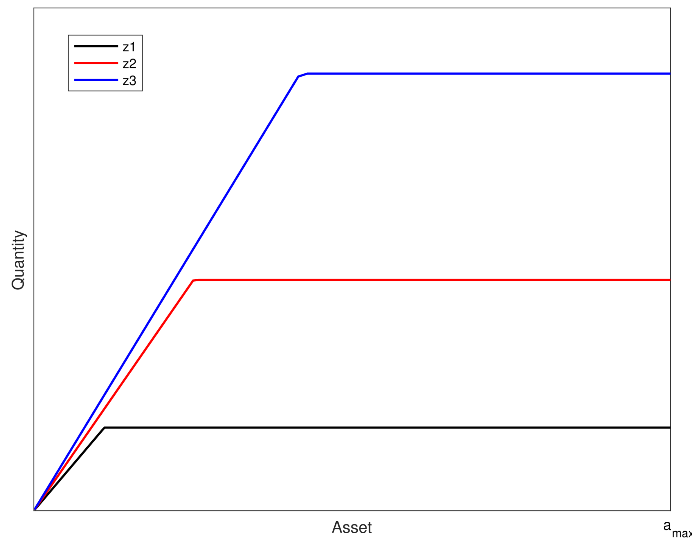
Having parameterized the model, I now analyze the mechanism in the model that explains the behavior of firms documented in section 1.3. I show that financial frictions affect the firms' savings, production and export decisions.

The calibrated model shows that indirect exporting is particularly important when the degree of financial frictions increase. The existence of indirect exporting provides firms with an additional channel to accumulate assets so that they can grow and eventually become direct exporters. Therefore, indirect exporting serves as a substitute for access to external finance and reduces the severity of financial frictions.

1.6.1 The effects of financial frictions

In a perfect credit economy ($\lambda = \infty$), firms are unconstrained and assets have no role in their production decisions. The unconstrained production for Home $q^{H,U}$ is the optimal level and is higher than what a constrained firm can produce. Therefore, in the presence of financial frictions, some

Figure 1.1: Home production, keeping productivity fixed at $z_1 < z_2 < z_3$



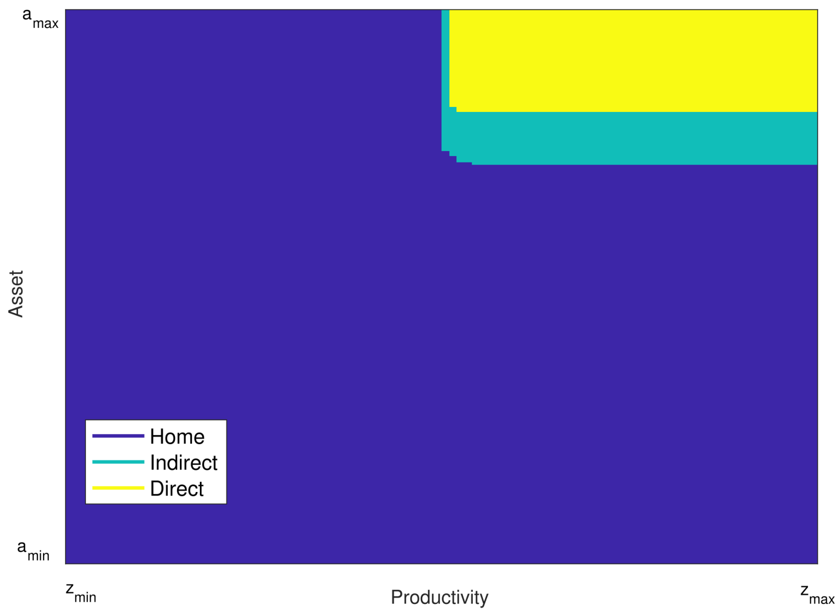
firms are constrained to producing below the optimal level. The effect of financial frictions on production is illustrated in Figure 1.1 which shows the quantity of $Home$ production against assets, fixing productivity at three levels $z_1 < z_2 < z_3$. The kink on each line shows the minimum asset required to achieve the optimal unconstrained production associated with each productivity. The more productive a firm is, the more assets they need to hold in order to reach the unconstrained level of output.

In the absence of financial frictions, all firms have unlimited access to finance and operate at the optimal scale. As a result, a firm's assets have no effect on their export profits, only productivity determines the sorting pattern into exporting. However, under financial frictions, the cutoff for exporting depends on both a firm's productivity and assets. Figure 1.2 plots the regions for different export decisions to demonstrate the cutoffs for different modes of exporting. Firms with low productivity z and low asset a do not export and only serve at Home. If their productivity z is high enough, the firm's export decision depends on the firm's asset a. Figure 1.2 shows that direct exporters are firms that are most productive and have the highest assets.[15]

Table 1.9 reports the aggregate implications of different values for the borrowing parameter λ.

[15]The stark trade-off between productivity and asset in figure 1.2 is due to the discretized grids. A finer grid for asset would produce a smoother convex curve.

Figure 1.2: Export decisions



The two extreme values of $\lambda = 1$ and $\lambda = \infty$ respectively reflect an economy where firms cannot borrow (financial autarky) and an economy where firms have unlimited access to finance. All other calibrated parameters remain the same so that the only source of difference comes from the different values of λ.

Table 1.9: Aggregate implications of financial frictions

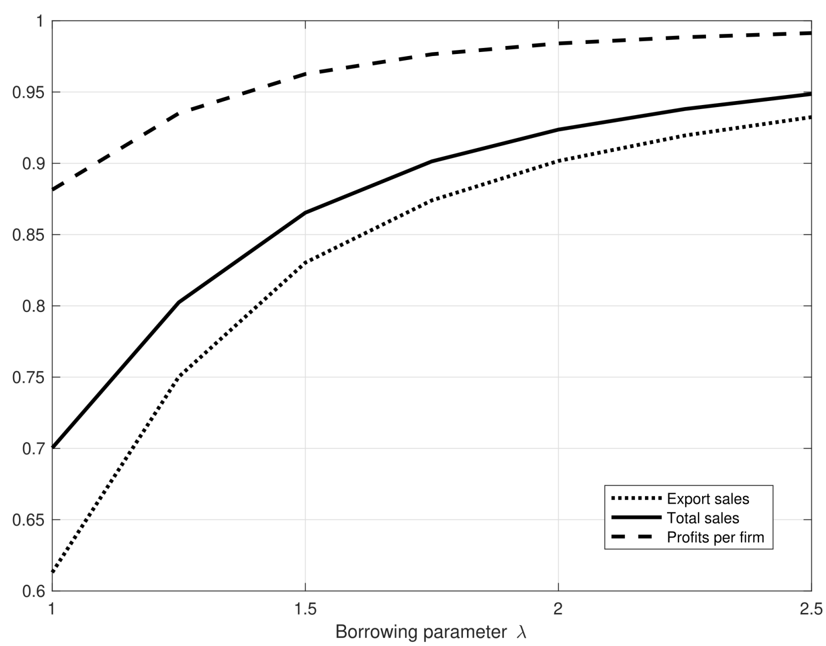
	Borrowing parameter λ					
	∞	2.5	2	1.5	1.25	1
Fraction of firms constrained (%)	0	20.53	23.63	31.04	38.89	49.58
Fraction of firms as indirect exporters (%)	9.43	11.08	11.46	12.68	12.83	15.52
Exports carried indirectly(%)	10.32	13.16	14.30	16.64	17.93	25.73

Note: Financial constraint is calculated at the intensive margin, i.e. a firm is identified as constrained if they produce less than they would with unlimited borrowing. Calculations come from varying the parameter λ in the friction model.

Smaller values of λ results in more firms being financially constrained.[16] When $\lambda = \infty$, firms have unlimited access to finance and therefore, all firms are unconstrained and produce at their optimal level according to their productivity. However, in financial autarky when $\lambda = 1$, almost 50% of firms are financially constrained.

Figure 1.3 plots the values of total sales, export sales and profit per firm for different values of λ. Each value is normalized by their frictionless value when $\lambda = \infty$. As the borrowing parameter λ increases and the financial friction level decreases, these values get closer to the frictionless level. Financial frictions can reduce the values for total sales and export sales by 30% and 40%. At the firm level, profits can be approximately 12% lower.

Figure 1.3: The effects of financial frictions



Notes: The horizontal axis shows different degrees of financial frictions by varying the borrowing parameter λ. Each series is normalized by their respective frictionless values when $\lambda = \infty$.

1.6.2 The role of indirect exporting

The last two rows of table 1.9 show the role of indirect exporting as λ decreases. When access to finance becomes more limited, more firms choose to be indirect exporters. Moving to financial

[16]Firms are identified as financially constrained if they produce less than the optimal quantity given their productivity and export status.

autarky from unlimited borrowing leads to a 6.1 percentage point increase in the shares of firms as indirect exporters (9.43% to 15.52%). As a result, the share of industry exports carried by indirect exporters also increases from 10.32% to 25.73%. As the degree of financial frictions becomes larger, the role of indirect exporting becomes even more important.

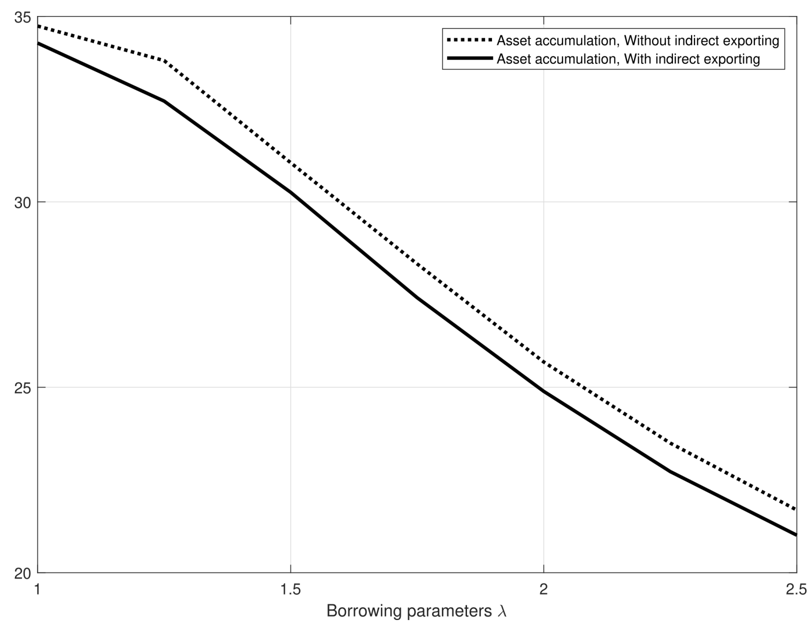
Figure 1.4 shows the average assets held by firms for a range of friction levels in two different scenarios: with and without indirect exporting. In both cases, as the borrowing constraint relaxes (higher λ), firms on average save less and asset accumulation decreases. Under all friction levels, firms have to save more assets when there is no indirect exporting.[17] Consider an economy that allows indirect exporting and the financial friction parameter is $\lambda = 2$. On average, a firm saves approximately 25 units. Comparing this to a scenario without indirect exporting, in order for a representative firm to save the same amount of 25 units, the degree of financial frictions must be lower (borrowing parameter must be higher $\lambda \approx 2.1$). In other words, the existence of indirect exporting as an option available to firms mitigates the severity of financial frictions as much as a 5% increase in the borrowing power.

1.6.3 Transition into direct exporting

One mechanism through which firms transition into direct exporting is asset accumulation to overcome financial constraints. The model suggests that indirect exporting provides firms with a channel to accumulate more assets due to higher profits. To analyze the importance of the indirect exporting technology, I eliminate this channel and compare how firms transition into direct exporting. For this experiment, I track the behaviors of two identical cohorts of Home firms in $t = 0$ to $t = 10$ in two scenarios with and without indirect exporting. The firms in these cohorts have the same initial characteristics in $t = 0$, but the endogenous choices are different starting from $t = 1$ when indirect exporting is not available. All other parameters remain the same between two scenarios so that the only difference is the existence of indirect exporting. Figure 1.5 shows the behaviors of firms in these two cases. The dotted black line shows the share of firms that become direct exporters in each period when indirect exporting is available to firms. The red line shows the same value in each pe-

[17] As the degree of financial friction decreases and λ increases, the gap between the two lines closes. When the borrowing constraint is completely relaxed, i.e. $\lambda = \infty$ (not shown in Figure 1.4), asset accumulation is the same in both scenarios with and without indirect exporting. This is because when firms have unlimited access to finance, they save the minimum amount and use the rest of their income as dividend distributions.

Figure 1.4: Financial frictions and indirect exporting



Notes: The horizontal axis shows different degrees of financial frictions by varying the borrowing parameter λ.

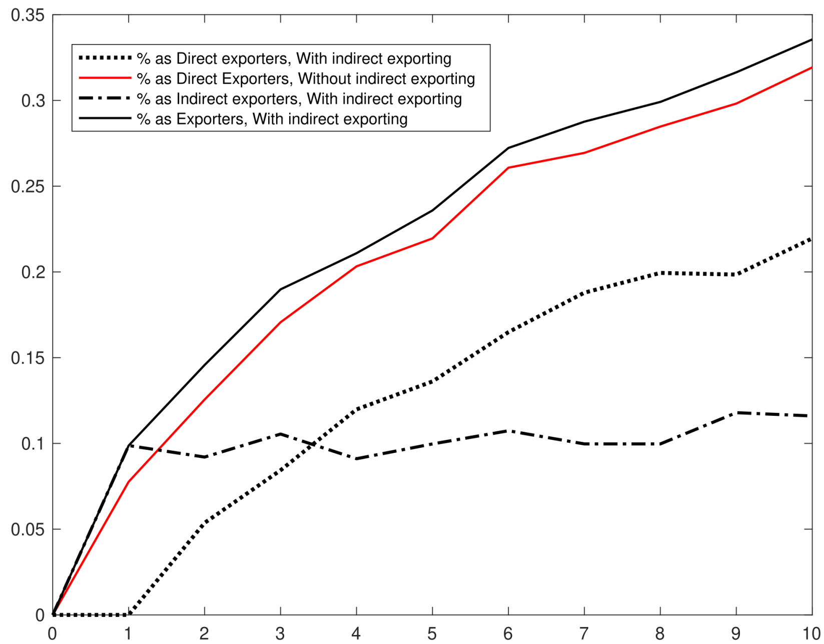
riod when indirect exporting is not available. The dashed black line shows the shares of the original $Home$ cohort in $t = 0$ that choose to become indirect exporter in each period.

There are more firms from the $Home$ cohort in $t = 0$ that become direct exporters in each period when indirect exporting is shut down, compared to when firms are allowed to trade indirectly. However, the total number of exporters is lower when there is no indirect trade. Direct exporters and $Home$ producers do not change their export status between two scenarios. The only firms which change their export modes are indirect exporters in the benchmark scenario. These switching firms either become direct exporters or revert back to being $Home$ producers. They also earn lower profits than they would as indirect exporters in the benchmark case.

Figure 1.6 plots the shares of direct exporters in each period that are constrained. Over time, as direct exporters accumulate assets faster due to higher profits, fewer of them are constrained by the borrowing limit. As a result, the shares of direct exporters that are constrained decrease in both scenarios.[18] However, when indirect exporting is not available, more of the direct exporters

[18]There are no constrained direct exporter in period $t = 1$ in the benchmark since none of the $Home$ firms in $t = 0$ switch to direct exporting in $t = 1$, the only exporters in $t = 1$ from the cohort are indirect exporters.

Figure 1.5: Switching behaviors for cohort of *Home* firms from $t = 0$



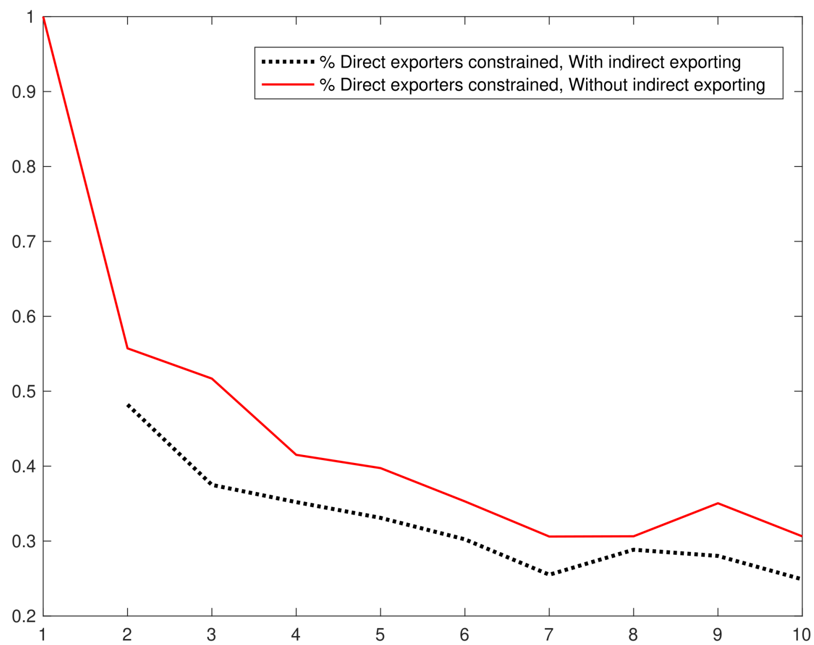
Notes: Each line shows the shares of the original cohort of Home firms in $t = 0$ that become direct or indirect exporters in each period $t = 1, 2 \ldots 10$ after the elimination of indirect exporting at the beginning of $t = 1$. The black line shows the shares of cohort as direct exporters when indirect exporting is available. The red line shows the shares of firms as direct exporters if indirect exporting is not available. Firms in two scenarios are initialized to have the same characteristics for comparison.

are constrained. This is because some of the direct exporters in each period would have preferred to be *unconstrained* indirect exporters in the benchmark case. The existence of indirect exporting provides these firms with a stepping stone to accumulate assets and to eventually transition into direct exporting.

1.7 Policy experiments

In this section, I use the calibrated model to consider three policy experiments. First, I investigate the impact of a trade liberalization on the aggregate measures such as total sales and export revenues. The second experiment considers the implications of a subsidy on indirect exporting. Lastly, I analyze the impact of a financial reform that raises the level of financial development in Vietnam. In each experiment, I simulate the model for 10 years after the policy change and compare the results to the benchmark values in each period.

Figure 1.6: Constrained direct exporters



Notes: Each line shows the shares of the original cohort of Home firms in $t = 0$ that become direct exporters in t and are constrained. The black dotted line shows the shares of the cohort as constrained direct exporters when indirect exporting is available. The red line shows the shares of firms in the cohort that become constrained direct exporter when indirect exporting is not available. Firms in two scenarios are initialized to have the same characteristics for comparison.

1.7.1 Trade liberalization

In this policy experiment, I reduce the variable trade costs (τ^D, τ^I) for both direct and indirect exporting by 5%. This can be interpreted as a 5% reduction in tariffs across the board. The results are reported in table 1.10.

Table 1.10: Trade liberalization: (variable costs decrease by 5%)

Year	1	3	10
Aggregate sales(%)	17.27	23.31	23.75
Aggregate export(%)	37.21	46.46	47.26
Home to D/I contribution (%)	45.52	42.02	42.67
Indirect to Direct contribution (%)	8.13	14.27	14.34
Average asset savings (%)	16.87	21.20	21.99
Export participation (pp.)	14.20	15.70	16.03
Indirect exporters fraction (pp.)	6.30	-0.53	-0.27
Direct exporters fraction (pp.)	7.90	16.23	16.30

Note: Results are compared to the benchmark values for each period. Both variable costs for direct and indirect exporting are reduced.

The first row shows the change in aggregate sales as a result of the policy change. The following columns report the changes compared to the benchmark values for years 1, 3 and 10 after the policy was implemented. In the first year, the increase in aggregate sales after a trade liberalization is 17.27% while aggregate export sales increase by 37.21%. Therefore, the industry benefits from a trade liberalization.

Table 1.10 also decomposes the contribution of export status switchers to the gains from a trade liberalization compared to the benchmark case. Following a trade liberalization, the export market becomes more attractive. Therefore, no exporters in the benchmark switch to being Home producers in the counterfactual. The gains in the industry as a result of a trade liberalization come both from the increase in the export sales among incumbent exporters (direct/indirect) and from producers that switch their export status (home to direct/indirect and indirect to direct exporting). More than half of the increase in aggregate exports in each period is attributed to the changes in the extensive margin, i.e. from producers that switch their export modes.

1.7.2 Indirect exporting subsidies

In the previous sections, I show that as the degree of financial frictions increases, the role of indirect exporting becomes more important: more firms choose to be indirect exporters and a larger share of total exports is carried indirectly. I investigate a policy experiment that promotes indirect exporting. Specifically, I lower the fixed cost of indirect exporting by 25%. This cost represents the per period expenditures associated with trading through an intermediary such as a warehouse cost or a search cost for a middleman. A policy that improves the infrastructure for trade intermediation (more trade intermediaries etc.) could result in a lower fixed cost of indirect exporting.

Table 1.11: 25% reduction in fixed costs of indirect exporting (F_I)

Year	1	3	10
Aggregate sales (%)	1.96	3.18	3.96
Aggregate export sales (%)	4.36	6.72	8.21
Export participation (pp.)	22.20	22.83	22.87
Indirect exporters fraction (pp.)	50.33	52.47	51.78
Direct exporters fraction (pp.)	-28.10	-29.63	-28.90
Average asset savings (%)	-3.61	-2.40	-1.73

Note: Results are compared to the benchmark values for each period. Export subsidies are in the form of a 25% reduction in fixed costs for indirect exporting.

Table 1.11 presents the results of the policy experiment. Compared to the benchmark without subsidy, when a policy of 25% subsidy on indirect exporting fixed costs is implemented, the total export revenues increases by 1.96% in the first year.

Following an indirect export subsidy, the export participation rate increases by 22.20 percentage point in the first year: the shares of firms as indirect exporters increase over time, while the shares of firms that are direct exporters decrease. The reason for this is that as fixed costs of indirect exporting decrease due to the subsidy, indirect exporting becomes more attractive compared to direct exporting. Therefore, some of the changes in the extensive margin comes from direct exporters in the benchmark scenario switching to indirect exporting after the policy changes. As more firms become indirect exporters and more direct exporters switch to indirect exporting, the average asset savings also decrease compared to the benchmark of no subsidy in each period. Indirect exporting serves as a substitute for savings to overcome the borrowing constraint.

1.7.3 Financial reform

In this section, I investigate the effects of a financial reform. I follow Buera and Shin (2013) and Arellano et al. (2012) [19] to calculate a country's financial development as the ratio of private credit by deposit money banks and other financial institutions over GDP using the database from Beck et al. (2000) in 2019. I compare this indicator between Vietnam and the U.S, a country with a highly developed financial market, from 2005 to 2015 (the years in the World Bank Survey sample) to calculate the relative financial development between two countries.[20] To conduct a financial reform experiment, I multiply the borrowing parameter λ by the relative difference between the U.S and Vietnamese financial development. The results of this experiment are in table 1.12.

Table 1.12: The effects of a financial reform

Year	1	3	10
Aggregate sales(%)	3.05	1.95	1.97
Aggregate export sales(%)	4.31	2.73	2.89
Average asset savings (%)	-49.62	-49.95	-49.79
Export participation (pp.)	0.57	0.27	0.60
Indirect exporters fraction (pp.)	-2.27	-1.67	-1.17
Direct exporters fraction (pp.)	2.83	1.93	1.77
Fraction of firms constrained (pp.)	-14.47	-8.07	-6.93

Note: Results are compared to the benchmark values for each period. Financial reform is a result of relaxing the borrowing parameter by a multiple that represents the relative financial development between Vietnam and the U.S.

After a financial reform, a firm does not have to save as much asset to overcome the constraint

[19] Arellano et al. (2012) suggest measuring a country's financial development using three statistics: (1): average private credit to GDP ratio, (2) banks' overhead costs as share of total assets and (3) the percentage of adults included in the public and private credit bureaus.

[20] The average external finance ratio of the U.S. between 2005 and 2015 is 1.83, while that of Vietnam is 0.84. This implies that the U.S financial development is 2.18 times that of Vietnam.

as they would in an economy with higher financial frictions. Therefore, over the 10 year period, the average asset savings decrease by about 50 percentage points. Export participation increases only by a marginal amount (0.57 percentage points in the first year and 0.60 percentage points by year 10). As the degree of financial frictions decreases, the share of firms as indirect exporters decreases while the share of firms as direct exporters increases. This demonstrates the effects as described in section 6.2: the role of indirect exporting diminishes as financial frictions become less severe.

The impact on aggregate sales, aggregate exports, and proportion of constrained firms illustrates the effect of a financial reform in both the short and medium term. Following a larger jump in the first period, a financial liberalization has diminished but persistent effects. In the first year after the reform, aggregate sales increase by 3.05% while export sales increase by 4.31%. The fraction of firms that are constrained decreases by 14.47 percentage points. By year 10, the magnitude of the change gets smaller: aggregate sales increase by 1.97% and export sales increase by 2.89%. A financial reform gives constrained firms a boost in the first year. Over time, firms in the benchmark scenario with more severe financial frictions grow and catch up so that the difference due to the financial reform is less than in the first year of the reform. Overall, the industry still benefits from a financial reform as sales and exports increase relative to the benchmark case.

Table 1.13: The effects of a financial reform on export participation

	With indirect exporting			Without indirect exporting		
Year	1	3	10	1	3	10
Small firms	1.45	1.16	0.87	2.89	2.02	0.87
Medium firms	0.00	0.00	0.76	0.91	0.30	0.46
Large firms	0.00	0.00	0.15	0.00	0.00	0.46

Note: Results are compared to the benchmark values for each period. Financial reform is a result of relaxing the borrowing parameter by a multiple that represents the relative financial development between Vietnam and the U.S. Firms are split into terciles by their labor employment size before the reform takes place.

To evaluate the impact of financial reform on firms' export mode choice, I break down firms into three groups (small, medium and large) based on their pre-reform labor employment. I track the changes in export participation rates in each group following the reform. I also perform the same exercise in a model without indirect exporting by shutting down this channel and setting the fixed costs F_I to infinity. The results are shown in the table 1.13. When compared to the results in a model with indirect exporting, the financial reform has a greater impact on firms when there is no indirect exporting. This further illustrates that the existence of indirect exporting alleviates the needs for assets and mitigates the impact of financial frictions. As a result, a reform has a lower impact than when indirect exporting is shut off.

The financial reform has the highest impact on small firms' export decisions. In the first year, the policy increases the participation rate by 1.45 percentage points with indirect exporting. In a model without indirect exporting, a financial reform increases the participation rate even more (2.89 percentage points). However, the effects of the policy on small firms in both models fade over time as the initially small firms in the benchmark pre-reform accumulate more assets and eventually become exporters by year 10.

For medium sized firms, the effects are smaller. In a model without indirect exporting, there is no change in the export participation. As the borrowing power increases due to the constraint being relaxed, these firms switch from indirect exporting to direct exporting so that the total shares of firms as exporters remain unchanged. By year 10, there is an increase in the number of exporters compared to the benchmark. In model without indirect exporting, there is a positive increase in the export rate in the short-run for medium firms compared to the model without indirect exporting. This is because for some of these medium firms, they would have preferred to be indirect exporters. Taking away this channel, they have to be *Home* producers. The additional borrowing power due to the reform allows them to switch up to direct exporting and become exporters. Over time, the effect on medium firms when there is no indirect exporting diminishes, similar to what we observe for small firms.

For large firms, the effects are small in both models. This is because these firms are likely unconstrained so that they are less likely to be affected by financial frictions. By year 10, there is only a marginal increase in export participation in both models.

1.8 Conclusion

In this paper, I investigate how financial frictions distort firms' export behaviors and the role trade intermediation plays in alleviating such frictions. I incorporate a borrowing constraint and two channels of exporting into a standard international trade model. I show that due to financial frictions, the decision to export is a function of both a firm's productivity and their assets. The model is calibrated using a firm-level dataset covering Vietnamese firms from 2005 to 2015. I show that indirect exporting is a platform for firms to transition into direct exporting. Firms with indirect exporting experience are more likely to become direct exporters than non-exporters. This is because they earn higher profits from indirect exporting and accumulate assets faster. As financial frictions become larger, the role of indirect exporting becomes even more important: more firms become indirect exporters and more of total exports are carried indirectly. Furthermore, indirect exporting is a substitute for financial development as it alleviates the needs for assets: firms do not have to save as much as they would without indirect exporting.

Using the calibrated model, I analyze three policy experiments. In the first experiment, I find that a trade liberalization, represented by a 5% reduction in trade costs, increases both total sales and total exports but the change occurs gradually over 10 years. The second policy experiment examines the effect of an indirect export promotion due to a 25% decrease in the fixed costs of indirect exporting. This reduces the amount of assets that a firm must save by 3.61% in the first year. Lastly, a financial reform increases aggregate exports and sales by 4.31% and 3.05%, but the effects fade over time. Moreover, this reform has the highest impact in increasing the export participation rates for small firms. The policy has higher effects in a model without indirect exporting. This provides further evidence that the existence of indirect exporting already works as a platform to mitigate the effects of financial frictions. These findings have important implications for policies in developing countries where financial institutions might be weaker.

CHAPTER 2

Multi-product firms, product switching and learning about demand

2.1 Introduction

The prevalence and importance of multi-product exporters have been widely documented in the literature (Mayer et al. (2014), Manova and Yu (2017), Bernard et al. (2010b)). Among these multi-product exporters, product switching (product adding or dropping) is a common activity. About 54% of U.S. firms change their product mix every 5 years (Bernard et al., 2010b). Despite growing empirical evidence of the significance of product switching firms, the trade literature has mostly focused on modelling exporters in a single-product model as in Melitz (2003) to explain the firms' entry and exit decisions. Consequently, the within-firm product churning is often overlooked. In this paper, I investigate how multi-product firms decide to add and drop products to a destination when facing demand uncertainty.

Product switching can be costly and risky to exporters. Adding or dropping a product requires adjustments at the firm level such as adjusting for a new assembly line, new production plants or a change in the firms' distribution network at home and abroad. In addition to being costly, product switching also brings uncertainty. Firms do not have perfect information of how their products will be received in the market and what the demand for the products will be. This uncertainty about demand from the perspective of a firm has been documented in marketing research as one of the causes of failures for new product introduction as firms might overestimate the product's value to the potential buyers (Nguyen, 2012). Facing such uncertainty, an exporter could fund their own market research or start experimenting with different products. An additional channel to overcome uncertainty is to observe the information from other firms that supply the same products in the market and learn from their experience. In this paper, I develop a model in which the demand for a product is uncertain from the perspective of a firm due to the existence of some specific product-market characteristics (the appeal of a product to the customers in the destination market). They resolve this demand uncertainty by learning from other firms in the market and when applicable, from their own experience. Based on this information, a firm evaluates the profitability of each product in a market and makes product switching decisions accordingly.

The model provides a number of testable predictions for the empirical analysis. I verify these predictions using a sample of Chinese exporters from 2000 to 2006. The first prediction is that positive signals increase the likelihood of a firm adding a new product in a destination market. A one standard deviation increase in the value of signals relative to the mean raises the likelihood of a firm adding that product to their mix by 3.3%. The effect is even stronger when there are more firms revealing the signal. The second prediction is that firms are less likely to drop an existing products when there are more positive signals about the demand from both themselves and other firms. One standard deviation increase in the value of signals from a firm's experience and from other firm's signals decreases the likelihood of dropping a product by 8.9% and 4.1% respectively. When a firm decides whether to drop a product, the model finds that the effect of learning is stronger in the number of years that the firm has supplied that product, while the effect of learning from other firms is weaker when product tenure increases. With an additional year of product tenure, learning from a firm's own experience results in an 8.4% decrease in the probability of a product being dropped, while learning from other firms only decreases the same likelihood by 2.7%. These results highlight the benefits of information spillover among firms in international trade.

The paper is organized as follows. Section 2.2 briefly outlines the related literature. Section 2.3 is an overview of the dataset and some motivating evidence. Section 2.4 presents the theoretical framework. Section 2.5 reports empirical findings and section 2.6 concludes.

2.2 Related Literature

This project is related to two strands of literature. The first is the literature on multi-product firms and product switching which has documented the high rates of product turnover. Mayer et al. (2014) find that in markets with tougher competition, less productive firms exit and among those that survive, they drop their worst performing products in the mix. Bernard et al. (2010b) in a multi-product extension of Melitz (2003), show that there is a substantial amount of product switching among U.S. manufacturing firms. This observation of firms frequently engaging in product switching is also confirmed by Timoshenko (2015) using a Brazilian dataset on exporters. Specifically, product switching is more common among younger firms. Iacovone and Javorcik (2010) also find significant product churning among Mexican firms in response to trade liberalization. On the contrary, Goldberg et al. (2010) find a surprising observation that Indian firms do not engage in product switching as frequently and intensively as expected, despite trade liberalization in the country. Moreover, these product switching firms are far more likely to add new products than to drop existing ones. My paper extends the standard multi-product firm framework in this literature to characterize the behavior of adding and dropping a product among Chinese firms.

The second contribution is to the literature on learning. This is seen in the earlier papers on social learning models by Jovanovic (1982) and Banerjee (1992). Recent works on social learning aim to model and quantify how individuals observe other individuals in the same social network (other firms, friends, family members etc.) to resolve uncertainty. Kaustia and Rantala (2015), among many other studies on peer effects in corporate decisions, show that firms are more likely to split their stocks after having observed other firms doing so. Moretti (2011) models the uncertainty of movie quality to consumers and shows how peers' information influences individuals' learning about movie quality. In his paper, the product quality of a movie is unknown and consumers must form a an expectation for the quality of that movie. They update their beliefs based on information revealed to them by peers in their social circle who have seen the movie. He finds that the peer effects are stronger for individuals with a larger social network. The more information a consumer gathers from other peers, the less weight he puts on his own prior.

Recent literature on learning in international trade builds on these works of social learning. The common theme in these papers is that demand is uncertain and firms form some beliefs about the demand. They update these beliefs using information revealed to them. Berman et al. (2019) examines how firms learn about the demand in a market that they serve and the effect of learning on firm dynamics. In Albornoz et al. (2012), the value of a firm to customers (the brand appeal) in different destinations are correlated. Firms learn about their appeal from previous markets to evaluate their decision to enter a new destination. Nguyen (2012) uses a similar model to Albornoz et al. (2012) to explain export entry delays as firms wait for more information to arrive before deciding to enter a new market. Fernandes and Tang (2014) apply a similar learning model to a set of Chinese exporters where firms are uncertain about the demand in a potential market. In their model, a potential entrant in a market observes signals from other firms in the same city that also export to that market so that the learning spillovers are within a geographical cluster. In contrast, my model does not limit the learning spillover to be local and allows firms to learn from all other firms. Moreover, my paper focuses on the product dimension and the within-firm product churning in a market rather than the entry decision of a firm in a country. My model also shares similar elements as the model in Timoshenko (2015), which shows that older firms are less likely to switch products because they have more information about market demand. In her paper, firms frequently add or drop a product because they do not know the overall attractiveness of their brands. As they grow older and become more certain about the demand, they respond less to demand uncertainty and switch products less frequently. In Timoshenko (2015), since demand uncertainty comes from the brand appeal uncertainty, a firm only needs to learn from their overall experience and does not need to learn about the demand for each specific product. Product switching results from changes in the product scope (the number of products exported). The firm's decisions of which product to add or drop are not specified. I add to this analysis by allowing firms to learn about the product appeal for a specific product from both other firms and from their own experience.

2.3 Data

In this section, I describe the dataset and provide motivating evidence for the model. The main source of data for this project is from the Customs data collected by the Chinese Customs Office. The raw dataset covers the universe of Chinese firms that export (or import) from 2000 to 2006. It reports f.o.b value of firm's monthly transactions for exports/imports in U.S. dollars, the quantity of each exported (imported) products, prices, destinations, trade partners, contact information, types of firms (state-owned, private firms, foreign invested and joint ventures) and types of trades (processing versus ordinary trade).

There are over 7000 HS-8 product codes and over 200 destination countries recorded in the dataset. The Customs Data report transactional level values at a monthly frequency. However, a firm might not export to a market in every month. In addition, monthly level data would likely contain some seasonality.[1] To overcome these challenges, I aggregate the monthly raw data to the annual level. I also omit the category of processing trade and only include ordinary exporters. The reason for this is that for processing exporters, it is often the case that they export goods back to their parent company. The room for learning about the market demand is therefore limited as they often would not have to conduct market research. I also exclude all trade intermediaries (wholesalers).[2]

[1] See Manova and Zhang (2012).

[2] Trade intermediaries are identified by the keywords in their registered names, such as: jin3chu1kou3, jingmao, maoyi. This has been a common practice in the literature.

Table 2.1: Comparisons between multi-product firms and single product firms

Firm Type	Percentage of firms	Export Sales Shares
Single-Product	29.13%	13.52%
Multi-Product	70.87%	86.48%
2	17.31%	9.56
3	11.24	7.21
4	7.87	5.61
5	5.76	4.74
6	4.30	3.80
7-10	9.82	10.82
11-20	7.98	12.60
21-50	4.30	11.69
50+	2.79	20.45

Note: Mean across all years 2000-2006. Products are defined at HS-6 level.

This leaves me with a sample of only manufacturing firms that produce and export their own goods.

The raw data series spans from 2000 to 2006 with products coded at the 8-digit level. The HS product classification is used to identify products going through customs. The first two digits identify the broad categories of the product. The remaining digits describe the subcategories to which the product belongs.[3] However, the HS product classification was revised in 2002 and the matching between the old and the new classification is not available. Since the project relies on the analysis at the product level among multi-product firms, I aggregate products to the HS-6 digit level.

Table 2.1 reports the breakdown of firms across years in the Customs dataset. The majority of Chinese firms export more than one product in a year (almost 71% of manufacturers). On average, a Chinese firm exports 9.32 products in a year, and the median number of exported products is 3. Moreover, multi-product firms also make up most of the total export sales from China (86% of the sales).

Table 2.2 shows the descriptive statistics for the Customs Data. Panel A provides the broad characteristics of the market conditions. On average, in a given product-market, there are 7.69 Chinese firms in a year. Out of these firms, about 5.06 firms are new entrants and 3.93 will exit in the next period. Panel B provides more insights into the perspective of firms when they add or drop

[3]For example, HS code 620920 refers to babies' clothings made of cotton.

Table 2.2: Descriptive statistics for Chinese Customs Data

Panel A: Descriptive Statistics at the product-market level						
	Mean	Median	St. Dev.	25^{th}	75^{th}	90^{th}
Number of firms	7.69	2	28.04	1	6	15
New entrants	5.06	2	17.83	1	4	10
Exiting firms	3.93	1	15.87	0	3	8

Panel B: Descriptive statistics at the firm-product-market level						
	Mean	Median	St. Dev.	25^{th}	75^{th}	90^{th}
Group size before adding	7.24	2	27.54	0	6	15
Group size before dropping	8.25	2	28.28	1	6	16

Note: Mean across all years. Products are defined at HS-6 digit level. A group size consists of all firms that export a product to a market in a year.

a product. Firms observe 7.24 firms that supply a product to a market in the previous year before adding that product in the current period. Before a firm drops a product in the next period, they observe 8.25 firms (including themselves). The median group size in the data is smaller than the mean (2 firms). This means that the dataset has a large right tail in the number of signals that a firm can observe. In the empirical analysis, I only consider surviving firms' decisions. This is to ensure that I capture firm product switching behaviors rather than entry and exit into a market.

2.3.1 Product switching at the firm level

Next, I provide some stylized facts about firm's product switching. These facts are motivating evidence for how I model firms' behavior in the theory section.

2.3.1.1 Firms frequently change their product mix

The first observation from the data is that firms frequently change their product mix. Table 2.3 decomposes firms into four mutually exclusive groups: (i) Inactive: firms that do not change their product mix between t and $t+1$, (ii) Add only: firms that only add product(s), (iii) Drop only: firms that only drop product(s) and (iv) Both: firms that do both adding and dropping. Product switching firms are those that change their product mix between two periods by either adding a new product, dropping an existing product or both. I include only surviving firms between t and $t+1$ and exclude new entrants or exiting firms. Bernard et al. (2010b) found that over 50% of American firms

Table 2.3: Product Switching among Chinese Firms

Firm activity	World	North America	South America	Asia	Europe	Africa	Oceania
Inactive	38.03%	41.56	53.36	36.28	41.67	53.2	52.07
Product Switching	61.97%	58.44	46.64	63.72	58.33	46.8	47.93
Add only	14.37%	8.61	8.61	8.0	8.67	8.76	8.44
Drop only	13.97%	20.44	17.29	21.36	19.45	16.4	17.31
Both	33.64%	29.39	20.74	34.36	30.21	21.64	22.18

Note: This table shows the average annual activity of surviving exporters. A firm is classified as having added a product if they did not export any in the previous two years, but do in this period. In a similar manner, firms drop a product when they reported positive revenue in the previous year but do not export this year. Mean across all years.

change their product mix every 5 years. Among Chinese firms in the sample, I found a similarly large percentage (almost 62%) that change their product mix in a year. When broken down into continental markets, the shares of product switching firms are smaller than in the full sample, but still remain fairly large. Compared to markets that are further away, such as South America or Africa, Asia is arguably the most familiar market for Chinese exporters and also has the highest rate of product switching. This suggests that firms are able to respond more to the changes in demand in more familiar markets as more information is available to them.

2.3.1.2 Older firms are less likely to switch products

Another observation established from the data is that more experienced firms are less likely to do product switching. Table 2.4 shows the OLS regression of a firm being a product switcher on a firm's export age and the total export sales for a firm. The dependent variable is a dummy indicator for whether the firm changes their product mix between two consecutive years. I include only surviving firms, excluding those that only exist for one period. Column (1) shows that age has a statistically significant and negative impact on a firm being a product switcher. Column (2) includes other controls, such as export sales and the number of products a firm exports. Conditional on sales and product scope, the more experienced a firm is (higher export age), the less likely they are to switch products. The results remain robust at both the aggregate level (firm-year) and the

Table 2.4: Age dependence

VARIABLES	(1) switchers	(2) switchers	(3) switchers	(4) switchers
Export Age	-0.103***	-0.0626***	-0.0770***	-0.0481***
	(0.00206)	(0.00161)	(0.00105)	(0.000662)
Log sales		-0.0126***		-0.0117***
		(0.000905)		(0.000390)
Log scope		0.262***		0.412***
		(0.00215)		(0.00228)
Constant	0.902***	0.680***	0.585***	0.451***
	(0.00533)	(0.0117)	(0.00302)	(0.00460)
Observations	78,860	78,860	531,128	531,128
R-squared	0.133	0.392	0.078	0.393
Level of obs	Firm-year	Firm-Year	Firm-Country-Year	Firm-Country-Year
Sector FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: Dependent variable is a dummy for whether a firm changes their product mix between two consecutive periods. Sample includes only surviving firms between 2001-2006 since switching activities are not observed in the first year of the data. Scope is the number of products that a firm exports in a given year.

destination level (firm-country-year) of observations. This is consistent with the hypothesis that firms learn about the demand in the market. Not only does a firm learn from other firms, but they also gain information themselves from serving in the market. Younger firms are more likely to experiment with products because they have less information about the market demand and their product appeal to the consumers than older and more experienced firms. As a firm grows older, they are able to gather more information to resolve market uncertainty.

Overall, the motivating evidence in the data suggests that the majority of exporters are multi-product exporters and these firms frequently add or drop products from their product mix to a destination market. These product switching behaviors are affected by the degree of market uncertainty (proxied by geographical or economic distance from China) and a firm's accumulation of knowledge from experience. I build a model of demand uncertainty that builds on these facts.

2.4 Model

In this section, I present a simple model of demand learning where firms face an uncertainty about demand in a market. In every period, firms decide whether to revise their product mix (product switching). Firms consider adding new products by forming expectations of the consumer demand based on signals they observe from other firms that have previously exported these products in that market. When a firm considers dropping an existing product, they use the information from their own experience and from other firms to re-evaluate that product's profitability. The learning effect only occurs within a destination market and does not affect the strategic behavior across markets.

2.4.1 Consumers

Each country j has measure l_j of identical consumers. Preferences are given by the CES utility function where the consumption of the composite good is given by:

$$C_{jt} = \left(\sum_{i=1}^{N+1} \int_{\Omega_{ijt}} (e^{a_{jgt}(\omega)})^{1/\sigma} c_{jt}(\omega)^{(\sigma-1)/\sigma}) d\omega) \right)^{\frac{\sigma}{\sigma-1}}$$

where Ω_{ijt} is the mass of available products in country j imported from country i in period t, $c_{jt}(\omega)$ is the consumption of a product $\omega \in \Omega_{ijt}$ in country j, and $a_{jgt}(\omega)$ is demand shock for product in country j. The composite product index takes the following CES form:

$$c_{jt}(\omega) = \left(\sum_{g=1}^{G_{ijt}(\omega} c_{jgt}(\omega)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma-1}{\sigma}}$$

where g indicates varieties within product ω; $c_{jgt}(\omega)$ is the consumption of variety g of product ω in country j. The aggregate price index is given as:

$$P_{jt} = \left(\sum_{i=1}^{N+1} \int_{\Omega_{ijt}} e^{a_{jgt}(\omega)} \sum_{g=1}^{G_{ijt}(\omega)} p_{jgt}(\omega)^{1-\sigma} d\omega \right)^{\frac{1}{\sigma}}$$

where $p_{jgt}(\omega)$ is the price of variety g of product ω in country j.

The demand function for a specific product in a given market is:

$$q_{jgt}(\omega) = e^{a_{jgt}(\omega)} \frac{p_{jgt}(\omega)^{-\sigma}}{P_{jt}^{1-\sigma}} Y_{jt}$$

2.4.2 Firms

There exists a continuum of firms and each of these firms has a brand ω. They each have a firm-specific constant productivity level φ; the higher the productivity is, the more efficient they are and the lower the cost of production is. For each product that a firm exports to a market, the profitability of that product depends on two factors:

1. Product-specific productivity φ_g. This is the same across all destinations and time.

2. Destination-product specific demand shock a_{jgt} that is different across products, destinations and time. This demand shock is written mathematically as:

$$a_{jgt}(\omega) = \lambda_{jg} + \varepsilon_{jgt}(\omega) \tag{2.1}$$

where λ_{jg} is the product appeal index in destination j. This is common among all firms supplying product g to market j and reflects the attractiveness of product g to customers in j. Firms do not know this index prior to supplying the good and can only form expectations about the product appeal, that is $\lambda_{jg} \sim N(\bar{\lambda}_{jg}, \sigma_{\lambda}^2)$. For tractability, the i.i.d intertemporal preference shock is $\varepsilon_{jgt} \sim N(0, \sigma_{\varepsilon}^2)$ and for simplicity, these components in the demand shocks are assumed to be independent of each other.

In each period, firms face a constant fixed cost of exporting to a market j from source country i for each product f_{ij}. This reflects the cost of a firm setting up the distribution network or marketing research to introduce a new product to the market. The more products they produce, the higher the total fixed costs in that market.

Within a firm associated with a constant productivity φ, their products are arranged in a product ladder. Each product has a product efficiency associated with the ranking of the product $\frac{\varphi}{g^{\alpha}}$ where $\alpha > 0$. The firm is most productive at producing their core product (i.e. when g = 1). As they go down the product ladder, a firm becomes less productive at producing each product.

Given the firms' beliefs about the individual product appeal λ_{jg}, they choose the number of products exported to market j and the quantity for each product before entering the market. Their expected profit for all products in destination j is the sum of profits of all G goods that they export to j. A firm from source country i exporting to country j solves the following maximization problem of choosing their product scope and the quantity of each product:

$$\max_{\{q_{ijgt}\},G_{jt}} \Pi_t = \mathbb{E}\sum_{g=1}^{G_{jt}} \left[q_{ijgt}^{\frac{\sigma-1}{\sigma}} e^{a_{jgt}/\sigma} P_{jt}^{\frac{\sigma-1}{\sigma}} Y_{jt}^{1/\sigma} - \frac{\tau w_{it} g^{\alpha}}{\varphi} q_{ijgt} - f_{ij} \right] \tag{2.2}$$

The expectation operator in equation (3.3) is applied to the demand shock $a_{jgt} = \lambda_{jg} + \varepsilon_{jgt}$ and f_{ij} is the recurring fixed cost of exporting a product to market j. Solving this maximization problem gives the optimal quantity for a product g:

$$q_{ijgt} = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} \left(\frac{\varphi}{\tau w_{it} g^{\alpha}}\right)^{\sigma} [\mathbb{E}(e^{\lambda_{jg}+\varepsilon_{jgt}})]^{\sigma} P_{jt}^{\sigma-1} Y_{jt} \tag{2.3}$$

The market clearing price is:

$$p_{ijgt} = \frac{\sigma}{\sigma-1} \left(\frac{\varphi}{g^{\alpha}}\right)^{-1} e^{a_{ijgt}/\sigma} \left[\frac{\tau w_{it}}{b_{ijgt}}\right] \tag{2.4}$$

where $b_{ijgt} = \mathbb{E}(e^{\lambda_{jg}+\varepsilon_{jgt}})$. The realized sales of a firm for a product g in destination j can be written as:

$$R_{ijgt}(\omega) = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1} \left(\frac{\varphi}{g^{\alpha}}\right)^{\sigma-1} (b_{jgt}^{\sigma-1}) e^{a_{jgt}/\sigma} (\tau w_{it})^{1-\sigma} A_{jt} \tag{2.5}$$

where A_{jt} is an aggregate demand component.

Given the above results, we can write the expected profits for the firm given the quantity of each product g in the range of G products that they export to j :

$$\mathbb{E}(\Pi_{ijt}) = \sum_{g=1}^{Gijt} \left[\frac{(\sigma-1)^{\sigma-1}}{\sigma} [E(exp(\theta+\lambda+\varepsilon)]^{\sigma} \left(\frac{\varphi}{\tau w_{it} g^{\alpha}}\right)^{\sigma-1} P_{jt}^{\sigma-1} Y_{jt} - f_{ij} \right] \tag{2.6}$$

2.4.3 The product scope decision

Given the optimal quantity of each product, a firm makes the decision of how many products to export to market j. The expected profit of a product g exported to market j is:

$$\Pi_{ijgt} = \underbrace{\frac{(\sigma-1)^{\sigma-1}}{\sigma^{\sigma}} \left(\frac{\varphi}{g^{\alpha}}\right)^{\sigma-1} E_{a_{jgt}} \left[e^{\frac{\lambda_{jg}+\varepsilon_{jgt}}{\sigma}} \right] \frac{P_{jt}^{\sigma-1} Y_{jt}}{(\tau_{ij} w_{it)^{\sigma-1}}}}_{\text{operating profit}} - \underbrace{f_{ij}}_{\text{fixed cost}} \tag{2.7}$$

A firm decides to export a product g if they can earn positive profit for that good. Because the product-specific efficiency $\frac{\varphi}{g^{\alpha}}$ decreases as the firm goes down the product ladder, adding more products decreases the expected variable profits from each successive product. The firm continues to go down the product ladder and adds more products as long as they can cover the fixed costs of exporting. In a model without demand uncertainty, firms with the same productivity φ produce the same number of products. However, the existence of the uncertainty in the product appeal λ_{jg} induces product switching at the firm level in their export mix to destination j. Because of this, conditional on entry into a destination market, a firm makes adjustments regarding their product mix in each period: whether to add a new product or to drop an existing product from their mix. Next, I show how the decisions for product switching are made.

2.4.4 Decision to add/drop a product

From equation (2.7), we can solve for the productivity cutoff from the zero profit condition as follows:

$$\frac{(\sigma-1)^{\sigma-1}}{\sigma^{\sigma}}\left(\frac{\varphi}{g^{\alpha}}\right)^{\sigma-1} E_{a_{jgt}}\left[e^{\frac{a_{jgt}}{\sigma}}\right]\frac{P_{jt}^{\sigma-1}Y_{jt}}{(\tau_{ij}w_{it)^{\sigma-1}}} = f_{ij}$$

where again, $\frac{\varphi}{g^{\alpha}}$ is the firm efficiency associated with producing product g. As discussed above, the demand for product g in market j is uncertain and firms form beliefs for the product appeal λ_{jg}. Given these beliefs, we can solve for the firm's prior belief of the productivity cutoff for each product g in destination j:

$$\varphi_g^{\text{prior}} = \underbrace{\frac{\varphi}{g^{\alpha}} = \left(\frac{\sigma^{\sigma}}{\sigma-1}\right)(f_{ij})^{\frac{1}{\sigma-1}}\left[\frac{(\tau_{ij}w_{it})}{P_{jt}(Y_{jt})^{\frac{1}{\sigma-1}}}\right]}_{\text{market conditions}}\underbrace{\left(\frac{1}{exp\left[\frac{\bar{\lambda}_{jg}^{prior}}{\sigma}+\frac{1}{2\sigma^2}(v_{\lambda}+v_{\varepsilon})\right]}\right)^{\frac{\sigma}{\sigma-1}}}_{\text{demand uncertainty}}$$

This cutoff depends on overall market conditions in the destination market j, the firms' productivity level and a component that reflects the demand uncertainty for each product. In each period, a firm evaluates the profitability of a product by comparing their productivity for producing a product g to their belief for the cutoff for that product in destination j. Based on the information that a firm receives, they update their beliefs for the cutoff and re-evaluate their decisions. This generates product switching at the firm level.

2.4.4.1 Adding a product:

Firms observe n incumbent firms exporting product g to market j in the previous period and the average demand shock for all these firms $\bar{a}_{jg,t-1}$. Given these signals, a firm updates their beliefs about the product appeal so that the posterior distribution of the product attribute λ_{jg} is distributed normally with the following posterior mean and variance:[4]

$$\bar{\lambda}_{jgt}^{\text{posterior}} = \left(\frac{\sigma_{\varepsilon}^2}{\sigma_{\varepsilon}^2 + n\sigma_{\lambda}^2}\right)\bar{\lambda}_{jg} + \left(\frac{n\sigma_{\lambda}^2}{\sigma_{\varepsilon}^2 + n\sigma_{\lambda}^2}\right)(\bar{a}(n)) \tag{2.8a}$$

$$v_n = \frac{\sigma_{\lambda}^2\sigma_{\varepsilon}^2}{\sigma_{\varepsilon}^2 + n\sigma_{\lambda}^2} \tag{2.8b}$$

where $\bar{a}(n)$ is the average signal of the demand shock for the product in that market that the firm observes from all other existing firms. The posterior mean of the product appeal λ_{jg} in equation (2.8a) is a weighted average of the firm's prior belief of the product appeal $\bar{\lambda}_{jg}$ and the average of all signals that they observe $\bar{a}(n)$. As they observe more signals or n increases, the weight on the firm's prior belief decreases, firms place more weight on the value of the signals. Additionally, as more signals are observed, the posterior variance in (2.8b) decreases and beliefs become more accurate.

Given the posterior distribution of the product appeal, a firm can update their beliefs for the productivity threshold for a product g as:

$$\varphi_g^{\text{post}} = \left(\frac{\sigma^{\sigma}}{\sigma-1}\right)(f_{ij}g^{\alpha})^{\frac{1}{\sigma-1}}\left[\frac{(\tau_{ij}w_{it})}{P_{jt}(Y_{jt})^{\frac{1}{\sigma-1}}}\right]\left(\frac{1}{exp\left[\frac{\bar{\lambda}_{jg}^{\text{post}}}{\sigma} + \frac{1}{2\sigma^2}(v_{\lambda}+v_{\varepsilon})\right]}\right)^{\frac{\sigma}{\sigma-1}} \tag{2.9}$$

where $\bar{\lambda}_{jg}^{post}$ is defined in equation (2.8a). Since $\bar{a}(n)$ represents the average of all signals from other firms, we can find the effect of learning from this average signal on the productivity cutoff for product g as follows:

$$\frac{\partial ln\varphi_g}{\partial\bar{a}} = -\frac{1}{\sigma-1}\left(\frac{2n\sigma_{\lambda}^2}{\sigma_{\varepsilon}^2 + n\sigma_{\lambda}^2}\right) = \frac{-1}{\sigma-1}\left(\frac{\sigma_{\varepsilon}^2}{2n\sigma_{\lambda}^2} + \frac{1}{2}\right)^{-1} < 0 \tag{2.10}$$

[4]The derivation for the posterior mean and variance is in the Appendix

The effect of the number of firms revealing signals on the magnitude of the change in elasticity is:

$$\frac{\partial}{\partial n}\left|\frac{\partial \ln \varphi_g}{\partial \bar{a}}\right| = \left(\frac{-1}{2(\sigma-1)}\right)\left[\frac{\sigma_\varepsilon^2}{2n\sigma_\varepsilon^2}+\frac{1}{2}\right]^{-2}\left[\frac{\sigma_\varepsilon^2}{n\sigma_\lambda^2}\right] > 0 \tag{2.11}$$

Equation (2.10) shows that more positive signals on average revealed by other firms in the market lowers the productivity cutoff of a product g in market j. In equation (2.11), the magnitude of the effect of learning on lowering the posterior cutoff is higher as the number of signals increases. As the productivity cutoff determines the firm's profitability for a product in a market, lower productivity cutoff induces the firm to start exporting a product. Equations (2.10) and (2.11) lead to the following proposition:

Proposition 1 *: The probability that a firm adds a given product to a market is increasing in the strength of signals revealed by other firms and more so if positive signals are revealed by more firms.*

2.4.4.2 Dropping a product

In this section, I assume that once a firm is in a product-market, they only look at their experience to decide whether to drop a product from their mix. This is the case when a firm has no other peers in the same product market (i.e. they are the only supplier) and the only source of learning about demand is from their own past history. Suppose that the firm has supplied the product g for T periods. For each period $t = \{1, 2, \dots, T\}$, they receive a signal from themselves as they observe the demand shocks. The signal that they receive each period can be written as:

$$a_{jg,t}(\omega) = \lambda_{jg} + \varepsilon_{jg,t}(\omega) \tag{2.12}$$

where $\varepsilon_{jg,t} \sim N(0, \sigma_\varepsilon^2)$ and $\lambda_{jg} \sim N(\bar{\lambda}, \sigma_\lambda^2)$.

After having received T signals from T periods, the firm updates their beliefs of the product appeal λ_{jg} with the following posterior distribution:

$$\lambda_{jg}^{post} = \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + T\sigma_\lambda^2}\bar{\lambda}_{jg} + \frac{T\sigma_\lambda^2}{\sigma_\varepsilon^2 + T\sigma_\lambda^2}\bar{a}(T) \tag{2.13}$$

$$V_T = \frac{\sigma_\lambda^2 \sigma_\varepsilon^2}{\sigma_\varepsilon^2 + T\sigma_\lambda^2} \tag{2.14}$$

where $\bar{a} = \frac{1}{T}(\sum_{t=1}^{T} a_1 + a_2 + \ldots a_T)$ is the mean of the T observed shocks that a firm has received. Since this is at the product-market level, the number T of signals that they observe is the product tenure in that market. Similar to the case of adding, the posterior mean of the product appeal λ_{jg} is a weighted average of the firm's prior $\bar{\lambda}_{jg}$ and the firm's average signals, with more weight on the firm's own signals $\bar{a}(T)$ if product tenure T increases.

Comparative statics show the effect of learning on lowering the productivity cutoff as:

$$\frac{\partial ln\varphi_g}{\partial \bar{a}} = \frac{-1}{\sigma - 1}(T\sigma_\lambda^2)(\sigma_\varepsilon^2 + T\sigma_\lambda^2)^{-1} < 0 \tag{2.15}$$

$$\frac{\partial}{\partial T}\left|\frac{\partial ln\varphi_g}{\partial \bar{a}}\right| = \frac{1}{\sigma - 1}\left[\frac{\sigma_\lambda^2}{\sigma_\varepsilon^2 + T\sigma_\lambda^2}\right]\left[1 + \frac{1}{(\sigma - 1)}\frac{T\sigma_\lambda^2}{(\sigma_\varepsilon^2 + T\sigma_\lambda^2)}\right] > 0 \tag{2.16}$$

The effect of demand shocks is magnified as the product tenure in the firm increases. In response to a positive signal, for example, the threshold for product g decreases, the increase is even larger as the firm supplies the product longer. Moreover, as product tenure increases, the variance of the posterior distribution decreases, and the firm has a more precise estimate of the true product appeal λ_{jg}.

2.4.5 Learning from both a firm's own signal and from other firms' signals

Unlike the previous case when a firm is the sole supplier of a product in a market, in this section, I assume that once a firm has supplied a product g to a market j, they have access to two forms of signals: (1) signals from their own experience of having supplied the product and (2) signals from other firms in the market that also supply the same product. In this section, I study the case where the firm accumulates signals from past experience while also observing signals from others in deciding whether to drop an existing product. While I assume that firms accumulate their own information over time, I only let firms look at their peers' signals in the current period t, not a full history of signals. In other words, the model implies that firms forget about past signals from peers. For tractability and simplicity, I assume firms only consider other firms' signals in the same period. In the empirical results, I relax this assumption and test the effect of learning a full history of signals on a firm's decision to drop a product.

The posterior distribution of the product appeal has the following mean and variance:

$$\mu^{posterior} = \left(\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + T\sigma_\lambda^2 + n\sigma_\lambda^2}\right)\bar{\lambda} + \left(\frac{T\sigma_\lambda^2}{\sigma_\varepsilon^2 + T\sigma_\lambda^2 + n\sigma_\lambda^2}\right)\bar{a}(T) + \left(\frac{n\sigma_\lambda^2}{\sigma_\varepsilon^2 + T\sigma_\lambda^2 + n\sigma_\lambda^2}\right)\bar{A}(n) \tag{2.17}$$

$$v^{posterior} = \frac{\sigma_\lambda^2\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + T\sigma_\lambda^2 + n\sigma_\lambda^2} \tag{2.18}$$

where $\bar{a}(T)$ is a firm's own signal for the product appeal, averaged across T years that the firm has supplied product g in market j. $\bar{A}$ is the average signal revealed by n other firms in the product-market jg in period t. Compared to the case in the previous section, where a firm only observes their own signal, the variance of the posterior distribution when the firm observes signals from other firms is lower. Another implication for the posterior mean is that as a firm gathers more information, either by having supplied the product longer in the market (higher T) or by having received more signals from other firms (higher n), the prior $\bar{\lambda}$ becomes less important.

The effect of learning from other firms on the productivity cutoff is:

$$\frac{\partial ln\varphi_g}{\partial \bar{A}} = \left(\frac{-1}{\sigma - 1}\right)\left[\frac{\sigma_\lambda^2 n}{\sigma^\varepsilon + T\sigma_\lambda^2 + n\sigma_\lambda^2}\right] < 0 \tag{2.19}$$

The more positive the average signal from other firm $\bar{A}$, the lower the productivity cutoff for product g in market j, the less likely the firm will drop that product.

The effect of learning from a firm's own signal on the cutoff is:

$$\frac{\partial ln\varphi_g}{\partial \bar{a}(T)} = \left(\frac{-1}{\sigma - 1}\right)\left[\frac{\sigma_\lambda^2 T}{\sigma^\varepsilon + T\sigma_\lambda^2 + n\sigma_\lambda^2}\right] < 0 \tag{2.20}$$

Positive signals from a firm's own history of signals lower the expected productivity cutoff. The likelihood of dropping a product decreases as a result.

$$\frac{\partial}{\partial T}\left|\frac{\partial ln\varphi_g}{\partial \bar{a}}\right| = \frac{-1}{\sigma-1}\left[\frac{(\sigma_\varepsilon^2+n\sigma_\lambda^2)\sigma^\lambda}{(\sigma_\varepsilon^2+T\sigma_\lambda^2+n\sigma_\lambda^2)^2}\right] > 0 \tag{2.21}$$

Equation (2.21) shows that the effect of a firm's own signal on the likelihood of dropping a product increases as the product tenure increases. Longer product tenure (higher T) implies that the posterior variance of the belief is also smaller. The uncertainty about the product appeal in the market decreases because beliefs are more accurate. Therefore, if a firm has been receiving positive signals of a product's demand from their own experience of selling that product, they are more likely to trust their own positive signal as accurate and more likely to continue selling the product. This leads to the following proposition:

Proposition 2 *: The probability that a firm drops a product from a market is decreasing as the firm receives more positive signals from their own experience. The effect of learning from their experience is stronger the longer they have supplied a product in a market.*

Recall that the effect of other firms' signals on lowering the productivity cutoff is:

$$\frac{\partial ln\varphi_g}{\partial \bar{A}} = \left(\frac{-1}{\sigma-1}\right)\left[\frac{\sigma_\lambda^2 n}{\sigma^\varepsilon+T\sigma_\lambda^2+n\sigma_\lambda^2}\right] < 0$$

This effect of other firms' signals depends on both the number of signals revealed n (i.e. the number of firms) and how long the firm has supplied the same product in that market T (i.e. product tenure). Comparative statics show that:

$$\frac{\partial}{\partial n}\left|\frac{\partial \ln\varphi_g}{\partial \bar{A}}\right| = \frac{1}{\sigma-1}\left[\frac{(\sigma_\varepsilon^2+T\sigma_\lambda^2}{(\sigma_\varepsilon^2+T\sigma_\lambda^2+n\sigma_\lambda^2)^2}\right] > 0 \tag{2.22}$$

More positive signals revealed by other firms lower the productivity cutoff. The magnitude of this drop is even higher when there are more firms revealing the signals.

$$\frac{\partial}{\partial T}\left|\frac{\partial \ln\varphi_g}{\partial \bar{A}}\right| = \frac{-1}{\sigma-1}\left[\frac{n\sigma_\lambda^4}{(\sigma_\varepsilon^2+T\sigma_\lambda^2+n\sigma_\lambda^2)^2}\right] < 0 \tag{2.23}$$

Equation (2.23) shows that the effect of signals from other firms is mitigated as product tenure increases. On the other hand, Equation (2.21) shows that the effect of a firm's own signal is strengthened by the number of years that they have supplied the product. This is summarized in the following proposition.

Proposition 3 *The likelihood of dropping a product for a firm decreases when there are positive signals about the market demand from other firms. The learning effect from other peers is stronger when there are more firms revealing signals but weaker as product tenure increases.*

To summarize, Propositions 2 and 3 show that as a firm's product tenure in a market increases, the effect of learning from a firm's own experience is stronger while the effect of learning from other firms is weaker. Intuitively, as a firm survives longer in that product-market, they have gained more experience and accumulated more information in the form of signals about the market demand and their profitability. As a result, they are more likely to trust their own experience than others. This can be seen in equation (21): the weight on other firms' signal $\bar{A}(n)$ decreases as T increases. Moreover, the variance of their beliefs decreases when product tenure increases, beliefs become more accurate.

2.5 Empirical Evidence

In the previous section, I describe the environment of the model and derive the theoretical predictions for how firms decide to add or drop products. In this section, I test these predictions using the dataset on Chinese firms from 2000 to 2006.

2.5.1 Adding a new product

This section examines Proposition 1 and the likelihood that a firm will add a new product after having observed other firms' signals about the demand. The dependent variable is defined as:

$$Add_{ijgt} = \begin{cases} 1, & \text{if Value}_{jg,t-1} = 0, \text{Value}_{jgt} > 0 \\ 0, & \text{otherwise} \end{cases}$$

A firm i is classified as having added a new product g in market j in year t if they report positive sales this period but zero in the previous period. The dummy indicator is zero otherwise. Note that continuing exporters who report positive sales for product g in market j in both t and $t-1$ are not defined and therefore excluded.

The regression to test the theoretical prediction is:

$$\text{Add}_{ijg,t} = \beta_1 \text{ Signal}_{jg,t} + \beta_2 \text{ Signal}_{jg,t} \times \text{N}_{jg,t-1} + \beta_3 \text{ N}_{jg,t-1} + \{FE\} \tag{2.24}$$

The regressors of interest are the average signal revealed by other firms and its interaction with the number of existing firms. The first year in the sample (2000) is not included because I do not observe the previous year's sale. Proposition 1 predicts that the likelihood of a firm adding a product g is increasing the average signal revealed by other firms and more so if there are more firms revealing signals. Therefore, I expect $\beta_1 > 0$ and $\beta_2 < 0$. The sign of β_3 cannot be determined in the model.

In the model, I have derived that the realized sales of a firm is:

$$R_{ijgt}(\omega) = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1} \left(\frac{\varphi}{g^{\alpha}}\right)^{\sigma-1} (b_{jgt}^{\sigma-1}) e^{a_{jgt}/\sigma} (\tau w_{it})^{1-\sigma} A_{jt} \tag{2.25}$$

It is clear from the above equation that the logarithm of the realized sales is a function of the demand signal a_{jgt} in the model, the country-year aggregate components and the firm-product-year components. In the model, a firm receives a signal from other firm a_{jgt} to decide whether they want to add a new product. As a result, the log residual sales after partialling out the fixed effects give us the demand signal a_{jgt}.[5] Therefore, to construct the signal revealed by a firm, I estimate the following regression :

$$\ln R_{ijgt} = \delta_{jt} + \delta_{igt} + a_{ijgt} \tag{2.26}$$

where R_{ijgt} is a a firm's export sales of product g to market j at time t. δ_{jt} and δ_{ijgt} are country-year and firm-product-year fixed effects. The residuals of this regression equal to the demand signal a_{jgt} that is revealed by each firm.

A signal about the market demand from a firm's perspective is defined as the average value of

[5]Fernandes and Tang (2014) use the growth rates of revenues of continuing firms as a proxy for signals. I used a model consistent approach to estimate the demand signal a_{jgt}. This approach is similar to what was done in Kasahara and Tang (2019), Berman et al. (2019), Chen et al. (2018) and Chen et al. (2019). This allows me to include signals from firms that only exist for one period in addition to continuing firms. This is consistent with the models, where signals are revealed by all existing firms. Moreover, this approach allows me to construct a firm's own signal from having supplied a product for the next section even if they only participate for one period. Firms frequently add and drop products in the same period. About 10% of a firm's products in a market in a year are experimental products (products that exist only in one period). Using growth rates of revenue would exclude these experimental products.

signals from all other firms that sell that product in market j at time t:

$$\text{Signal}_{jgt} = \frac{1}{N_{jgt}} \times \sum_{i \in N_{jgt}} a_{ijgt} \tag{2.27}$$

where a_{ijgt} is obtained as seen above and N_{jgt} is the number of firms that sell product g to market j in t.

The regression results are in table 2.5. Signal is calculated as shown in equations (2.26) and (2.27). I include a set of fixed effects to control for the unobservables that can determine a firm's decision in product switching. In all regressions, I control for firm-product-year and country-year fixed effects. These fixed effects control for firm's product specific productivity and any macroeconomic shocks in the destination countries that can influence a firm's production and export decisions. In columns (1) and (2), I include firm-country fixed effects to control for a firm's brand appeal in a market and whether a firm could have an affiliate or receive preferential treatment by the destination country. Firm-year fixed effects control for factors such as financial constraints, supply or productivity shocks at the firm level. In column (1), after controlling for firm-product-year, country-year and firm-country fixed effects, there is a positive and statistical significant relationship between the signal revealed by other firms and the likelihood of a firm adding a new product. The coefficient of 0.0054 suggests that a one standard deviation change above the mean in the value of signals revealed by other firms about the demand for a product raises the likelihood of a firm adding that product by 0.05 percentage points. Evaluating at the mean adding rate, a one standard deviation increase in the value of signals by other firms raises the probability of adding a product by almost 3%.[6] The relationship remains positive and significant when I control for the interaction terms between signal and the number of firms that reveal the signals. The learning effect is stronger if there are more firms revealing the signal, confirming the theoretical predictions of the model. An additional signal from other firms raises the likelihood of adding by 0.49 percentage points, which is about 2.85% when evaluated at the mean adding rate. These results remain robust when I control for other fixed effects in columns (4)-(6).

[6] Fernandes and Tang (2014) estimate a similar result for the extensive margin at the firm level using the same Chinese dataset.

Table 2.5: The effect of learning from other firms on adding a new product

VARIABLES	(1) $\text{Add}_{ijg,t}$	(2) $\text{Add}_{ijg,t}$	(3) $\text{Add}_{ijg,t}$	(4) $\text{Add}_{ijg,t}$
Signal	0.0053683***	0.0048265***	0.0073752***	0.0068365***
	(0.0002693)	(0.0002687)	(0.0003630)	(0.0003356)
Signal × Total Number of firms		0.0000173**		0.0000168**
		(0.0000083)		(0.0000085)
Total number of firms		0.0000274***		0.0000177**
		(0.0000068)		(0.0000077)
Observations	23,997,791	23,997,791	24,037,028	24,037,028
R-squared	0.6348291	0.6348648	0.6170571	0.6170833
Firm-Product-Year	Y	Y	Y	Y
Country-Year	Y	Y	Y	Y
Firm-Country	Y	Y		
Firm-Year			Y	Y

Note: Sample does not include surviving firms in the product-market.
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

2.5.2 Dropping an existing product

Next, I examine the effect of learning on the likelihood of a firm dropping a product g from their product mix to country j. A product is characterized as "dropped" from a firm's product mix to a destination market j if the firm reports positive value of sales in this period but zero in the next period.[7] Once a firm has supplied a product, there are two channels of learning: they can observe the signals from their own experience of selling that product as well as observe signals from other firms selling the same product. After having observed these signals, at the end of period t, they decide whether to continue selling the product in the next period. I define a dummy variable that characterizes whether a firm drops a product in a market:

$$\text{Dropped}_{jgt} = \begin{cases} 1, & \text{if Value}_{jg,t-1} > 0, \text{Value}_{jg,t} = 0 \\ 0, & \text{if Value}_{jg,t-1} > 0, \text{Value}_{jg,t} > 0 \end{cases}$$

[7]The last year in the sample (2006) is not included in the empirical analysis for this section because I do not observe a firm's sale in the following year.

2.5.2.1 Learning from own signal

In this section, I test the theoretical predictions of Proposition 2. The likelihood of a firm dropping a product is decreasing when they have a history of positive signals. The effect of learning from their experience is stronger when they have supplied the product longer. To verify this learning mechanism, I estimate the following regression:

$$\begin{aligned}\text{Dropped}_{ijg,t} = \beta_1 \text{Own Signal}_{ijgt} + \beta_2 \text{Own Signal}_{ijgt} \times \text{Tenure}_{ijgt} \\ + \beta_3 \text{Tenure}_{ijgt} + \{FE\} + \varepsilon_{ijgt}\end{aligned} \quad (2.28)$$

A firm's own signal in period T is the average of the history of all signals from their own experience that they have observed up to period T:

$$\text{Own Signal}_{ijg,t} = \frac{1}{T}\sum_{k=1}^{T} a_{ijgk} \quad (2.29)$$

where a firm's observed demand shock a_{ijgt} from a given period t is estimated in the same way as in equation (2.26), T is the number of years that they have sold product g in market j (product tenure).[8] Theory predicts that positive signals decrease the likelihood that a firm drops a product, therefore, I expect $\beta_1 < 0$. The effect of learning is amplified when product tenure is higher, i.e. β_2 should be smaller than zero. The sign of β_3 is ambiguous and cannot be determined in the model.

Table 2.6 presents the results for the regression. Column (1) shows that there is a negative and significant effect of a firm's history of signals on the likelihood of a product being dropped. The more positive a signal is, the less likely a firm will drop that product. A one standard deviation change in the value of a firm's own observed demand signal reduces the probability of dropping a product by 4.49 percentage points. When evaluated at the mean dropping rate, this corresponds to a 8.9% decrease in the probability of a product being dropped. Controlling for the interaction between signal and product tenure, the effect of signal remains negative and significant. The magnitude of signal on the probability is even higher when product tenure increases. When signals are one standard deviation higher, an additional year of the product tenure is associated with a 4.27 percentage point decrease in the likelihood of a product being dropped. This translates to about 8.25% decrease

[8] Product tenure is reset if a firm stops selling a product at any given period. In other words, firms forget their past signals if they exit the market.

Table 2.6: The effects of learning from a firm's own signal on dropping a product

VARIABLES	(1) Dropped_{ijgt}	(2) Dropped_{ijgt}	(3) Dropped_{ijgt}	(4) Dropped_{ijgt}
Own Signal	-0.0449028***	-0.0362009***	-0.0448587***	-0.0362549***
	(0.0004178)	(0.0005367)	(0.0004187)	(0.0005317)
Own Signal × Product Tenure		-0.0064958***		-0.0064797***
		(0.0003655)		(0.0003677)
Product Tenure		-0.0017130		-0.0004991
		(0.0011449)		(0.0011428)
Observations	2,256,865	2,256,865	2,256,879	2,256,879
R-squared	0.6552919	0.6554439	0.6546116	0.6547574
Firm-Product-Year	Y	Y	Y	Y
Country-Year	Y	Y		
Firm-Country	Y	Y	Y	Y
Firm-Year			Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

in the probability of dropping a product in a destination. While the model cannot determine the direction of the effect of product tenure on a product being dropped, the negative coefficient in the results suggests that longer product tenure is associated with a decrease in the probability of the firm dropping that product. This is similar what Bernard et al. (2010b) observe among U.S. exporters. When I control for other fixed effects in columns (3) and (4), the effect of learning remains negative and significant. Overall, the empirical evidence supports the theoretical predictions that having received good demand signals decreases the likelihood of a product being dropped from a firm's mix. This effect is stronger the longer the firm serves in the market.

2.5.2.2 Learning from others

In addition to learning from their own experience, a firm also observes other peers in the market to update their beliefs about the market demand. I examine this channel of learning from other firms by estimating the following regressions:

$$\begin{aligned}\text{Dropped}_{ijg,t} = \beta_1 \text{Others' Signal}_{ijgt} + \beta_2 \text{Others' Signal}_{ijgt} \times \text{N}_{jgt} \\ + \beta_3 \text{N}_{jgt} + \{FE\} + \varepsilon_{ijgt}\end{aligned} \tag{2.30}$$

where Others' Signal is defined in the same way was equation (2.27), and N_{jgt} is the number of firms (excluding the firm itself) that sell the same product g to market j in t.

Table 2.7: Effect of learning from other firms on dropping a product

VARIABLES	(1) Dropped_{ijgt}	(2) Dropped_{ijgt}	(3) Dropped_{ijgt}	(4) Dropped_{ijgt}
Others' Signal	-0.0204340***	-0.0165511***	-0.0203752***	-0.0165986***
	(0.0009816)	(0.0008614)	(0.0009770)	(0.0008678)
N_{jgt}		-0.0001589***		-0.0001471***
		(0.0000228)		(0.0000201)
Others' Signal $\times N_{jgt}$		-0.0000662***		-0.0000699***
		(0.0000168)		(0.0000176)
Observations	2,760,133	2,760,133	2,760,186	2,760,186
R-squared	0.6351548	0.6359000	0.6343774	0.6350688
Firm-Product-Year	Y	Y	Y	Y
Country-Year	Y	Y		
Firm-Country	Y	Y	Y	Y
Firm-Year			Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results are shown in table 2.7. In column (1), other firms' signal has a negative effect on the probability of a product being dropped from a firm's mix. This means that a firm is less likely to drop a product in response to more positive signals revealed by others. In column (2), I control for the interaction between signal from other firms and the number of firms in the market. Results in column (2) show that the effect of learning from others increases as more firms reveal signals. This confirms Proposition 3 in the theory section. Results remain robust when I include other fixed effects in columns (3)-(4).

2.5.2.3 Learning effects and product tenure

Proposition 3 states that as a firm's product tenure increases, they have accumulated more information (i.e. signals) about the demand of the market, therefore, they depend less on information from others and more on information from their own experience. To empirically verify this, I estimate:

$$\begin{aligned}\text{Dropped}_{ijg,t} &= \beta_1 \text{Others' Signal}_{ijgt} + \beta_2 \text{Others' Signal}_{jgt} \times \text{Tenure}_{ijgt} \\ &+ \beta_4 \text{Own Signal}_{ijgt} + \beta_5 \text{Own Signal}_{jgt} \times \text{Tenure}_{ijgt} + \{FE\} + \varepsilon_{ijgt}\end{aligned} \tag{2.31}$$

More positive signals from other firms and signals from a firm's own experience are predicted to lower the likelihood of a firm dropping a product. Therefore, the signs of β_1 and β_4 should be negative. Product tenure strengthens a firm's own signal while reducing the effect of others' signals, so I expect that β_2 should be positive while β_5 should be negative. Results are presented in Table 2.8. In column (1), I found that an additional year of product tenure reduces the impact of other firms' signal by 0.005. When the value of signals from the other firms increases by one standard deviation from the mean, an additional year in the product tenure decreases the likelihood of dropping a product by 1.34 percentage points or 2.7% decrease in the probability of dropping a product. The coefficients suggest that it takes about 3 years of the product tenure to cancel out the effect of the other firms' signals. On the other hand, an additional tenure year raises the learning effect from a firm's own experience by 0.0067. As product tenure increases by 1 year, a one standard deviation increase in the value of a firm's own signal decreases the probability of a product being dropped by 4.2 percentage point (or 8.4% decreases in the probability of dropping). Compared to the effects of learning from other firms, the effect of learning from a firm's own experience is a lot higher (8.4% versus 2.7%). The results are similar when I control for other fixed effects (firm-product-year, firm-country and firm-year) in column (2).

2.5.3 Past history of signals

In the model, I assume that firms only look at one period's signal before making a decision to add or drop a product. In the case of adding a new product, they look at the previous period's signals. When they decide to drop an existing product, a firm only looks at the same period's signal from other firms in time t while they look at their entire history of accumulated signals. This is likely to be not true in reality. It is possible that a firm would consider signals about the market demand from their peers many periods before making their decisions to start selling a new product. In this subsection, I relax the assumptions in the model and let firms consider all observed signals from

Table 2.8: Comparing effects of learning

VARIABLES	(1) Dropped_{ijgt}	(2) Dropped_{ijgt}
Others' Signal	-0.0185716***	-0.0183225***
	(0.0015202)	(0.0015225)
Others' Signal × Tenure	0.0051648***	0.0050516***
	(0.0007335)	(0.0007312)
Own Signal	-0.0353304***	-0.0353927***
	(0.0005510)	(0.0005457)
Own Signal × Tenure	-0.0067828***	-0.0066925***
	(0.0003549)	(0.0003573)
Observations	2,134,884	2,134,925
R-squared	0.6586546	0.6580227
Firm-Product-Year	Y	Y
Country-Year	Y	
Firm-Country	Y	Y
Firm-Year		Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

previous periods.

The average of the accumulated signals from other peers is calculated as:

$$\text{Signal}_t = \frac{1}{T} \times \left[\sum_{k=1}^{T} \frac{1}{N_k} \sum_{i \in N_k} a_{ijgk} \right] \tag{2.32}$$

where N_t is the number of firms in a given period, T is the number of periods before time t that they have serve in the destination market, a_{ijgk} is the demand signal for product g revealed by firm i in market j at time k. This signal is estimated in the same way as shown in equation (2.26) from the residuals regression. In other words, equation (2.32) shows the average of all past history of signals that a firm observes before period t.

Next, I examine the theoretical predictions in the model when accounting for firm's history of observed signals from other firms using equation (2.32) as the new proxy for average signals. Table 2.9 shows the effects of learning on the probability of adding or dropping a product using a full history of cumulative signals from other peers. As shown in column (1), after controlling

Table 2.9: Learning with full history of signals

VARIABLES	(1) Add_{ijgt}	(2) Add_{ijgt}	(3) Dropped_{ijgt}	(4) Dropped_{ijgt}
All firms' past signals	0.0027417***	0.0019600***		
	(0.0002925)	(0.0003428)		
Others' past signals			-0.0235066***	-0.0423905***
			(0.0013882)	(0.0015839)
Observations	17,790,510	17,839,220	2,147,038	2,319,944
R-squared	0.6884900	0.6638617	0.6657559	0.5156453
Firm-Product-Year	Y	Y	Y	Y
Country-Year	Y	Y	Y	Y
Firm-Country	Y		Y	
Firm-Year		Y		Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

for firm-product-year fixed effects, country-year fixed effects and firm-country fixed effects, there is a positive and significant effect of other firms' signals on the likelihood of a firm adding a new product. The effect remains significant when controlling for other fixed effects (firm-product-year, country-year and firm-year) in column (2). Column (3) and (4) show the effect of the strength of cumulative signals from other firms on the probability of a product being dropped. More positive signals in the past decrease the likelihood that a firm will drop a product. Compared to results in Table 2.7, the size of the coefficients on learning in Columns (3) and (4) in Table 2.32 is bigger.

2.6 Conclusion

In this paper, I show that firms frequently engage in product switching. Firms tend to switch products more in markets that are more familiar. Older firms also are less likely to be product-switchers. The data suggest that there is uncertainty in the market that influences a firm's decision to add or drop a product. I developed a model of learning about demand where firms form a prior expectation of the product's appeal in a market. Firms update these beliefs based on signals that they observe from other firms in the market while also taking into account their own observations whenever possible. I use the Chinese Customs Dataset from 2000 to 2006 to document firm-level learning about market demand. Good signals from other firms who supply a product in a destination market raise the probability that a firm will add that same product to their mix by 3%. Once they have started supplying a product, they are able to observe signals themselves from their experience or from other incumbents in the same product-market. I found that good historical signals from a firm's own experience and good signals from other incumbents decrease the probability of a firm dropping a product by 8.9% and 4.1% respectively. As product tenure increases, the effect of learning from other firms decreases while learning from a firm's own signal becomes more important. This is because firms that have supplied a product longer hold a more precise belief of the true demand. Therefore, they place more importance on their own signals than those received from other firms. Specifically, when product tenure increases by 1 year, the effect of a firm's own experience is 8.4% while the effect of observed competitors' signals is only a third of that, about 2.7%.

CHAPTER 3

Cross market learning about demand

3.1 Introduction

Uncertainty about the market demand is one of the many challenges that a firm faces when exporting abroad. Firms often do not have perfect knowledge of how well their products will be received in the destination markets because of unknown consumers' taste and preferences that affect the demand for their products. Recent works in international trade show how firms can resolve the demand uncertainty issue by learning from other firms in the same market (Berman et al., 2019; Fernandes and Tang, 2014; Kasahara and Tang, 2019). These papers incorporate demand uncertainty components to the standard Melitz (2003) model. However, firms can learn from sources outside of the destination markets. Previous export experience can provide them with crucial information for future markets. In this paper, I investigate how firms can learn from their experience of having exported a product to other markets in the past.

Since the focus of the paper is on how firms learn from their previous experience, it is important to identify how countries are correlated in terms of taste preferences for products from an origin. In this paper, I apply two methods of comparing country-pair similarity: Jaccard and cosine similarity indices. Both methods measure how similar two countries are in terms of their taste for products from an origin country. Based on these indices, I am able to classify destination markets into similar and dissimilar markets relative to a new potential market.

This paper uses the Chinese customs dataset from 2000 to 2006 at the HS-6 product code level. I document that firms export a wide range of products in a given year globally. However, for each destination market, the number of products that they export is smaller. This suggests that firms choose specific products to each market potentially to cater to the demand of that market. Additionally, I find that firms display some sequential exporting behavior as documented in Albornoz et al. (2012). Half of the new products in a given year were previously exported to some other market in the year before, particularly to countries that are considered similar to the new market.

Motivated by the stylized facts from the data, I develop a learning model with demand uncertainty. Similar to other existing learning papers, firms do not have perfect knowledge of the demand in a destination market in my model. This destination-product specific demand shock is different across products and different across destinations but also are assumed to be imperfectly correlated across markets. Before introducing a new product, firms form a prior belief about the distribution of this demand shock and update their beliefs from observing demand signals from their own experience serving the same products in other markets. An important feature in this model is that preferences for a product across markets are correlated. As a result, firms are able to form an expectation of how well they will do in one market based on their experience in past destinations. They will then evaluate whether to introduce a new product to a given market.

The model provides some predictions that guide the empirical analysis for the paper. The first is that a firm is more likely to add a new product to a market if they have received good signals about demand from a similar market. On the other hand, they are less likely to export a product if that product has been doing well in a dissimilar market. These predictions are tested using transaction data from China between 2000 and 2006.

This paper is organized as follows. Section 3.2 briefly outlines the related literature and the contributions. Section 3.3 summarizes the dataset used in the paper and some motivating evidence. Section 3.4 presents the theoretical model and its predictions. Section 3.5 show the empirical results. Section 3.6 concludes.

3.2 Related Literature

This paper contributes to the literature on learning. Existing papers in this literature build on the model of social learning in earlier works by Jovanovic (1982), Banerjee (1992) and Bikhchandani et al. (1992). A common theme in these papers is there exists some uncertainty that firms or individuals can overcome by observing information from peers in their network (Kaustia and Rantala, 2015; Moretti, 2011; Foster and Rosenzweig, 1995). They form expectations for the unknown component and update their beliefs based on these signals to make decisions accordingly.

The literature on learning in international trade applies these social learning concepts to the international context. In these papers, there is uncertainty about the demand at the destination market. Firms resolve these uncertainty through different channels. Timoshenko (2015) models how firms can learn about their brand appeal in a market from their overall experience of supplying to that market. This affects the firm's product switching decision in the destination. As the firm grows, they learn more about their appeal so that they are more likely to resolve demand uncertainty and less likely to switch their products. Berman et al. (2019) and Kasahara and Tang (2019) examine how firms learn about the demand in a market that they serve and the effect of learning on firm dynamics. Fernandes and Tang (2014) also apply a similar learning model to a set of Chinese exporters where firms are uncertain about the demand in a potential market. In their model, a potential entrant in a market observes signals from other firms in the same city that also export to that market so that the learning spillovers are within a geographical cluster. My paper shares elements with these papers on learning in international trade. However, these papers only consider the learning effects in the destination market, whether it is through observing information from a firm's own experience or from other firms in that market. This ignores the channel where firms can obtain information from their experience in previous markets, which is a focus of my paper.

This paper is closely related on papers in the sequential exporting literature. In Albornoz et al. (2012), the brand appeal of a firm is uncertain but correlated across markets. Firms can learn from their previous destinations to infer their profitability in a new market. In a closely related paper, Nguyen (2012) shares similar features of demand uncertainty and cross market learning as in Albornoz et al. (2012) to study firm entry and delays. While these papers assume the same correlation between markets, I allow the correlation between markets to be different to account for different learning result from similar and dissimilar destinations. Moreover, I also focus my analysis on the product level. In addition, my paper is able to quantify the similarities of countries' taste preferences instead of using extended gravity indicator (Morales et al., 2019; Albornoz et al., 2012).

3.3 Data

This chapter uses the Chinese Customs dataset from 2000 to 2006. A detailed description of the dataset can be found in section 2.3.

3.3.1 Quantifying similarity between countries

This paper seeks to identify how firms make decisions to export based on their past experience. It is important to identify how countries are correlated in terms of their taste preferences. I present two methods that can be employed to quantify this: Jaccard and Cosine similarity indices. [1]

3.3.1.1 Jaccard Similarity Index

The similarity between countries A and B can be measured as the ratio of the number of products that they have in common over the total number of products exported from an origin country to either market. Mathematically, this can be written as:

$$\text{Similarity(A,B)} = \frac{\text{\# common products}}{\text{Total products to either market}}$$

Table 3.1 shows the Jaccard similarity index for a select pairs of export destinations from China in 2006. By construction, the diagonal terms in the table are equal to 1. For example, out of all products exported to either Denmark or Sweden from China, 68% of those products are exported to both Denmark and Sweden. It is not surprising that countries that share a common border such as Canada and America have a high percentage of shared products (74%). However, Canada has more in common with Australia than with the US (77% of products are the same) despite not sharing a border. One potential explanation for this is that both countries share the same common language and are both Commonwealth countries with history ties. From the table, Bulgaria and Korea also have the lowest in common. This is not surprising since they do not share a common border or a common language. It is also interesting to note that Denmark and Sweden have almost the same pattern in the shares of common products with other countries. This table shows that Chinese exporters tend to export a similar product mix to destinations that are similar to each other.

3.3.1.2 Cosine Similarity Index

The second method to measure taste similarity between countries is based on vector similarity. This assumes that each country has a vector of products that they import from an origin country (in this case, China). This index measures the similarities between these product vector of countries A and B.[2]

As an example, consider a simple case of 2 destination countries A and B and two goods (x_1, x_2)

[1]These are popular measures used in machine learning applications for recommendation systems to quantify the similarities between users.

[2]To my best knowledge, Kawada (2018) is another paper in economics that uses cosine similarity to measure voter's similar preferences for voting rules.

Table 3.1: Shares of common products between two countries

	Denmark	Sweden	Bulgaria	S.Africa	Korea	Canada	USA	Brazil	Australia
Denmark	**1.00**								
Sweden	0.68	**1.00**							
Bulgaria	0.55	0.55	**1.00**						
S.Africa	0.59	0.60	0.52	**1.00**					
Korea	0.47	0.48	0.39	0.66	**1.00**				
Canada	0.59	0.59	0.48	0.72	0.70	**1.00**			
USA	0.50	0.50	0.40	0.68	0.82	0.74	**1.00**		
Brazil	0.58	0.58	0.52	0.68	0.59	0.65	0.61	**1.00**	
Australia	0.57	0.57	0.46	0.74	0.73	0.77	0.77	0.65	**1.00**

Note: The above table was calculated at the country level using 2006 data.

that they both import from a source country. Country A imports 10 units of good 1 and 20 units of good 2, while country B imports 20 units of each good. The product vectors for both countries can be written as:

$$CountryA = \begin{pmatrix} q_{1,A} \\ q_{2,A} \end{pmatrix} = \begin{pmatrix} 20 \\ 20 \end{pmatrix}$$

$$CountryB = \begin{pmatrix} q_{1,B} \\ q_{2,B} \end{pmatrix} = \begin{pmatrix} 10 \\ 20 \end{pmatrix}$$

where each entry in the vector represents the number of units that each country imports of each good.

The cosine similarity between the two countries A and B is defined as:

$$Cosine(\theta_{A,B}) = \frac{A \cdot B}{||A||\;||B||}$$

where $\theta_{A,B}$ is the angle between the product vectors for countries A and B. By definition $Cosine(\theta_{A,B})$ ranges from -1 to 1. However, in our case, this *Cosine* value always ranges from 0 to 1. If two vectors are highly similar, then the cosine values get very close to 1. To illustrate, in figure 3.1, I plot the vectors that represent Country A and Country B. The angle between these two vectors is θ.

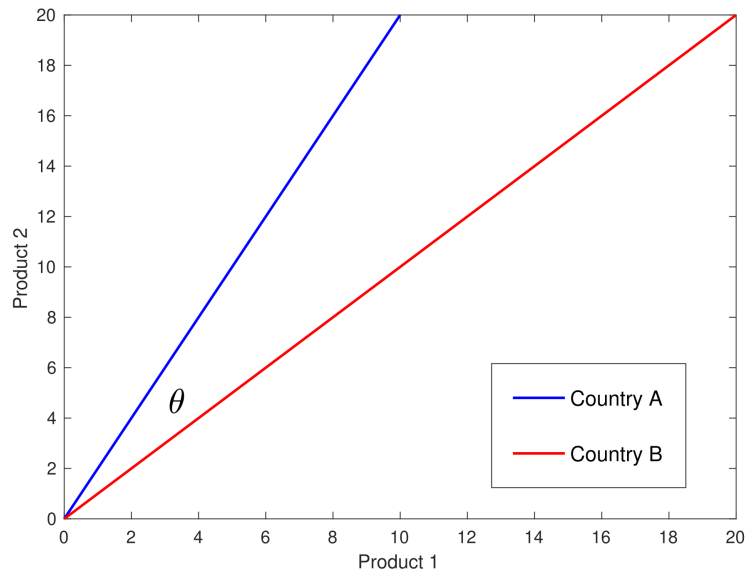


Figure 3.1: $0 \leq cos(\theta) \leq 1$

The more similar the taste preference is between countries, the closer the product vectors will be. Therefore, a smaller angle θ indicates a closer similarity between countries.

To generalize, for J countries and N products, we have the following vectors:

$$CountryA = \begin{pmatrix} q_{1,A} \\ q_{2,A} \\ q_{3,A} \\ \vdots \\ q_{N,A} \end{pmatrix} CountryB = \begin{pmatrix} q_{1,B} \\ q_{2,B} \\ q_{3,B} \\ \vdots \\ q_{N,B} \end{pmatrix} \dots CountryJ = \begin{pmatrix} q_{1,J} \\ q_{2,J} \\ q_{3,J} \\ \vdots \\ q_{N,J} \end{pmatrix}$$

where each entry in the vector indicates a country's quantity for each product in $\{1,2,\dots,N\}$. Using Cosine similarity calculation, we can calculate the similarity between each pair of countries in the set of J countries.

To verify that cosine similarity is a plausible measurement, I plot the index for each country pair against their distance between the countries in figure 3.2. Most country pairs have very small similarity values. The relationship between distance and similarity seems to be negative. The further away two countries are, the less likely they are to have similar taste preferences.

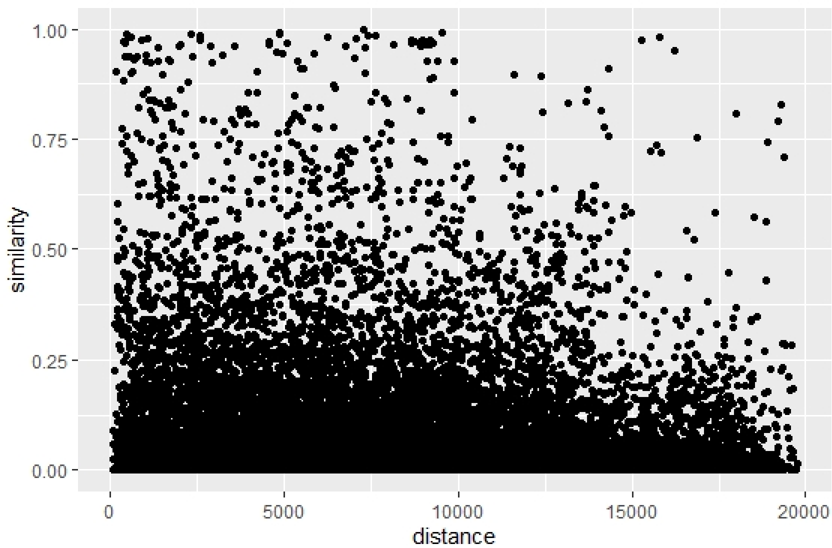


Figure 3.2: Cosine similarity against distance between a country pair

While Jaccard and cosine similarity indices can both be used to measure the taste similarities between countries, Jaccard index does not consider the quantity of each product that a country imports. On the other hand, cosine similarity takes into account how much a country imports of a product. This index will be the primary choice for taste similarity measurement.

3.3.2 Firm level behaviors

Table 3.2: Firm's global and destination (product) characteristics

	Year	Mean	Std. Dev	Max
Number of products	2001	12.80	38.98	1260
	2003	13.51	39.56	1121
	2005	11.71	33.02	1086
Number of products in a destination	2001	3.00	7.88	489
	2003	3.00	8.71	797
	2005	2.73	7.00	631

Note: The statistics are calculated only for firms that export more than one product to more than one destination.

Table 3.2 shows some descriptive statistics for Chinese exporters and product selection. The first set of rows shows the average number of products that a Chinese exporters export in a given year. This includes all products that are exported globally within a firm. For example, in 2001, a Chinese firm on average exports 12.8 products. The second set of rows shows the average number of products that a firm exporters to a destination. This table shows that the number of products that a firm exports to a specific market is smaller than the total number of products that they export globally in a year. This illustrates that a firm only sells a portion of their global products to a specific market and that they seem to diversify their export baskets. One of the potential reasons for this could be because firms cater to the specific demand and taste of a country in their product selection.

In table 3.3 shows some descriptive statistics at the firm level. I document the average number of new products that a firm adds in a year to a destination. Additionally, I also calculate how many of the newly added products were previously exported to similar and dissimilar countries. I classify previous markets for a product into similar and dissimilar country bins based on the country-pair cosine similarity index between a country and the destination market. A country is classified as being a similar (dissimilar) country with the destination market if the cosine similarity index is greater (smaller) than 0.5. This table shows that almost half of the new products were previously exported to at least one market before being introduced in a new market. More of the newly added products were previously exported to a *similar* country in the previous period than to a *dissimilar* country. This suggests that firms experiment with products in other markets first before introducing them to a new market.

Table 3.3: Firm's export decisions for products

Year	Average new products in t	% to similar countries in $t-1$	% to dissimilar countries in $t-1$
2001	7.75	30.85	10.87
2003	7.29	33.68	10.99
2005	5.69	41.20	11.15

Note: Similar countries are those with cosine similarity index greater than 0.5. Dissimilar countries are those with similarity index less than 0.5. The statistics are calculated only for firms that add a new product to a destination in a year.

3.4 Model

Motivated by the empirical observations in the previous section, I develop a model that describes how firms make decisions to introduce a new product to a market. I incorporate elements of demand learning from Fernandes and Tang (2014) and sequential exporting in Albornoz et al. (2012) to the standard Melitz (2003) model in trade. For simplicity, I assume that the world consists of only 3 markets: markets 1, 2 and 3[3].

3.4.1 Consumers

Each country j has measure l_j of identical consumers. Preferences are given by the CES utility function where the consumption of the composite good is given by:

$$C_{jt} = \left(\sum_{i=1}^{N+1} \int_{\Omega_{ijt}} (e^{a_{jgt}(\omega)})^{1/\sigma} c_{jt}(\omega)^{(\sigma-1)/\sigma}) d\omega) \right)^{\frac{\sigma}{\sigma-1}}$$

where Ω_{ijt} is the mass of available products in country j imported from country i in period t, $c_{jt}(\omega)$ is the consumption of a product $\omega \in \Omega_{ijt}$ in country j, and $a_{jgt}(\omega)$ is demand shock for product g in country j. The composite product index takes the following CES form:

$$c_{jt}(\omega) = \left(\sum_{g=1}^{G_{ijt}(\omega} c_{jgt}(\omega)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma-1}{\sigma}}$$

where g indicates varieties within product ω; $c_{jgt}(\omega)$ is the consumption of variety g of product ω in country j. The aggregate price index is given as:

$$P_{jt} = \left(\sum_{i=1}^{N+1} \int_{\Omega_{ijt}} e^{a_{jgt}(\omega)} \sum_{g=1}^{G_{ijt}(\omega)} p_{jgt}(\omega)^{1-\sigma} d\omega \right)^{\frac{1}{\sigma}}$$

where $p_{jgt}(\omega)$ is the price of variety g of product ω in country j.

The demand function for a specific product in a given market is:

$$q_{jgt}(\omega) = e^{a_{jgt}(\omega)} \frac{p_{jgt}(\omega)^{-\sigma}}{P_{jt}^{1-\sigma}} Y_{jt}$$

[3]This could be extended to more than 3 countries, but the rankings of the cross correlations between markets could get complicated in the derivations.

3.4.2 Firm decisions

In each market, there exists a continuum of firms. Each firm has a brand ω. Firms produce differentiated varieties of a products. Each firm is associated with a constant productivity level φ. Higher productivity implies lower cost of production. The profitability of a firm depends on two factors:

- Product-specific productivity φ_g. This is the same across all destinations and time.
- Destination-product specific demand shock a_{jgt} that is different across products and different across destinations j and time.

$$a_{jgt}(\omega) = \theta_{jg} + \varepsilon_{jgt} \tag{3.1}$$

θ_{jg} is the product appeal in destination $j \in \{1,2,3\}$. The firms do not know this index prior to supplying the good and can only form expectation about the product appeal $\theta_{jg}(\omega) \sim N(\bar{\theta}_j, \sigma^2_{\theta,j})$. This product appeal θ_j is also assumed to be imperfectly correlated across 3 markets: $0 < \rho_{jk} < 1$ is the correlation between the product appeals in markets j and k. The iid intertemporal preference shock is $\varepsilon_{jgt} \sim N(0, \sigma^2_\varepsilon)$. For simplicity, these components in the firm's demand shock are assumed to be independent of each other.

Firms face a per period fixed cost of exporting to a market j from source country i for each product f_{ij}. This reflects the cost of a firm setting up the distribution network or marketing research to introduce a new product to the market. The more products they produce, the higher the total fixed costs in that market. Given the optimal quantity of each product, a firm makes the decision of how many products to export to market j. The expected profit of a product g exported to market j is:

$$\Pi_{ijgt} = \underbrace{\frac{(\sigma-1)^{\sigma-1}}{\sigma^\sigma}\left(\frac{\varphi}{g^\alpha}\right)^{\sigma-1} E_{a_{jgt}}\left[e^{\frac{\theta_j+\varepsilon_{jgt}}{\sigma}}\right]\frac{P_{jt}^{\sigma-1}Y_{jt}}{(\tau_{ij}w_{it})^{\sigma-1}}}_{\text{operating profit}} - \underbrace{f_{ij}}_{\text{fixed cost}} \tag{3.2}$$

A firm would export a product g if they earn positive profit for that product i.e. if $\Pi_{ijgt} > 0$

Given the firms' beliefs about the individual product appeal λ_{jg}, they decide on the number of products exported to market j and the quantity for each product before entering the market. Their expected profit for all products in destination j is the sum of profits of all G goods that they export to j. A firm from source country i exporting to country j solves the following maximization problem of choosing their product scope and the quantity of each product:

$$\max_{\{q_{ijgt}\},G_{jt}} \Pi_t = \mathbb{E}\sum_{g=1}^{G_{jt}} \left[q_{ijgt}^{\frac{\sigma-1}{\sigma}} e^{a_{jgt}/\sigma} P_{jt}^{\frac{\sigma-1}{\sigma}} Y_{jt}^{1/\sigma} - \frac{\tau w_{it} g^{\alpha}}{\varphi} q_{ijgt} - f_{ij} \right] \tag{3.3}$$

The expectation operator in equation (3.3) is applied to the demand shock $a_{jgt} = \lambda_{jg} + \varepsilon_{jgt}$ and f_{ij} is the recurring fixed cost of exporting a product to market j. Solving this maximization problem gives the optimal quantity for a product g:

$$q_{ijgt} = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} \left(\frac{\varphi}{\tau w_{it} g^{\alpha}}\right)^{\sigma} [\mathbb{E}(e^{\lambda_{jg}+\varepsilon_{jgt}})]^{\sigma} P_{jt}^{\sigma-1} Y_{jt} \tag{3.4}$$

The market clearing price for each product g is:

$$p_{ijgt} = \frac{\sigma}{\sigma-1} \left(\frac{\varphi}{g^{\alpha}}\right)^{-1} e^{a_{ijgt}/\sigma} \left[\frac{\tau w_{it}}{b_{ijgt}}\right] \tag{3.5}$$

where $b_{ijgt} = \mathbb{E}(e^{\lambda_{jg}+\varepsilon_{jgt}})$. The realized sales of a firm for a product g in destination j can be written as:

$$R_{ijgt}(\omega) = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1} \left(\frac{\varphi}{g^{\alpha}}\right)^{\sigma-1} (b_{jgt}^{\sigma-1}) e^{a_{jgt}/\sigma} (\tau w_{it})^{1-\sigma} A_{jt} \tag{3.6}$$

where A_{jt} is an aggregate demand component.

3.4.2.1 Decision to export a new product

Suppose that a firm in market $j = 1$ is now deciding whether to introduce a new product g to market 1. They also supply the same product g to the other two markets in the world (markets 2 and 3) so that they have observed the demand shocks a_2, a_3 from these two markets. Without any prior experience in selling product g in market 1, the firm forms a belief of the expected profit for product g in market 1. As a result, the productivity cutoff based on the expected value of the product appeal $(\theta_{1,g})$ for market 1 is:

$$\varphi_g^{\text{prior}} = \frac{\varphi}{g^{\alpha}} = \left(\frac{\sigma^{\sigma}}{\sigma-1}\right) (f_{i1})^{\frac{1}{\sigma-1}} \left[\frac{(\tau_{i1} w_{it})}{P_{1,t} (Y_{1,t})^{\frac{1}{\sigma-1}}}\right] \left(\frac{1}{exp\left[\frac{\bar{\theta}_{1,g}}{\sigma} + \frac{1}{2\sigma^2}(v_{\theta} + v_{\varepsilon})\right]}\right)^{\frac{\sigma}{\sigma-1}} \tag{3.7}$$

Conditional on having observed the demand signals from the other two markets a_2, a_3, the firm can form beliefs about the product appeal in market 1. Using Bayesian updating, we can derive the posterior mean of the product appeal in market 1 in the same way as Nguyen (2012):

$$\mu_{1,g} = \frac{1}{A}(\rho_{12}\sigma_1\sigma_2((\sigma_3^2 + \sigma_{\varepsilon,3}^2)(a_2 - \bar{\theta}_2) - \rho_{23}\sigma_2\sigma_3(a_3 - \bar{\theta}_3) \tag{3.8}$$

$$+ \rho_{13}(-\rho_{23}\sigma_2\sigma_3(a_2 - \bar{\theta}_2) + (\sigma_2^2 + \sigma_{\varepsilon,2}^2)(a_3 - \bar{\theta}_3))) \tag{3.9}$$

where

$$A = \sigma_3^2\sigma_2^2(1 - \rho^{23}) + \sigma_{\varepsilon,2}^2\sigma_3^2 + \sigma_2^2\sigma_{\varepsilon,3}^2 + \sigma_{\varepsilon,2}^2\sigma_{\varepsilon,3}^2 \qquad > 0 \tag{3.10}$$

3.4.3 Learning from a similar market

The effect of the demand signal from market 2, a similar market to market 1, on the posterior cutoff for market 1 is:

$$\frac{\partial \ln \varphi_g}{\partial a_2} = \left(\frac{-1}{\sigma - 1}\right)\frac{1}{A}\left(\sigma_1\sigma_{23}^2(\rho_{12} - \rho_{13}\rho_{23}) + \rho_{12}\sigma_1\sigma_2\sigma_{\varepsilon,3}^2)\right) \tag{3.11}$$

The sign of equation 3.11 determines the prediction for the learning effect from a similar market. If it is positive then a good demand signal from market 2 raises the productivity cutoff for supplying product g to market 1. On the other hand, if equation 3.11 is negative, then the positive signal a_2 revealed from serving in market 2 lowers the cutoff for market 1. To summarize, the effect of cross market learning depends on the sign of $(\rho_{12} - \rho_{13}\rho_{23})$. Suppose market 1 is highly similar to market 2 in taste preferences for product g but market 1 is not very similar to market 3 (for example: America is similar to Canada but not very similar to China). Under this assumption, ρ_{12} has a high value while ρ_{13} would be low so that $\rho_{12} > \rho_{13} > 0$. If market 1 and market 2 are highly similar but market 1 is not similar to market 3, then we can assume that market 2 and market 3 also have a low correlation. The assumption that $\rho_{12} > \rho_{13} > 0$ is enough to conclude that $\rho_{12} - \rho_{13}\rho_{23} > 0$. [4] so

[4]If ρ_{23} is really high in the extreme case and equal to 1 then at most, the largest value that $\rho_{13}\rho_{23}$ can be is ρ_{13} which is less than ρ_{12} by assumption. Therefore, if $\rho_{12} > \rho_{13} > 0$ then ρ_{12} is always greater than $\rho_{13}\rho_{23}$.

that the sign of equation 3.11 becomes:

$$\frac{\partial \ln \varphi_g}{\partial a_2} < 0$$

This means that good signals from selling product g in market 2 raises the likelihood of the firm supplying the same product to market 1 in the next period.

3.4.4 Learning from a dissimilar market

On the other hand, the effect of learning from market 3 on the posterior cutoff for market 1 is:

$$\frac{\partial \ln \varphi_g}{\partial a_3} = \left(\frac{-1}{\sigma - 1}\right)\frac{1}{A}\left[\sigma_1\sigma_3(\rho_{13} - \rho_{12}\rho_{23}) + \rho_{13}\sigma_1\sigma_3\sigma_{\varepsilon,2}^2\right] \tag{3.12}$$

For simplicity, suppose that market 3 and market 1 are perfectly uncorrelated so that $\rho_{13} = 0$, then we have:

$$\frac{\partial \ln \varphi_g}{\partial a_3} = \left(\frac{-1}{\sigma - 1}\right)\frac{1}{A}\left[\sigma_1\sigma_3(-\rho_{12}\rho_{23})\right] > 0 \tag{3.13}$$

This is because $\rho_{12} > 0$ and $\rho_{23} > 0$ by assumption. As a result, a good signal from supplying product g to market 3 reduces the likelihood of the firm supplying the same product to market 1.

3.5 Empirical Evidence

In this section, I provide the empirical evidence for the theoretical predictions in section 3.4. These predictions are tested using the Chinese customs dataset from 2000 to 2006. Specifically, I will test the impact of learning from similar and dissimilar markets on the firm's likelihood of exporting a product to a new market. I define a new product in a market as follows:

$$NewProduct_{ijgt} = \begin{cases} 1, & \text{if Value}_{jg,t-1} = 0, \text{Value}_{jgt} > 0 \\ 0, & \text{otherwise} \end{cases}$$

A firm i is classified as having added a new product g in market j in year t if they report positive sales this period but zero in the previous period. The dummy indicator is zero otherwise. Note that continuing exporters who report positive sales for product g in market j in both t and $t-1$ are not defined and therefore excluded.

The regression to test the theoretical predictions is:

$$\text{NewProduct}_{ijg,t} = \beta_1 \ \text{Signal}_{jgt}^{similar} + \beta_2 \ \text{Signal}_{jg,t}^{dissimilar} + \{FE\} \tag{3.14}$$

The independent variables ($\text{Signal}_{jgt}^{similar}$ and $\text{Signal}_{jgt}^{dissimilar}$) indicate the average signals received from a firm's experience in similar and dissimilar countries relative to the destination j. Specifically, these variables are defined as:

$$\text{Signal}_{jgt}^{similar} = \frac{1}{(w_1 + w_2 + \dots w_n)} \sum_{i \in \Theta} (w_i \times a_i) \tag{3.15}$$

where w_i represents the similarity between country i and the destination country j, a_i represents the signal that a firm receives from country i in the previous period, Θ is the set of countries that are identified as *similar* to country j with similarity index greater or equal to 0.5. These similarity weights are calculated using either the Jaccard or the Cosine similarity method from section 3.3.

In a similar way, the independent variable for the weighted average signals from *dissimilar* countries are defined as:

$$\text{Signal}_{jgt}^{dissimilar} = \frac{1}{(w_1 + w_2 + \dots w_n)} \sum_{i \in \Lambda} (w_i \times a_i) \tag{3.16}$$

where Λ is the set of countries that are identified as *dissimilar* to country j with similarity index smaller or equal to 0.5.

Recall that in section 3.4, I have derived that the realized sales of a firm is:

$$R_{ijgt}(\omega) = \left(\frac{\sigma - 1}{\sigma}\right)^{\sigma-1} \left(\frac{\varphi}{g^{\alpha}}\right)^{\sigma-1} (b_{jgt}^{\sigma-1}) e^{a_{jgt}/\sigma} (\tau w_{it})^{1-\sigma} A_{jt} \tag{3.17}$$

It is clear from the above equation that the logarithm of the realized sales is a function of the demand signal a_{jgt} in the model, the country-year aggregate components and the firm-product-year components. The log residual sales after partialling out the fixed effects give us the demand signal

a_{jgt}. Therefore, to construct the signal for a product in a market, I estimate the following regression:

$$\ln R_{ijgt} = \delta_{jt} + \delta_{igt} + a_{ijgt} \tag{3.18}$$

where R_{ijgt} is a a firm's export sales of product g to market j at time t. δ_{jt} and δ_{ijgt} are country-year and firm-product-year fixed effects. The residuals of this regression are the demand signal a_{jgt}.

3.5.1 Results

Table 3.4: Preliminary result using cosine similarity

VARIABLES	(1) NewProduct	(2) NewProduct	(3) NewProduct
Avg. Signal from similar countries	0.0039069***		0.0047065***
	(0.0011022)		(0.0011299)
Avg. Signal from dissimilar countries		-0.0060161***	-0.0049451***
		(0.0006889)	(0.0015931)
Observations	722,059	3,103,046	722,059
R-squared	0.4955653	0.5969690	0.4955747
Firm-Product_year	Y	Y	Y
Ctry_year	Y	Y	Y

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3.4 presents the preliminary result using cosine similarity method to classify countries into similar and dissimilar groups. Average signals from similar and dissimilar countries are calculated using equations 3.15 and 3.16. For computational reason, I restrict the set of products to only the apparel/clothing industry, one of the top export industries of China. To control for macroeconomic shocks and firm unobservables, I include firm-product-year and country-year fixed effects in all regressions.

In column (1), after controlling for fixed effects, I find that there is a positive and statistical significant relationship between average signals from similar countries on the likelihood of a firm exporting a new product. On the other hand, in column (2), there is a negative and significant effect of a firm's signals from dissimilar market on the likelihood of introducing a new product. These results are consistent with the theoretical predictions found in section 3.4. Specifically, the coefficient of 0.004 in column (1) suggests that a one-standard deviation increase in the signal from similar countries increases the probability of a product being introduced in this market by 0.4 percentage point. Evaluated at the mean adding rate, this is approximately a 2.36% increase. On the other hand, a one standard deviation increase in the positive signals from dissimilar countries discourage the firm from adding that product to a new market by 0.6 percentage point (or an approximate 3.5% decrease in the likelihood).[5]

For comparison, I also test the theoretical predictions using the Jaccard similarity definition. The results are in table 3.5. I find that the predictions of the model still hold when a different similarity definition is used in the empirical evidence.

Table 3.5: Preliminary Result - Jaccard Similarity

VARIABLES	(1) New Product	(2) New Product	(3) New Product
Avg. Signal from similar countries	0.0047612***		0.0050154***
	(0.0006841)		(0.0010775)
Avg. Signal from dissimilar countries		-0.0042070***	-0.0054530***
		(0.0008198)	(0.0008543)
Observations	1,611,791	392,859	392,859
R-squared	0.5396682	0.3522699	0.3523124
Firm-Product_year	Y	Y	Y
Ctry_year	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.6 Conclusion

Uncertainty about demand is one of the many challenges that an exporter faces in a market. In this paper, I show how firms can overcome this demand uncertainty. I present a model where firms observe information from their own experience of supplying a product in previous markets. There are two groups of countries: similar and dissimilar markets relative to any given destination. Based on signals that they receive in these markets, a firm can infer about the profitability of a new product in a new market. There are two main predictions from the theoretical model. The first is that when a

[5]For both tables 3.4 and 3.5, the number of observations are different for the similar and dissimilar regressions.This is because of the classification of countries into similar/dissimilar regions. In some cases, there are more similar countries than there are dissimilar countries and vice versa. The similarity indices can change over time. Countries in period t are categorized based on the values of the indices in period $t-1$.

firm considers adding a new product to a market, they are more likely to do so if they have received good signals about that product from similar markets in the previous period. On the other hand, good signals from *dissimilar* markets reduce the likelihood of a product being introduced.

There are some potential extensions to the paper. The model features a simple framework of only 3 countries. However, this can be extended into a multi-country framework. To do this, we need to develop a method to rank countries by the correlation of preferences. Additionally, in the paper, I quantify countries by their overall similarity in taste for all products from a source countries and assume that countries' specific product preferences are the same as the overall similarity index. Given that the analysis is at the product level, a potential extension is to quantify country-pair similarity at the product level.

3.7 Appendix

In the data and empirical sections of chapter 3, I use 0.5 as the cutoff to classify countries into similar and dissimilar markets. In this appendix, I show how the results change when a different cutoff is used. Specifically, I use 0.70 as the cutoff so that countries with similar index values greater (smaller) than 0.70 are classified as similar (dissimilar) to a destination market.

In table 3.6, I show the sensitivity of the results in table 3.3 to a different threshold for classifying countries. The results remain similar to the results in section 3.3: firms are more likely to introduce a new product that was previously exported to a similar market than to a dissimilar market.

Table 3.6: Firm's export decisions for products

Year	Average new products in t	% to similar countries in $t-1$	% to dissimilar countries in $t-1$
2001	7.75	24.59	19.94
2003	7.29	29.61	16.13
2005	5.69	35.51	20.80

Note: Similar countries are those with cosine similarity index greater than 0.7. Dissimilar countries are those with similarity index less than 0.7. The statistics are calculated only for firms that add a new product to a destination in a year.

Table 3.7 shows the additional regression results given the new threshold to classify countries. I find that the results from 3.5 still hold when a new definition of similarity cutoff is used. A one standard deviation increase in the signals from similar markets raises the likelihood of a product being introduced by 2.35% while a one standard deviation increase in positive signals from dissimilar markets reduces the probability of that product introduction by 4.41%. Compared to the empirical results in section 3.5, the effects of signals from similar markets remain mostly the same. However, the effects of learning from dissimilar markets have a slightly larger impact when a different threshold is used to classify countries.

Table 3.7: Result - Cosine Similarity

VARIABLES	(1) New Product	(2) New Product	(3) New Product
Avg. Signals from Similar markets	0.0011779		0.0040958***
	(0.0008003)		(0.0008649)
Avg. Signals from dissimilar markets		-0.0054938***	-0.0075275***
		(0.0006514)	(0.0008530)
Observations	1,568,744	2,156,299	1,568,744
R-squared	0.5461185	0.5554197	0.5461545
Firm-Product_year	Y	Y	Y
Ctry_year	Y	Y	Y

Note: Similar countries are those with cosine similarity index greater than 0.7. Dissimilar countries are those with similarity index less than 0.7. Signals are calculated as the average weighted signals from a firm's experience in previous markets. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

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