Federal Reserve Bank of Dallas
Globalization and Monetary Policy Institute
Working Paper No. 185
http://www.dallasfed.org/assets/documents/institute/wpapers/2014/0185.pdf

Learning to Export from Neighbors*

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June 2014

Abstract

This paper studies how learning from neighboring firms affects new exporters' performance. We develop a statistical decision model in which a firm updates its prior belief about demand in a foreign market based on several factors, including the number of neighbors currently selling there, the level and heterogeneity of their export sales, and the firm's own prior knowledge about the market. A positive signal about demand inferred from neighbors' export performance raises the firm's probability of entry and initial sales in the market but, conditional on survival, lowers its post-entry growth. These learning effects are stronger when there are more neighbors to learn from or when the firm is less familiar with the market. We find supporting evidence for the main predictions of the model from transaction-level data for all Chinese exporters from 2000 to 2006. Our findings are robust to controlling for firms' supply shocks, countries' demand shocks, and city-country fixed effects.

JEL codes: F1, F2

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1 Introduction

Research shows that firms' turnover rates (entry and exit) in foreign markets are much higher than those in the domestic market.[1] Moreover, firms often quit exporting to a country after a short spell of selling a small amount of goods there.[2] These findings reflect a considerable amount of uncertainty facing new exporters. To explain these findings, theoretical studies have hypothesized 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 (e.g., Rauch and Watson, 2003). While self-learning and experimentation are important mechanisms behind these dynamics, in reality, firms usually try hard to obtain information from their neighbors before undertaking risky investments (Hausmann and Rodrik, 2003). This is particularly the case when self-discovery in export markets entails high sunk costs.[3] While development economists have for years studied how learning from neighbors determines firms' technology adoption (e.g., Foster and Rosenzweig, 1995, 2010; Conley and Udry, 2010), it has been a relatively neglected channel to explain exporters' dynamics and performance.

We develop a model of social learning to study how firms learn from their neighbors about foreign market demand. The model delivers several micro-founded hypotheses about how learning from neighbors shapes new exporters' entry decisions, survival, initial sales, and post-entry growth, which we then examine using detailed transaction-level data for all Chinese exporters. In addition to the rich information available in the data, the especially high degree of industrial agglomeration in China provides a good setting for such an analysis.

Our model incorporates social learning pioneered by Jovanovic (1982) into a standard heterogeneous-firm model of trade, starting with Melitz (2003). We think of a firm's export profits in a market as depending on three factors – firm-specific productivity, firm-market-specific product appeal, and market-specific demand. A new exporter knows its productivity before entry, but is uncertain about country-specific demand and its own market-specific product appeal.[4] Based on information

[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] For example, Eaton et al. (2008) and Albornoz et al. (2012) find that in Colombia and Argentina respectively, only 40% to half of new exporters continue to export after the first year. Firms that survive the first year of exporting end up driving the bulk of a country's long-run export growth.

[3] 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.

[4] While our model focuses on learning about demand, the theoretical results can be generalized and the interpretation of our empirical results can be much broader. For example, learning from neighbors can be about foreign importers or about how to adapt the product to the specific tastes or legal requirements of the destination market. We abstract from learning about production, but by no means we think it is unimportant for export. Regarding the supply-side uncertainty, existing producers would have learned about their own capability by producing for the domestic market. It is conceptually difficult to explain why firms would enter a foreign market with a small order and then exit if they are initially uncertain about their production capability.

inferred from neighbors' export performance in a market, a firm can update its prior about the market's demand that is common across firms. Since observed neighbors' export performance could be affected by their unobserved product appeals, signals about foreign market demand are noisy. Based on a standard learning model, when more neighboring firms reveal information, the observed signal converges to the true state of demand as firm-specific noises tend to average out to zero.

We show that a firm's export decision and post-entry performance depend not only on the prevalence of neighboring export activities, as has been shown in the literature on information and technology spillover in trade, but also on other (measurable) factors, including the number of neighbors currently selling there, the level and heterogeneity of their export sales, and the firm's own prior knowledge about the market. More neighbors may not encourage export entries. The relationship depends on the strength of the signal (average neighbors' export sales or growth). An increased prevalence of neighboring export activities will increase the rate of exporters' entry into new markets when the signal is positive, whereas it will deter entry when the signal is negative. Our model proposes the use of an interaction between the signal and the prevalence of neighboring export activities, rather than the prevalence measure only, as a more direct variable to empirically identify information spillover in trade.

Our model yields several predictions. It predicts that a positive signal about foreign market demand from neighbors induces more export entries and larger initial sales among the entrants in the same market. This effect is stronger when the signal is more precise, due to more firms revealing it. Given the positive relationship between the strength of the signal, its precision, and new exporters' initial sales, new exporters' average export growth after entry, conditional on survival, is lower the stronger and more precise the signal is. In other words, a firm is less likely to be surprised and increase exports significantly ex post when the ex ante signal about the foreign market is more precise. The model also shows a weaker response in export entry to a positive signal when observed neighbors' performance is more dispersed (i.e., a lower signal-to-noise ratio), and a stronger response when the firm is less informed about the new market ex ante and needs to rely more on information from neighbors.

Finally, our model shows that conditional on the signal and firm productivity, a new exporter's survival rate in a market is independent of the prevalence of neighbors serving the same market. However, since the prevalence of neighbors revealing a positive signal is correlated with the mass of export entrants, it will also affect the fraction of export survivors. Given sunk entry costs and firm heterogeneity, a more positive or precise signal induces more low-productivity firms to enter. In the presence of per-period fixed export costs, the less productive export entrants are more likely to exit ex post. The fraction of surviving export entrants will be decreasing in the strength of the signal, more so if it is revealed by more neighbors. Thus, our model highlights that existing evidence on the positive information spillover effect on survival can be determined by more low-productivity entrants on the one hand, and a more accurate neighbors' revealed signal on the other.[5]

[5]By using transaction-level data, we address the selection bias in the empirical analysis by focusing on the within-firm variation in performance across markets by controlling for firm-year fixed effects.

Using transaction-level trade data for the universe of Chinese exporters over 2000-2006, we find supporting evidence for the main theoretical predictions. In particular, controlling for firm-year fixed effects (firms' supply shocks), city-year fixed effects (countries' demand shocks), and city-country fixed effects, we find that the entry rate and initial sales of new exporters in a market are both positively correlated with the strength of the signal, measured by the average level or growth rate of neighboring firms' exports to the same market.[6] The positive correlation is increasing in the prevalence of neighbors located in the same city.[7] The learning effects on new exporters' entry and initial sales are both quantitatively important. Controlling for firm supply shocks and country demand shocks, the sample mean growth rate of neighbors' exports to a country (20%) is associated with a one-third increase in export entry, evaluated at the median entry rate (0.3%) of the pooled sample. At the sample mean export growth, a one standard-deviation increase in the (log) density of neighboring firms (5 more neighbors per squared mile) exporting to a country is associated with a 10% higher entry rate in the same country, evaluated at the median entry rate. The corresponding positive effect of the interaction between the signal and the prevalence of neighbors on new exporters' initial sales is about 0.5%.

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.

To further confirm that it is learning rather than other channels through which positive externalities are identified from neighbors, we empirically examine the theoretical predictions regarding the relations between export entry rates, the precision of the signal, and the firm's prior knowledge about the new markets. While our empirical results do not support the specific prediction about the negative effects of a noisier signal on export entry rates, they reveal stronger learning effects for firms exporting to new markets that are farther away from China, which Chinese firms are presumably less familiar with; and weaker learning effects for firms entering new markets that share similar characteristics (e.g., official language) with the firms' previously served markets. Our findings also reveal stronger learning effects in situations when neighbors are domestic rather than foreign, consistent with the hypotheses that foreign firms are more attentive in restricting the leakage of trade secrets, or that there is less information exchange between domestic and foreign exporters. We also

[6] 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.

[7] 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.

find that firms learn from both neighbors in the same city, as well as those outside the city but in the same province. Collectively, these findings confirm that information inferred from neighbors reduces exporters' uncertainty about selling in new foreign markets, which in turn shapes their sales dynamics and performance there.

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.

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.[8] 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).[9] Most of these models focus on firms' *own* export experiences to look for determinants of export dynamics.[10] We focus instead on learning from neighbors.[11]

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.[12] 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

[8] 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.

[9] 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.

[10] 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.

[11] 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.

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

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 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).[13] 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).[14] Finally, our paper contributes to the literature on the role of fixed and sunk costs of

[13] 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.

[14] 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

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 Model

We develop a simple model to guide our empirical analysis on exporters' dynamics. The model features normal learning, similar to a variety of models by Jovanovic (1982), Foster and Rosenzweig (1995), Conley and Udry (2010), and Moretti (2011). We focus on learning about demand rather than production, as in Moretti (2011).[15] Our model is static in nature. Specifically, we focus on a simple two-period structure when analyzing new exporters' entry and post-entry performance. Time subscripts will only be introduced when necessary.

3.1 Set-up

Before exporting to a country, a firm holds a prior belief about the demand of that country. After observing its neighbors' export performance in the same country, a firm updates both the expectation about the country's demand and the precision of its expectation. The model features heterogeneous firm productivity, monopolistic competitive goods markets, and constant-elasticity-of-substitution preferences, as in Melitz (2003). Each firm faces its own downward-sloping demand. Before entering a new market, a firm draws productivity ρ from a cumulative distribution function $G(\rho)$.

Specifically, consider firm i with productivity ρ selling to market m.[16] Its gross (operating) profit will be $\pi^o(D_{im}, \rho) = D_{im}\rho^{\sigma-1}$, where $\sigma > 1$ is the elasticity of substitution between varieties available in all markets. While each firm knows its own productivity before entry, it is uncertain about its export profit due to random firm-market-specific demand. In particular, firm i's (log) demand shifter, $\ln(D_{im})$, can be decomposed into three components as follows:

$$\ln(D_{im}) = \kappa + d_m + z_{im},$$

where κ is a constant.[17] $d_m = \ln(P_m^{\sigma} Y_m)$ is the market-specific component that is common for all

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.

[15] We abstract from learning about production for simplicity, but by no means we think it is unimportant for export. The reason why only a small fraction of firms exports is because (a) they are uncertain about the foreign market demand or (b) they know that they do not have sufficiently high productivity to make profits by selling abroad. Segura-Cayuela and Vilarrubia (2008) and Freund and Pierola (2010) have developed alternative models to analyze uncertainty in trade costs. They also abstract away from learning about production technology. As reviewed above, Foster and Rosenzweig (1995) and Conley and Udry (2010) focus on learning from neighbors about production technology.

[16] A market is defined as a country to be consistent with our empirical analysis below. Since learning can be market-product-specific, we will repeat our baseline empirical analysis focusing on specific industries.

[17] With monopolistic competition and constant-elasticity-of-substitution utility, $D_{im} = \left(\frac{1}{\sigma}\right)^{\sigma}\left(\frac{\sigma-1}{\sigma w}\right)^{\sigma-1} Z_{im} P_m^{\sigma} Y_m$, where P_m is the ideal price index of market m; Y_m is the total expenditure in market m; w is the factor input cost (e.g., the wage rate if labor is the only factor input). κ equals $\ln\left[\left(\frac{1}{\sigma}\right)^{\sigma}\left(\frac{\sigma-1}{\sigma w}\right)^{\sigma-1}\right]$.

firms, where P_m and Y_m are the ideal price index and total expenditure in market m, respectively. $z_{im} = \ln(Z_{im})$ is firm i's market-specific product appeal in market m, which cannot be inferred from neighbors' performance but is realized right after the firm's first year of exporting. For simplicity, we assume that all three components of $\ln(D_{im})$ are time-invariant.[18] If $\ln(D_{im})$ is time-varying (e.g., the market-specific factor contains a time subscript, d_{mt}), as long as it is autocorrelated across time with a permanent component, firms will still learn from neighbors about future export profitability.[19]

Before selling in market m, a firm faces uncertainty about both d_m and z_{im}; but after selling there, firm i learns about both d_m and z_{im} with certainty and there is nothing more to learn.[20] Without any experience in serving market m, firm i does not know d_m and holds a prior belief that d_m is distributed normally with mean $\bar{d}_m$ and variance v_{dm}:

$$d_m \sim N\left(\bar{d}_m, v_{dm}\right).$$

The assumption that d_m is time-invariant implies that once it is learned upon entry, there is no more uncertainty about d_m. Suppose d_m is time-varying and is positively correlated across time, all the theoretical results will still hold with mild assumptions.[21]

Two firms with the same productivity can have different realized export profits in market m due to different product appeals, z_{im}, which is assumed to be ex ante unknown to the firm itself and normally distributed with mean zero and variance v_{zm}:

$$z_{im} \sim N\left(0, v_{zm}\right).$$

Both v_{dm} and v_{zm} can vary across m. A higher v_{dm} can be interpreted as the firm having less prior knowledge about market m. A higher v_{zm} can be a result of more heterogeneous export performance observed from neighbors, who export to market m (more below). We assume that firm productivity ρ and product appeal z_{im} are independently distributed, similar to Bernard et al. (2010).

Without any information about market m from its own export experience or those of others,

[18] The model can be extended along the lines of Timoshenko (2013), who explores learning from one's own experience. To our understanding, keeping the stock of information in a dynamic setting is challenging and has not been done in the literature. We will leave it for future research.

[19] In our empirical specifications below, we effectively control for these time-varying components by including firm-year, market-year, and city-year fixed effects.

[20] These assumptions are consistent with the findings of Eaton el al. (2008), who show that in Colombia, firms that survive the first year of exporting have an average survival rate of 90% in the second and subsequent years.

[21] In a dynamic setting, d_m can be allowed to vary over time and to be positively correlated across time with a permanent component. More formally, the autocorrelation of $d^*_{m,t}$ should be described by the following equation:

$$d^*_{mt} - d^*_{m,t-1} = \gamma\left(d^*_{m,t-1} - d^*_{m,t-2}\right) + \xi_{mt},$$

where $\gamma > 0$ and ξ_{mt} is the permanent shock. See Section 4 for an exposition of the high persistence of demand shocks.

firm i expects to obtain an operating profit from exports to m as follows:

$$\begin{aligned} E\left[\pi^o\left(D_{im},\rho\right)\right] &= \rho^{\sigma-1}E\left[D_{im}\right] \\ &= \zeta\rho^{\sigma-1}\left[\exp\left(\overline{d}_m+\frac{v_m}{2}\right)\right], \end{aligned}$$

where $\zeta = \exp(\kappa)$, a constant, and $v_m = v_{dm} + v_{zm}$. Notice that the firm's expected revenue depends not only on the mean value of D_m, but also on its variance, v_m. To the extent that a market is perceived as more uncertain, the higher level of uncertainty should deter entry. But since the log-normal distribution is not mean preserving, a larger dispersion in D_{im} actually encourages more firms to experiment because of a higher upside for export sales. As will be shown below, all theoretical results are independent from this counter-intuitive result.[22]

Each firm has to pay a sunk cost, K_m^e, to enter market m. Firms that expect an export revenue lower than K_m^e will not enter. The ex ante zero-profit condition (i.e., $E\left[\pi^o\left(D_{mt},\rho\right)\right] = K_m^e$) pins down the productivity of the least productive exporter serving market m as follows:

$$\widetilde{\rho}\left(\overline{d}_m, v_m\right) \equiv \underline{\rho}^{\sigma-1} = \frac{K_m^e}{\zeta\exp\left(\overline{d}_m+\frac{v_m}{2}\right)}. \tag{1}$$

Conditional on exporting, the firm chooses quantity of export, which equals the expected export sales divided by its price, $E\left[R\left(D_{im},\rho\right)\right]/p\left(\rho\right)$, where $E\left[R\left(D_{im},\rho\right)\right] = \sigma E\left[\pi^o\left(D_m,\rho\right)\right]$ and $p\left(\rho\right) = \frac{\sigma}{\sigma-1}\frac{c}{\rho}$, a constant mark-up over marginal cost, c/ρ. After the first period of exporting, the firm realizes D_{im} and there is no more to learn either from its own experience or neighbors.

3.2 Learning from Neighbors

Suppose firm i is surrounded by $n_{m,t-1}$ neighbors, who entered at period $t-1$ or before and export to market m at period $t-1$. Two assumptions are needed for solving the model in closed form. First, we assume that the firm observes the average neighbors' export revenue to market m at $t-1$, $\overline{R}_{m,t-1}$.[23] Second, we assume that the firm knows the time-varying conditional mean of neighbors' productivity, $\widehat{\rho}_{t-1} = E\left[\rho|\rho^{\sigma-1} > \widetilde{\rho}_{t-1}\right]$, where $\widetilde{\rho}_{t-1}$ is the productivity threshold for export entry at $t-1$, taking the form of eq. (1). In other words, similar to Dinlersoz and Yorukoglu (2012), we implicitly assume that new exporters have limited memory and cannot recall the productivity thresholds, $\widetilde{\rho}_{t-k}$, for the cohort of neighbors that enter in year $t-k$ for all $k \in [2,\infty)$.[24] If firm

[22] However, this is a partial-equilibrium result. If we fully develop a general-equilibrium model, the expected discounted value of the future stream of profits could be decreasing in v_m, potentially offsetting the positive effect of a higher variance of the distribution of v_m on the entry rate.

[23] A more restrictive assumption is that it observes each neighbor's export value, which is not required here. We are aware that the reality can be quite different from this simplifying assumption. For instance, firms only observe some of the firms, especially the large ones. Depending on their networks, different firms will have different sets of observed neighbors. While partial observability could potentially be incorporated in the model, we prefer to keep the model simple and instead explore differential learning effects in the empirical section below.

[24] Notice that $\widetilde{\rho}_{t-k}$ can fluctuate across time depending on the underlying process of the destination's true state of demand. Without a dynamic model, we cannot say much about the cohorts of entrants and will need to rely on the "memoryless" assumption.

i is an export pioneer in market m (i.e., there is no existing firm selling there), it holds a belief that $\widetilde{\rho}_{t-1} = \widetilde{\rho}\left(\overline{d}_m, v_m\right)$ as in eq. (1). If it has neighbors that entered at $t-1$, it holds a belief that $\widetilde{\rho}_{t-1} = \widetilde{\rho}\left(\overline{d}^{post}_{m,t-1}, v_{m,t-1}\right)$, where the posterior mean for period $t-1$, $\overline{d}^{post}_{m,t-1}$, and the posterior variance, $v_{m,t-1}$, will be discussed below. Based on $\widetilde{\rho}_{t-1}$, the knowledge about the distribution of ρ, the number of neighbors, n_{mt}, and their average export revenue observed, $\overline{R}_{m,t-1}$, the firm infers the demand level of market m as $\overline{d}^{nb}_{mt} = \frac{\left(\overline{R}_{m,t-1}/n_{m,t-1}\right)}{\widetilde{\rho}^{\sigma-1}_{t-1}}$.[25]

Based on $\overline{d}^{nb}_{m,t-1}$ inferred from $n_{m,t-1}$ neighbors', the firm updates its prior, in the way proposed by Degroot (2004).[26] The posterior is normally distributed with the following mean:[27]

$$\overline{d}^{post}_{mt}\left(n_{m,t-1}, \overline{d}^{nb}_{m,t-1}\right) = E\left[d_{mt}|n_{m,t-1}, \overline{d}^{nb}_{m,t-1}\right] = \delta_t \overline{d}^{nb}_{m,t-1} + (1-\delta_t)\,\overline{d}_m, \tag{2}$$

where δ_t is the weight the firm puts on $\overline{d}^{nb}_{m,t-1}$ when updating its belief. According to Degroot (2004), δ_t can be derived as

$$\delta_t\left(n_{m,t-1}, v_{dm}, v_{zm}\right) = \frac{n_{m,t-1}v_{dm}}{v_{zm} + n_{mt}v_{dm}} = \left(1 + \frac{1}{n_{m,t-1}}\frac{v_{zm}}{v_{dm}}\right)^{-1}. \tag{3}$$

The conditional variance of d_{mt}, given $n_{m,t-1}$ and $\overline{d}^{nb}_{m,t-1}$, can be expressed as

$$v_{mt}\left(n_{m,t-1}, v_{dm}, v_{zm}\right) = \frac{v_{zm}v_{dm}}{v_{zm} + n_{m,t-1}v_{dm}} = \left(\frac{1}{v_{dm}} + \frac{n_{m,t-1}}{v_{zm}}\right)^{-1}. \tag{4}$$

Notice that $\overline{d}^{nb}_{m,t-1}$ depends on the true state of demand (d^*_m) in market m:

$$\overline{d}^{nb}_{mt}\left(d^*_m\right) = d^*_m + \frac{1}{n_{m,t-1}}\sum_{j=1}^{n_{m,t-1}} z_{im}. \tag{5}$$

Partial differentiation yields the following comparative statics regarding the relationship between the number of neighbors, the precision of the prior, and the precision of the signal:

$$\frac{\partial \delta_t}{\partial n_{m,t-1}} > 0;\ \frac{\partial \delta_t}{\partial\left(v_{zm}/v_{dm}\right)} < 0. \tag{6}$$

In words, when updating the prior, a potential entrant will put a larger weight (δ_t) on its neighbors' signals about demand in market m and a smaller weight on its own prior belief, if there are more neighbors revealing the signal. On the other hand, when the signal from neighbors is less precise (higher v_{zm}) due to more heterogeneous product appeals, all else being equal, the firm will

[25] One can argue that in addition to observing its neighbors' export value, a firm can also potentially learn about its neighbors' decisions to continue exporting or not. We assume that a firm only observes its neighbors' past export performance and does not communicate with its neighbors about their future plans. To the extent that most neighbors are competitors, this assumption is reasonable.

[26] We can relax the assumption a bit by assuming that the firm does not necessarily observe each individual firm's export performance in country m, but knows their average export sales in each market.

[27] See Chapter 9 of DeGroot (2004).

put a smaller weight on the signal. Similarly, the firm will put a larger weight on the signal if it is less informed about market m ex ante, captured by a higher v_{dm}.

On the other hand, the posterior variance of the signal, v_{mt}, depends on $n_{m,t-1}$, v_{dm}, and v_{zm} as follows:

$$\frac{\partial v_{mt}}{\partial n_{m,t-1}} < 0; \frac{\partial v_{mt}}{\partial v_{dm}} > 0; \frac{\partial v_{mt}}{\partial v_{zm}} > 0.$$

The precision of the posterior, v_{mt}^{-1}, increases with the number of neighbors revealing the signal. In the extreme case when the number of neighbors approaches infinity, the firm observes the true demand in market m, d_m^*, according to (5) as the variance of the signal approaches 0. The firm will then ignore its own prior and rely solely on its neighbors' revealed signal. The last two inequalities are intuitive.

3.2.1 Entry into New Export Markets

We first analyze how learning from neighbors affects exporters' entry decision. A firm's decision to enter market m depends not only on how many neighbors are already exporting to m, but also on whether the demand level inferred from the average neighbors' export revenue exceeds the firm's prior.[28] By building a static model, we restrict ourselves from analyzing the potentially interesting strategic interactions among firms.[29] That is, we do not analyze how a firm may take into account the impact of its entry on other firms' entry decisions and thus its own revenue in the future. In reality, firms have strong incentives to hide information from potential competitors. One strategy is to delay entry so as to avoid information spillover to other potential entrants. Another benefit of delaying entry is to obtain information from more existing exporters in the future. While incorporating strategic interactions and the option value of waiting into the model will deliver new insights, it will complicate the model substantially. In section 3.2.5 below, we will discuss in greater detail how such extensions will affect the robustness of our theoretical results.

A firm will start exporting after receiving a signal that lowers the entry threshold. Similar to (1), the posterior entry productivity threshold is

$$\widetilde{\rho}_t\left(\overline{d}_{mt}^{post}, v_{mt}\right) \equiv \underline{\rho}_t^{\sigma-1} = \frac{K_m^e}{\zeta \exp\left(\overline{d}_{mt}^{post} + \frac{v_{mt}}{2}\right)}, \tag{7}$$

where $\overline{d}_{mt}^{post}$ and v_{mt} are defined in (2) and (4) above, respectively.

Consider a neighborhood with $n_{m,t-1}$ firms exporting to market m. A positive shock to market m's demand at $t-1$ causes $\overline{d}_{m,t-1}^{nb} > \overline{d}_{mt-2}^{nb}$. The entry threshold at t will be lower than that at $t-1$, i.e., $\widetilde{\rho}_t^{post} < \widetilde{\rho}_{t-1}^{post}$. Specifically, firms with $\rho^{\sigma-1}$ that is lower than $\widetilde{\rho}_{t-1}^{post}$ but higher than $\widetilde{\rho}_t^{post}$

[28] To keep the model tractable, we sidestep from explaining why some firms start exporting before others. A natural extension of the model is to consider firms' heterogeneous private signals.

[29] Notice that the dynamic model on learning and export entry by Segura-Cayuela and Vilarrubia (2008) also abstracts from strategic interactions between firms. It does, however, solve for the option value of waiting. Despite this obvious strength, learning is modelled in a rather reduced-form fashion in their paper. Our model builds on a class of well-known normal learning models, which pay closer attention to the micro-foundation of learning.

will start exporting to market m at t. To formally study the learning effects on entry, let us denote the semi-elasticity of $\widetilde{\rho}_t^{post}$ with respect to $\overline{d}_{m,t-1}^{nb}$ by $\varepsilon_{\rho t} \equiv \frac{\partial \ln \widetilde{\rho}_t^{post}}{\partial \overline{d}_{m,t-1}^{nb}}$, which can be solved as

$$\varepsilon_{\rho t} = -\delta_t \left(n_{m,t-1}\right) = -\left(1 + \frac{v_{zm}}{v_{dm} n_{m,t-1}}\right)^{-1} < 0. \tag{8}$$

That is, in the presence of neighbors serving market m, an increase in the signal will lower the entry threshold $\widetilde{\rho}_t^{post}$, thus increasing entry. The effect of $n_{m,t-1}$ on $|\varepsilon_{\rho t}|$ will depend on the number of exporters, the dispersion (the inverse of the precision) of the prior, v_{dm}, and the dispersion of the neighbors' signals, v_{zm}. Notice that while an increase in the prevalence of neighbors can affect the variance of the posterior, it only affects the updating process through changing the weights a firm puts on the observed signal and on its own prior. More formally:[30]

$$\frac{\partial \left|\varepsilon_{\rho t}\right|}{\partial n_{m,t-1}} = \frac{v_{zm}}{v_{dm}} \left(n_{m,t-1} + \frac{v_{zm}}{v_{dm}}\right)^{-2} > 0. \tag{9}$$

In other words, more neighbors will result in a larger drop in the threshold, $\widetilde{\rho}_t^{post}$, in response to a positive signal. The rationale is that when there are more firms revealing the signal, it becomes more precise, inducing a potential entrant to put a higher weight on the signal than on its own prior belief. This is the main theoretical result of the paper and is summarized in the following proposition:

Proposition 1 (Entry I) *The likelihood of a firm's entering a new foreign market is increasing in the strength of the signal about the market's demand inferred from neighbors' export performance, and more so if the signal is revealed by more neighbors.*

Notice that the sign of the relationship between the prevalence of existing exporters and the export entry threshold, $\frac{\partial \widetilde{\rho}_t^{post}}{\partial n_{m,t-1}}$, is generally indeterminate. The reason is that more neighbors can help spread both good and bad news, which will lead to opposite effects on firm entry.

We now analyze the effect of the precision of the signal and the precision of the prior, respectively, on the elasticity of the entry threshold with respect to the signal, $|\varepsilon_{\rho t}|$. Differentiating $|\varepsilon_{\rho t}|$ with respect to the signal yields:

$$\begin{aligned} \frac{\partial \left|\varepsilon_{\rho t}\right|}{\partial v_{zm}} &= -\left(v_{dm} n_{m,t-1}\right)^{-1} \left(1 + \frac{v_{zm}}{v_{dm} n_{m,t-1}}\right)^{-2} < 0 \\ \frac{\partial \left|\varepsilon_{\rho t}\right|}{\partial v_{dm}} &= v_{zm} \left(v_{dm}^2 n_{m,t-1}\right)^{-1} \left(1 + \frac{v_{zm}}{v_{dm} n_{m,t-1}}\right)^{-2} > 0. \end{aligned} \tag{10}$$

These results are intuitive. On the one hand, a noisier signal (higher v_{zm}) is associated with a

[30] Moreover, learning from neighbors exhibits decreasing returns. $\frac{\partial |\varepsilon_{\rho t}|}{\partial n_{m,t-1}} = \left[\left(1 + \frac{v_{dm} n_{m,t-1}}{v_{zm}}\right)^{-1} - 1\right] \frac{2 v_{zm}}{v_{dm} n_{m,t-1}^3} \left(1 + \frac{v_{zm}}{v_{dm} n_{m,t-1}}\right)^{-2} < 0.$

smaller entry response, conditional on the level of the (average) signal. On the other hand, a less precise prior (higher v_{dm}) is associated with a larger response to a given average signal, as the firm will put a larger weight on the signal and a smaller weight on its own prior. The relationships above are summarized in the following proposition:

Proposition 2 (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.*

We will empirically examine both propositions in Section 5 below.

3.2.2 Entrants' Initial Sales

Our model also has predictions about exporters' initial sales in a new market. Recent literature shows that new exporters often start selling small quantities in new markets (Eaton et al., 2008; Albornoz et al., 2011). The standard explanation is that uncertainty about exporting induces firms to "start small" to test a new market (Rauch and Watson, 2003; Eaton et al., 2012), which may require a smaller ex-ante investment. In this section, we explore if the size of initial sales is related to the strength and the precision of the signals from neighboring exporters. The first-year sales of a new exporter with productivity ρ can be expressed as:

$$\begin{aligned} x_t\left(n_{m,t-1}, \overline{d}^{nb}_{m,t-1}\right) &= \epsilon\sigma\rho^{\sigma-1}E\left[D_{im}|n_{m,t-1}, \overline{d}^{nb}_{m,t-1}\right] \\ &= \epsilon\sigma\rho^{\sigma-1}\exp\left(\overline{d}^{post}_{mt}\left(n_{m,t-1}, \overline{d}^{nb}_{m,t-1}\right) + \frac{v_{mt}\left(n_{m,t-1}\right)}{2}\right) \end{aligned}$$

In addition to the known productivity, ρ, $x_t\left(n_{m,t-1}, \overline{d}^{nb}_{m,t-1}\right)$ also depends on the (posterior) expected demand factor in market m and on the variance of the signal. Intuitively, a higher $\overline{d}^{nb}_{m,t-1}$ increases new exporters' initial sales in market m as shown by

$$\frac{\partial \ln\left(x_t\left(n_{m,t-1}, \overline{d}^{nb}_{m,t-1}\right)\right)}{\partial \overline{d}^{nb}_{m,t-1}} = \delta_t\left(n_{m,t-1}\right) = \left(1 + \frac{1}{n_{m,t-1}}\frac{v_{zm}}{v_{dm}}\right)^{-1} > 0.$$

The effect of the number of neighbors on the size of initial exports is ambiguous. This is because on the one hand, more neighbors will increase the effect of a positive signal on initial sales (i.e., $\frac{\partial \overline{d}^{post}_{mt}}{\partial n_{m,t-1}} > 0$). On the other hand, an increase in the number of neighbors will increase the precision of the signal (i.e., $\frac{\partial v_{mt}(n_{m,t-1})}{\partial n_{m,t-1}} < 0$) and lower the spread of the (posterior) expected operating profits. The net effect on initial sales will depend on the relative strength of each of the two effects.

However, if we focus on the interactive effect between the signal, $\overline{d}^{nb}_{m,t-1}$, and the prevalence of neighbors, $n_{m,t-1}$, we are able to pin down a more deterministic spillover effect as follows:

$$\frac{\partial}{\partial n_{m,t-1}}\left(\frac{\partial \ln(x_t)}{\partial \overline{d}^{nb}_{m,t-1}}\right) = \frac{v_{zm}}{v_{dm}}\left(n_{m,t-1} + \frac{v_{zm}}{v_{dm}}\right)^{-2} > 0.$$

In other words, there is a positive interactive effect on exporters' initial sales in a new market, based on the same reasons behind the interactive effect on entry. The result regarding new exporters' initial sales is summarized as follows.

Proposition 3 (Initial Sales) *An exporter's initial sales in a new market is increasing in the strength of the signal about the market's demand inferred from neighbors' export performance, and more so if the signal is revealed by more neighbors.*

3.2.3 Survival

Our learning model also has predictions about the survival of exporters in a new market. Consider a firm with productivity ρ, the probability of its survival in market m at $t+1$, after the first year of exporting at t, will depend on its draw of product appeal, z_{im}. If the actual operating profit $\pi^o(D_{im}, \rho)$ is higher than the per-period fixed cost to export, the firm will continue into the second year $(t+1)$. Specifically, the probability of survival is

$$\begin{aligned}\Lambda^S_{t+1}(\rho, d^*_m) &= \Pr\left[\rho^{\sigma-1}\exp(d^*_m + z_{im}) \geq K_m\right] \\ &= 1 - \Phi\left(\frac{1}{\sqrt{v_{zm}}}\left(\ln\left(\frac{K_m}{\rho^{\sigma-1}}\right) - d^*_m\right)\right),\end{aligned}$$

where Φ is the standard normal cumulative distribution function and K_m is the per-period fixed cost, which can be different from K^e_m. A lower K_m, a higher firm productivity (ρ), and a higher true demand factor in the destination country (d^*_m), all have independently positive effects on export survival. Specifically,

$$\frac{\partial \Lambda^S_{t+1}(\rho, d^*_m)}{\partial d^*_m} = \frac{1}{\sqrt{v_{zm}}}\phi\left(\frac{1}{\sqrt{v_{zm}}}\left(\ln\left(\frac{K_m}{\rho^{\sigma-1}}\right) - d^*_m\right)\right) > 0,$$

where ϕ is the probability distribution function of z_{im}. Notice that $\Lambda^S_{t+1}(\rho, d^*_m)$ depends on the true state of demand rather than the observed average demand factor of neighbors, $\overline{d}^{nb}_{mt}$. But since d^*_m is unobservable we will use $\overline{d}^{nb}_{mt}$ to proxy for it in the empirical section below, based on eq. (5).

While the number of neighbors, $n_{m,t-1}$, affects the number of entrants by changing the entry threshold $\underline{\rho}^{\sigma-1}_t$ as discussed above, $n_{m,t-1}$ should have no effect on an exporter's decision to continue exporting. Hence, an exporter's survival rate is not related to $n_{m,t-1}$. However, since $\overline{d}^{nb}_{m,t-1}$ and $n_{m,t-1}$ affect the probability of entry, the sample of entrants and thus the average survival rate (the fraction of new exporters that survive) will also be affected. Specifically, given sunk entry costs, a more positive or precise signal induces more low-productivity firms to enter. In the presence of per-period fixed export costs, the less productive export entrants are more likely to exit ex post. The fraction of surviving export entrants will be decreasing in the strength of the signal, more so if it is revealed by more neighbors. In the empirical section below, we account for this selection bias. If productivity is firm-specific and product appeal is ex ante unknown, our model shows that focusing on the within-firm variation in survival by controlling for firm-year fixed effects can fully address the selection issue.[31] Controlling for firm-year fixed effects, we expect a positive impact of the strength of the signal on survival, but no relationship with the prevalence of neighbors or its interaction with the signal.[32] The learning effects on new exporters' survival are summarized as follows:

Proposition 4 (Survival) *Exporters' survival probability in a new market is positively correlated with the strength of the signal about the market's demand, but is independent of the prevalence of neighbors' export activities.*

3.2.4 Growth Conditional on Survival

Finally, for a firm with productivity ρ that continues to export in market m after realizing z_{im}, we can derive its export growth rate, conditional on survival, as follows:

$$E\left[g_{imt}\left(\rho\right)|n_{m,t-1},\overline{d}_{m,t-1}^{nb}\right]=\ln\left[\epsilon\sigma\rho^{\sigma-1}\int_{-\infty}^{\infty}\exp\left(d_m^*+z_{im}\right)d\Phi\left(z_{im}\right)\right]-\ln\left(x_t\left(n_{m,t-1},\overline{d}_{m,t-1}^{nb}\right)\right).$$

By the law of large numbers, the first term on the right hand side is constant for market m in year t. Given $\frac{\partial}{\partial n_{m,t-1}}\left(\frac{\partial\ln(x_t)}{\partial\overline{d}_{m,t-1}^{nb}}\right)>0$ as shown by Proposition 3, the interactive effect on post-entry growth is

$$\frac{\partial}{\partial n_{m,t-1}}\left(\frac{\partial E\left[g_{imt}\left(\rho\right)\right]}{\partial\overline{d}_{m,t-1}^{nb}}\right)<0.$$

In words, in the presence of learning from neighbors, there is less potential for the new exporter to be surprised after entry. When neighbors' signals become stronger and more precise, a new exporter was more informed ex ante and is less likely to form a posterior that is very different from its prior. For the same reason, new exporters will also be less likely to have downside surprises. However, since new exporters that have realized z_{im} significantly lower than expectations are no

[31] An alternative way to address this issue is to implement the Heckman's selection procedure. However, with millions of observations, such an approach proves computationally impractical.

[32] As the average productivity of new exporters is decreasing in the number of exporters, a negative correlation between the number of exporters and the firms' survival rate could be incorrectly identified, if firm fixed effects are not controlled for. While our model predicts no spillover effect from neighbors to new exporters' survival, it points to the need of controlling for firm fixed effects when examining the spillover effects on survival.

longer in the sample, the incidence of reduced downside surprises is not observed in the sample of survivors. We therefore focus on the negative effect on upside surprises and empirically investigate the following proposition.

Proposition 5 (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.*

One may be worried about potential biases when exits are not taken into account. Notice that according to Proposition 4, the survival rate of new exporters is independent of $n_{m,t-1}$. The direction of the bias due to selection is unclear but once we control for firm fixed effects in the empirical analysis below, our results are independent of the standard problem of selection across firms.

3.2.5 Discussion

Several remarks are in order regarding the robustness of our results to potentially incorporating two dynamic considerations in the model, namely the option value of waiting and firms' strategic interactions. Intuitively, with the implicit assumption that the underlying true state of demand, d^*_{mt}, is positively correlated across time, there are benefits associated with waiting for a more precise signal in the future. Waiting will raise the productivity threshold of entry in the current period. When the number of firms selling in a market increases, both the competitive pressure and the precision of the signal will increase. In a dynamic model, firms will consider these intertemporal trade-offs, but without solving a dynamic model, we can logically postulate that the more productive firms, who have higher forgone expected profits in the first period and relatively smaller expected losses in the future, will enter first. Building a dynamic model would permit a more formal analysis of firms' sequence of entry, this however is beyond the scope of our empirical analysis.

The second dynamic consideration is about firms' strategic interactions. In a world with monopolistic competition, each firm is assumed to be too small to affect aggregate variables in equilibrium. However, this standard assumption may not hold in terms of information spillover, as even some information revealed by a small number of firms is way better than having no information. To avoid competition, firms may intentionally delay entry to reduce information spillover to others, even upon receiving a positive signal. Similar to the remarks on optimal waiting, information hiding will also raise the productivity threshold of entry for all periods. We can again postulate that entry decisions of the more productive (large) firms' will be less affected by this consideration, as their opportunity costs of not entering in the current period are higher than those of the less productive ones. In sum, the main predictions of the model that firms positively respond to a more positive and precise signal (Propositions 1, 3, 4, and 5) should remain robust to the incorporation of both types of dynamic considerations. The learning effects may be weakened quantitatively, which work against us in the empirical analysis below.

However, our predictions about the dispersion of the signals and entry (Proposition 2) may be sensitive to the incorporation of dynamic considerations in the model. Productive firms, who have higher opportunity costs of staying put and lower expected losses in the future, may react positively to a noisier signal. The heterogeneous responses to the precision of the signal across firms may offset each other, working against us empirically. We will include different fixed effects to control for many unobserved determinants of new exporters' dynamics in the empirical analysis below.[33]

4 Data

4.1 Description

The main data set used in the empirical analysis covers monthly export and import transactions of all Chinese firms between 2000 and 2006.[34] For each transaction, the data set contains information about its value (in US dollars) and quantity, what product it is for (over 7000 HS 8-digit categories), and to/from which country (over 200 destination and source countries).[35] 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 noises due to 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.[36] In our empirical analysis, we always 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.[37] 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 isolate information provided by foreign buyers, we focus on the sample of non-processing firms as learners, presuming that the learning effects for ordinary exporters are larger and more relevant than those for processing exporters.

[33] For instance, we include firm-year fixed effects in the regressions below to control for firm-level time-varying productivity, which can isolate the effects of heterogeneous strategic waiting by firms with different levels of productivity.

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

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

[36] 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.

[37] A registered processing firm is required by law to maintain higher standards for accounting practices and warehouse facilities. Moreover, the terms of transactions for processing firms are to be specified in greater detail in written contracts than ordinary exporters. An exporter can hold several export licenses and operate part of its business under the processing regime and another part under the ordinary regime. Readers are referred to Naughton (1996), Feenstra and Hanson (2005) and Fernandes and Tang (2012) for more details about the two trading regimes.

We rely on the cross-city variation in the prevalence of neighbors to identify the learning effects. Fig. 4 illustrates the geographic distribution of the cities. There are on average 425 cities plus municipalities, according to China's Customs' definition.[38] We also explore the potentially differential learning effects across destination 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 CEPII.[39] See Mayer and Zignago (2006) for details. Summary statistics of and the correlations between the main variables used in the empirical analysis are reported in Tables A2-A3 in the online appendix.

4.2 Basic Patterns

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 permits a study of within-firm variation in export performance, when firm-year fixed effects are controlled for. 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.

These summary statistics of firms hide considerable entry and exit, as well as active destination switching for each firm over time. Recent literature reports that a large fraction of new exporters stops exporting in their first year.[40] Fig. 1 shows that in China, the rate of export survival beyond the first year is relatively high and is averaged at around 75% over 2000-2006. Among new export transactions to a country, the survival rate is about 45%. Table A1 in the online appendix, reports the patterns of successful entries and one-time exporting across countries between 2001-2005.

5 Empirical Evidence

This section presents the empirical examination of the five propositions of the paper using Chinese transaction-level data.

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

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

[40] See Besedes and Prusa (2006) for the US; Eaton et al. (2008) for Colombia; Amador and Opromolla (2008) for Portugal; Albornoz et al. (2011) for Argentina; and Cadot et al. (2011) for select African countries.

5.1 Entry

5.1.1 Baseline Results

To examine Propositions 1 and 2 about firms' entry into new foreign markets, we first define the dependent variable of the regression as follows:

$$Entry_{icmt} = \begin{cases} 1 \text{ if } x_{icm,t-1} = 0,\ x_{icmt} > 0 \\ 0 \text{ if } x_{icm,t-1} = 0,\ x_{icmt} = 0 \end{cases}. \tag{11}$$

That is, $Entry_{icmt} = 1$ if firm i in city c was not exporting to country m before year t in the sample, but started exporting to m in t. The sample includes both brand-new exporters and existing exporters that enter at least one new market in year t. To study the probability of entry, we set firm i's $Entry_{icmt} = 0$ for all potential destination countries that were not served by firm i before year t (inclusive).[41] Note that exporters that were already serving country m in year $t-1$ are not included in the sample.[42] Moreover, since we need information from the previous year's export status to define export entry, all observations from the first year (i.e., 2000) of the sample are dropped. All observations from the last year (2006) are also dropped since information from that year is required to construct the export survival dummy and the measure of post-entry growth of entrants.

The main empirical challenge is to find a convincing measure of the signal inferred from neighbors, that is, the demand factor $\overline{d}^{nb}_{cm,t-1}$ in the model. In practice, $\overline{d}^{nb}_{cm,t-1}$ is not observed by new exporters nor by statisticians. To isolate time-invariant neighbors' heterogeneous productivity from the proxy (firms in the model are assumed to do exactly that), we use the average growth rate of existing firms' exports to country m from city c between year $t-1$ and t as the baseline proxy for $\overline{d}^{nb}_{cm,t-1}$. Specifically, neighbors' average export growth, $\triangle \ln (x_{cmt})$ is defined as

$$\triangle \ln (x_{cmt}) = \frac{1}{n_{cm,t-1}} \sum_{i \in \mathbf{N_{cm,t-1}}} [\ln (x_{icmt}) - \ln (x_{icm,t-1})],$$

where $\mathbf{N_{cm,t-1}}$ is the set of existing firms that export to m in city c in *both* year $t-1$ and t, and $n_{cm,t-1}$ is the number of exporters in the set. In other words, new entrants in year t and one-time exporters from year $t-1$ are not included in $\mathbf{N_{cm,t-1}}$. To ensure that we are extracting the "signal" component from neighbors' export growth (or average exporters' sales in market m), we will control for a wide range of fixed effects to absorb the country-specific and city-specific levels and trends of exports in the regressions below. We will perform a battery of robustness checks by using alternative proxies for the signal, which include neighbors' average export growth lagged by one year (i.e., $\triangle \ln (x_{cm,t-1})$), the (log) average level of neighbors' exports, $\ln (x_{cmt})$, and its lag.

[41] Since the focus of our analysis is on learning, for each firm that started exporting to a new country, we define its set of potential new destinations as the countries that have been served by at least one neighbor in the same city in $t-1$. Countries that have not been served by any neighbors are not included in the set.

[42] They are, however, included in the group of the information providers, as they are existing exporters in the neighborhood.

To verify that $\triangle \ln(x_{cmt})$ is a convincing choice of proxy for the signal, we plot the (log) export volume to country m from city c in year t against the corresponding value in year $t-1$, after partialling out city-destination fixed effects. Fig. 3 shows that the two values are positively correlated, suggesting that export sales at the destination and city-destination levels are positively correlated over time. Therefore, exports in a market today reveal information about the average export profitability of selling in the same market in the future; learning is thus profitable since deviations from city-destination (e.g., Beijing-US) averages tend to last.[43]

Proposition 1 predicts that the probability of a firm entering a new market is positively correlated with the level of the signal about the market, and more so if there are more neighboring exporters currently selling there. We examine this proposition by estimating a probit model of entry decisions, with both the stand-alone signal and its interaction with the prevalence of same-market neighboring exporters as the regressors of interest. Specifically, we estimate the following specification:

$$\begin{aligned} \Pr[Entry_{icmt}] &= \alpha + \beta\left[\ln(n_{cm,t-1}) \times \triangle \ln(x_{cmt})\right] + \gamma \triangle \ln(x_{cmt}) + \delta \ln(n_{cm,t-1}) \\ &\quad + Z'\delta + \{FE\} + \zeta_{icmt}, \end{aligned} \tag{12}$$

where $Entry_{icmt}$ is defined in eq. (11). The regressors of interest include the proxy for the signal $\triangle \ln(x_{cmt})$, the (log) number of neighbors in city c continuously exporting to market m in both $t-1$ and t, $\ln(n_{cm,t-1})$, and the interaction between the two. Figs. 4-5 show the geographic distribution of these variables of interest. The values of these variables are widespread across Chinese cities, and high values are not all concentrated near the coast.

Since cities vary in size and bigger cities have more firms, we need to take into account geographic frictions that affect the probability of meeting a neighbor and thus learning. To this end, we use the density of neighbors, which equals the number of neighbors divided by the area of the city, as our baseline measure of $n_{cm,t-1}$. All our empirical findings remain robust to the use of the raw number of neighbors as the prevalence measure. $\mathbf{Z}$ is a vector of firm controls, including the density of neighbors exporting to other countries, their average export growth, and the interaction between the two. If information about other destinations also affects export dynamics in country m, including $\mathbf{Z}$ ensures that the identified learning effect, if any, is market-specific.

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

[43] When we aggregate neighbors export volume from the city-country levels to the country levels, we continue to find a positive correlation between the current and lagged export volume to country m, after partialling out destination fixed effects.

city to a country.[44] In addition to city-country fixed effects, we control for city-year, country-year, or firm-year fixed effects, respectively. Country-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.[45] City-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 supply 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.

We estimate eq. (12) using a linear probability model, similar to Bernard and Jensen (2004) and Albornoz et al. (2011).[46] Since our regressors of interest are at a higher level of aggregation (cmt) than our dependent variables ($icmt$), we cluster standard errors at the city-country (cm) level (Moulton, 1990). Table 3 reports the estimates of (12). All columns include city-country fixed effects. In addition, columns 1 and 2 include country-year fixed effects, and columns 3 and 4 city-year fixed effects. Coefficients on the regressors of interest - the signal from neighboring exporters serving market m from city c, and its interaction with the density of neighbors are all positive and statistically significant (at the 1% level). These results show that the probability of entering market m is increasing in the average performance of neighboring exporters in the same market, more so if there are more neighbors revealing the signal. If it is updating of the prior that triggers firms to start exporting, we should expect weaker or no effect from neighbors serving other markets. While in column 2, the coefficients on the signal about other markets, $\triangle \ln \left(x_{c(-m)t} \right)$, and its interaction with the (log) density of firms exporting to those markets, $\ln(n_{c(-m),t-1})$, are both positive and significant, they become insignificant when city-year fixed effects are included in column 4, suggesting that the positive coefficients on the "other-market" variables possibly capture other city-wide, time-varying shocks (e.g., policies) on entry.[47]

In columns 5 and 6 we include city-country and firm-year fixed effects, which further absorb exporters' supply shocks and any time-varying factors that affect entry.[48] We continue to obtain a positive and significant coefficient on the interaction between the density and export growth of

[44] For instance, city-market fixed effects capture the European connection in Shanghai in the 1930s. Moreover, simultaneity biases due to unobserved time-invariant factors are largely alleviated.

[45] By 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.

[46] The benefit is that we can control for firm-year fixed effects, which cannot be done with a Probit model. The well-known critique is that the relation explored can be non-linear. However, it has been shown extensively (see, for example, Wooldridge, 2002 and Angrist and Pischke, 2009) that the average marginal effects from the Probit estimates are usually very close to the linear estimates.

[47] The coefficient on the stand-alone density measure is marginally significant, but now becomes negative. The negative correlation could arise from competition in the factor markets, driving up the production costs for all firms. If there is no market-specific information from those firms, competition from neighboring exporters may reduce entry.

[48] The number of observations per firm-year is the number of potential destinations that a firm considers entering in a particular year. Given that new markets include all destinations that were served by neighbors but not the firm itself, there is enough degree of freedom to identify the effects within a firm-year.

neighboring firms serving the same country from the same city. The coefficients are also of similar magnitude to those reported in columns 3 and 4. These results show that, conditional on its capability and knowledge, a firm is more likely to enter a new market if it gets a positive signal from neighbors about that market, and increasingly so if there are more neighbors revealing the signal. Specifically, the coefficient of 0.449 on $100 \times \triangle \ln(x_{cmt})$ in column 6 suggests that the (pooled) sample mean export growth of neighbors exporting from city c to country m (20%) is associated with a 0.1 percentage-point increase in the probability of entry into the market.[49] The numbers appear to be small, but as reported in Table 2, the median entry rate in a country (after averaging across city-years) is about 0.3%.[50] So a 20% higher growth rate of exports to a particular country is associated with about a one-third increase in the export entry rate, evaluated at the median. In addition, the coefficient of 0.052 on the interaction term, $100 \times \ln(n_{cm,t-1}) \times \triangle \ln(x_{cmt})$, suggests that an increase in neighbors' export growth equal to the sample mean (20%) is associated with an increase in the entry probability by 0.02 percentage points when the log density of neighbors revealing the signal increases by one standard-deviation (that is, 1.7, or about 5 firms).[51] This corresponds to an increase of about 10% in the entry rate evaluated at the median entry rate in the sample.

In the online appendix, we confirm the robustness of the results by measuring the prevalence of neighbors by the (log) number of firms instead of the density (columns 1 and 2 of Table A4). We also conduct further robustness checks by using the average export value of neighbors to market m in year t, $\ln(x_{cmt})$, in year $t-1$, $\ln(x_{cm,t-1})$; and neighbors' average export growth lagged by one year, $\triangle \ln(x_{cm,t-1})$, to proxy for the signal (columns 1 and 2 of Tables A5 and A6).[52]

There is no particular reason to impose a linear relationship when estimating Proposition 1. In Table 4, we estimate specifications that allow for non-linear relationships between the signal from neighbors and the entry probability, by including quantiles of the density of neighbors interacted with the signal. Specifically, we divide city-markets into quantiles according to their ranking in the density of neighboring exporters. We include dummies (I_{denq}) for different quantiles as well as their interactions with the signal, $\triangle \ln(x_{cmt})$. Columns 1 and 2 divide the sample into four quartiles of neighbor density, whereas columns 3 and 4 further split the sample into five quintiles. Columns 2 and 4 additionally include quantile dummies interacted with neighbors' export growth in other markets. All specifications control for firm-year and city-country fixed effects. Results show that in city-markets with high quantiles of density of neighbors, the entry probability is increasing in the signal, but in low quantiles the relationship is insignificant. In particular, the cut-off seems to be at around the fourth quartile or quintile. When the sample is split into five quintiles, results show that

[49] $0.20 \times \frac{0.449}{100}$.

[50] The way that we calculate the median entry rate is by first taking the average of entry rates across firms and years within the same city-country. Then we take the median of these averages for each country. Alternatively, we can just take the average of the entry rates across firm-years for each country. The order of magnitudes of the entry rates and thus the quantitive effect of spillover remain similar.

[51] $0.052 \times \frac{0.20 \times 1.697}{100} = 0.00018$, or 0.018 percentage points.

[52] We report results controlling for firm-year and city-country fixed effects in Tables A3-A6 for space considerations, but results remain robust for other combinations of fixed effects included, as in Table 3.

the probability of entering a market is increasing with the neighbors' same-market export growth mostly in the top 20% city-markets in terms of density of neighbors.[53] In sum, by relaxing the assumption of a linear relationship between the prevalence of neighbors and the learning effects, we still find evidence supporting Proposition 1.

5.1.2 Firms' Own Prior Uncertainty and Variability of Observed Neighbors' Export Performance

Proposition 2 states that a firm's entry into exporting is less sensitive to its neighbors' signal if their export sales are more dispersed within a market, but is more sensitive if the firm itself has less precise prior knowledge about the market. We now empirically examine the relationship between the precision of the signal, the precision of the prior, and the learning effects revealed in export entry. Any robust results will provide confirming evidence that learning is a channel through which neighboring export activities shape new exporters' entry and post-entry export performance. A firms' less precise prior (higher v_{dm}) can be interpreted as higher uncertainty about the foreign market. Since a firms' information before entry is not available in the data, we use both the geographic distance between the destination and China, and the extended gravity measures, proposed by Morales et al. (2012), to proxy for the firm's uncertainty about the new market.[54] The extended gravity variables capture the similarity between the new markets and those previously served by the firm.[55] The measures we use include indicators for whether a potential new market shares the same language or the same border with any existing markets served by the firm.

To measure the dispersion of signals (v_{zm}), we adopt the conventional approach and use the (log) standard deviation of neighbors' exports in the same city-country-year cell. If heterogeneity in neighbors' exports is large, a firm will perceive the signal as noisy and will reduce the weight on the signal when updating its prior. To empirically examine Proposition 2, we estimate the following specification:

$$\begin{aligned} \Pr\left[Entry_{icmt}\right] &= \alpha + \theta_1\left[V \times \triangle \ln\left(x_{cmt}\right)\right] + \theta_2 V \\ &\quad +\beta\left[\ln(n_{cm,t-1}) \times \triangle \ln\left(x_{cmt}\right)\right] + \delta \ln(n_{cm,t-1}) \\ &\quad +\gamma \triangle \ln\left(x_{cmt}\right) + Z'\delta + \{FE\} + \zeta_{icmt}, \end{aligned} \tag{13}$$

In addition to the three main variables of interest, $\ln(n_{cm,t-1}) \times \triangle \ln(x_{cmt})$, $\triangle \ln(x_{cmt})$, and

[53] F-tests cannot reject the null that the interactions with I_{den1} and I_{den2} are jointly equal to 0. F-tests, however, reject the null that the interactions with I_{den3}, I_{den4}, and I_{den5} are jointly equal to 0; as well as the null that the interactions with I_{den4} and I_{den5} are equal to 0 individually.

[54] The assumption that information asymmetry is positively correlated with distance between countries is often used in the trade and FDI literature, while the use of extended gravity measures has been recently used by Albornoz et al. (2012) to study firms' export dynamics.

[55] For example, if two firms are contemplating to export to the U.S., the one that had export experience to Canada will have a more informed view about the U.S. market compared to those that have businesses in Asia. The U.S. and Canada are not only close to each other, but both of them also use English as the official language, share the same border, and have similar income level per capita.

$\ln(n_{cm,t-1})$, we add V and its interaction with $\triangle \ln(x_{cmt})$, where V is either (i) a proxy for the heterogeneity of the market signal, which varies across city-countries and time (cmt); (ii) a proxy for the ex-ante uncertainty about demand in country m, which varies across countries (m); or (iii) the firm-specific extended gravity measures, which vary across firm-country-years ($icmt$).[56] According to Proposition 2, the sign of the estimated θ_1 is expected to be negative for the first measure; positive for the second; and negative for the last, because a small learning effect is expected when the new markets are more similar to the markets currently served by the firm.

Table 5 reports the first set of results from estimating (13). In column 1, we interact the measure of v_{zmt}, the (log) standard deviation of neighbors export growth to market m in year t, with the signal, $\triangle \ln(x_{cmt})$. The coefficient on $V \times \triangle \ln(x_{cmt})$ is positive and marginally significant (at the 5% level), in contrast with Proposition 2, which predicts less learning when the signal is noisier. In column 2, we follow the same approach used in Table 4 by allowing for a non-linear relationship between the signal inferred from neighbors and the entry probability. We divide city-markets into quintiles according to their ranking of the standard deviation of neighbors' export growth in the sample.[57] We then include the quintile dummies (I_{Vq}) and their interactions with the signal, $\triangle \ln(x_{cmt})$, along with the regressor included in the last column of Table 3. While the estimated coefficients on the quintile interactions are positive and statistically significant, they are not decreasing in quantile ranks, as is expected based on Proposition 2. Importantly, we continue to find a positive and significant effect of the density of neighbors on the entry learning effects, consistent with our findings in Table 3.

In column 3, we explore the differential learning effects across destination markets, based on their distance from China. From the specification in column 5 of Table 3, we additionally include an interaction term between the (log) distance of country m from China and the signal measure. We find a positive and marginally significant (at the 10% level) coefficient on the interaction term, lending some support to Proposition 2, which predicts that learning is stronger for markets which firms are less familiar with. In column 4, we explore the potential non-linear relationship between distance from China and learning, by including interactions between quintile dummies of the distance and the signal. The coefficients on all interaction terms are positive and significant, with the smallest coefficient found on the first quintile interaction and the highest found on the fourth one. Though the coefficient on the interaction term is not monotonically increasing in quintile rank, the average of the coefficients on the fourth and fifth quintile interactions is larger than the average of the first three. The difference is also statistically significant.

We then investigate whether a firm's previously served markets can affect a new exporter's prior and shape its entry patterns. We use the extended gravity measures explained above to capture market similarity. As reported in Table 6, when we use common official language to group countries (column 1), we find supporting evidence that new exporters have less to learn from neighbors about markets that are similar to the exporters' previously served markets. The coefficient on the

[56] Note that for the extended gravity measures, $v_{icmt} = 1$ if firm i has served a country in year $t-1$ that is close (in terms of one of the two criteria) to new market m in year t, and $v_{icmt} = 0$ otherwise.

[57] We use the city-market sample rather than the firm sample to assign observations to quantiles.

interaction between the signal and the indicator for whether the new market shares a common language with any of the firms' existing markets is negative and significant. When we use the "common border" criteria to define country similarity, the coefficient on the interaction term is positive but insignificant (column 2). Column 3 includes simultaneously interactions between the signal and both the indicators for common language and common border. The interaction term remains negative and significant for language and insignificant for common boarder. In sum, results from two of the three sets of regressions in Tables 4 and 6 support Proposition 2.

5.2 Entrants' Initial Sales

Next, we study the effects of learning from neighbors on exporters' initial sales in a new market. Proposition 3 states that new exporters' initial exports are increasing in the strength of the signal, more so if it is revealed by more neighbors. To examine this proposition, we estimate eq. (12) but with the entry dummy replaced by the (log) firm i's initial exports to market m from city c in year t, $\ln(x_{icmt})$, as the dependent variable. Table 7 reports the regression results. Different columns correspond to specifications with different sets of fixed effects, as explained in the previous section.

Across all specifications, the coefficients on both the neighbors' average export growth and its interaction with the density of neighbors are positive and statistically significant at the 1% level. The stand-alone density of neighbors measure is statistically insignificant. These results suggest that exporters start with a larger order in a new market when the signal is stronger, especially when it is revealed by more neighbors.[58] Specifically, in column 6 we control for firm-year and city-market fixed effects, thus identifying the effects within firm-years, controlling for city-market characteristics. We also include variables for spillovers from neighboring firms that export to other countries. In this specification, the estimated coefficient on neighbors' average export growth is 0.165, suggesting that if neighbors' exports to a market grow at the sample mean rate (i.e., 20%), a new exporter's initial sales in the same market will be about 3.3% higher on average,[59] relative to markets with zero average neighbors' export growth. The estimated coefficient on the interaction term between the signal and the log density of exporters is 0.016, suggesting that based on the same sample average export growth of neighbors, one standard-deviation increase in the (log) density of neighbors exporting to a market (about 5 firms per squared mile) is associated with an additional 0.5% initial exports in the same market.[60]

The findings in this section are consistent with Proposition 3 and also existing studies that investigate why exporters tend to start small when exporting to a new market (Rauch and Watson, 2004; Albornoz et al., 2012). Our results suggest that neighboring market-specific export activities reveal information about foreign demand, encouraging firms to enter a new market with a larger order.

[58] Results remain robust when we measure the prevalence of neighbors by the log of their raw number (see columns 3 and 4 of Table A4). In particular, the coefficient on the interaction term between the signal and the ln(number) of neighbors is positive and statistically significant.

[59] $0.165 \times 0.20 \times 100$.

[60] $0.016 \times 0.20 \times 1.7 \times 100$

5.3 Survival

Proposition 4 predicts that conditional on entry, a new exporter's survival rate is increasing in the strength of the signal revealed by neighbors' export activities, but is independent of the number of neighbors. The reason is that while the number of neighbors affects the number of entrants by changing the entry threshold, conditional on entry, any ex ante information was already taken into account by the entrant at the time of entry and will no longer affect its exit decision.

To empirically examine this proposition, we construct the survival dummy as follows:

$$Survival_{icm,t} = \begin{cases} 1 \text{ if } x_{icm,t-1} = 0,\, x_{icm,t} > 0, x_{icm,t+1} > 0 \\ 0 \text{ if } x_{icm,t-1} = 0,\, x_{icm,t} > 0, x_{icm,t+1} = 0 \end{cases}, \tag{14}$$

That is, $Survival_{icmt}$ equals 1 if the firm was not exporting to market m in year $t-1$, but starts exporting in year t and continues in $t+1$. If the firm exports in year t but not in $t+1$, $Survival_{icmt} = 0$. In the literature, $Survival_{icmt} = 1$ corresponds to successful export entrants, while $Survival_{icmt} = 0$ are referred to as one-time or occasional exporters. We examine Proposition 3 by estimating eq. (12), but with the entry dummy replaced by $Survival_{icm,t}$ as the dependent variable. We use the same baseline proxy for signal and interaction terms as above. The results are reported in Table 8. According to Proposition 4, there should be no relation between the number of neighbors and the exit rate. However, the strength of the signal affects entry and thus the sample of new exporters. Thus, our model highlights the importance of controlling for firm fixed effects to account for the potential selection bias. For comparison, we continue to use specifications with different combinations of fixed effects as above.

Columns 1 and 2 of Table 8 control for city-country and country-year fixed effects, while columns 3 and 4 control for city-year and city-country fixed effects instead. The coefficients on both the signal term, $\triangle \ln(x_{cmt})$, and its interaction with the log density of neighbors, $\ln(n_{cm,t-1}) \times \triangle \ln(x_{cmt})$, are statistically insignificant. Moreover, we obtain a negative and statistically significant coefficient on $\ln(n_{cm,t-1})$, suggesting that an increased entry due to more neighboring exporters may lead to more exits of the less productive ones ex post. All these results remain the same regardless of whether we include controls to capture potential learning effects from exporters to other countries or not.

Columns 5 and 6 control for firm-year fixed effects, in addition to city-market characteristics. In these specifications, which account for selection by identifying the effects from within firm-year variation in survival, we obtain a positive and (marginally) significant coefficient on $\triangle \ln(x_{cmt})$, while that on $\ln(n_{cm,t-1}) \times \triangle \ln(x_{cmt})$ is positive but insignificant. The empirical support for Proposition 4 is weak at best. Importantly, we find no significant relation between the prevalence of neighbors and survival, which is consistent with our prediction but contrasts with what has been documented in the literature.

5.4 Post-entry Growth

According to our model, the effect of neighbors' export activities may also affect new exporters' growth in the same market. Proposition 5 states that the post-entry growth rate, conditional on survival, is decreasing in the signal about the foreign market's demand, increasingly so if there are more neighboring firms revealing it. Intuitively, a more precise signal from neighbors about foreign demand implies less surprises that the firm did not anticipate before entry, and thus a lower post-entry export growth.

To examine Proposition 5, we first define the dependent variable, new-market export growth, as $\triangle \ln(x_{icm,t+1}) = \ln(x_{icm,t+1}) - \ln(x_{icm,t})$. This growth rate is for sales in each new foreign market by an exporter, conditional on surviving in the market into year $t+1$. We then estimate eq. (12) but with $\triangle \ln(x_{icm,t+1})$ as the dependent variable. Table 9 reports the results with different sets of fixed effects included, as in the previous sections. We find negative and statistically significant coefficients on the three regressors of interest: the density of existing exporters serving a market from the city, $\ln(n_{cm,t-1})$; the strength of the signal, $\triangle \ln(x_{cmt})$; and the interaction between those two variables.[61] This suggests that export growth after entry in a market is decreasing in the performance of existing exporters serving that market from the same city, and more so with a higher density of neighbors. These results lend support to Proposition 5. In particular, in column 6 where we control for firm-year and city-country fixed effects, we obtain an estimated coefficient on the interaction term of -0.024. This suggests that in city-markets with an average growth of neighbors' exports (20%), a one standard-deviation increase in the density of neighbors lowers post-entry export growth of a new exporter in the same market by about 1 percentage point.

5.5 Robustness Checks

We also perform several robustness checks for the analyses conducted so far. First, in addition to city-country and firm-year fixed effects, we include country-year fixed effects in our regressions to make sure that new exporters' dynamics are not driven by country demand shocks, in addition to firm supply shocks and city-country unobserved determinants of entry that we always controlled for. Including simultaneously city-country, firm-year and country-year fixed effects, however, proves computationally impractical for a sample with over 10 million observations. For this robustness check, we restrict our sample to the textile sector (HS2 codes from 50 to 63), China's largest non-processing export sector in terms of the number of exporting firms and export value. The results for entry and initial sales, as reported in the first two columns of Table A7 in the online appendix, show that the coefficients on both the stand-alone signal term and its interaction with the density of neighbors remain positive and statistically significant at the 1% level. The regression results for post-entry growth (column 4) also remain largely robust, with negative and significant coefficients obtained on both terms. In the survival specification (column 3), we obtain positive coefficients on both the interaction term and the stand-alone term for the signal, although insignificant.

[61] In column (6), when we add the controls for spillover effects from firms serving markets other than the one the firm entered, the coefficient on the stand-alone density term loses significance.

Another robustness check we conduct is to investigate whether new exporters learn from neighbors located only in the same city or farther away as well. As reported in Table A8 in the online appendix, we continue to find that the entry probability and initial sales in a market increase in the average performance of neighboring exporters in the same city, and more so with more neighbors revealing the signal. There is also evidence of positive and statistically significant spillover from neighbors in the same province but outside the city. For survival, results also show evidence for learning from neighbors that are farther away (column 3). However, results for post-entry export growth (column 4) show no effect from the performance of exporters located in the province but outside the city.

In Table A9 in the online appendix, we compare the learning effects between foreign-owned versus domestic new exporters. The first four columns study whether spillovers to new exporters in a market differ depending on the ownership type (foreign-owned versus domestic) of the information providers. Results for the coefficients of interest remain robust in sign and significance, for the four measures of export performance, but the magnitude of spillover is larger from domestic exporters than from foreign exporters, with the exception of post-entry growth. The last four columns of Table A9 separately identify the learning effects in four different directions – domestic to domestic, foreign to foreign, domestic to foreign, and foreign to domestic. For both ownership types of recipients, the spillover effect is strongest if the source is from existing domestic exporters. For domestic recipients, the learning effects are stronger from domestic exporters than from foreign exporters. And for foreign recipients, with the exception of post-entry growth, the learning effects are also stronger from domestic exporters than from other foreign exporters. These findings are consistent with the hypothesis that foreign firms are more attentive in restricting the leakage of trade secrets. Another reason is that foreign firms are more informed about foreign markets and have less to learn from other foreign exporters.

6 Conclusions

Research in international trade shows that new exporters often start selling small quantities and many of them give up exporting in the first year. These findings suggest high uncertainty facing new exporters. Whereas existing research has focused on a firm's own export experience in explaining its future export dynamics and performance, we explore instead how neighbors' export activities may matter.

We build a statistical decision model to study how learning from neighboring exporters affects exporters' performance and dynamics in new markets. A firm updates its expectation about the demand of a new foreign market, using the weighted average between its prior and the demand level inferred from neighboring exporters. How much a firm updates depends on several factors, including the number of neighbors currently selling there, the level and heterogeneity of their export sales, and the firm's own prior knowledge about the market. Our model predicts that the probability of entry and the level of initial sales in a new market are both increasing in the strength of the signal about the market, more so if it is revealed by more neighboring exporters. New exporters' decisions to exit are independent of the prevalence of neighboring export activities, whereas post-entry export growth, conditional on survival, is decreasing in the strength and the precision of the signal. We find supporting evidence for these predictions using transaction-level trade data covering all Chinese exporters over 2000-2006. We also find that new exporters' responses to a positive signal about foreign demand are decreasing in the firm's prior knowledge about the market, proxied by either the geographic distance between China and the destination, or the similarity between the new market and the existing markets served by the firm.

Our results highlight an important source of learning to export, not from a firm's own experience but from its neighbors. The findings shed light on an under-explored benefit of agglomeration, uncovered as reduced uncertainty facing new exporters. Available information from neighbors can lower the cost of entry into foreign markets and the amount of turnover due to experimentation. For simplicity we abstract from learning about one's production capability, as studied by Hausmann and Rodrik (2003). A direction for future research is to examine how that may explain some of the export dynamics documented in this paper. Another natural extension of our research is to explore learning not only about demand in different countries, but also about demand for different products.

7 References

1. Ahn, J., A. Khandelwal, and S.J. Wei (2010), "The Role of Intermediaries in Facilitating Trade," forthcoming, *Journal of International Economics*.

2. Aitken, B., G. Hanson and A. Harrison (1997), "Spillovers, foreign investment, and export behavior," *Journal of International Economics*, 43, 103-132.

3. Albornoz, F., H. Calvo-Pardo, G. Corcos, and E. Ornelas (2012), "Sequential Exporting," *Journal of International Economics*, 88, 1, 17–31.

4. Alvarez, R., H. Faruq, and R. Lopez (2008), "New Products in Export Markets: Learning From Experience and Learning from Others," Mimeo, Bank of Chile.

5. Angrist, J. and S. Pischke (2009), "Mostly Harmless Econometrics", Princeton University Press.

6. Amador, J. and L. Opromolla (2008), "Product and Destination Mix in Export Markets," Bank of Portugal Working Paper.

7. Araujo, L., G. Mion, and E. Ornelas (2014), "Institutions and Export Dynamics," LSE Working Paper.

8. Bartelsman, E., J. Haltiwanger, and S. Scarpetta (2009), "Measuring and Analyzing Cross-country Differences in Firm Dynamics," in *Producer Dynamics: New Evidence from Micro Data*, ed. T. Dunne, J. Bradford, and M. Roberts.

9. Bernard, A. and B. Jensen (2004), "Why some firms export," *The Review of Economics and Statistics*, 86(2), 561–569.

10. Bernard, A. and B. Jensen, J. Eaton and S. Kortum (2003), "Plants and Productivity in International Trade," *American Economic Review*, 93(4), 1268-1289.

11. Bernard, A., J. Jensen, S. Redding and P. Schott (2007), "Firms in International Trade," *Journal of Economic Perspectives*, 21(3), 105–130.

12. Bernard, A., S. Redding and P. Schott (2010), "Multiple-Product Firms and Product Switching," *American Economic Review*, 100(1), 70-97.

13. Bikhchandani, S., Hirshleifer, D. and Welch, I. (1992), "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades", *Journal of Political Economy*, 100, 992–1026.

14. Bikhchandani, S., Hirshleifer, D. and Welch, I (1998), "Learning from the Behavior of Others: Conformity, Fads, and Informational Cascades", *Journal of Economic Perspectives*, 12, 151–170

15. Blum, B.S., S. Claro, I.J. Horstmann (2013) “Occasional and Perennial Exporters”, *Journal of International Economics,* 90(1), 65–74.

16. Brandt, L., J. Van Biesebroeck, and Y. Zhang (2011) Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing, *Journal of Development Economics,* forthcoming.

17. Broda and Weinstein (2006), “Globalization and the gains from variety,” *Quarterly Journal of Economics*, 541-585.

18. Cadot, O., L. Iacovone, D. Pierola and F. Rauch (2013), “Success and Failure of African Exporters,” *Journal of Development Economics*, 101, pp. 284–296.

19. Chaney, T. (2008), “Distorted Gravity: The Intensive and Extensive Margins of International Trade,” *American Economic Review*, 98(4), 1707–1721.

20. Chaney, T. (2011), “The Network Structure of International Trade,” NBER Working Paper No. 16753.

21. Chen, H. and D. Swenson (2008),“Multinational Firms and New Chinese Export Transactions.” Mimeo, University of California, Davis.

22. Clerides, S., S. Lach, and J. Tybout (1998), “Is Learning by Exporting Important? Micro-dynamic Evidence from Colombia, Mexico, and Morocco,” *Quarterly Journal of Economics*, 113(3), 903–947.

23. Conley, T. and C. Udry (2010), “Learning about a New Technology: Pineapple in Ghana,” *American Economic Review*, 100(1): 35-69.

24. Das, S. and M. Roberts, and J. Tybout (2007), “Market entry costs, producer heterogeneity, and export dynamics,” *Econometrica*, 75 (3), 837–873.

25. DeGroot, M. H. (2004), *Optimal statistical decisions* (Vol. 82). Wiley-Interscience.

26. Dinlersoz, E.M. and M. Yorukoglu (2012), “Information and Industry Dynamics,” *American Economic Review*, 102(2): 884-913.

27. Duranton, G. and Puga, D. (2004) “Micro-foundations of urban agglomeration economies,” Henderson, J.V., Thisse, J.F. (Eds.), Handbook of Regional and Urban Economics, vol. 4. 2063-2117.

28. Eaton, J., M. Eslava, M. Kugler (2008), “The Margins of Entry into Export Markets: Evidence from Colombia,” in Elhanan Helpman, Dalia Marin, and Thierry Verdier, eds., *The Organization of Firms in a Global Economy*, Cambridge, MA: Harvard University Press, 2008.

29. Eaton, J., M. Eslava, C. J. Krizan, M. Kugler, and J. Tybout (2009), “A Search and Learning Model of Export Dynamics,” Penn State University mimeo.

30. Fernandes, A. and H. Tang (2012), "Determinants of Vertical Integration in Export Processing: Theory and Evidence from China," *Journal of Development Economics*, 99(2), 396-414.

31. Fernandes, A. and H. Tang (2013), "Scale, Scope, and Trade Dynamics of Export Processing Plants." Johns Hopkins University mimeo.

32. Feenstra R. and G. Hanson (2005), "Ownership and Control in Outsourcing to China: Estimating the Property-Rights Theory of the Firm," *Quarterly Journal of Economics* 120(2), 729-761.

33. Foster, A. and M. Rosenzweig (1995) "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture," *Journal of Political Economy*, 103(6), 1176-1209.

34. Foster, A. and M. Rosenzweig (2010) "Microeconomics of Technology Adoption," *Annual Review of Economics*, Vol. 2: 395-424.

35. Freund, C. and Pierola M.D. (2010), "Export entrepreneurs: Evidence from Peru," World Bank Working Paper.

36. Javorcik, B and L. Iacovone (2010), "Multi-product Exporters: Product Churning, Uncertainty and Export Discoveries," *Economic Journal*, 120(544), 481-499.

37. Hausmann, R. and Rodrik, D. (2003) "Economic Development as Self-discovery," *Journal of Development Economics*, 72(2), pp. 603–633.

38. Khandelwal, A. (2010), "The Long and Short (of) Quality Ladders," *Review of Economic Studies*, 77(4), 1450-1476.

39. Koenig, P. F. Mayneris and S. Poncet (2010), "Local Export Spillovers in France," *European Economic Review*, 54, 622-641.

40. Krugman, P. (1991) "Increasing Returns and Economic Geography," Journal of Political Economy, 99(3), 483-499.

41. Krugman, P. and Venables, A.J. (1995) "Globalization and the Inequality of Nations," Quarterly Journal of Economics, 110, 857–880.

42. Manova, K. and Z. Zhang (2009), "China's Exporters and Importers: Firms, Products and Trade Partners," Mimeo, Stanford University.

43. Mayer, T. and S. Zignago (2006), "Notes on CEPII's distances measures," MPRA Paper 31243.

44. Melitz, M. (2003), "The impact of trade on intra-industry reallocations and aggregate industry productivity," *Econometrica,* 71(6), 1695–1725.

45. Moretti, E. (2011), "Social Learning and Peer Effects in Consumption: Evidence from Movie Sales," *Review of Economic Studies*, 78(1), 356-393.

46. Moulton B.R. (1990), "An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Unit," *The Review of Economics and Statistics*, 72(2), 334-38.

47. Nguyen, Dan (2012) "Demand Uncertainty: Exporting Delays and Exporting Failures," *Journal of International Economics*, 86, 336-344.

48. Ottaviano, G., & Puga, D. (1998). "Agglomeration in the global economy: A survey of the 'New Economic Geography," The World Economy, 21(6), 707–731.

49. Rauch J. and Watson M. (2003), "Starting small in an unfamiliar environment," *International Journal of Industrial Organization,* 21(7)*,* 1021-1042.

50. Segura-Cayuela, R. and J. Vilarrubia (2008), "Uncertainty and Entry into Export Markets," Bank of Spain Working Paper.

51. Timoshenko (2013) "Product Switching in a Model of Learning," George Washington University Working Paper.

52. Wooldridge, J. (2002) "Econometric Analysis of Cross Section and Panel Data", The MIT Press.

Figure 1: New Exporters - Fraction of Exporters and Survival Rate

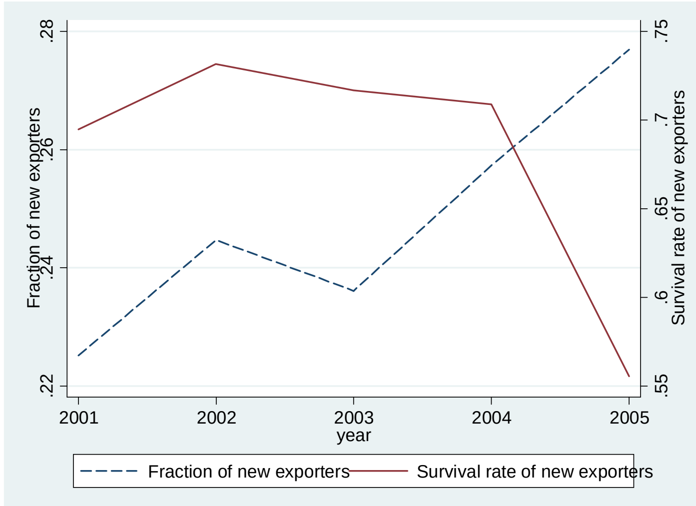

Figure 2: New Exporters - Fraction of Exporters and Average Initial Sales over Average Sales of Existing Exporters

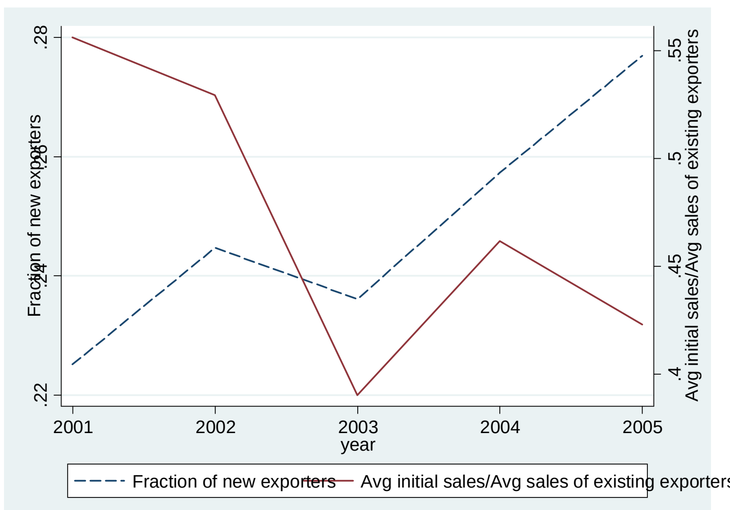

Figure 3: (log) Export Volume from City c to Country m between Year t and $t-1$

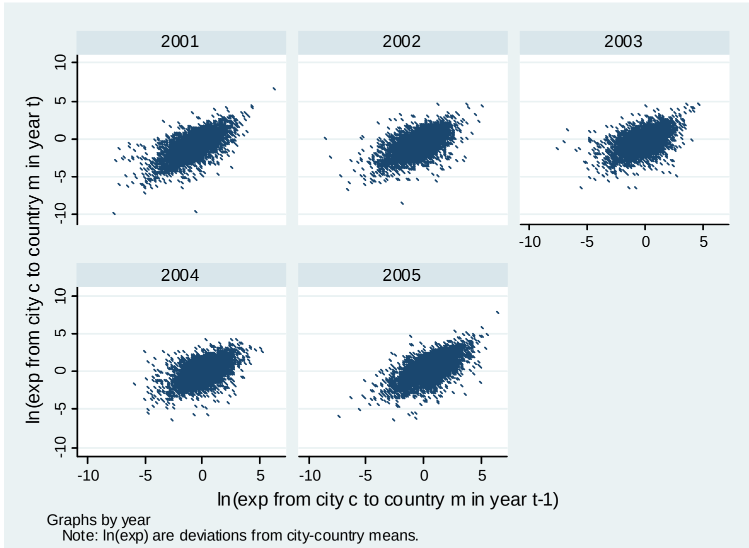

Figure 4: Number and Average Export Growth of Neighboring Exporters to the U.S. (Different Cities)

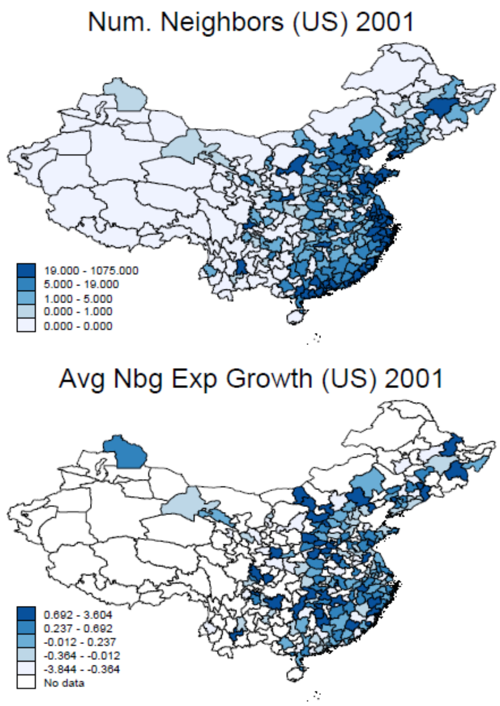

Figure 5: The Rate of Entry into the U.S. Market (Different Cities)

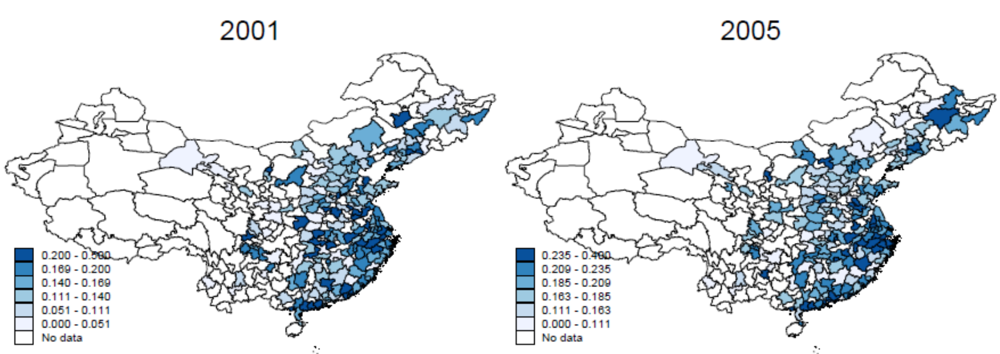

Table 1: Trade Patterns

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

Source: Authors' calculation based on China's Customs transaction-level trade data (2001-2005). Only non-processing (ordinary) exporters are included.

Table 2: Top and Bottom 10 Countries based on Average Export Entry Rates

Top 10			
2001		2005	
Country	Entry Rate	Country	Entry Rate
Japan	0.171	United States	0.207
United States	0.161	Korea	0.136
Korea	0.133	Japan	0.133
Germany	0.087	Germany	0.120
Taiwan	0.086	United Kingdom	0.100
Singapore	0.084	Italy	0.098
Australia	0.077	Canada	0.095
United Kingdom	0.076	Australia	0.094
Italy	0.072	Taiwan	0.084
Canada	0.066	Spain	0.082

Bottom 10			
2001		2005	
Country	Entry Rate $(\times 100^{-2})$	Country	Entry Rate $(\times 100^{-2})$
Mali	0.102	Monaco	0.054
Rwanda	0.097	Saint Lucia	0.053
Guyana	0.095	Niger	0.046
Uzbekistan	0.090	Antigua and Barbuda	0.040
Mozambique	0.087	Marshall Islands	0.038
Djibouti	0.086	St. Vincent & Grenadines	0.037
Somalia	0.084	Bermuda	0.030
New Caledonia	0.062	Solomon Islands	0.030
Albania	0.053	Somalia	0.023
Zambia	0.044	Lesotho	0.023

Source: Authors' calculation based on China's Customs transaction-level trade data. Hong Kong is excluded as a destination in our sample. The entry rate of a country is computed as the average over all city-level entry rates for that country.

Table 3: Export Entry and Learning from Neighbors

	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(n_{cm,t-1}/Area_c)\times \triangle\ln(x_{cmt})$	0.0359***	0.0325***	0.0554***	0.0659***	0.0553***	0.0520***
	(4.63)	(3.79)	(7.06)	(7.43)	(7.04)	(6.82)
$\triangle\ln(x_{cmt})$ [signal]	0.309***	0.268***	0.477***	0.556***	0.476***	0.449***
	(4.71)	(3.77)	(7.24)	(7.59)	(7.21)	(7.00)
$\ln(n_{cm,t-1}/Area_c)$	-0.0517	-0.0633***	0.0640***	-0.0262	0.0623***	0.004
	(-0.27)	(-3.26)	(3.65)	(-1.17)	(3.53)	(0.19)
$\ln(n_{c(-m),t-1}/Area_c)\times\triangle\ln(x_{c(-m)t})$		0.213***		-2.22		-2.45
		(4.31)		(-1.01)		(-1.12)
$\triangle\ln(x_{c(-m)t})$		1.54***		-12.6		-7.48
		(8.58)		(-0.56)		(-0.36)
$\ln(n_{c(-m),t-1}/Area_c)$		0.180***		-2.78**		-2.93**
		(2.69)		(-2.09)		(-2.21)
City-year Fixed Effects			Yes	Yes		
Country-year Fixed Effects	Yes	Yes				
Firm-year Fixed Effects					Yes	Yes
City-country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Nb of Obs.	14,756,513	14,756,442	14,756,513	14,756,442	14,756,513	14,756,442
R-squared	.0477	.0477	.0478	.0478	.102	.102

See eq. (12) for the estimation specification. All coefficients are already multiplied by 100 for clearer reporting. The sample excludes outlying city-countries, which have average neighbors' export growth above the 99th percentile or below the 1st percentile of the year. Transactions to Hong Kong are also excluded. The dependent variable, $Entry_{icmt}$, is equal to 1 for the firm-city-country-year observation if firm i started exporting to country m in year t. $Entry_{icmt}$ is set to zero for all destination countries that a new exporter did not export before and in year t. The source of spillover is measured by the (log) number of "same-market" neighboring exporters divided by the area of the city, $\ln(n_{cm,t-1}/Area_c)$. Columns (1) and (2) include city-country and country-year fixed effects. Columns (3) and (4) include city-year and city-country fixed effects. Columns (5) and (6) include firm-year and city-country fixed effects. t statistics, based on standard errors clustered at the city-country level, are reported in parentheses. * p<0.10; ** p<0.05; *** p<0.01.

Table 4: Entry and Learning from Neighbors (Quantile Dummy Interactions)

	(1)	(2)	(3)	(4)
Dummy Categorization	quartile	quartile	quintile	quintile
$\triangle \ln(x_{cmt})$ interacted with:				
I_{den1}	0.0108	0.0194	-0.00247	0.00888
	(0.81)	(1.52)	(-0.16)	(0.59)
I_{den2}	-0.0169	-0.0105	0.00714	0.0104
	(-1.42)	(-0.95)	(0.57)	(0.88)
I_{den3}	0.0242	0.0211	-0.0230	-0.0130
	(1.59)	(1.40)	(-1.54)	(-0.90)
I_{den4}	0.206***	0.168***	0.0328*	0.0238
	(7.34)	(6.06)	(1.76)	(1.29)
I_{den5}			0.277***	0.230***
			(7.85)	(6.62)
$\triangle \ln(x_{c(-m)t})$ interacted with:				
I_{den1}		-4.50		-4.53
		(-0.25)		(-0.25)
I_{den2}		-3.91		-3.98
		(-0.22)		(-0.22)
I_{den3}		-2.79		-3.36
		(-0.15)		(-0.19)
I_{den4}		-1.81		-2.40
		(-0.10)		(-0.13)
I_{den5}				-1.61
				(-0.09)
Quantile dummies	Yes	Yes	Yes	Yes
Firm-year Fixed Effects	Yes	Yes	Yes	Yes
City-country Fixed Effects	Yes	Yes	Yes	Yes
Nb of Obs.	14,756,513	14,756,513	14,756,513	14,756,513
R-squared	.102	.102	.102	.102

All coefficients are already multiplied by 100 for clearer reporting. The sample excludes outliers (defined in Table 3) of neighbors' export growth and export transactions to Hong Kong. The dependent variable, $Entry_{icmt}$, is equal to 1 for the firm-city-country-year observation if firm i started exporting to country m in year t. $Entry_{icmt}$ is set to zero for all destination countries that a new exporter did not export before and in year t. City-markets-years are put into different quantile bins, based on their ranking of density of neighbors exporting to the same market in a year. Dummies for different quantiles are included as well as their interactions with the growth rate of neighbors' exports to the same market. Even-numbered columns also include quantile dummies interacted with neighbors' export growth in other markets. All columns include firm-year and city-country fixed effects. t statistics, based on standard errors clustered at the city-country level, are reported in parentheses. * $p<0.10$; ** $p<0.05$; *** $p<0.01$.

Table 5: Entry and Learning from Neighbors (Heterogeneous Effects)

	(1)	(2)	(3)	(4)
Uncertainty Measure (V)	(log) Std. Dev. Exp Growth		(log) Distance	
$V \times \triangle\ln(x_{cmt})$	0.0869**		0.0287*	
	(2.09)		(1.71)	
$\triangle\ln(x_{cmt})$ interacted with:				
I_{V1}		0.924***		0.545***
		(5.85)		(6.81)
I_{V2}		0.977***		0.552***
		(6.33)		(7.17)
I_{V3}		0.994***		0.567***
		(6.56)		(7.00)
I_{V4}		1.00***		0.595***
		(6.56)		(6.72)
I_{V5}		1.03***		0.570***
		(6.38)		(7.16)
$\ln(n_{cm,t-1}/Area_c) \times \triangle\ln(x_{cmt})$	0.136***	0.135***	0.0667***	0.0672***
	(6.61)	(6.32)	(7.11)	(7.01)
$\triangle\ln(x_{cmt})$ [signal]	0.979***		0.303*	
	(6.67)		(1.88)	
$\ln(n_{cm,t-1}/Area_c)$	-0.0618	-0.0289	-0.0467**	-0.0468**
	(-1.20)	(-0.56)	(-1.97)	(-1.97)
V_{cmt}	0.00960			
	(0.38)			
Additional Controls	$\triangle\ln(x_{c(-m)t})$ interacted with I_{V1}, I_{V2} ... I_{V5} in col 2 & 4; $\ln(n_{c(-m),t-1}/Area_c)$, $\triangle\ln(x_{c(-m)t})$; and $\ln(n_{c(-m),t-1}/Area_c) \times \triangle\ln(x_{c(-m)t})$			
Quintile dummies interacted w/ signal to other countries	n/a	Yes	n/a	Yes
Quintile dummies	n/a	Yes	n/a	Yes
Firm-year Fixed Effects	Yes	Yes	Yes	Yes
City-country Fixed Effects	Yes	Yes	Yes	Yes
Nb of obs.	10,403,464	10,403,464	13372087	13372087
R-squared	.111	.111	.104	.104

See eq. (13) for the estimation specification. All coefficients are already multiplied by 100 for clearer reporting. The sample excludes outliers (defined in Table 3) of neighbors' export growth and export transactions to Hong Kong. The dependent variable, $Entry_{icmt}$, is equal to 1 for the firm-city-country-year observation if firm i started exporting to country m in year t. $Entry_{icmt}$ is set to zero for all destination countries that a new exporter did not export before and in year t. In column (2), city-market-years are split into quintiles of the standard deviation of neighbors' export growth in the same year, with I_{V1} being the lowest quintile. In column (4), city-markets are split into quintiles of distance between the destination and China in the pooled sample. Quintile dummies are included as well as their interactions with the growth rate of neighbors' exports to the same market. Also included are quintile dummies interacted with neighbors' export growth in other markets. All columns include firm-year and city-country fixed effects. t statistics, based on standard errors clustered at the city-country level, are reported in parentheses. * p<0.10; ** p<0.05; *** p<0.01.

Table 6: Entry, Learning from Neighbors, and Extended Gravity

	(1)	(2)	(3)
$I_{lang,t} \times \triangle \ln(x_{cmt})$	-0.123***		-0.162***
	(-4.70)		(-6.07)
$I_{lang,t}$	-2.08***		-2.51***
	(-22.03)		(-20.75)
$I_{border,t} \times \triangle \ln(x_{cmt})$		0.0713*	0.0593
		(1.65)	(1.27)
$I_{border,t}$		0.0253***	0.0248***
		(48.33)	(27.28)
$\ln(n_{cm,t-1}/Area_c) \times \triangle \ln(x_{cmt})$	0.0705***	0.0681***	0.0688***
	(6.85)	(6.66)	(6.68)
$\triangle \ln(x_{cmt})$ [signal]	0.654***	0.595***	0.642***
	(7.50)	(6.91)	(7.38)
$\ln(n_{cm,t-1}/Area_c)$	0.0884***	0.0648**	0.0737***
	(3.27)	(2.42)	(2.75)
Additional Controls	$I_{lang,t} \times \triangle \ln(x_{cmt})$ in col 1 & 3; $I_{border,t} \times \triangle \ln(x_{cmt})$ in col 2 & 3; $\ln(n_{c(-m),t-1}/Area_c)$, $\triangle \ln(x_{c(-m)t})$, and $\ln(n_{c(-m),t-1}/Area_c) \times \triangle \ln(x_{c(-m)t})$		
Firm-year Fixed Effects	Yes	Yes	Yes
City-country Fixed Effects	Yes	Yes	Yes
Nb of Obs.	7,102,425	7,102,425	7,102,425
R-squared	.0755	.0756	.0774

See eq. (13) for the estimation specification. Only exporters that were selling in other markets in year t-1 are included. The sample excludes outliers (defined in Table 3) and transactions to Hong Kong. All coefficients are already multiplied by 100 for clearer reporting. The dependent variable, $Entry_{icmt}$, is equal to 1 for the firm-city-country-year observation if firm i started exporting to country m in year t. $Entry_{icmt}$ is set to zero for all destination countries that a new exporter did not export before and in year t. The source of spillover is measured by the (log) number of "same-market" neighboring exporters divided the area of the city, $\ln(n_{cm,t-1}/Area_c)$. Column (1) uses language as the basis to group countries. Column (2) uses the fact that an existing country and the new country served by the firm share the same border. Column (3) includes both extended gravity measures and their corresponding interactions. All columns include the extended gravity dummies interacted with the neighbors' growth rate in other countries, neighbors export growth and its interaction with the corresponding prevalence, as well as firm-year and city-country fixed effects. t statistics, based on standard errors clustered at the city-country level, are reported in parentheses. * p<0.10; ** p<0.05; *** p<0.01.

Table 7: Initial Sales and Learning from Neighbors

	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(n_{cm,t-1}/Area_c)\times \triangle \ln(x_{cmt})$	0.0125***	0.0114***	0.0163***	0.0162***	0.0158***	0.0157***
	(2.92)	(2.67)	(3.79)	(3.78)	(3.26)	(3.22)
$\triangle \ln(x_{cmt})$ [signal]	0.148***	0.133***	0.174***	0.174***	0.166***	0.165***
	(4.60)	(4.18)	(5.45)	(5.43)	(4.62)	(4.57)
$\ln(n_{cm,t-1}/Area_c)$	-0.0814***	-0.0463***	-0.00708	-0.0213	0.00930	0.00256
	(-7.30)	(-4.10)	(-0.62)	(-1.62)	(0.75)	(0.18)
$\ln(n_{c(-m),t-1}/Area_c) \times \triangle \ln(x_{c(-m)t})$		-0.0147		0.152		0.0671
		(-0.79)		(0.78)		(0.21)
$\triangle \ln(x_{c(-m)t})$		0.0633		3.317		1.124
		(0.77)		(0.35)		(0.23)
$\ln(n_{c(-m),t-1}/Area_c)$		-0.199***		-0.320*		-0.178
		(-7.64)		(-1.87)		(-0.83)
City-year Fixed Effects			Yes	Yes		
Country-year Fixed Effects	Yes	Yes				
Firm-year Fixed Effects					Yes	Yes
City-country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Nb of Obs.	513433	513402	513433	513402	513433	513402
R-squared	.102	.102	.105	.105	.546	.546

See equation (12) for the estimation specification. The sample excludes outliers (defined in Table 3) and transactions to Hong Kong. The dependent variable is $ln(ExpSales)_{icmt}$. The source of spillover is measured by the (log) number of "same-market" neighboring exporters divided by the area of the city, $\ln(n_{cm,t-1}/Area_c)$. Columns (1) and (2) include country-year and city-country fixed effects. Columns (3) and (4) include city-year and city-country fixed effects. Columns (5) and (6) include firm-year and city-country fixed effects. t statistics, based on standard errors clustered at the city-country level, are reported in parentheses. * p<0.10; ** p<0.05; *** p<0.01.

Table 8: Export Survival and Learning from Neighbors

	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(n_{cm,t-1}/Area_c)\times \triangle\ln(x_{cmt})$	0.0129	-0.0640	-0.134	-0.0591	0.145	0.185
	(0.11)	(-0.55)	(-1.24)	(-0.55)	(1.21)	(1.53)
$\triangle\ln(x_{cmt})$ [signal]	0.0856	-0.629	-1.13	-0.575	1.22	1.51*
	(0.10)	(-0.72)	(-1.41)	(-0.72)	(1.38)	(1.70)
$\ln(n_{cm,t-1}/Area_c)$	-8.87***	-8.54***	-7.63***	-6.84***	-4.95***	-4.52***
	(-30.12)	(-27.12)	(-23.78)	(-18.52)	(-14.49)	(-11.45)
$\ln(n_{c(-m),t-1}/Area_c)\times\triangle\ln(x_{c(-m)t})$		0.501		16.5**		12.2*
		(1.06)		(2.09)		(1.72)
$\triangle\ln(x_{c(-m)t})$		5.25**		87.0		-91.8
		(2.38)		(0.32)		(-0.75)
$\ln(n_{c(-m),t-1}/Area_c)$		-2.06***		14.5***		8.86*
		(-2.90)		(3.34)		(1.79)
City-year Fixed Effects			Yes	Yes		
Country-year Fixed Effects	Yes	Yes				
Firm-year Fixed Effects					Yes	Yes
City-country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Nb of Obs.	513433	513402	513433	513402	513433	513402
R-squared	.0702	.0702	.0742	.0742	.588	.588

See equation (12) for the estimation specification. The sample excludes outliers (defined in Table 3) and transactions to Hong Kong. All coefficients are already multiplied by 100 for clearer reporting. The dependent variable, $Survival_{icmt}$, equals 1 for a new exporter that survived the first year and continued to export in the second year. It is equal to zero if a new exporter exported only for 1 year. The source of spillover is measured by the (log) number of "same-market" neighboring exporters divided by the area of the city, $\ln(n_{cm,t-1}/Area_c)$. Columns (1) and (2) include country-year and city-country fixed effects. Columns (3) and (4) include city-year and city-country fixed effects. Columns (5) and (6) include firm-year and city-country fixed effects. t statistics, based on standard errors clustered at the city-country level, are reported in parentheses. * $p<0.10$; ** $p<0.05$; *** $p<0.01$.

Table 9: Post-entry Export Growth and Learning from Neighbors

	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(n_{cm,t-1}/Area_c)\times \triangle \ln(x_{cmt})$	-0.0256***	-0.0320***	-0.0297***	-0.0298***	-0.0241***	-0.0237***
	(-4.68)	(-5.72)	(-5.49)	(-5.45)	(-3.08)	(-3.00)
$\triangle \ln(x_{cmt})$ [signal]	-0.346***	-0.397***	-0.380***	-0.381***	-0.325***	-0.321***
	(-8.67)	(-9.71)	(-9.65)	(-9.56)	(-5.75)	(-5.66)
$\ln(n_{cm,t-1}/Area_c)$	-0.0574***	-0.0553***	-0.0677***	-0.0561***	-0.0452**	-0.0149
	(-4.17)	(-3.80)	(-4.42)	(-3.22)	(-2.16)	(-0.62)
$\ln(n_{c(-m),t-1}/Area_c) \times \triangle \ln(x_{c(-m)t})$		0.0788***		-0.180		-0.343
		(3.75)		(-0.62)		(-0.78)
$\triangle \ln(x_{c(-m)t})$		0.434***		0.0612		-3.387
		(4.53)		(0.00)		(-0.12)
$\ln(n_{c(-m),t-1}/Area_c)$		-0.0230		0.241		0.743**
		(-0.73)		(1.19)		(2.36)
City-year Fixed Effects			Yes	Yes		
Country-year Fixed Effects	Yes	Yes				
Firm-year Fixed Effects					Yes	Yes
City-country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Nb of Obs.	248424	248411	248424	248411	248424	248411
R-squared	.0589	.0589	.0627	.0626	.512	.512

See equation (12) for the estimation specification. The sample excludes outliers (defined in Table 3) and transactions to Hong Kong. The dependent variable is post-entry export growth, $ln(ExpSales_{t+1}) - ln(ExpSales_t)$. The source of spillover is measured by the (log) number of "same-market" neighboring exporters divided by the area of the city, $\ln(n_{cm,t-1}/Area_c)$. Columns (1) and (2) include country-year and city-country fixed effects. Columns (3) and (4) include city-year and city-country fixed effects. Columns (5) and (6) include firm-year and city-country fixed effects. t statistics, based on standard errors clustered at the city-country level, are reported in parentheses. * p<0.10; ** p<0.05; *** p<0.01.