

Excessive Entry and Exit in Export Markets

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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 over 180 destination countries and 7 years (2000-2006), 78% of exporters on average are new exporters. Among these new exporters, 62% on average did not continue serving the same country the following year. These rates are even higher for the new emerging markets for Chinese firms, such as those in Africa. We also find a strongly positive correlation between firms' exit rates and entry rates across destination countries. Both entry and exit rates are negatively correlated with destination countries' market size respectively, but positively correlated with their distance from China. We build a simple two-period model with imperfect information about foreign demand factors, in which firms have prior beliefs over their foreign demand and analyze how the mean and the variance of their prior distribution affect their entries 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 rational self-discovery of own demand in unfamiliar markets.

Key Words: learning to export, knowledge spillover, uncertainty, export dynamics

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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. The common theoretical argument is that firms can learn about their market demand mostly by experimenting the new markets themselves (e.g., Alborno et al., 2012; Timoshenko, 2015; Ruhl and Willis, 2017). In practice, however, firms usually try to obtain information from their neighbors before undertaking any risky decisions (Hausmann and Rodrik, 2003), especially when self-discovery in foreign 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 not received the same level of attention in the studies of international trade, particularly the work on firms' export dynamics.

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 of exporters to many foreign countries are new exporters (78% on average across 180 countries).
2. Among these new exporters, over half of them (62% on average) did not continue to serve the same country in the following year.
3. Firms' exit and entry rates are strongly and positively correlated across destination countries.
4. These entry and exit rates are particularly high for exports to developing countries, especially those in Africa (83% of exporters on average are new; with 69% of them stopped exporting to the same country in the following year).
5. Both firms' entry and exit rates are negatively correlated with the GDP of destination countries
6. Both firms' entry and exit rates are positively correlated with the distance from destination countries.

¹Bartelsman, 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), Alborno et al. (2011), and Blum et al. (2013). See the literature review below for a more detailed discussion.

²Research 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 majority 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 intriguing 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 the Chinese economy and its firms are growing rapidly during this period. However, it is surprising to see such high *exit* rates after the first year of exporting by Chinese firms to those countries. If sunk cost is high, as is commonly assumed in the heterogenous-firm models in trade, a simple extension of Melitz-type model to a dynamic setting where firm productivity is stochastically growing with perfect information on firm-specific productivity/demand will have a hard time explaining such high exit rates. These facts thus motivate us to consider a model in which there is ex-ante uncertainty in firm/market-specific demand, where individual firms form their prior distributions of market-specific demand and make export decisions.

So what could possibly explain these high firms' entry and exit rates? Intuitively, there are two potential explanations. The first possibility is that these new destinations are characterized with high risks but high returns, so that the distribution of firm-specific demand has a high variance, and potentially a thick right tail (e.g., a log-normal distribution of firm export sales). In this case, even if the Chinese firms know exactly the distribution of firm/market-specific demand, they will still rationally enter the market because the expected sum of profits exceeds the sunk cost of entry. Ex post, only a small fraction of firms survive with very high profits. The second potential explanation is that firms are irrationally optimistic about the market's demand, relative to the true level.

To more formally guide our empirical exploration of the reasons behind firms' excessive entries and exits in foreign markets, we develop a simple two-period model of a firm's export decision when it does not exactly know the true demand in foreign markets. At the beginning of the first period, it decides whether to export to a foreign market or not, given the prior distribution over the true demand; if it decides to export, it will learn about the true demand at the end of the first period. In the second period, it will then decide whether to continue exporting or exit from the foreign market.

The model shows that the profit function in the second period is convex in the market demand factor, independent of its distribution. By Jensen's inequality, a higher degree of uncertainty in foreign demand translates into a higher expected value of the second-period profit, leading to a higher probability of exporting in the first period. Thus, our model predicts that both high mean and variance of the prior distribution induce firms' entry into new markets. It is obvious why a higher expected profit will induce firms to enter. The reason for why a high variance of market demand will also encourage entry is less clear. The reason is that when the variance is high and the second-period profit function is convex, firms' expected profits will be higher, inducing firms to enter, while ensuring an option of exiting from the market if the true demand turns out to be lower than expected. Thus, our model rationalizes "optimism" based on the standard rational agent models, without any specific assumptions about the distribution of demand factors.

To strengthen the discussion of an information channel that drives firms' excessive entry and exit, we also 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 individual firms' 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 Sub-Saharan Africa, we find supporting evidence consistent with the main theoretical predictions. We first show that across countries, firms' entry and exit rates are both positively correlated with the distance from the countries, but negatively correlated with their GDP. Moreover, the number of new entrants in a market, presumably providing information about the market, is negatively correlated with the entry and exit rates, respectively. Such negative correlation is even stronger for homogeneous goods, for which neighbors' profitability should provide more relevant information, compared to differentiated goods. These results confirm the model predictions that self-experimenting entry and exit are more intense in unfamiliar markets, while other firms' information are useful, especially for homogeneous goods.

We then show at the country-sector level that the exit rate is higher on average if the markets are farther away, controlling for industry-year and city-year (or province-year) fixed effects. Such excessive exit rates for distant markets are lower for differentiated goods, consistent with the idea that firms' decisions are less responsive to new information from neighbors if market demand is more idiosyncratic. At the firm level, 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 a firm's probability of entry in a market is positively correlated with the strength of the signal, measured by the average demand inferred from firms in the neighborhood (same city or province) exporting to the same country-sector, more so if the number neighbors serving the market is higher.³

The paper is organized as follows. Section 2 briefly reviews the literature. Section 3 describes the data. Section 4 establishes some stylized facts. Section 5 introduces a simple model to guide empirical analysis. Section 6 presents results of our empirical analysis. The final section concludes.

³In 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.

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.⁴ 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).⁵ Most of these models focus on firms' *own* export experiences to look for determinants of export dynamics.⁶ We focus instead on learning from neighbors.⁷

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 (Foster and Rosenzweig, 1995; Conley and Udry, 2010; Moretti, 2011).⁸

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 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

⁴Among 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.

⁵For 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.

⁶A 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.

⁷The 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.

⁸See Foster and Rosenzweig (2010) for an extensive review of other micro evidence of technology adoption. 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.

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 some of the early studies on the spillover effects of existing exporters or multinational firms on new export linkages. Like ours, recent research uses transactions-level data (Alvarez et al., 2008; Cadot et al., 2011).⁹ 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, finally, we explore information spillover across destinations within firms, controlling for all firm-specific and market-specific shocks. It is worth noting that similar to this paper, Fernandes and Tang (2014) also use the same data set to explore the presence of information spillovers in firms' exporting. The main difference between ours and that paper is that we take the option value of waiting more carefully and also focus more on firms' excessive entries and exits in unfamiliar markets, especially those in Africa.

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).¹⁰ 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).

3 Data

The main data set used in the empirical analysis covers monthly export and import transactions of the universe of Chinese firms between 2000 and 2006.¹¹ 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

⁹ 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.

¹⁰ 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.

¹¹ The same data set has been used by Manova and Zhang (2010) and Ahn, Khandelwal and Wei (2010).

each country (over 200 destination and source countries) for each firm.¹² 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 country-sector in the empirical analysis.

Exporters in China are required by law to register as either processing exporters or non-processing (ordinary) exporters.¹³ 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, in the empirical analysis below, we will exclude all processing firms and trading companies (wholesale-retail firms) from the sample.

We study learning from neighboring exporters in the same city. There are on average 425 cities plus municipalities, according to China’s Customs’ definition.¹⁴

4 Stylized Facts

Our empirical analysis relies heavily 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 across destination countries and sectors, even when firm-year fixed effects are controlled for. The relatively small exporters’ median sales indicate that most of the firms in the sample are actually quite small, which should enter and exit markets actively according to existing evidence from other countries.

As we discussed in the introduction, we first document several stylized facts about Chinese firms’ exporting dynamics. The first set of stylized we aim to establish are the very high entry and exit rates into different foreign markets among Chinese exporters. Table 2 reports the mean and median entry and exit rates of Chinese exporters across destination countries by year. As shown in

¹²Example of a product: 611241 - Women’s or girls’ swimwear of synthetic fibres, knitted or crocheted.

¹³Since 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.

¹⁴The number of cities in our sample increases from 408 in 2000 to 425 in 2006. The Chinese government gradually added new cities.

the first row of Panel A, we find that across the 180+ countries in our sample across 6 years (2001-2006), the average entry rate, defined as the fraction of new exporters in total exporters selling in a country, is 78%.¹⁵ In other words, across more than 180 countries served by the Chinese, on average 78% of the exporters in a given year have not served that market before. Among these new exporters, a majority of them stopped exporting to the same market in the following year. As the second row reveals, 62% of the new exporters stopped exporting to the same country in the following year on average (across countries and years). These high rates could be driven by a few outliers that are new markets served by a few firms, which entered and dropped out immediately in the following year. To address this concern, we also show the median entry and exit rates across countries by year. The median numbers, as shown in the third and fourth rows, confirm the idea that turnovers in the median destination country in our sample are very high.

In Panel B, we show the same set of statistics but focus on the sample of firms that export to African nations. We find substantially higher entry and exit rates among firms that serve the African markets. In particular, the entry rates and exit rates among Chinese firms serving African countries across years are 83% and 69%, respectively. These findings are consistent with the prior that many Chinese firms are less familiar with the African markets than the big markets like the US or the nearby ones in East Asia.

Next, we show in Figure 1 a tightly positive relationship between the firms' entry and exit rates across countries (for 2005). Figure 2 shows the same positive relationship across countries for differentiated and homogeneous products, as defined by Rauch (1999), respectively. It appears that the slope that represents the positive relationship is higher for differentiated products, suggesting that for markets with proportionally more new entrants as exporters, the exit rate tends to be higher. To the extent that differentiated goods are intuitively associated with more firm-specific idiosyncratic demand factor, the degree of ex ante uncertainty should be higher, which will be reflected in higher average exit rates ex post.

These facts are, to the best of our knowledge, novel relative to the literature. High *entry* rates in African nations may not be surprising as the Chinese economy, its firms, and the economies of many African nations are growing during the sample period. However, it is surprising to see such high *exit* rates in those markets. If sunk cost is high, the standard dynamic heterogeneous-firm model in trade, say the dynamic extension of Melitz (2003), which features stochastically growing firm productivity and perfect information, cannot rationalize such high exit rates. To guide our empirical exploration for the reasons behind these intriguing stylized facts, we introduce a simple two-period model with imperfect information next.

¹⁵The average entry rate is computed as the mean of the average entry rates cross years, with the average entry rate per year computed first as a mean entry rate across destination countries in that year. The entry rate for 2000, the first year in our sample, is excluded in the calculation as it is always equal to 1 by definition.

5 A Simple Model

The facts we documented above motivate us to consider a model in which there is some ex-ante uncertainty in firm/market-specific demand, where firms form expectations about firm/market-specific demand when making export decisions. We develop a simple two-period model of firms' export decision when firms do not know the exact market demand in the foreign country. 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 to export, then it will learn about the true demand at the end of the first period. In the second period, the firm will decide if it will continue exporting or exit from the foreign market.

5.1 Setup and notations

To focus on the main mechanisms at work, we make 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.

In sum, our model shows 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.

5.4 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

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

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 exit rate 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 $x^* \rightarrow -\infty$ 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

Let us now extend the model to incorporate learning from neighboring firms. Realistic learning implies that firms will never be able to learn the true demand within finite time. As such, we need to introduce some frictions in learning in the form of firm-specific demand factor. Specifically, let us suppose that the per-period profit of exporting to foreign market is now given by

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

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

A firm updates its subjective distribution of x by observing neighborhood firms' (indexed by j) export sales in the same market. Suppose that the firm knows each neighbor's productivity. It can

then extract a signal for x from its revenue from selling in the same market as

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

In Section 6 below, we will discuss how to compute φ_j and thus ζ_j based on the the same formula, using only trade data.

Given the subjective mean and variance (μ, σ^2) in the previous period, the subjective mean and variance (μ', σ'^2) at the beginning of next period, after observing neighboring firms' exports, are determined by the number of *new* exporters n in neighborhood in the current period and the signal $\bar{\zeta} := \frac{1}{n} \sum_{j=1}^n \zeta_j$ as

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

Comparative static exercises show that

$$\begin{aligned} \frac{\partial \mu'}{\partial \bar{\zeta}} &> 0; & \frac{\partial^2 \mu'}{\partial n \partial \bar{\zeta}} &> 0; \\ \frac{\partial \sigma'^2}{\partial n} &< 0; & \frac{\partial^2 \sigma'^2}{\partial n \partial \sigma^2} &< 0. \\ \frac{\partial^2 \sigma'^2}{\partial \sigma_z^2} &> 0. \end{aligned}$$

Based on these standard equations describing Bayesian updating, along with Proposition 1 and Corollary 2 above, let us summarize the proposition and corollary in the following testable hypotheses as follows:

Prediction 1 (Average Exit Rates) *The exit rate among firms that start exporting to a foreign market is increasing in the expected level (μ) and uncertainty (σ^2) about the market's demand. The relationship between the exit rate and uncertainty is stronger for homogenous goods than for differentiated goods, as learning is more effective for homogenous goods.*

Prediction 2 (Option Value of Waiting) *The option value of waiting (i.e., postponed entry) is lower for differentiated products.*

The logic behind this prediction is the following: The incentive to enter a new market is higher for differentiated goods than for homogenous goods because the option value of waiting is higher for homogenous goods than for differentiated goods. In an extreme case of no learning from neighbours in differentiated goods, a firm producing differentiated goods can only learn about market demand

by entering into a new market, leading to higher entry rates. This implies that, other things equal, entry rates are higher for differentiated goods than for homogenous goods because firms producing differentiated goods have less incentive to wait for entry.

Prediction 3 (Firms’ Entry) *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’ exports, and more so if the signal is revealed by more neighbors (high n) and for the more differentiated products (high σ_z^2). The stand-alone effect of the number of neighboring firms serving the market is ambiguous.*

6 Empirical Evidence

6.1 Suggestive evidence

Motivated by the model predictions, we establish a few more facts before presenting our regression results. We first attempt to check whether the entry and exit rates are positively correlated with the uncertainty about the demand in a market. While the value of σ^2 for a given market is not observed, it should be positively correlated with a country’s (log) distance from China, as distance impedes information flows and communication. Figure 3 shows that indeed there is a positive and significant (with a t-stat of 2.16) cross-country correlation between the entry rate and the bilateral distance from China. Figure 4 shows instead a positive and significant (with a t-stat of 2.73) cross-country correlation between the exit rate and a country’s distance from China. The results in both figures are consistent with our model prediction that uncertainty about a country’s demand will encourage seemingly excessive firms’ entry.

Next we use the (log) number of Chinese entrants to a market as a proxy for the uncertainty about the market’s demand (σ^2). If firms offer information about a market, the measure of uncertainty about the market should be a decreasing function of the total number of entrants $\log n$. Thus, the exit rates and $\log n$ are negatively correlated. Furthermore, we expect that the slope is steeper for homogenous goods than differentiated goods because learning is more effective for homogenous goods (i.e., σ_z^2 is smaller for homogenous goods).

In Figure 5, we plot the firms’ entry rate of a country against the (log) total number of Chinese *new* exporters selling there.¹⁶ To address the concern that the relationship is simply capturing the market size effect, we partial out (log) GDP of the destination country by taking the residual from the regression with the (log) number of Chinese new exporters in a country regressed on (log) GDP of the same country.¹⁷ As is shown in Figure 5, there is a statistically significant and negative relationship between the number of current Chinese entrants in a market and the entry rate, supporting Prediction 1 that information actually discourages experimentation and thus the fraction

¹⁶The result is robust to using the lagged number of new Chinese exporters selling in a country, as well as to the use of the total number of all exporters, including the existing ones. We use the measure of new exporters rather than all exporters to identify flows of new information.

¹⁷The pattern is robust to simply using the (log) number of Chinese firms without partialling out GDP.

of firms in a market that are new. We show this negative relationship separately for differentiated and homogenous products, and find that the negative relationship is stronger for homogenous goods. Through the lens of our model, the idea is that given the idiosyncrasies of differentiated product market demand, information from other firms is less informative for differentiated products. Thus, new entrants offer more "useful" information in the homogenous-good markets. Figure 6 shows similar patterns for exit rates. Since entry and exit rate are highly correlated and essentially affected by information frictions in the same fashion, the rationales behind the significantly negative correlation between the exit rate and the (log) number of entrants are identical to those that we already offered to explain the patterns of Figure 5.

Figures 7 and 8 plot the entry and exit rates on the (log) GDP across countries for the year 2005. Both rates are tightly and negatively correlated with the market size of countries. While GDP can be correlated with many other economic fundamentals, the usual conjecture that firms are less likely to enter markets that are small and difficult to penetrate contrast with the negative correlations we find here. The conjecture that Chinese firms know more about big markets, either because they are more visible or there have been many existing firms selling there and hence offering information, seems to be more consistent with the negative correlation between entry (exit) rates and countries' market size.

To sum up, we find that the majority of exporters are new exporters in many countries (78% on average across 180 countries). Among these new exporters, a majority of them (62% on average) did not continue to serve the same country in the following year. The entry and exit rates are significantly and positively correlated across destination countries. They are particularly high for exports to small and developing countries, especially those in Africa (83% of exporters on average are new; with 69% of the entrants stopped exporting to the same country in the following year). Both firms' entry and exit rates are negatively correlated with the GDP of destination countries, but positively correlated with the distance from them. Though thought-provoking, all these are suggestive evidence so far. We now come to the regression analysis in which various usual suspects can be controlled for, including city-sector-specific supply shocks and destination-sector-specific demand shocks; as well as firm productivity shocks when we run regressions at the firm level.

6.2 Regressions

6.2.1 Average exit rates

Let us now test the various parts of Prediction 1. To recap, Prediction 1 postulates that the exit rate among new exporters in a market (country-sector) should be increasing in the expected level and uncertainty of the market's demand. The positive correlation between the measure of the uncertainty about market demand and entry rates should be *lower* for differentiated goods than homogeneous goods, as learning from others is more effective for homogeneous goods.

While it is intuitive that the perceived high demand in a market would induce entry, it is not easy to come up with a measure for that perception. However, it is relatively straight-forward to come up with proxies for uncertainty about market demand, as we have done in the previous

section. In the regressions below, we will focus on using total number of entrants ($\log n$) in a market and distance between China and the market as our proxies for uncertainty.

To offer more rigorous empirical results supporting the findings in Figures 4-5, we estimate the following specification:

$$y_{m,s,t} = \alpha + \beta p(\sigma_{m,s}^2) + \delta Diff_s \times p(\sigma_{m,s}^2) + \{FE\} + \epsilon_{m,s,t}, \quad (3)$$

where the dependent variable, $y_{m,s,t}$, stands for the fraction of firms that newly enter country m , sector s in year t , but stop exporting in year $t + 1$.

The dependent variable of interest, $p(\sigma_{m,s}^2)$, stands for a proxy for information friction, or uncertainty about a market. It is equal to either the (log) distance between China and country m (in that case, the sector subscript s is redundant); or equal to the (log) number of Chinese new exporters in market m, s in year t . The variable $Diff_s$ is an indicator for whether sector s contains at least half of their HS-4 digit products being differentiated, according to the Rauch (1999) classification. $\{FE\}$ includes sector (HS2)-year and neighborhood (city or province)-year fixed effects. Sector-year fixed effects are included to control for all global supply and demand shocks in a certain sector, while neighborhood-year fixed effects are included to control for any supply shocks coming from where the firm is located. ϵ is the residual.

The estimation results are reported in Table 3. Standard errors are clustered by city or province, depending on the unit of analysis. In column 1 when we use log distance as the proxy for the level of uncertainty (σ_m^2), we find that controlling for sector-year and province-year fixed effects, there is a statistically significant and positive correlation between the (log) distance and the rate of exit from the market. The positive correlation is lower for differentiated product markets, as indicated by the negative coefficient on $Diff_s \times p(\sigma_{m,s}^2)$. In column (2), when we use the (log) number of neighboring firms exporting to market m, s , we find results that are consistent with those in column (1). Specifically, we find a statistically significant and negative coefficient on (log) number of neighbor firms, suggesting that more neighbors, presumably by providing more information about market m, s to potential new entrants, may lower the entry and thus exit rates. This relation is smaller for differentiated products, as suggested by the opposite sign of the coefficient on the interaction term.

When we include both sets of proxies and their interaction terms in column (3), we continue to find statistically significant coefficients that take the signs as predicted by Proposition 1. Columns (4) through (6) repeat the same three exercises but by using city as the definition of neighbors. The results remain robust and consistent with those reported in the first three columns.

6.2.2 Option value of waiting

Our next exercise is to examine Prediction 2, which is about the option value of waiting (i.e., postponed entry). To test Prediction 2, we estimate the following specification

$$y_{i,c,m,s,t} = \alpha + \beta \ln(n_{c,m,s,t+n}) + \delta \ln(n_{c,m,s,t}) + \{FE\} + \epsilon_{i,c,m,s,t}, \quad (4)$$

where the dependent variable, $y_{i,m,t}$, is an indicator for firm i 's entry in market m , sector s in year t . It is thus equal to 1 if the firm exports to country m in sector s and year t , 0 otherwise.

The first task that we need to complete is to find a way to construct a proxy for the option value. In a model with perfect foresights, we can approximate option value by the realized number of entrants in next one or two years. Thus, the regressor of interest is the (log) number of future entrants, $\ln(n_{c,m,s,t+n})$, a proxy for option value of waiting. We will include two versions: $n = 1$ and 2, respectively.

We restrict our sample by dropping firms that already have those with $y_{i,m,t-1} = 0$. In other words, we drop all existing exporters in a market from the sample. As a reminder, we exclude trading companies (wholesale-retail firms) and processing firms from the sample. Furthermore, we restrict our regression sample to cover only 46 destination countries in Sub-Saharan Africa. The decision is made to reduce computational need, as the estimate the entry regressions we need to fill in all missing trade flow at the country-sector level by zeros.¹⁸ The second and more important reason is that Chinese firms have been actively engaged economically in Africa. Given that those markets are new and unfamiliar to many Chinese firms, studying information frictions and learning about exporting to those markets, relative to for example exporting to advanced economies in which many Chinese firms are experienced about, should be more interesting.

By exploiting information at the sub-firm level across years, we can include an exhaustive set of fixed effects ($\{FE\}$) to control for many unobserved determinants of new exporters' export dynamics. In particular, in all the regression specifications, we always include city-country fixed effects, which control for the bilateral distance between a city and a country, as well as physical distance and any unobserved city-market-specific determinants of export performance and dynamics, such as historical factors that may affect the available information and infrastructure for exports from a city to a country. In addition to city-country fixed effects, we control for city-sector-year, country-sector-year, and firm-year fixed effects, respectively. Country-sector-year fixed effects control for any aggregate shocks that may affect the general attractiveness of a market, such as time-varying demand, exchange rates, and economic policies in the importing countries.¹⁹ City-sector-year fixed effects control for any supply shocks, such as government policies, that affect all exporters in a city. Firm-year fixed effects further control for firm productivity shocks. Importantly, by focusing on the within-firm cross-country correlation between new exporters' performance and the prevalence of neighbors' export activities, we address the potential sample selection bias that arises from the endogenous entry decisions that vary across heterogeneous firms.

As reported in Table 4, we find across all specifications negative and significant coefficients on the (log) number of future entrants (in year t or $t+1$), our proxies for firms' (expected) option values. These results are robust to controlling the current number of entrants (all columns) and

¹⁸The sample size just for the 46-country sample is already 5.4 million.

¹⁹By including country-year fixed effects, any learning effects that can still be identified at the city level is due to neighbors' export performance that deviates from the national average. For example, there can be a demand surge in country m for a particular product that has been produced by neighboring exporters. This example fits the general pattern that industries are highly geographically concentrated in China.

also the lagged number of entrants. In columns (4) to (6), we find that the coefficient on the interaction terms between the differentiated-good dummy and the proxies for option values are positive and statistically significant, suggesting that the option value of waiting for other firms to provide information is lower for differentiated products, as our model predicts.

6.2.3 Learning from neighbors

Our final exercise is to empirically study how learning from neighbors will affect firms’ “entry” decisions.

$$y_{i,c,m,s,t} = \alpha + \beta \bar{\zeta}_{c,m,s,t} \times n_{c,m,s,t} + \theta \bar{\zeta}_{c,m,s,t} + \delta n_{c,m,s,t} + \gamma \ln(TFP_{i,c,s,t})\gamma + \{FE\} + \epsilon_{i,c,m,s,t}. \quad (5)$$

Once again, the dependent variable, $y_{i,m,t}$, is an indicator for firm i ’s entry in market m , sector s in year t . It is thus equal to 1 if the firm exports to country m in sector s and year t , 0 otherwise. The regressors of interest are the number of neighbors exporting to country m , sector s in year t ($n_{c,m,s,t}$) and its interaction term with a signal perceived from the neighbors $\bar{\zeta}_{c,m,s,t}$. Notice that we use $n_{c,m,s,t}$ instead of its log as (2) suggests that the non-log level should be used instead. The results remain qualitatively identical when we use the log of $n_{c,m,s,t}$. Our model predicts that $\beta > 0$, $\theta > 0$, $\gamma > 0$, while the sign of δ is ambiguous.

In addition to the fixed effects that we discuss in the previous regression exercises, we will also control for the estimated firm sector-specific productivity (TFP) in some specifications, as suggested by any Melitz-type model. The drawback of controlling for TFP is that the sample size will be substantially reduced, as only firms that already exported some products in the same sector to other countries will be included.

Let us now discuss how we estimate firms’ sector-specific TFP and how we use them and other observables to construct a city-market signal $\bar{\zeta}_{c,m,s,t}$ inferred from neighbors. The theoretical model suggest that the destination specific demand variable can be obtained from export sales to a specific destination after controlling for firm-level productivity measures.

We may obtain the firm-level productivity measure from export sales to destinations outside of Africa. For each sector (HS2), we may regress export sales on firm-fixed effects and destination-time-fixed effects as follows:

$$\ln R_{imt} = \phi_i + \phi_{mt} + \epsilon_{imt},$$

where $\ln R_{imt}$ is the log of export sales to country m at year t for a specific product, ϕ_i is a firm dummy that captures the firm-level productivity, and ϕ_{mt} is a dummy for destination country m in year t . We estimate this equation using the sample of export sales to countries outside of Africa.

Let

$$\hat{\phi}_{jt} = \hat{\phi}_j + \text{average of } \hat{\epsilon}_{jmt} \text{ over } m.$$

The estimate of ϕ_i corresponds to $(\sigma - 1) \ln \rho$ in our theoretical model. Therefore, we may construct a measure of signal (up to a constant) for an African country m from neighbor firm j

that exports to an African country m by $\zeta_j = \ln R_{jmt} - \hat{\phi}_{jt}$. The average value of the signal ζ_j 's among the neighboring exporters can be computed as

$$\bar{\zeta}_{c,m,s,t} = \frac{1}{|\mathcal{N}_{c,m,s,t}|} \sum_{j \in \mathcal{N}_{c,m,s,t}} \zeta_j,$$

where $\mathcal{N}_{c,m,s,t}$ is a set of neighborhood firms that export to market ms in year t .

Table 5 reports the results of estimating eq. (5). Standard errors are clustered at the city(or province)-destination level. The results remain robust to clustering by other groups. As shown in column (1), controlling for country-sector-year fixed effects (countries' demand shocks), city-sector-year fixed effects (city-level supply shocks), and city-country fixed effects (historical linkage), we find that a firm's probability of entry into a market (a country-sector pair) is positively correlated with the strength of the signal, $\bar{\zeta}_{c,m,s,t}$ observed from neighbors in the same city. The spillover effect is larger if there are more neighbors in the same city, as suggested by a positive coefficient on the interaction term between $\bar{\zeta}_{c,m,s,t}$.²⁰ In column (2), when we additionally control for firm-year fixed effects to capture firms' supply shocks, the results remain robust and quantitatively very similar. When we control for the firm's estimated sector-specific TFP, all results remain robust, even the sample size drops substantially as expected.

The last three columns repeat the same set of regressions, but with neighborhood defined as a province rather than a city. The results are consistent with our findings in the first three columns, and together support our model prediction, in particular, Prediction 3.

7 Conclusion

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. We find that in our sample that covers over 180 destination countries and the period of 2000-2006, 78% of exporters on average are new exporters. Among these new exporters, 62% on average did not continue serving the same country the following year. These rates are even higher for new emerging markets for Chinese firms, such as those in Africa.

We also find strongly positive correlation between firms' exit rates and entry rates across destination countries. Both entry and exit rates are negatively correlated with destination countries' market size, respectively, but positively correlated with their distance from China. We build a simple two-period model with imperfect information about foreign demand factors, in which firms have prior beliefs over their foreign demand and analyze how the mean and the variance of their prior distribution affect the firm's entry and exit. We then use our micro data to empirically examine several model predictions, and find supporting evidence that firms' excessive entries and exits are

²⁰In 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.

outcomes of rational self-discovery of own demand in unfamiliar markets. In research in progress, we extend the model to a dynamic one and structurally estimate it. The goal is to quantify the value of information offered by neighboring firms and the option value of waiting to enter foreign markets.

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9 Appendix

9.1 Proof of Proposition 1

Using a change of variable $x = \mu + \sigma\epsilon$, we have

$$V(\varphi) = \int \max\{\mu + \sigma\epsilon + \varphi - f, 0\}\phi(\epsilon)d\epsilon = (\mu + \varphi - f)\Phi((\mu + \varphi - f)/\sigma) + \sigma\phi((\mu + \varphi - f)/\sigma).$$

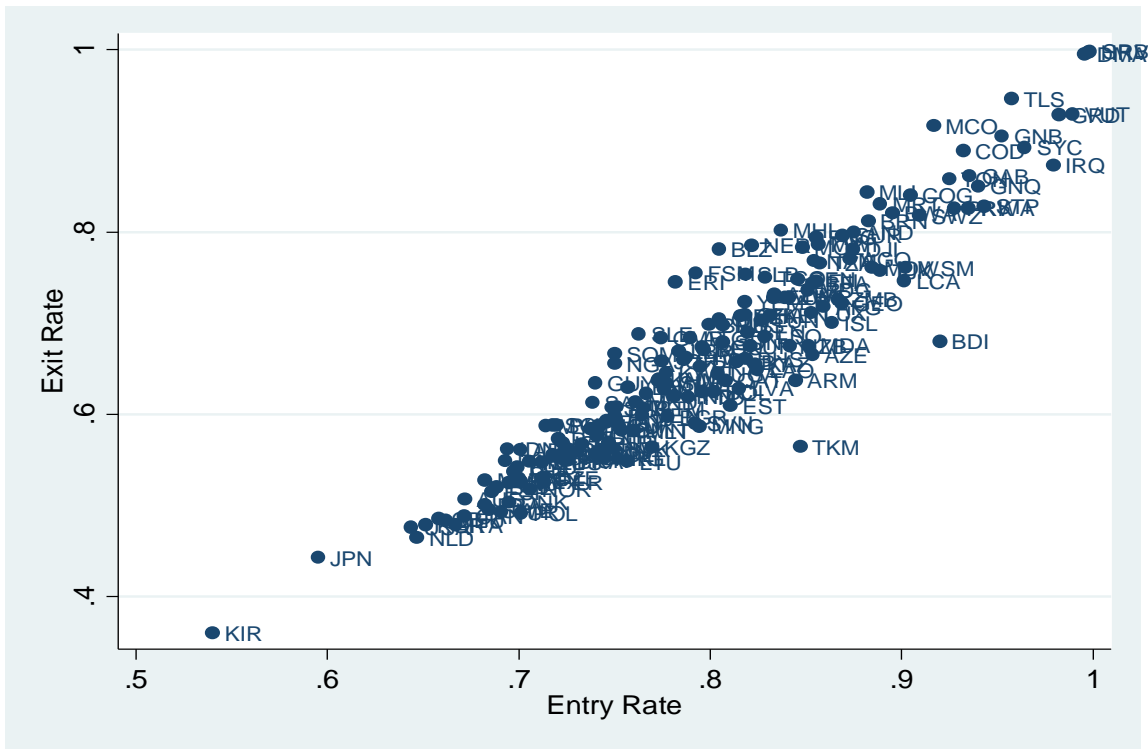
Define $W(\mu, \sigma, \varphi) = \mu + \varphi - f + \beta(\mu + \varphi - f)\Phi((\mu + \varphi - f)/\sigma) + \sigma\phi((\mu + \varphi - f)/\sigma)$. Taking a derivative of $W(\mu, \sigma, \varphi)$ with respect to φ , μ , $(1/\sigma)$, while noting the property of the standard normal density function $\phi'(t) = -t\phi(t)$, we have

$$\begin{aligned} \frac{\partial W(\mu, \sigma, \varphi)}{\partial \varphi} &= 1 + \beta\Phi((\mu + \varphi - f)/\sigma) + ((\mu + \varphi - f)/\sigma)\phi((\mu + \varphi - f)/\sigma) - ((\mu + \varphi - f)/\sigma)\phi((\mu + \varphi - f)/\sigma) \\ &= 1 + \beta\Phi((\mu + \varphi - f)/\sigma) > 0, \\ \frac{\partial W(\mu, \sigma, \varphi)}{\partial \mu} &= 1 + \beta\Phi((\mu + \varphi - f)/\sigma) > 0, \\ \frac{\partial W(\mu, \sigma, \varphi)}{\partial(1/\sigma)} &= (\mu + \varphi - f)^2\phi((\mu + \varphi - f)/\sigma) - \sigma^2\phi((\mu + \varphi - f)/\sigma) - (\mu + \varphi - f)^2\phi((\mu + \varphi - f)/\sigma) \\ &= -\sigma^2\phi((\mu + \varphi - f)/\sigma) < 0. \end{aligned}$$

Note that the last equation implies that $\frac{\partial W(\mu, \sigma, \varphi)}{\partial \sigma} > 0$.

Define $\varphi_2^*(\mu, \sigma)$ implicitly by $W(\mu, \sigma, \varphi_2^*(\mu, \sigma)) = 0$. It follows from the implicit function theorem and $\partial W/\partial \varphi$, $\partial W/\partial \mu$, $\partial W/\partial \sigma > 0$ that we have $\partial \varphi_2^*/\partial \mu = -(\partial W/\partial \mu)/(\partial W/\partial \varphi) < 0$ and $\partial \varphi_2^*/\partial \sigma = -(\partial W/\partial \sigma)/(\partial W/\partial \varphi) < 0$. ■

Fig 1: Firms' Entry and Exit Rates by Country (2005)



Note: Entry rate = New exporters(t)/ total exporters (t); Exit rate = # Entrants Exit (t+1) / Entrants (t)

Fig 2: Firms' Entry and Exit Rates by Country (2005)

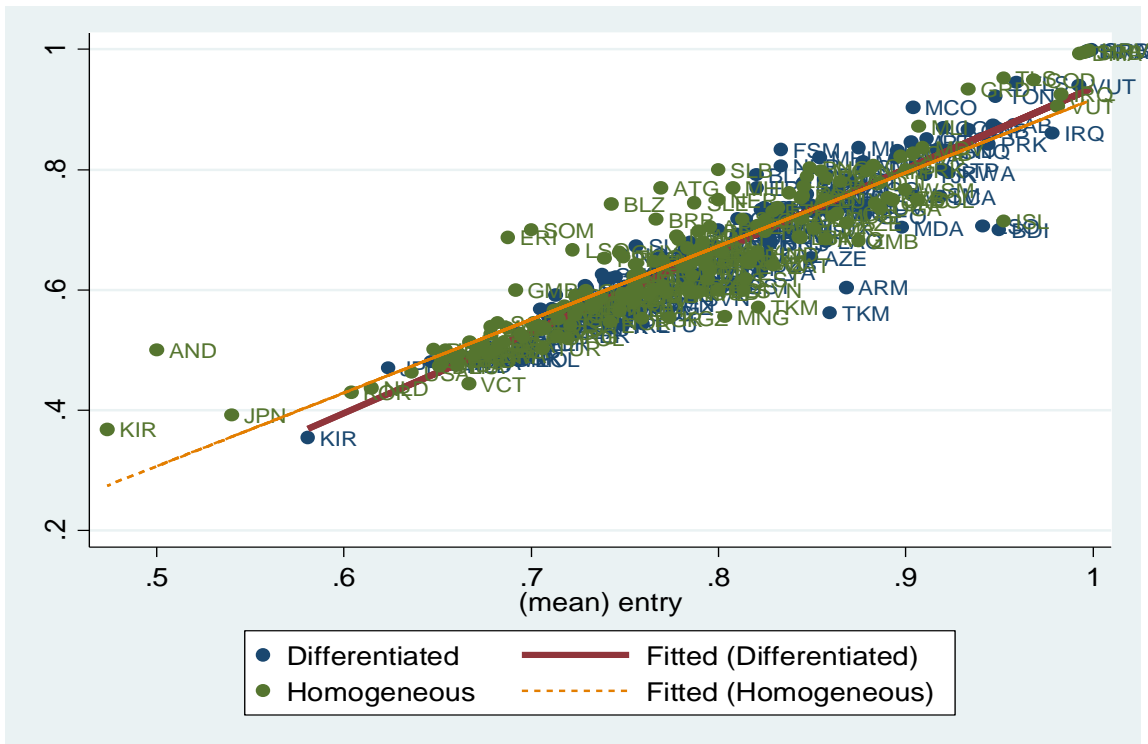


Fig 3: Firms' Entry and Distance by Country (2005)

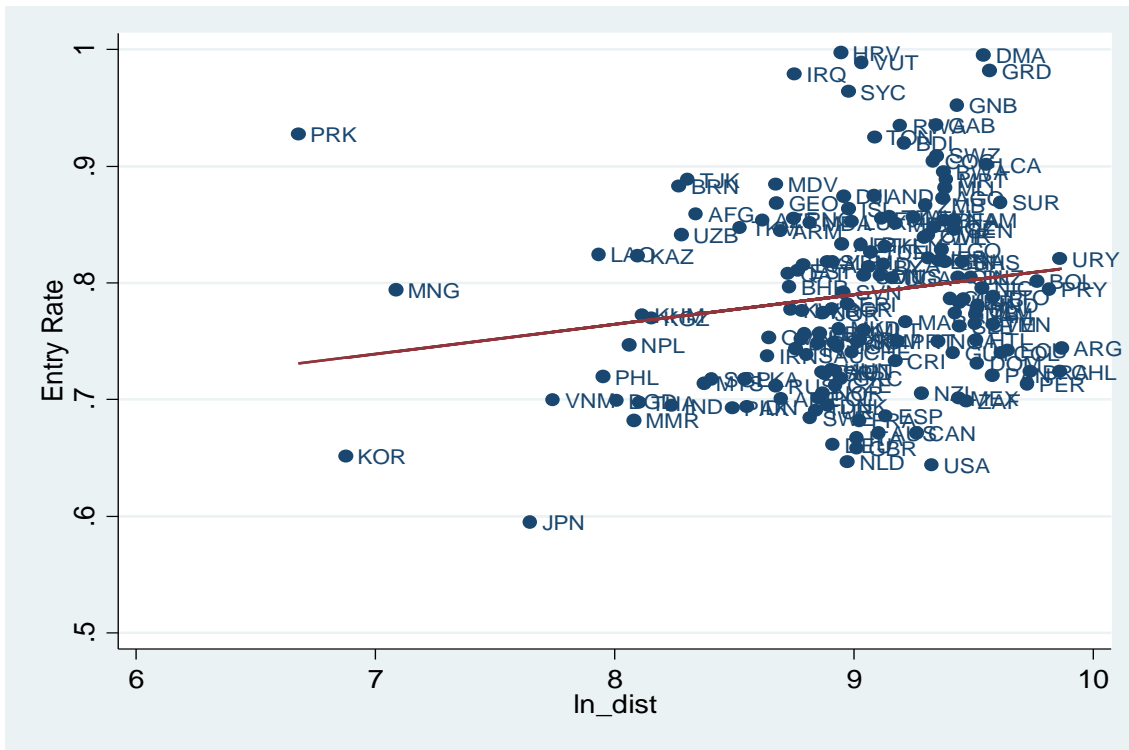


Fig 4: Firms' Exit Rate and Distance by Country (2005)



Fig 5: Firms' Entry Rate and log Nb of New Chinese Entrants by Country (2005)

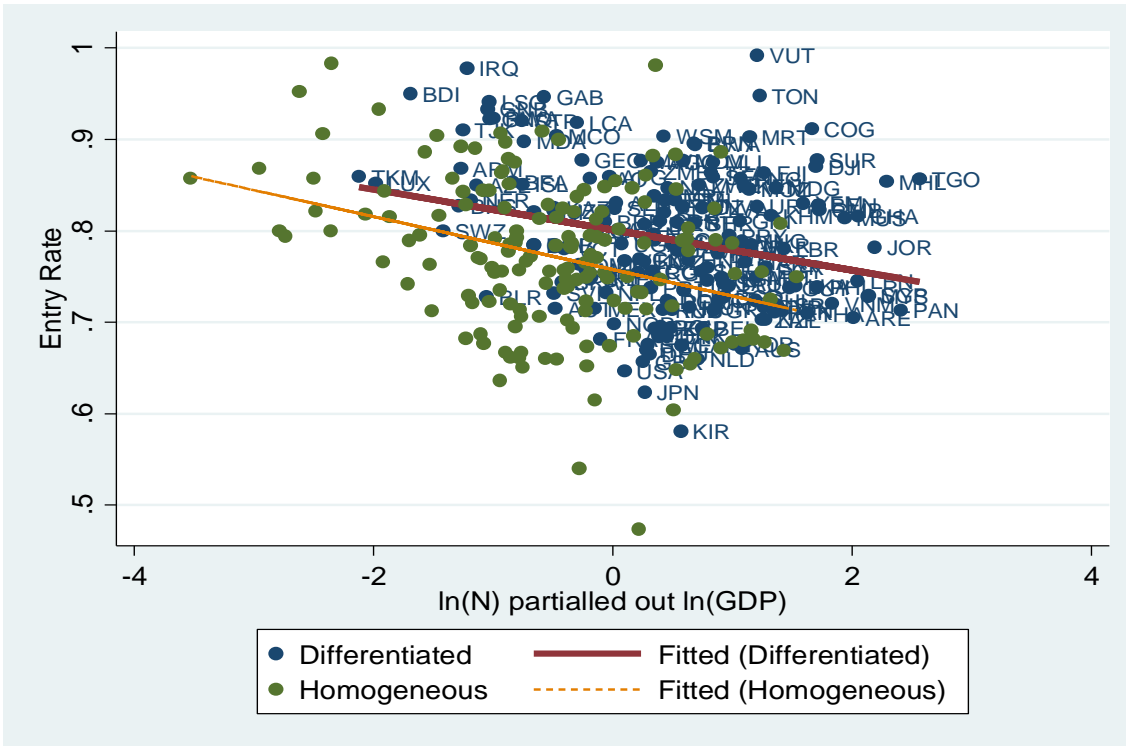


Fig 6: Firms' Exit Rate and log Nb of New Chinese Entrants by Country (2005)

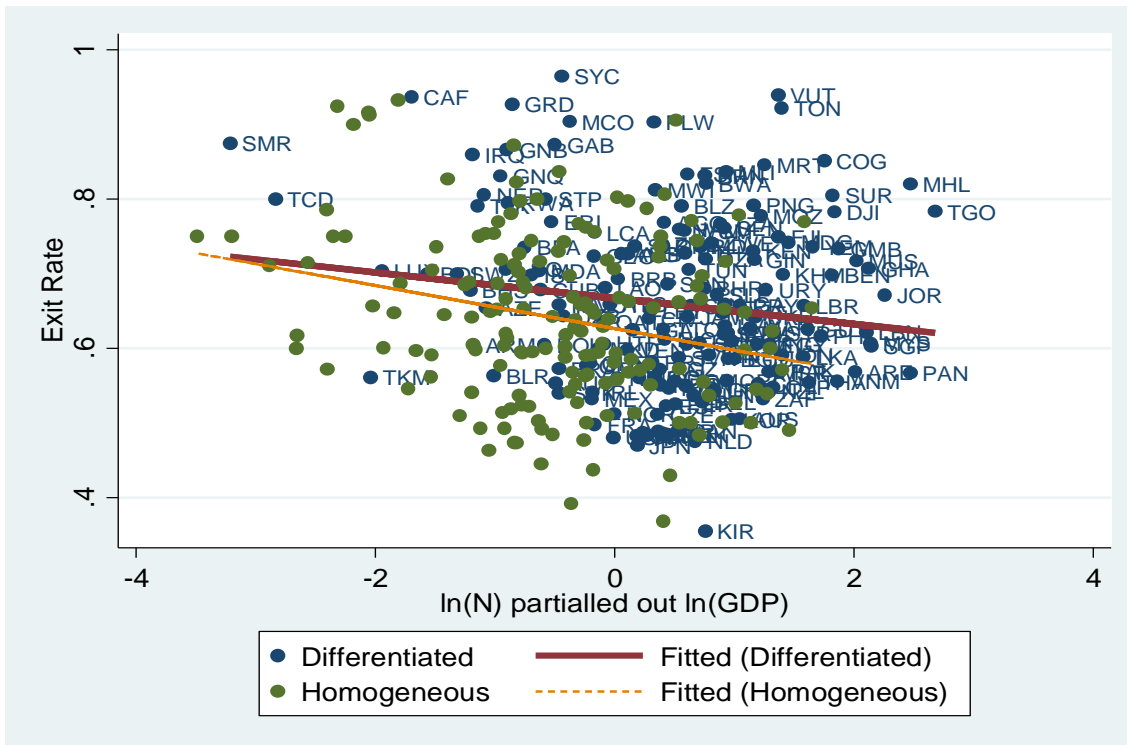


Fig 7: Firms' Entry and log GDP by Country (2005)



Fig 8: Firms' Exit and log GDP by Country (2005)

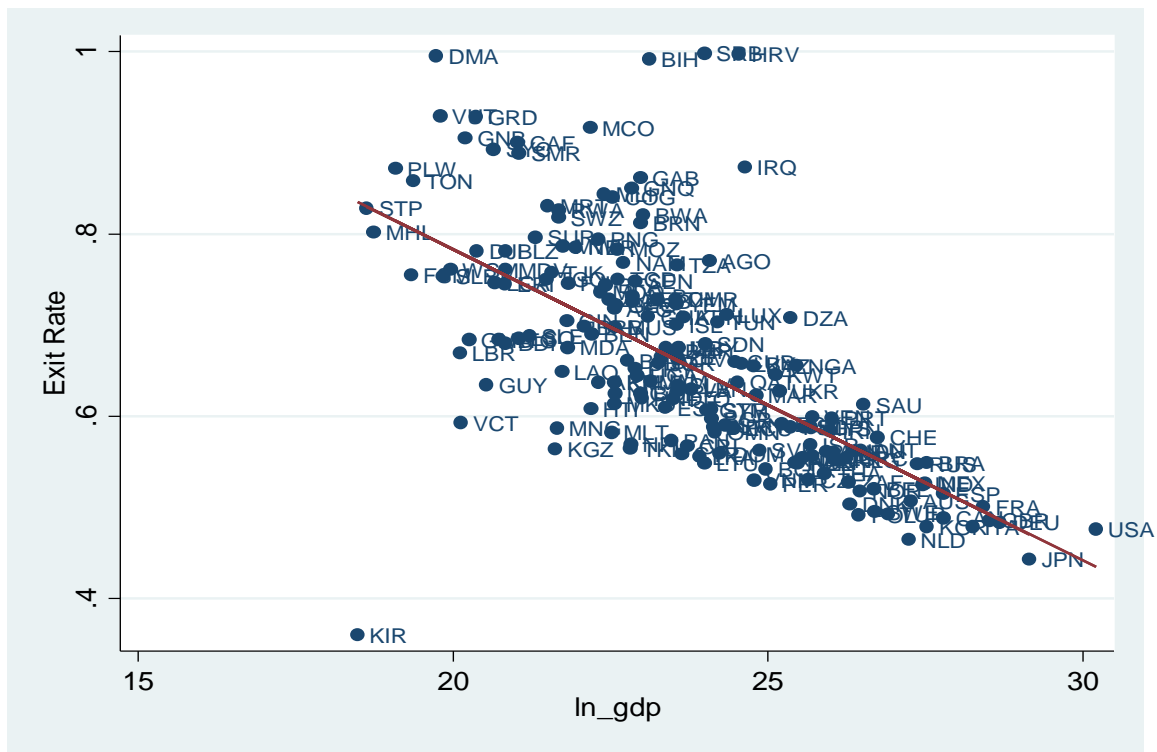


Table 1: Summary Statistics of China's Customs Data

Panel A: Firm level			
Number of destinations	2001	2003	2005
Mean	5	6	6
Median	2	2	3
Stand. Dev	7	8	9
Exports (thousands US\$)			
Mean	1011	1258	1462
Median	196	251	298
Stand. Dev	8893	9926	13816
Panel B: Aggregate Level			
Number of firms	27740	45471	82836
Number of destinations	173	182	195
Exports (US\$ millions)	28044	57202	121102

China's Customs transaction-level trade data (2001-2005). Only non-processing (ordinary) exporters are included. Trading companies (wholesale-retail firms) are all excluded.

Table 2: Average Firms' Entry and Exit Rates by Year

Year	2000	2001	2002	2003	2004	2005	2006	Average across years
<i>Panel A</i>								
Mean Entry Rate	1.000	0.809	0.793	0.766	0.778	0.806	0.717	0.778
Mean Exit Rate	0.742	0.609	0.585	0.576	0.610	0.677	0.554	0.622
Median Entry Rate	1.000	0.809	0.779	0.752	0.774	0.796	0.713	0.770
Median Exit Rate	0.720	0.592	0.556	0.563	0.591	0.658	0.532	0.602
Number of Countries	185	181	183	185	183	189	186	184.571
<i>Panel B</i>								
Mean Entry Rate	1.000	0.844	0.825	0.822	0.837	0.855	0.772	0.826
Mean Exit Rate	0.798	0.650	0.632	0.666	0.712	0.754	0.637	0.693
Median Entry Rate	1.000	0.846	0.816	0.817	0.825	0.846	0.754	0.817
Median Exit Rate	0.778	0.621	0.607	0.659	0.698	0.744	0.615	0.675
Number of Countries	51	53	53	53	53	53	53	52.714

China's Customs data and authors' calculation. The mean and median entry rates are both equal to 1 in 2000 as it is the first year in our sample. Those observations will be dropped in our regressions below.

Table 3: Information Asymmetry, Learning, and Exit Rates

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Rate of Exit from a Market (Country-Sector)					
Neighborhood	Province			City		
ln(dist)	0.0503*** (10.837)		0.00998*** (3.017)	0.0401*** (18.467)		0.0132*** (7.785)
Diff x ln(dist)	-0.0178*** (-5.727)		-0.00872*** (-2.884)	-0.0165*** (-8.260)		-0.0129*** (-6.853)
ln(nb neighbors)		-0.114*** (-61.654)	-0.112*** (-60.114)		-0.145*** (-91.600)	-0.143*** (-89.091)
Diff x ln(nb neighbors)		0.0109*** (8.161)	0.0101*** (7.329)		0.0100*** (8.684)	0.00882*** (7.426)
Fixed Effects	HS2-Year, Province-Year			HS2-Year, City-Year		
N	343516	354999	343516	745433	767165	745433
r2	.0913	.175	.173	.099	.168	.167

The sample includes all country-sector pairs in which Chinese firms ever sold during the sample period. Standard errors are clustered by city in columns (1)-(3) & by province in columns (4)-(6), and are robust to clustering at other levels. T-statistics are reported in parenthesis.

Table 4: Option Value of Waiting

Dep Var	(1)	(2)	(3)	(4)	(5)	(6)
	Entry Dummy					
ln(# entrants t+1)	-0.0364*** (-7.083)	-0.0292*** (-6.288)		-0.0556*** (-4.810)	-0.0458*** (-4.081)	
ln(# entrants t+2)			-0.0172*** (-5.604)			-0.0329*** (-4.063)
ln(# entrants t)	0.236*** (18.868)	0.236*** (18.733)	0.229*** (16.797)	0.236*** (18.735)	0.237*** (18.636)	0.230*** (16.671)
ln(# entrants t-1)		-0.0381*** (-6.146)	-0.0451*** (-6.360)		-0.0375*** (-6.114)	-0.0447*** (-6.359)
diff x ln(# entrants t+1)				0.0259** (2.041)	0.0222* (1.817)	
diff x ln(# entrants t+2)						0.0199** (2.194)
Fixed Effects	firm x year, city x hs2 x year, dest x hs2 x year, city x dest					
N	3722120	3014679	1959810	3722120	3014679	1959810
r2	.0716	.0695	.0701	.101	.0982	.101

The sample includes only exports to 46 Sub-Saharan African countries. Standard errors are clustered at the country-hs2 level, and are robust to clustering at other levels. T-statistics are reported in parenthesis.

Table 5: Learning from Neighbors and Firm's Entry

Dep Var	(1)	(2)	(3)	(4)	(5)	(6)
	Firm's Entry Dummy					
nb of neighbors (same city-country-hs2) x signal (city)	0.0297*** (14.096)	0.0294*** (13.957)	0.0450*** (26.952)			
nb of neighbors (same city-country-hs2)	-0.317*** (-15.407)	-0.314*** (-15.227)	-0.477*** (-32.163)			
signal (city)	0.0253*** (23.168)	0.0250*** (23.052)	0.0506*** (33.123)			
nb of neighbors (same prov-country-hs2) x signal (province)				0.00602*** (23.916)	0.00593*** (23.845)	0.0239*** (26.951)
nb of neighbors (same prov-country-hs2)				-0.0627*** (-24.686)	-0.0618*** (-24.579)	-0.248*** (-27.888)
signal (province)				0.0109*** (44.471)	0.0109*** (47.528)	0.0545*** (81.414)
tfp_est			0.00553*** (18.713)			0.0106*** (23.157)
Fixed Effects		city x hs2 x year, dest x hs2 x year, city x dest				
Additional Fixed Effects		firm x year				
N	5383708	5383697	339490	5383708	5383697	339490
r2	.462	.474	.808	.157	.18	.636

The sample includes only exports to 46 Sub-Saharan African countries. Existing exporters are dropped from the sample, so that a firm's entry propensity is compared with "no entry". Standard errors are clustered at the country-hs2 level, and are robust to clustering at other levels. T-statistics are reported in parenthesis.