Excessive Entry and Exit in Export Markets

Hiro Kasahara*
University of British Columbia

Heiwai Tang†
Johns Hopkins University

July 20, 2018
Preliminary and Incomplete (Please do not quote without permission)

Abstract

This paper studies the surprisingly high excessive entries and exits among Chinese firms in foreign markets. We first use transaction-level data for the universe of Chinese exporting firms to document several stylized facts that were previously overlooked in the trade literature. In our sample that covers the period of 2000-2006, 62% of exporters are new exporters on average across countries. Among these new exporters, 81% on average did not continue serving the same country the following year. These rates are even higher for new markets facing Chinese firms, particularly those in Africa. The average firms' exit rates and entry rates are strongly positively correlated across destination countries. The entry (exit) rates are negatively correlated with the GDP of destination countries, but positively correlated with the distance from them. We build a simple two period model with imperfect information on foreign demand factors, in which firms have prior belief over their foreign demand and analyze how the mean and the variance of their prior distribution affects the firm's entry and exits. We then use our micro data to empirically examine several model predictions, and find supporting evidence that firms' excessive entries and exits are outcomes of self-discovery of own demand in unfamiliar markets.

Key Words: learning to export, knowledge spillover, uncertainty, export dynamics
JEL Classification Numbers: F1, F2, D8.

*Email: hkasahar@mail.ubc.ca
†Email: hwtang@jhu.edu.

1 Introduction

Research in economics finds that firms' turnovers (entry and exit) in foreign markets are much more frequent than those in the domestic market.[1] These findings reflect a considerable level of uncertainty facing new exporters. To explain these findings, research has focused the phenomenon of self-learning and experimentation in an attempt to explain these export dynamics (e.g., Albornoz et. al, 2012; Timoshenko, 2015; Ruhl and Willis, 2017). The idea is that firms optimally start small in a foreign market, and only after most of the uncertainty is unveiled do they commit substantial resources to fulfill larger orders. In practice, however, firms usually also try to obtain information from their neighbors before undertaking any risky decisions (Hausmann and Rodrik, 2003). This is particularly true when self-discovery in export markets entails significant sunk costs.[2] While economists have for years studied how learning from neighbors determines individual decision making (e.g., Foster and Rosenzweig, 1995, 2010; Conley and Udry, 2010; Moretti, 2011), it has been an overlooked aspect in the study of exporters' dynamics and performance.

To study the relevance of information and learning in shaping firms' export dynamics, we first use transaction-level trade data for the universe of Chinese exporters over the period of 2000-2006 to document several new stylized facts. We find that

1. The majority (62%) of exporters are new exporters on average across countries.
2. Among these new exporters, most of them (81%) on average did not continue serving the same country the following year.
3. Average firms' exit rates and entry rates are highly positively correlated across destination countries.
4. These entry and exit rates pertained to exports to developing countries are particularly high, particularly in the new markets in Africa (69% of exporters on average a new; with 85% stopped exporting to the same country the following year).
5. The entry (exit) rates are negatively correlated with the GDP of destination countries but
6. The entry (exit) rates are positively correlated with the log distance from destination countries.

[1] Bartelsman, Haltiwanger, and Scarpetta (2009) found that the average turnover (entry + exit) rate in the domestic market is 5% for developed nations and 10% for transition economies. The turnover rate in foreign market is several orders of magnitude bigger, as shown by Eaton, et al. (2008), Albornoz et al. (2011), and Blum et al. (2013). See the literature review below for a more detailed discussion.

[2] Research in international trade has emphasized how high sunk costs of exporting shape export patterns. Das et al., 2007 and Morales et al., 2011, among others, have provided sizeable estimates of those costs. Notice that high sunk costs could explain low export entry rate, but not the marjority of small firms among export starters. One notable exception in the literature is Segura-Cayuela and Vilarrubia (2008), who show theoretically that neighbors' export activities, by lowering fixed export cost, can affect new exporters' dynamics. See Section 2 for a comprehensive literature review.

These facts are very interesting and, to the best of our knowledge, new to the literature. High *entry* rates in certain destinations, like those new markets in Africa, may not be surprising because Chinese firms are growing during this period. However, it is surprising to see such high *exit* rates after the first year of exporting by Chinese firms in those countries. If sunk cost is high, as is commonly assumed in heterogenous models in trade, the standard model of dynamic exporting which is a simple extension of Melitz-type model where firm productivity is stochastically growing with perfect information on firm-specific productivity/demand will have a hard time explaining such high exit rates. This motivates us to consider a model in which there is some ex-ante uncertainty in firm/market-specific demand, where individual firms form their prior distributions of firm/market-specific demand and make export decisions.

Specifically, we consider a simple two-period model of firm's export decision when a firm does not exactly know the true demand in foreign market. At the beginning of the first period, a firm decides whether it will export to a foreign market or not given the prior distribution over the true demand; if it decides to export, then a firm will learn about the true demand at the end of the first period. In the second period, a firm will decide if it will continue exporting or exit from the foreign market.

The model reveals that the high exit rates in the second period arises when the mean and the variance of the prior distribution over the true demand in the initial period are high. In the model, the high mean value of the prior distribution induces an entry due to "optimism" and will lead to exits after learning the true demand. The high value of variance also leads to an initial entry in the initial period because a firm has an incentive to learn the true demand for foreign market by hoping that the true demand really high while ensuring the risk of low true demand with an option of exiting from foreign market; when a firm subsequently learns that the true demand is not as high as they hoped and the profit turns out to be negative, a firm will exit from foreign market.

From the view point of learning model, there are two potential explanations for the observed high exit rates. First, these countries are characterized as high risk and high return markets where the distribution of firm-specific demand has high variance with potentially very heavy tail on the right of distribution. In this case, Chinese firms exactly know the distribution of firm/market-specific demand and they rationally enter the market because the expected sum of profits is larger than the sunk cost. Ex post, only a small fraction of firms survive with very high profits. Second, it is possible that the prior distribution of firm/market-specific demand is biased upward (i.e., they are overly or irrationally optimistic relative to the true distribution) and Chinese firms decide to export because they think they can earn high profits but they learn that the realized value of firm/market-specific demand is low.

We then discuss how firms' observations of neighboring firms' export performance in the same market will change their priors. Based on information inferred from neighbors' export performance in a market, a firm updates its prior about the part of the market demand that is common across firms. However, the signals about foreign market demand are noisy, more so for differentiated products, as observed neighbors' export performance could be affected by their unobserved product

appeals. The model shows that a firm's export decision and post-entry performance depend not only on the number of neighboring exporters, but also the levels and heterogeneity of their export sales, as well as the firm's own prior knowledge about the market. While more neighbors may offer a more precise signal about a foreign market's demand, all else being equal, the strength of the signal – the average performance of the neighbors in the market, also matter. A larger number of neighbors serving a foreign market will raise the rate of firms' entry into the same market only if the signal is positive, whereas it will deter entry when the signal is negative. Our model suggests that in addition to the stand-alone measures of the number neighbors serving a foreign market (defined as the country-sector level) and their average performance there, an interaction between the signal and the number of neighbors should be included as a regressor to identify potential information spillover in trade.

Using export transaction-level data for Chinese firms exporting to Africa, we find supporting evidence consistent with the main theoretical predictions. In particular, controlling for firm-year fixed effects (firms' supply shocks), country-sector-year fixed effects (countries' demand shocks), and city-country fixed effects (historical linkage), we find that the entry rate in a market are both positively correlated with the strength of the signal, measured by the average demand inferred from neighboring firms' (in the same city or province) selling in the same sector locate in the same African country.[3] The positive correlation is increasing in the prevalence of neighbors located in the same city.[4] The learning effects on new exporters' entry and initial sales are both quantitatively important.

Our regressions show that new exporters' post-entry growth, conditional on survival, is negatively correlated with both the strength of the signal and its interaction with the prevalence of neighbors, as predicted by our model. The survival rate of export entrants, however, does not appear to be correlated with either the prevalence of neighbors' export activities and the strength of their revealed signal, contrasting with part of our prediction and most existing findings in the literature. All empirical findings in the paper remain robust to controlling for the number of firms serving other markets and its interaction with the corresponding signal, including different sets of fixed effects, and in specifications that use alternative measures of the signal and of the prevalence of neighbors.

The paper proceeds as follows. Section 2 briefly reviews the literature. Section 3 presents a theoretical model. Section 4 discusses the data source and presents summary statistics of the data. Section 5 discusses our empirical strategy and presents the main results. The final section concludes.

[3] In particular, city-country fixed effects capture all path-dependent factors that may simultaneously determine new exporters' sales dynamics and neighbors' export performance, avoiding the common "reflection" problem often encountered in the literature on information or technology spillover.

[4] The prevalence of neighbors is measured by the density, a normalization of the number of firms by the size of the city, or by the number itself. Results remain robust to the use of either measure.

2 Related Literature

This paper relates to several strands of literature. First, it contributes to recent studies on firms' export strategies and dynamics (Eaton, et al., 2008; Albornoz et al., 2011, among others). It shows that new exporters often start selling small amount and many of them cease exporting after the first year.[5] The related theoretical research incorporates learning and/ or search in trade models to rationalize these findings (Rauch and Watson, 2003; Freund and Pierola, 2010; Iacovone and Javorcik, 2010; Albornoz et al., 2012; Eaton et al., 2012; Nguyen, 2012; among others).[6] Most of these models focus on firms' *own* export experiences to look for determinants of export dynamics.[7] We focus instead on learning from neighbors.[8]

Second, our paper applies the influential social learning models (e.g., Jovanovic, 1982; Banerjee, 1992; Bikhchandani, Hirshleifer and Ivo, 1992, 1998) to the study of international trade. Belief updating based on observed behaviors and/ or outcomes of others is a common feature in these models. There is a growing empirical literature that uses micro data to test these theories.[9] For instance, Foster and Rosenzweig (1995) examine the roles of learning by doing and learning from others in determining farmers' adoption of new seeds. Conley and Udry (2010) examine the pattern of fertilizer use by Ghanian pineapple farmers and underinvestment in fertilizers due to unobserved information cost. They find that information exchange between farmers shape expected profitability, which in turn affects the actual adoption of fertilizers. Built on a normal learning model, Moretti (2011) derives micro-foundations for the dynamics of movie sales in the U.S. by relating the learning-driven sales to the ex ante measurable priors about the quality of movies. He shows both theoretically and empirically that more precise priors about movies' quality is associated with less learning effects. We will examine a similar hypothesis using micro-level export data.

Building on the social learning models, we contribute to the literature on information spillover in exports. In particular, we relate surprises, networks, and the relative precision of priors and

[5] Among others, Eaton et al. (2008) find that over 60% of new exporters in Colombia do not survive into the next year, but those that do account for a significant share of the country's aggregate export volume. Consistently, Albornoz et al. (2011) find that about half of new exporters in Argentina export only for one year. By focusing on agricultural exports from Peru, Freund and Pierola (2010) find evidence of very large entry and exit in the export sector and in new destinations, with high exit rates after just one year (above 50% on average), especially among small starters. Blum et al. (2013) find that one-third of exporters enter into and exit from exporting multiple times in a 19-year panel of Chilean firms.

[6] For example, Albornoz et al. (2012) build a model that predicts firms' "sequential exporting" strategy, which arises when a firm realizes its export profitability through exporting and then decides whether to serve other destinations based on its past export performance. Nguyen (2012) develops a model that features uncertain foreign demands that are correlated across markets. Firms' export performance in a market can inform a firm about its future performance in other markets.

[7] A notable exception is Araujo, Mion, and Ornelas (2014), who explain firms' export dynamics in situations where exporters learn about the reliability of trade partners in the destination through repeated interactions. The learning process depends on both the destination's institutions and the producer's export experience.

[8] The one exception that we are aware of is Segura-Cayuela and Vilarrubia (2008). The authors develop a dynamic general equilibrium model, which features uncertainty and learning about country-specific fixed export costs. By observing existing exporters' profits in foreign markets, potential exporters can obtain an updated prior about the random fixed costs. We focus on learning about foreign demand instead as our data permit the construction of time-varying demand factors.

[9] See Foster and Rosenzweig (2010) for an extensive review of other micro evidence of technology adoption.

signals to firms' export dynamics. We show how learning affects export performance and dynamics in a fast growing developing country, where information about foreign sales opportunities is vastly asymmetric between firms. Our detailed transaction-level data permit an empirical examination of learning models, without relying on experiments or micro surveys that are often unavailable but are required for a study of learning.

Third, our paper relates to the early empirical studies on the determinants of exporters' entry and survival. Aitken et al. (1997), Clerides et al. (1998), Bernard and Jensen (2004), Chen and Swenson (2008) and Koenig et al. (2010) are among the early studies on how the prevalence of existing exporters or multinational firms induces new export linkages. More recent research has used transactions-level data (Alvarez et al., 2008; Cadot et al., 2011).[10] Adding to the literature, our work is distinct in several respects. First, we examine the effects not only on entry but on four different measures of export performance: entry, survival, initial sales, and export growth conditional on survival. Second, not only do we examine the relationship between the prevalence of existing market-specific export activities and new exporters' performance, we also examine the correlation between them, conditional on the strength of the signal. To the extent that learning is the main channel, the prevalence of existing exporters should matter differently for positive and negative signals. Third, our model shows that in the presence of firm heterogeneity and fixed costs, firm entry and survival are related, which requires controlling for firm or firm-year fixed effects in regression analyses. Fourth, we use city boundary to define geographic units, which are much finer than what has been commonly used in existing research on information spillover. Finally, we explore information spillover across destinations within firms, controlling for all firm-specific and market-specific shocks.

By analyzing the impact of the geographical agglomeration of exporters on firms' export performance, our paper is also related to the new economic geography literature represented by the landmark papers of Krugman (1991), Krugman and Venables (1995), and Duranton and Puga (2004).[11] Finally, our paper contributes to the literature on the role of fixed and sunk costs of exporting in shaping trade patterns and dynamics (see Bernard et al., 2003; Melitz, 2003; Bernard et al., 2007; Das, Roberts, and Tybout, 2007; Chaney, 2008).

[10] Alvarez et al. (2008) find firm-level evidence from Chile that the probability of exporting in a new market (product or destination) increases with the prevalence of other exporters in the same market. Cadot et al. (2011) find evidence for four Sub-Saharan African countries that the probability of export survival increases with the presence of other firms' exporting the same product to the same country.

[11] Greenaway and Kneller (2008) find that regional and sectoral agglomeration has a positive effect on new firm entry into export markets. Spillover from neighboring exporters, as the current paper studies, can affect a firm's export performance through similar mechanisms, by lowering the cost of obtaining information on export markets. See Ottaviano and Puga (2004) for a survey of the New Economic Geography literature.

3 Data

3.1 Description

The main data set used in the empirical analysis covers monthly export and import transactions of the universe of Chinese firms between 2000 and 2006.[12] For each transaction, the data set reports the value (in US dollars) and quantity at the product level (over 7000 HS 8-digit categories) to/from each country (over 200 destination and source countries) for each firm.[13] In addition, we also have information on the ownership type (domestic private, foreign, and state-owned) and trade regime (processing versus non-processing) of each trading firm, as well as the region or city in China where the firm trades. To average out noise due to high-frequency and infrequent trade patterns that may vary across countries or products, we aggregate all observations to the year level. We focus on learning about a foreign country's demand and collapse the product dimension. Thus, a market is defined as a destination-country in the empirical analysis.[14] Since we focus on learning effects, in our analysis, we exclude exports to Hong Kong from the sample because many firms have their headquarters in Hong Kong, who serve as intermediaries to re-export final products to foreign markets.

Exporters in China are required by law to register as either processing exporters or non-processing (ordinary) exporters.[15] The majority of processing exporters have long-time committed foreign buyers (e.g. the largest processing exporter in China, Foxconn, has a long-time committed buyer, Apple). One can argue that for this type of exporters, there is little to learn about both foreign demand and product design, as the related information is often provided directly by the foreign buyer. Without a perfect way to separate out information provided by foreign buyers, we focus on the sample of non-processing firms as learners, presuming that learning effects for ordinary exporters are larger and more relevant than for processing exporters.

We study learning from neighboring exporters in the same city. There are on average 425 cities plus municipalities, according to China's Customs' definition.[16] See Figure **??** for the geographic distribution of the cities. We also explore the potentially differential learning effects across countries. To this end, we use data on bilateral distance, common language, and common border, between China and the destination and between a firm's existing markets and new markets. Data are from

[12] The same data set has been used by Manova and Zhang (2010) and Ahn, Khandelwal and Wei (2010).

[13] Example of a product: 611241 - Women's or girls'swimwear of synthetic fibres, knitted or crocheted.

[14] This decision is made mainly due to the limit of computing power. We check robustness of the results by repeating the main regressions for major exporting sectors. See section 5.5.

[15] Since the beginning of economic reforms in the early 1980s, the Chinese government has implemented various policies to promote exports and foreign direct investment. Most notable of all is the exemption of tariffs on imported materials and value-added tax for processing plants, which assemble inputs into final products for foreign buyers. A registered EP firm is required by law to maintain certain standards for accounting practices and warehouse facilities. Moreover, the terms of transactions for EP firms are to be specified in greater detail in written contracts than ordinary exporters. Readers are referred to Naughton (1996), Feenstra and Hanson (2005) and Fernandes and Tang (2012) for more details about the EP regulatory regimes.

[16] The number of cities in our sample increses from 408 in 2000 to 425 in 2006. The Chinese government gradually added new cities.

CEPII.[17] See Mayer and Zignago (2006) for a detailed description.

4 Stylized facts

We now use the transaction-level trade data from China to empirically verify the five propositions in the model.

Our empirical analysis relies largely on firms' active entry and exit in each market (destination countries). Table 1 provides summary statistics of the country scopes of non-processing (ordinary) exporters, the focus of this paper. The average number of countries served by an exporter is between 5 and 6, while the median is between 2 and 3. The large number of multi-country exporters will let us identify the within-firm variation in export performance, when we control for firm-year fixed effects. The relatively small exporters' median sales indicate that there are many small firms in our data, which should exhibit active entry and exit according to existing evidence for other countries.

As we discussed in the introduction, we first document several stylized facts about Chinese firms' exporting dynamics.

1. High positive correlation between exit rates and entry rates across countries.

2. Negative correlation between entry rates and the log distance of destination countries.

3. The entry and exiting rates among Chinese exporting firms to developing countries, such as those in Sub-Sahara Africa and Latin America, are very high. For instance, the average exit rate for first-time exporters to Sub-Sahara Africa is xx percent.

These three facts are very interesting and, as far as we know, they are new findings. High *entry* rate in African countries might not be surprising because Chinese firms are growing during this period but it is surprising to see such high *exit* rates in those countries. If sunk cost is high, the standard model of dynamic exporting which is a simple extension of Melitz-type model where firm productivity is stochastically growing with perfect information on firm-specific productivity/demand will have a hard time to explain such high exit rates. This motivates us to consider a model in which there is some ex-ante uncertainty in firm/market-specific demand, where Chinese firms form the prior distribution of firm/market-specific demand and make an export decision.

To guide our empirical exploration for an information story behind these stylized facts, we introduce a simple two-period model with imperfect information next.

5 Simple Model

We consider a simple two-period model of firm's export decision when a firm does not exactly know the true demand in foreign market. At the beginning of the first period, a firm decides whether it will export to foreign market or not given the prior distribution over the true demand; if it decides

[17] http://www.cepii.fr/distance/dist_cepii.dta.

to export, then a firm will learn about the true demand at the end of the first period. In the second period, a firm will decide if it will continue exporting or exit from the foreign market.

We will show that the high exit rates in the second period arises when the mean and the variance of the prior distribution over the true demand in the initial period are high. In the model, the high mean value of the prior distribution induces an entry due to "optimism" and will lead to exits after learning the true demand. The high value of variance also leads to an initial entry in the initial period because a firm has an incentive to learn the true demand for foreign market by hoping that the true demand really high while ensuring the risk of low true demand with an option of exiting from foreign market; when a firm subsequently learns that the true demand is not as high as they hoped and the profit turns out to be negative, a firm will exit from foreign market.

5.1 Setup and notations

To highlight the mechanism, we consider a number of simplifying assumptions. Consider a set of firms with heterogenous productivities. Each firm is endowed with firm-specific productivity φ which is known to the firm and does not change over time. The density function of φ for firms that are not exporting at the beginning of first period is given by $g(\varphi)$.

The true demand in foreign market, denoted by x^*, is fixed and non-stochastic. On the other hand, a firm does not know the value of x^* at the beginning of the first period; a firm holds a prior belief that x is distributed normally with mean μ and variance σ^2, i.e.,

$$x \sim N(\mu, \sigma^2).$$

Given the productivity φ and the demand level x, the per-period profit of exporting to foreign market is given by

$$\pi(x, \varphi) = x + \varphi - f$$

where $x + \varphi$ is interpreted as the gross profit while f is interpreted as the per-period fixed cost of exporting.

Denote the firm's export decision in the period t by $d_t \in \{0, 1\}$ for $t = 1, 2.$, where $d_t = 1$ indicates that a firm exports in period t.

5.2 The second period after exporting in the first period

At the end of the first period, the true value of foreign demand x^* is revealed to the firms who exported in foreign market. A firm will export in the second period if $\pi(x^*, \varphi) \geq 0$, i.e.,

$$d_2 = 1 \quad \text{if} \quad x^* + \varphi \geq f.$$

In this case, a firm with $\varphi < \varphi_2^* := f - x^*$ will exit from foreign market in the second period. Note that the value of φ_2^* does not depend on the prior belief.

5.3 The first period

In the first period, given the prior belief $x \sim N(\mu, \sigma^2)$, a firm's *subjective* expected profit from the second period is given by

$$V(\varphi) := E_x[\max\{\pi(x,\varphi), 0\}] = \int \max\{x + \varphi - f, 0\}(1/\sigma)\phi((x-\mu)/\sigma)dx,$$

where $\phi(t) = (1/\sqrt{2\pi})\exp(-t^2/2)$.

A firm will receive zero profit in both periods if it decides not to export. On the other hand, the discounted sum of *subjective* expected profits from two periods when a firm decides to export is $E_x[\pi(x,\varphi)] + \beta V(\varphi)$, where $\beta \in (0,1)$ is a discount factor. Therefore, a firm will export in the first period if $E_x[\pi(x,\varphi)] + \beta V(\varphi) \geq 0$, i.e.,

$$d_1 = 1 \quad \text{if} \quad \mu + \varphi - f + \beta \int \max\{x + \varphi - f, 0\}(1/\sigma)\phi((x-\mu)/\sigma)dx \geq 0.$$

In this case, a firm with $\varphi \geq \varphi_1^*$ will export in the first period, where φ_1^* is uniquely defined by $\mu + \varphi_1^* - f + \beta \int \max\{x + \varphi_1^* - f, 0\}(1/\sigma)\phi((x-\mu)/\sigma)dx = 0$.

The following proposition states that, as the value of μ or σ increases, a firm with lower productivity will be induced to export in the first period.

Proposition 1 *φ_1^* is strictly decreasing in μ and σ^2 and is independent of x^*.*

Therefore, when a firm is more optimistic (higher value of μ) or a firm is more uncertain about foreign demand (higher value of σ^2), a firm has a higher incentive to export. It is intuitive that a firm is more likely to export when it is more optimistic about foreign demand (i.e., a higher value of μ).

On the other hand, the effect of σ^2 on an incentive to export is related to an option of exiting from foreign market in the second period when the demand turns out to be low; as a result, the profit function in the second period is given by $\max\{x + \varphi - f, 0\}$, which is a convex function of x. By Jensen's inequality, the higher degree of uncertainty in x translates into the higher expected value of $\max\{x + \varphi - f, 0\}$, leading to a higher incentive to export in the first period.

5.4 Average exit rates in the second period

Consider a set of firms who have different productivities $\varphi \sim_{iid} g(\varphi)$ but who share the common prior belief over the true demand. We now analyze how the average exit rates in the second period among firms who start exporting in the first period depends on their prior belief characterized by the value of μ and σ^2.

The density function of φ among firms who decided to export in the first period is given by $g(\varphi)/(1 - G(\varphi_1^*))$ if $\varphi \geq \varphi_1^*$ and 0 if $\varphi < \varphi_1^*$, where $G(\varphi)$ is the cumulative distribution function of φ. Because any firm whose productivity is below φ_2^* will exit in the second period, the average

exit rates in the second period among firms who start exporting in the first period is given by

$$\text{the average exit rates} \;=\; \frac{\max\{0, G(\varphi_2^*) - G(\varphi_1^*)\}}{1 - G(\varphi_1^*)}. \tag{1}$$

We impose the following assumption to exclude a trivial case that all firms continue to export in the second period.

$\varphi_2^* > \varphi_1^*$.

Because φ_2^* is independent of μ and σ^2, together with $G(\varphi_2^*) < 1$, the following is a corollary of Proposition 1.

Corollary 2 *Suppose that Assumption 5.4 holds and x^* is finite. Then, the average exit rates among in the second period among firms who start exporting in the first period defined in (1) is increasing in the value of μ and σ^2.*

In an extreme case, as $x^* \to -\infty$ so that exporting becomes not profitable to any firms, the exit rate in the second period approaches 1 while some firms will choose to export in the first period as long as their prior mean μ is finite.

5.5 Learning from neighbors

Suppose now the per-period profit of exporting to foreign market is given by

$$\pi(x, \varphi) = x + \varphi + z - f$$

where $z \sim N(0, \sigma_z^2)$, which can be interpreted as a firm-market specific demand attribute, is unknown to the firm when it makes a decision to export.

A firm updates its subjective distribution for x by observing a signal about the market demand x from the export sales of neighborhood firms (indexed by j) who exported to the same market. Suppose we assume that the firm knows the neighbor's productivity and extracts a signal for x from neighbour's export revenue from the same market as

$$\zeta_j := x + z_j = \ln R_j - \varphi_j$$

In Sectio x below, we will discuss how to compute φ_j and thus ζ_j using only trade data.

Given the subjective mean and variance (μ, σ^2) in the next period, the beginning of next period's subjective mean and variance (μ', σ'^2) are determined by the current period's number of new exporters n in neibhorhood and their average signal $\bar{\zeta} := \frac{1}{n}\sum_{j=1}^{n} \zeta_j$ as

$$\mu' = \delta\bar{\zeta} + (1 - \delta)\mu \quad \text{with} \quad \delta = \frac{n\sigma^2}{\sigma_z^2 + n\sigma^2}, \tag{2}$$

$$\sigma'^2 = \frac{\sigma_z^2\sigma^2}{\sigma_z^2 + n\sigma^2}. \tag{3}$$

Based on these standard formula, we have the following testable hypotheses about firms' learning.

Prediction 1 (Average Exit Rates) The average exit rate among firms who start exporting to a foreign market is increasing in the expected demand and uncertainty about its demand.

1. For a given destination, the higher value of σ^2 at the time of entry implies (i) higher average exit rates and (ii) higher export growth conditional on survival.

2. Given the the same value of σ^2 at the time of entry, average exit rates and export growth conditional on survival would be higher would be higher for differentiated goods (high σ_z^2) than for homogeneous goods (low σ_z^2).

3. The value of σ^2 is not observed but the value of σ^2 should be a decreasing function of the total number of entrants $\log N$. So, average exit rates and $\log N$ should be negatively correlated. Furthermore, we expect that the slope is steeper for homogenous goods than differentiated goods because learning is faster for homogenous goods (i.e., σ_z^2 is smaller for homogenous goods).

Prediction 2 (Entry I) *The likelihood of a firm's start exporting to a foreign market is increasing in the strength of the signal about the market's demand (high $\bar{\zeta}$) inferred from neighbors' export performance, and more so if the signal is revealed by more neighbors (high n) and for more differentiated products (high σ_z^2).*

Prediction 3 (Entry II) *The likelihood of a firm's entering a new foreign market is lower if its neighbors' export performances in the same market are more dispersed, all else being equal. On the other hand, it is higher if the firm itself has less prior knowledge about the market (both proxied by σ_z^2).*

Prediction 4 (Post-entry Growth) *The post-entry growth rate firms' exports to a new market, conditional on survival, is decreasing in the level of the ex ante signal about the market's demand, and more so if the signal is revealed by more neighbors.*

Proof: *See proof in the appendix.*

Prediction 5 (Post-entry Growth) *The option value of waiting (i.e., postponed entry) is higher for differentiated products.*

The option value can be approximated by the realized value of the number of entrants in next two years under prefect foresight.