Learning to Export from Neighbors*

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Abstract

This paper studies how learning from neighboring firms affects new exporters' performance and dynamics. We develop a statistical decision model in which a firm updates its prior belief about demand of a foreign market based on the number of neighbors currently selling there, the level and heterogeneity of their export sales, and the firms' 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 lowers post-entry growth, conditional on survival. These learning effects are stronger when there are more neighbors revealing the signal or when the firm is less familiar with the market. Decisions to exit are independent of the prevalence of neighboring export activities. We find supporting evidence from the transaction-level export data for all Chinese exporters over 2000-2006. Our findings are robust to controlling for firms' supply shocks, countries' demand shocks, and city-country fixed effects.

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

Firms face considerable uncertainty when selling in new markets, especially in new foreign markets where consumer tastes and demand are highly unpredictable. Recent research in international trade shows that new exporters often start selling small quantities and many of them give up exporting in the first year.[1] The earlier theoretical literature (e.g., Rauch and Watson, 2003) studies how uncertainty in export markets drives firms' export dynamics.[2] When facing uncertainty in export profitability, firms naturally enter small to learn about both the market and their own export capability, before committing to larger sales.

Existing research has focused mainly on a firm's own export experience in explaining its export dynamics and performance.[3] In reality, however, self discovery can be costly and learning from others can be a potentially more advantageous strategy (Hausmann and Rodrik, 2003). Research in development economics has for years shown that learning from others plays an important role in determining technology adoption in developing countries (e.g., Foster and Rosenzweig, 1995; Conley and Udry, 2010). Separately, research in international trade has emphasized sunk costs of exporting in shaping export patterns and has provided sizeable estimates of those costs (see Das et al., 2007, and Morales et al., 2011). With the high sunk costs firms need to incur to start exporting, self-experimentation in foreign markets can be costly, more so than in the domestic market. Information about foreign markets is thus particularly valuable.

This paper examines whether learning from neighbors plays a role in shaping firms' export entry and post-entry performance. We develop a model of social learning to study how firms learn from their neighbors about foreign market demand.[4] 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 of all Chinese exporters. In addition to the rich information available in the data, China's high regional specialization of industrial activities provides a good context for such an analysis.

Our model incorporates social learning pioneered by Jovanovic (1982) and later Moretti (2011) 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

[1] 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.

[2] See Section 2 for a comprehensive literature review.

[3] The one exception that we are aware of is Segura-Cayuela and Vilarrubia (2008), who show theoretically that neighbors' export activities, by lowering fixed export cost, can affect new exporters' dynamics.

[4] For simplicity, our model focus on learning about the level of demand. The 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 do 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.

entry, but is uncertain about the overall market demand and its own market-specific product appeal. Based on information 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 driven by their unobserved product appeals, signals about foreign market demand are noisy. Based on a standard learning model, when there are more neighboring firms revealing a positive signal, firm-specific noises tend to average out and the signal becomes more informative.

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) attributes of neighbors. These attributes include neighbors' average export performance, their heterogeneity, and the firm's own prior knowledge about the new market. Importantly, spillover from neighbors' export activities to new exporters depends on the strength of the signal (average neighbors' export sales or growth). An increased presence of neighboring export activities would increase the rate of exporters' entry into new markets when the signal is positive, while it would lower the rate when the signal is negative. As such, using an interaction between the signal and the prevalence of neighboring export activities, rather than the prevalence measure only, is a more direct way to empirically identify information spillover in trade.

Our model yields several predictions. It predicts that a positive signal about foreign market demand inferred from neighbors' export performance 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, there is less scope for a firm 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 levels of the signal and firm productivity, a new exporter's survival rate in a market is independent of the prevalence of existing neighbors serving the same market. However, since the prevalence of neighbors revealing a positive signal is correlated with the number of export entrants, it will affect the fraction of export survivors. In particular, the endogenously higher entry rate, given sunk entry costs, implies more low-productivity export entrants. In the presence of fixed export costs and firm heterogeneity, low-productivity exporters are less likely to survive ex post and the fraction of new exporters that survive will be decreasing in the level of the signal, more so if there are more neighbors revealing it. Our model thus highlights that the observed spillover effect on survival, including some documented in the existing literature, can be determined by an increase in the number of low-productivity entrants on the one hand, and a more accurate signal from neighbors on the other.[5]

Using transaction-level trade data for the universe of Chinese exporters over 2000-2006, we find supporting evidence for all theoretical predictions. Controlling for firm-year fixed effects (firms' supply shocks), city-year fixed effects (countries' demand shocks), and city-country fixed effects,[6] 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. The positive correlation is increasing in the prevalence of neighbors.[7] The coefficients on the signal and its interaction with the prevalence of neighbors become negative but remain significant when new exporters' post-entry growth rate is used as the dependent variable. The survival rate of export entrants is positively related with the strength of the signal from neighbors, but is independent of the prevalence of export activities in the neighborhood, as predicted by our model. All these findings remain robust to controlling for the number of firms serving other markets and its interaction with the corresponding signal, as well as different sets of fixed effects. They are also robust in specifications that use alternative measures of the signal and the prevalence of neighbors.

We also uncover evidence for the theoretical predictions regarding the specific relationships between the rate of export entry, the measures of signal dispersion, and the firm's prior knowledge about the new markets. In particular, a firm is less likely to enter a market if the signals based on its neighbors' export performance are more dispersed, but are more likely to enter countries that are more distant from China, which new exporters presumably have less prior knowledge about. 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 to domestic firms, or that there is less information exchange between domestic and foreign exporters. We also find that firms learn both from neighbors in the same city as well as those in the same province but outside the city. Collectively, these findings provide evidence that information provided by neighboring exporters reduces new exporters' uncertainty in export sales.

The learning effects on new exporters' entry, initial sales, and post-entry growth are quantitatively significant. 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 the export entry rate, evaluated at the median entry rate (0.3%) of the pooled sample. At 20% export growth, a one standard-deviation increase in the (log) density of exporters (at the city-destination-level) (5 neighboring firms) is associated with an increase in the entry rate by about 10%, relative to the median. The corresponding positive effect of the interaction between the signal and the

[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.

[6] 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] 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 when either measure is used.

prevalence of exporters on new exporters' initial sales is about 0.5%, and that for the post-entry growth rate is about an additional percentage-point.

The rest of the paper is organized as follows. Section 2 briefly reviews the literature. Section 3 outlines the theoretical model of the paper. Section 4 discusses our 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 a recent literature that studies firms' export strategies and dynamics (Eaton, et al., 2008; Albornoz et al., 2011, among others). It shows that new exporters often start selling small quantities 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 the 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 the models rationalize new exporters' small entry and substantial post-entry export growth based on learning about their *own* export profitability.[10] We focus instead on learning from neighbors.[11]

Second, our paper incorporates the influential literature on social learning (e.g., Jovanovic, 1982; Banerjee, 1992; Bikhchandani, Hirshleifer and Ivo, 1992, 1998) with the study of international trade. These studies have provided precise analytical results about how learning from neighbors takes place and affects equilibrium choices and outcomes. There is a large and growing empirical literature that examines the learning hypotheses using micro data.[12] For instance, Foster and Rosenzweig (1995) examine the roles of learning by doing and learning from others using data for farmers' adoption of new seeds. Conley and Udry (2010) examine the pattern of fertilizer use by Ghanian pineapple farmers and find that information exchange between farmers shape expected profitability, which

[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.

[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.

in turn affects the actual adoption of fertilizers. This implies underinvestment in fertilizers due to unobserved information cost. 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.

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 data permit an empirical verification of a learning model, 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 this growing set of papers, 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 a positive and a negative signal. Third, our model shows that in the presence of firm heterogeneity and fixed costs, the incidence of firm entry and survival are related, which requires controlling for firm or firm-year fixed effects. Fourth, we define neighborhood as cities rather than larger geographic units to better identify the source of spillover. Finally, we explore information spillover within firms across destinations, controlling for any 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 exporting in shaping trade patterns and dynamics (see Bernard et al., 2003; Melitz, 2003; Bernard

[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 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.

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]

3.1 Set-up

Before exporting to a country, a firm holds a prior about the demand of that country. After observing its neighbors' export performance in the same country, a firm updates both its expectation of the foreign demand and the precision of the 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 $G(\rho)$.

While each firm knows its own ρ prior to entry, it is uncertain about its export profit due to the uncertain firm-market-specific demand. Specifically, firm i with productivity ρ selling to market m will obtain a gross (operating) profit of $\pi^o(D_{im}, \rho) = D_{im}\rho^{\sigma-1}$, where $\sigma > 1$ is the elasticity of substitution between varieties in the market and D_{im} is firm i's demand factor of market m.[16] A firm's export performance in a market depends on three factors – firm-specific productivity, firm-market-specific product appeal, and market-specific demand. Specifically, $\ln(D_{im})$ can be decomposed into three separate demand shifters:

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

where κ is a constant.[17] $d_m = \ln(P_m^\sigma Y_m)$, where P_m and Y_m are the ideal price index and total expenditure in market m, respectively. $z_{im} = \ln(Z_{im})$ is the firm's market-specific product appeal in market m. z_{im} is the only component that is firm-specific, and cannot be inferred from neighbors but is realized after the firm's first year of exporting. For simplicity, we assume that all three

[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. Alternative models have been developed to analyze uncertainty in trade costs (Segura-Cayuela and Vilarrubia, 2008; Freund and Pierola, 2010), which also do not focus on production technology. As reviewed above, Foster and Rosenzweig (1995) and Conley and Udry (2010) both study learning from neighbors about production technology.

[16] A market is defined as a country to be consistent with our empirical analysis below. Learning and thus information spillover 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, $D_{im} = \left(\frac{1}{\sigma}\right)^\sigma \left(\frac{\sigma-1}{\sigma w}\right)^{\sigma-1} P_m^\sigma Y_m$, 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 $\ln\left[\left(\frac{1}{\sigma}\right)^\sigma \left(\frac{\sigma-1}{\sigma w}\right)^{\sigma-1}\right]$.

components of $\ln D_{im}$ are time-invariant.[18] If the demand components are time-varying (e.g., the market-specific factor contains a time subscript, d_{mt}), as long as d_{mt} is autocorrelated, firms will still learn from neighbors about d_{mt}.[19]

Before selling abroad, a firm faces uncertainty about both d_m and z_{im}. In particular, without any experience in serving market m, the firm 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} as follows:

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

The assumption that d_m is time-invariant implies that once it is learned upon entry, there is no more uncertainty about d_m.[20] With positive (not necessarily perfect) correlation of d_m across time, all our theoretical results hold.[21] Another factor that determines firm i's market demand is the appeal of its products in market m, z_{im}, which is firm-market-specific and time-invariant. Therefore, two firms with the same productivity can have different realized export profits in market m due to different z_{im}, which is assumed to be normally distributed with mean zero and variance v_{zm} as follows:

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

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 observed neighbors' export performance in market m (more below). After selling in market m, the firm learns about both d_m and z_{im} with certainty and there is nothing more to learn.[22] We assume that firm productivity ρ and product appeal z_{im} are independently distributed, similar to Bernard et al. (2010).

Consider firm i that is contemplating the option to export to a new market m. Without observing other firms' export patterns and performance, it expects to obtain an operating profit from exports as follows:

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

[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 considered 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] In a more 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.

[21] See Section 4 for an exposition of the high persistence of demand shocks.

[22] 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.

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.[23]

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

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

Conditional on exporting, the firm chooses quantity of export, which equals the expected export sales divided by its price, $E[R(D_{im}, \rho)]/p(\rho)$, where $E[R(D_{im}, \rho)] = \sigma E[\pi^o(D_m, \rho)]$ and $p(\rho) = \frac{\sigma}{\sigma-1}\frac{c}{\rho}$, 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 from its own experience, or from its neighbors.

3.2 Learning from Neighbors

Consider the situation of a new exporter deciding to enter market m at t, after observing its neighbors' export performance there at $t-1$. There are $n_{m,t-1}$ neighbors serving country m. We assume that a firm observes all its neighbors' export activities, though in reality, firms can observe different signals, depending on their local networks.[24]

The firm observes neighbors' export values but not their individual demand levels. We make an intuitive assumption that the firm uses the (known) conditional mean of $\rho : \widetilde{\rho} = E\left[\rho | \rho > \underline{\rho}\right]$ to infer the demand level from its neighbors' exports (i.e., $\overline{d}^{nb}_{m,t-1} = \frac{1}{n_{m,t-1}} \sum_{j=1}^{n_{m,t-1}} \left(R_{jmt}/\widetilde{\rho}^{\sigma-1}\right)$).[25] After observing $\overline{d}^{nb}_{m,t-1}$ 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]

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

where δ_t is the weight the firm puts on $\overline{d}^{nb}_{m,t-1}$ when updating its prior. According to Degroot

[23] 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. As we will show below, the comparative static is independent of this relation.

[24] The model can be extended to incorporate partial observability. In the empirical section, we examine some of the measurable features of firms and neighbors that affect the learning effects.

[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 competitiors, this assumption seems 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).

(2004), δ_t can be derived as

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

The conditional variance of $d_{m,t}$, 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 the destination's demand (d^*_m) facing all firms:

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

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:

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

In words, a potential entrant will put a higher weight (δ_t) on the signal from neighbors about foreign market m's demand, and a lower weight on its own prior belief when updating its prior, if there are more neighbors revealing the signal. On the other hand, when neighbors' signals become more dispersed due to more heterogeneous product appeals, all else being equal, the potential entrant will put a smaller weight on the signal.

Consistently, the precision of the posterior, v^{-1}_{mt}, will also increase 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 of 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.

3.2.1 Entry into New Export Markets

We first analyze how neighbors' export activities affect exporters' entry decision. A firm's decision to enter market m depends not only on how many existing neighbors are already exporting to m, but also on whether the demand level inferred from the average export revenue of its neighbors exceeds the firm's prior.[28]

The firm will start exporting if it receives a positive signal that lowers the entry threshold.

[28] To keep the model tractible, we sidestep from the discussion about why some firms would start exporting before others. A natural extension of the model will consider heterogenous private signals of firms.

Similar to (1), the posterior entry productivity cutoff is

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

where $\overline{d}_{m,t}^{post}$ 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 $\overline{d}_{m,t}^{nb} > \overline{d}_{m,t-1}^{nb}$. The entry cutoff 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 $\widetilde{\rho}_t^{post}$ 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 the signal, $\overline{d}_{m,t}^{nb}$, by $\varepsilon_{\rho t} \equiv \frac{\partial \ln \widetilde{\rho}_t^{post}}{\partial \overline{d}_{m,t}^{nb}}$, 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 cutoff $\widetilde{\rho}_t^{post}$, thus increasing entry. The effect of n_{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:[29]

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

In other words, more neighbors will result in a larger drop in the cutoff, $\widetilde{\rho}_t^{post}$, 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 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 there are more neighbors revealing the signal.*

Note that the sign of the relationship between the prevalence of existing exporters and the export entry cutoff, $\frac{\partial \widetilde{\rho}_t^{post}}{\partial n_{m,t-1}}$, is generally indeterminate. The reason is that more neighbors can help spread both good and bad news, which should lead to opposite effects on firm entry.[30]

We now look at the effect of the precision of the signal and the precision of the prior, respectively,

[29] It can be easily shown that the second derivative of ε_ρ with respect to $n_{m,t-1}$ is negative, implying decreasing returns to learning from neighbors.

[30] Moreover, learning from neighbors exhibits decreasing returns. $\frac{\partial|\varepsilon_{\rho t}|}{\partial n_{m,t-1}} =$

on the elasticity of the entry cutoff with respect to the signal, $|\varepsilon_{\rho t}|$. Differentiating the semi-elasticity of entry with respect to the signal, $|\varepsilon_{\rho t}|$, shows that:

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

These results are intuitive. On the one hand, a noisier signal (higher v_{zm}) is associated with a 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) *A firm's propensity to start exporting in a new 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 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 are given by:

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

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

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

$\left[\left(1+\frac{v_{dm}n_{m,t-1}}{v_{zm}}\right)^{-1}-1\right]\frac{2v_{zm}}{v_{dm}n^3_{m,t-1}}\left(1+\frac{v_{zm}}{v_{dm}n_{m,t-1}}\right)^{-2} < 0.$

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., $\frac{\partial \overline{d}_{m,t}^{post}}{\partial n_{m,t-1}} > 0$). On the other hand, an increase in the number of neighbors will increase the precision of the signal (i.e., $\frac{\partial v_{mt}(n_{t-1})}{\partial n_{m,t-1}} < 0$) 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 received from neighbors $\overline{d}_{m,t-1}^{nb}$ and their prevalence, n_{t-1}, similar to the analysis above for the impact on entry, we are able to pin down a more deterministic spillover effect as follows:

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

In other words, there is a positive interactive effect on exporters' initial sales in a new market, summarized in the following proposition:

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 neighboring exporters, and more so when there are more neighbors revealing the signal.*

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

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

where Φ is the standard normal cumulative distribution function. A lower fixed cost of export (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,

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

where ϕ is the probability distribution function of z_{im}. Notice that $\Lambda_{t+1}^S (\rho, d_m^*)$ depends on the true state of demand rather than the observed average demand factor of neighbors, $\overline{d}_{m,t-1}^{nb}$. But since d_m^* is unobservable we will use $\overline{d}_{m,t-1}^{nb}$ 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 cutoff $\underline{\rho}_t^{\sigma-1}$, as discussed in the previous section, conditional on entry, $n_{m,t-1}$ 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 $\overline{d}_{m,t-1}^{nb}$ and n_{t-1} affect the entry probability, the sample of entrants and thus the average survival rate (the fraction of new exporters that survive) will also be affected. In the empirical section below, we need to account for firms' selection into exporting. If productivity is firm-specific and product appeal is ex ante unknown, our model shows that controlling for firm fixed effects, and focusing on the within-firm variation in survival, can fully address the selection issue.[31] Controlling for firm 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 strength of 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 neighboring export activities.*

3.2.4 Growth Conditional on Survival

Finally, for firms that continue to export in market m after realizing z_{im}, we can derive the firm-level export growth rate. Conditional on survival, the growth rate of exports to market m of a firm with productivity ρ can be expressed as

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

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 post-entry surprises to new exporters. When neighbors' signal becomes stronger and more precise, a new

[31] An alternative way to adress this issue is to implement the Heckman's selection procedure. But 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.

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, but the counterfactual of smaller downside surprises is not observed in the sample of survivors, since those that have realized z_{im} significantly lower than expectation are no longer in the sample. Thus, we focus on the reduced upside surprise and empirically investigate the following proposition in Section 5:

Proposition 5 (Post-entry Growth) *The post-entry growth rate of exports to a new market, conditional on survival, is decreasing in the level of the ex ante signal about the market's demand, more so if there are more neighboring exporters revealing the signal.*

This result is for the sample of survivors. Exit decisions should also be taken into account. However, as we showed in Proposition 4, the survival rate of new exporters is independent of $n_{m,t-1}$. The direction of the bias is unclear but once we control for firm fixed effects in the empirical section below, our results are independent of the standard problem of selection across firms.

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.[33] For each transaction, the data set reports the value (in US dollars) and quantity at the product level (over 7000 HS 8-digit categories) to/from each country (over 200 destination and source countries) for each firm.[34] In addition, we also have information on the ownership type (domestic private, foreign, and state-owned) and trade regime (processing versus non-processing) of each trading firm, as well as the region or city in China where the firm trades. To average out noise due to high-frequency and infrequent trade patterns that may vary across countries or products, we aggregate all observations to the year level. We focus on learning about a foreign country's demand and collapse the product dimension. Thus, a market is defined as a destination-country in the empirical analysis.[35] Since we focus on learning effects, in our analysis, we exclude exports to Hong Kong from the sample because many firms have their headquarters in Hong Kong, who serve as intermediaries to re-export final products to foreign markets.

Exporters in China are required by law to register as either processing exporters or non-processing (ordinary) exporters.[36] The majority of processing exporters have long-time committed

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

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

[35] 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.

[36] Since the beginning of economic reforms in the early 1980s, the Chinese government has implemented various policies to promote exports and foreign direct investment. Most notable of all is the exemption of tariffs on imported materials and value-added tax for processing plants, which assemble inputs into final products for foreign buyers. A registered EP firm is required by law to maintain certain standards for accounting practices and warehouse facilities.

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

We study learning from neighboring exporters in the same city. There are on average 425 cities plus municipalities, according to China's Customs' definition.[37] See Fig. 4 for the geographic distribution of the cities. We also explore the potentially differential learning effects across countries. To this end, we use data on bilateral distance, common language, and common border, between China and the destination and between a firm's existing markets and new markets. Data are from CEPII.[38] See Mayer and Zignago (2006) for a detailed description.

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 will let us identify the within-firm variation in export performance, when we control for firm-year fixed effects. The relatively small exporters' median sales indicate that there are many small firms in our data, which should exhibit active entry and exit according to existing evidence for other countries.

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.[39] Figure 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 appendix, reports the patterns of successful entries and one-time exporting across countries between 2001-2005. Tables A2 and A3 report summary statistics of the main variables used in the empirical analysis and their correlations, respectively.

Moreover, the terms of transactions for EP firms are to be specified in greater detail in written contracts than ordinary exporters. Readers are referred to Naughton (1996), Feenstra and Hanson (2005) and Fernandes and Tang (2012) for more details about the EP regulatory regimes.

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

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

[39] 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 Empirical Evidence

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

5.1 Entry

5.1.1 Baseline Results

To examine Propositions 1 and 2 about firms' patterns of entry in foreign markets, we first define the dependent variable of the entry 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).[40] Note that exporters that were already serving country m in year $t-1$ are not included in the sample.[41] Moreover, since we need information from the previous year's export status to define export entry, we need to drop the first year (i.e., 2000) of the sample. We also have to drop observations from the last year (2006) since that information is used to construct the variables for export survival and post-entry growth of entrants, studied in the next sections.

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. We use the average growth rate of exports to country m by exporters in city c, from year $t-1$ to t, $\triangle \ln(x_{cmt})$, as the baseline proxy for $\overline{d}^{nb}_{m,t-1}$. Specifically, $\triangle \ln(x_{cmt})$ is defined as follows:

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

where $\mathbf{N_{cmt-1}}$ 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. 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 also perform robustness checks by using the (log) average level of neighbors exports, $\ln(x_{cmt})$, as an alternative proxy for the signal.

[40] 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.

[41] They are, however, included in the group of the signal transmitters, as they are existing exporters in the neighborhood.

To verify that our choice of the signal captures profitable learning from neighbors, 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, and exports in a market today reveal information about the average export profitability of selling in the same market in the future learning is profitable since deviations from the city-destination (e.g., Beijing-US) averages tend to last.[42]

Proposition 1 predicts that the probability of a firm entering a market is positively correlated with the level of the signal about the market, and more so if there are more existing neighboring exporters selling there. We examine this proposition by estimating a probit model of entry, 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:

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

where $Entry_{icmt}$ is defined in eq. (11). The regressors of interest include the proxy for the signal $\triangle\ln\left(x_{cmt}\right)$, 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.[43] Figs 4-6 show the geographic distribution of these variables of interest.

Our benchmark measure of the number of neighbors is normalized by the geographic size of the city. Since bigger cities have more firms, this "density" measure will take into account geographic frictions that affect information transmission, which will affect the probability of meeting a neighbor and thus learning in a city.[44] **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 **Z** ensures that the identified learning effect, if any, is market-specific.

By exploiting information at the sub-firm-year level, 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. In addition to geographic distance, city-country fixed effects will also capture any unobserved city-market-specific determinants of export performance and dynamics, such as historical factors that may affect the available information and infrastructure for exports from a city to a country.[45] In addition to city-country fixed effects, we control for city-year, country-year, or firm-year fixed effects, respectively. Country-year fixed

[42] 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.

[43] Notice that entrants are not included in the count of $n_{cm,t-1}$.

[44] We check the robustness of the results to using the raw number of neighbors to measure the source of spillover.

[45] E.g. the European connection in Shanghai in the 1930s.

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. 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 is 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 existing 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 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 $100 \times \triangle \ln\left(x_{cmt}\right)$ in column 6 suggests that the (pooled) sample mean export growth of neighbors exporting from city c to country m (20%) is associated

[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.

with an increase in the probability of entry into the market by 0.1 percentage points.[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, relative to 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 of 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 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 A3), and by using the average exports of neighbors to market m in year t, $\ln(x_{cmt})$, to proxy for the signal (columns 1 and 2 of Table A4).[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 and the corresponding interaction terms. Specifically, we divide city-markets into quantiles according to their ranking in the density of neighboring exporters in a year. We include dummies (I_{denq}) for different quantile 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, while 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 quintiles 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 the probability of entering a market is increasing with the neighbors' export growth in the same market, in the top 40% 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.

[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 rate 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 and A4 for space considerations, but results remain robust for other combinations of fixed effects included, as in Table 3.

[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} respectively, are equal; as well as the null that the interactions with I_{den4} and I_{den5} are equal to 0 individually.

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 prior to 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 are indicators for whether a potential new market shares the same language or 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.[56] To empirically examine Proposition 2, we estimate the following specification:

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

In addition to the three main variables of interest, $\ln(n_{cm,t-1}) \times \triangle \ln(x_{cmt})$, $\triangle \ln(x_{cmt})$, and $\ln(n_{cm,t-1})$, 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 ($icmt$).[57] According to Proposition 2, the sign of the estimated θ_1 is expected to be negative for the first measure;

[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.

[56] We also check that results are robust to the use of variability of neighbors' export sales, rather than export growth. These results are available upon request.

[57] 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 three criteria) to new market m in year t, and $v_{icmt} = 0$ otherwise.

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 negative and marginally significant (at the 10% level), consistent with Proposition 2, which states that new exporters exhibit less learning if the signal is noisier. Importantly, we continue to find a positive and significant effect of the density of neighbors on the entry learning effects, consistent with our findings above.

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 separate observations into ten deciles of the standard deviation of neighbors' export growth in a year. We then include the decile dummies (I_{Vq}), their interactions with the signal, $\triangle \ln (x_{cmt})$, as well as their interactions with $\triangle \ln \left(x_{c(-m)t}\right)$, the average growth rate of neighbors' exports to other countries. We continue to control for the density of neighbors, both exporting to the same market and to different markets, and their interactions with the corresponding average export growth. While the estimated coefficients on the decile interactions are positive and statistically significant, they are not monotonically decreasing as predicted. The highest coefficients are found in the fifth and sixth deciles. Despite the fluctuation, the average of the coefficients on the decile interactions is significantly larger before the fifth decile. This pattern provides some, though not very strong, support to Proposition 2.

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 term. While we find a positive coefficient on the interaction term, it is not statistically significant at the conventional level. In column 4, we explore the possibility that the relationship could be non-linear and include interactions between deciles of distance from China and the signal from neighboring exporters. While the coefficients are positive and significant, the coefficient on the first decile interaction is not the lowest, contrary to our expectation. However, from the sixth to seventh decile, the coefficients on the interactions increase significantly. The average of these coefficients is also significantly larger after the sixth decile than that before, lending support to Proposition 2 that learning is stronger for more distant markets where firms have less information about.

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 common language is the basis to group countries (column 1), we find supporting evidence that exporters have less potential to learn about markets that are more familiar. The coefficient on the interaction between the signal from neighbors and the indicator for whether the new market shares the same language with any of the firms' existing markets is negative and significant. In column 2, we use border to group countries, the coefficient on the interaction term is positive but insignificant. In column 3, we include simultaneously interactions between the signal from neighbors and both the indicators for common language and common border. The interaction term remains negative and significant for language and insignificant for common boarder, supporting the hypothesis that new exporters have less to learn from neighbors about markets that are similar to those previously served.

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 when there are more neighbors revealing it. To examine this proposition, we estimate eq. (12) but with the entry dummy replaced by the (log) initial exports of firm i from city c to market m 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 there is a strong signal and more so if there are more neighbors revealing it.[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; and also include variables for spillover from neighboring firms that export to other countries. In this specification, the estimated coefficient on the partial effect of neighbors average export growth is 0.165, suggesting that if neighbors' exports to a market grow at the rate of the sample mean (i.e., 20%), new exporter's initial sales in the same market will be about 3.3% higher on average,[59] relative to markets with zero average export growth of neighbors. The estimated coefficient on the interaction term between the strength of 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 exporters at the city-market level (about 5 neighboring firms exporting to the same country) is associated with an additional 0.5% higher initial exports in the same market.[60]

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

[58] Results remain robust when we measure the prevalence of neighbors by the log of their raw number (see columns 5 and 6 of Table A3). 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. This is because while the number of neighbors affects the number of entrants by changing the entry cutoff, conditional on entry, any ex ante information was already taken into account at entry and will not affect an exporter's 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 effect of selection. 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 city-market and 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 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. These results provide support to Proposition 4, which predicts a positive relationship between the signal and the survival rate, but no relationship between the prevalence of neighbors and survival.

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 A6, 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 strength of 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 new exporters learn from neighbors located only in the same city or farther away as well. As reported in Table A7, 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 2). 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 A8, we compare the learning effects between foreign-owned versus domestic new exporters. The first four columns study whether spillover to new exporters in a market differ depending on the ownership type (foreign-owned versus domestic) of the signal transmitters. 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 A8 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

Recent 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 export dynamics and performance, we explore instead how neighbors' export activities may be related to the documented exporters' performance and dynamics.

We build a statistical decision model to study how learning from neighbors affects firms' export performance and dynamics in new markets. A firm's expectation about a potential destination's market demand equals the weighted average between its prior and foreign market demand observed from neighboring exporters. How much a firm updates depends on the number of neighbors, the strength of the signal, the heterogeneity of export sales, and the firm's prior knowledge about the new market. The probability of entry and initial sales to the same destination are both increasing in the strength of the signal for a market, more so if there are more neighboring firms revealing it. 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, which is proxied by 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 the firm's experience itself but from others. 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 market and the amount of turnover due to experimentation. For simplicity we abstract from learning about one's production capability, which is the core of Hausmann and Rodrik (2003). Future research should 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 about demand in different countries, but also for different products.

7 References

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8 Tables and Figures

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

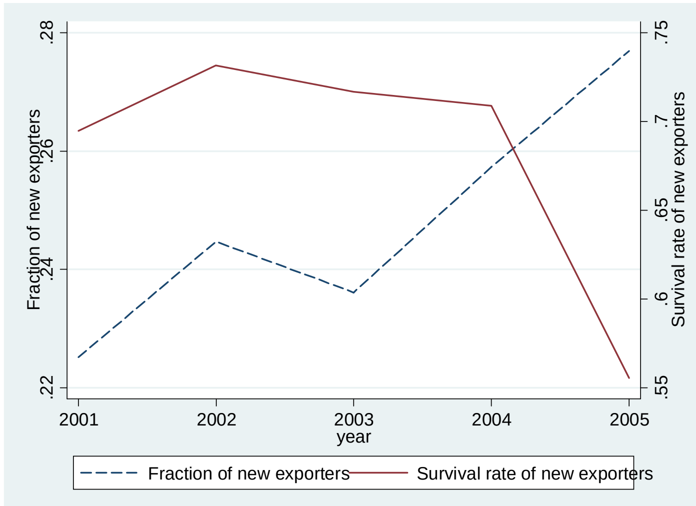

Figure 2: New Exporters - Fraction of Exporters and Average Initial Sales over Average Sales of Existing Exporters

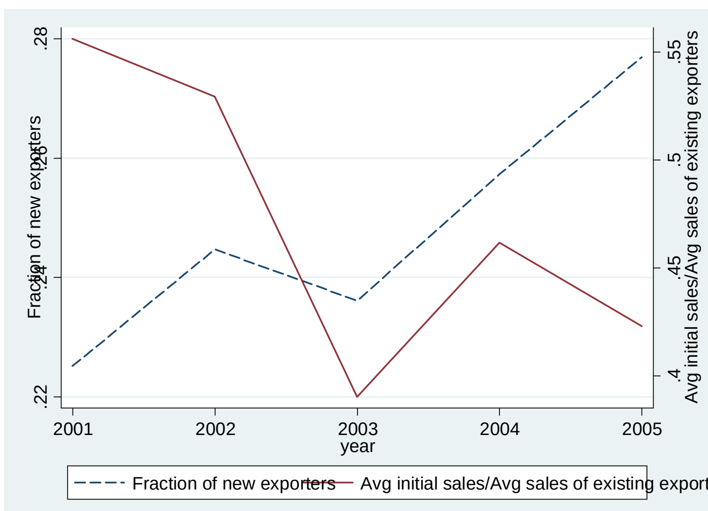

Figure 3: (log) Export Volume from City c to Country m between Year t and $t-1$

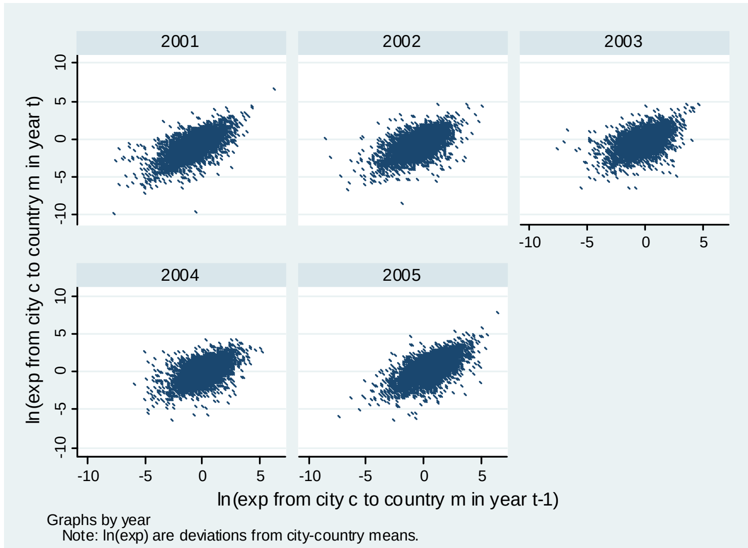

Figure 4: The Number of Neighboring Firms Exporting to the U.S. from Different Chinese Cities

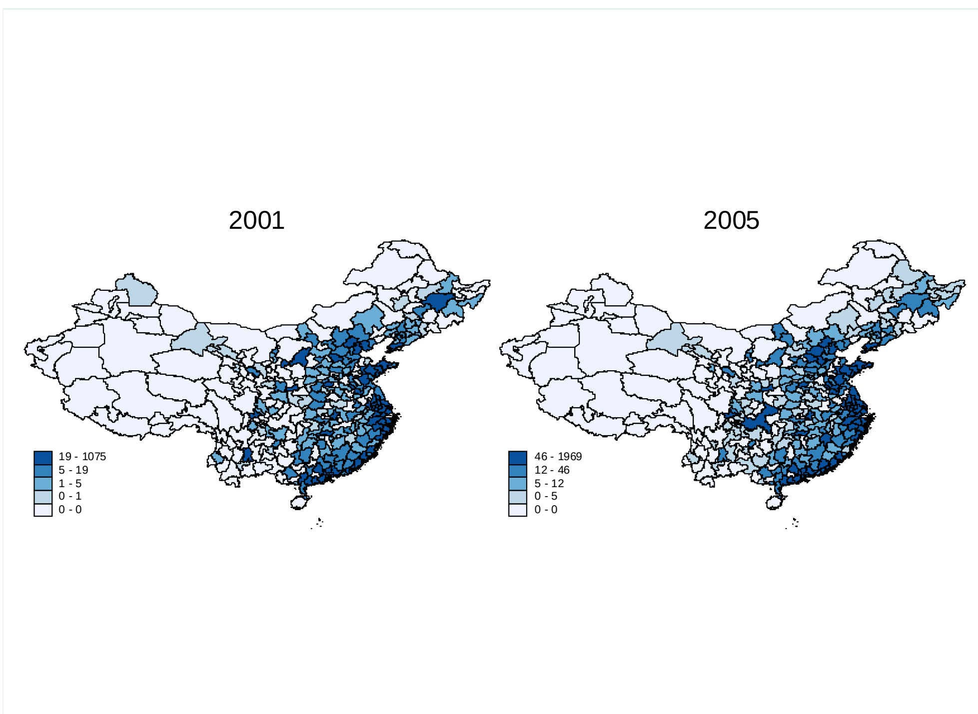

Figure 5: Growth of Neighbors' Exports to the U.S. from Different Cities

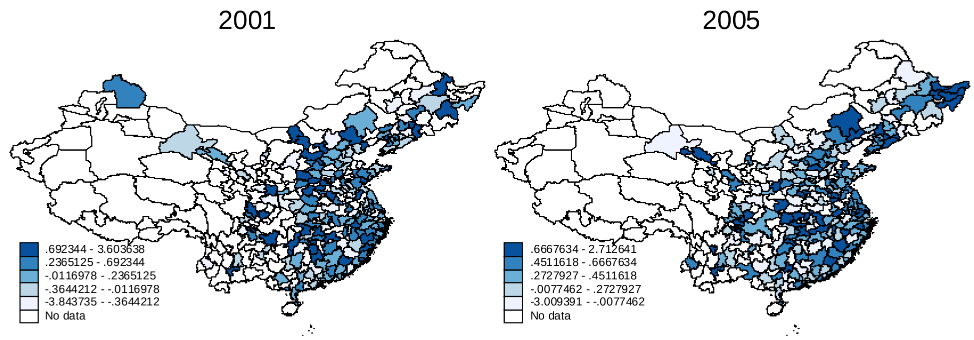

Figure 6: The Rate of Export Entry in the U.S. across Cities

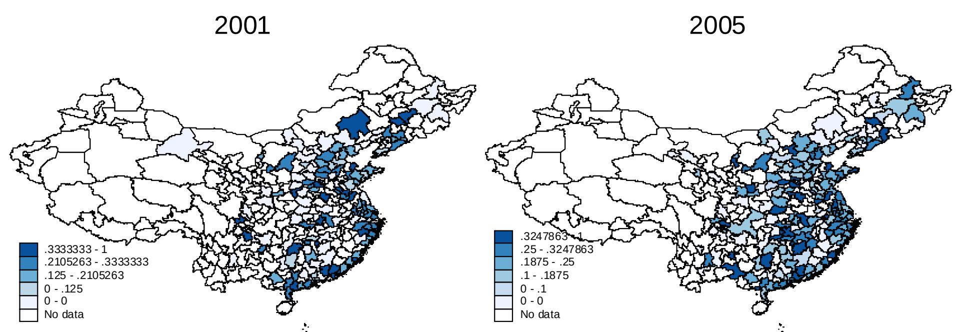

Table 1: Trade Patterns

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$)			
Mean	1011	1258	1462
Median	196	251	298
Stand. Dev	8893	9926	13816
Panel B: Aggregate Level			
Number of firms	27740	45471	82836
Number of products	1077	1114	1147
Number of destinations	173	182	195
Exports (US$ 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 in terms of Export Entry Rates

Top 10

2001		2003		2005	
Country	Entry Rate	Country	Entry Rate	Country	Entry Rate
Japan	0.171	United States	0.179	United States	0.207
United States	0.161	Japan	0.153	Korea	0.136
Korea	0.133	Korea	0.142	Japan	0.133
Germany	0.087	Germany	0.105	Germany	0.120
Taiwan	0.086	Taiwan	0.100	United Kingdom	0.100
Singapore	0.084	United Kingdom	0.089	Italy	0.098
Australia	0.077	Singapore	0.086	Canada	0.095
United Kingdom	0.076	Australia	0.085	Australia	0.094
Italy	0.072	Canada	0.084	Taiwan	0.084
Canada	0.066	Italy	0.079	Spain	0.082

Bottom 10

2001		2003		2005	
Country	Entry Rate $(\times 100^{-2})$	Country	Entry Rate $(\times 100^{-2})$	Country	Entry Rate $(\times 100^{-2})$
Mali	0.102	Mali	0.089	Monaco	0.054
Rwanda	0.097	Bermuda	0.084	Saint Lucia	0.053
Guyana	0.095	Iraq	0.082	Niger	0.046
Uzbekistan	0.090	Liberia	0.066	Antigua and Barbuda	0.040
Mozambique	0.087	Solomon Islands	0.059	Marshall Islands	0.038
Djibouti	0.086	Gabon	0.055	St. Vincent & Grenadines	0.037
Somalia	0.084	Bahamas	0.049	Bermuda	0.030
New Caledonia	0.062	Rwanda	0.048	Solomon Islands	0.030
Albania	0.053	Guadeloupe	0.045	Somalia	0.023
Zambia	0.044	Georgia	0.042	Lesotho	0.023

Source: Authors' calculation based on China's Customs transaction-level trade data.

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 outliers of neighbors'export growth and 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. The source of spillover is measured by the (log) number of "same-market" neigboring firms divided 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}	0.00265	0.00799	0.00989	0.0149*
	(0.32)	(0.98)	(1.14)	(1.72)
I_{den2}	-0.00108	0.00147	-0.0210*	-0.0117
	(-0.09)	(0.12)	(-1.65)	(-0.93)
I_{den3}	0.0577***	0.0421*	0.0229	0.0154
	(2.66)	(1.95)	(1.21)	(0.82)
I_{den4}	0.463***	0.397***	0.137***	0.103***
	(7.30)	(6.20)	(4.29)	(3.31)
I_{den5}			0.516***	0.455***
			(6.16)	(5.27)
$\triangle \ln(x_{c(-m)t})$ interacted with:				
I_{den1}		-0.315		-0.477
		(-0.01)		(-0.03)
I_{den2}		0.769		0.276
		(0.03)		(0.02)
I_{den3}		1.70		1.27
		(0.07)		(0.07)
I_{den4}		2.13		1.91
		(0.09)		(0.11)
I_{den5}				1.99
				(0.11)
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 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 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)	Standard Dev of Sales Growth		Distance	
$V \times \triangle \ln(x_{cmt})$	-0.0346*		0.0160	
	(-1.95)		(1.10)	
$\triangle \ln(x_{cmt})$ interacted with:				
I_{V1}		0.842***		0.486***
		(7.12)		(6.54)
I_{V2}		0.811***		0.430***
		(6.78)		(5.87)
I_{V3}		0.910***		0.411***
		(7.72)		(5.63)
I_{V4}		0.854***		0.439***
		(7.12)		(6.27)
I_{V5}		0.915***		0.424***
		(6.87)		(5.87)
I_{V6}		0.892***		0.430***
		(7.34)		(5.90)
I_{V7}		0.775***		0.497***
		(6.42)		(6.63)
I_{V8}		0.869***		0.490***
		(7.33)		(6.03)
I_{V9}		0.779***		0.470***
		(6.55)		(6.37)
I_{V10}		0.846***		0.476***
		(7.33)		(6.61)
$\ln(n_{cm,t-1}/Area_c) \times \triangle \ln(x_{cmt})$	0.0701***	0.111***	0.0536***	0.0531***
	(4.84)	(7.44)	(6.54)	(6.31)
$\triangle \ln(x_{cmt})$ [signal]	0.439***		0.316**	
	(3.94)		(2.23)	
$\ln(n_{cm,t-1}/Area_c)$	-0.0863***	-0.0395	-0.0170	-0.0202
	(-2.67)	(-1.04)	(-0.74)	(-0.88)
V_{cmt}	0.0097			
	(0.64)			
Decile dummies interacted w/ signal to other countries	n/a	yes	n/a	yes
Decile 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.	11,895,896	11,895,896	13,502,824	13,502,824
R-squared	.045	.107	.104	.104

All coefficients are already multiplied by 100 for clearer reporting. The sample excludes outliers 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 deciles of the standard deviation of neighbors' export growth in the same year, with I_{V1} being the lowest decile. In column (4), city-markets are split into deciles of distance between the destination and China in the pooled sample. Decile dummies are included as well as their interactions with the growth rate of neighbors' exports to the same market. Also included are decile 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)
Firm-year Fixed Effects	Yes	Yes	Yes
City-country Fixed Effects	Yes	Yes	Yes
Nb of Obs.	7102425	7102425	7102425
R-squared	.0755	.0756	.0774

See equation (12) for the estimation specification. The sample excludes outliers 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" neigboring firms 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 the 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 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" neigboring firms divided 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 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" neigboring firms divided 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 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" neigboring firms divided 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.

9 Appendix Tables

Table A1: Summary Statistics of Exporting Firms' Entry and Exit

Year	Num. Firms	Continuing	Exit	Successful Entrants	One-timers
				% of total	
2001	52434	0.607	0.156	0.189	0.048
2002	61180	0.590	0.134	0.225	0.051
2003	73651	0.610	0.110	0.224	0.056
2004	95544	0.580	0.106	0.243	0.070
2005	123647	0.574	0.116	0.187	0.122
Avg		0.592	0.124	0.214	0.070

Source: Authors' calculation based on China's Customs transaction-level trade data (2001-2005).

Table A2: Summary Statistics of Key Regressors

Variable	10%	25%	50%	75%	90%	Mean	Std Dev.	Nb. of Obs.
$\triangle \ln(x_{cmt})$	-0.807	-0.254	0.192	0.651	1.214	0.200	0.838	68008
$\triangle \ln(x_{c(-m)t})$	-0.016	0.106	0.210	0.319	0.423	0.205	0.210	68008
$\ln(x_{cmt})$	9.617	10.519	11.476	12.375	13.205	11.440	1.449	68008
$\ln(x_{c(-m)t})$	13.346	13.641	13.950	14.359	14.911	14.034	0.662	67777
$\ln(n_{cm,t-1}/Area_c)$	-9.561	-8.943	-7.810	-6.533	-5.227	-7.604	1.697	68008
$\ln(n_{c(-m),t-1}/Area_c)$	-6.641	-5.545	-4.165	-2.812	-1.738	-4.188	1.930	67777
$\ln(n_{cm,t-1}/Area_c) \times \triangle \ln(x_{cmt})$	-9.939	-4.840	-1.236	1.857	6.608	-1.508	7.046	68008
$\ln(n_{c(-m),t-1}/Area_c) \times \triangle \ln(x_{c(-m)t})$	-2.167	-1.227	-0.699	-0.291	0.080	-0.845	1.277	67777
$\ln(n_{cm,t-1})$	0.00	0.00	0.69	1.95	3.00	1.15	1.26	68008
$\ln(n_{c(-m),t-1})$	2.64	3.50	4.61	5.71	6.54	4.59	1.53	67777
New entry Rate (cmt)	0.000	0.002	0.024	0.063	0.112	0.044	0.060	68008
Survival Rate (cmt)	0.000	0.000	0.308	0.500	0.750	0.324	0.301	51579
(ln) Initial Exp Sales (cmt)	8.485	9.204	9.840	10.503	11.252	9.840	1.230	51579
Post-entry Growth ($cmt, t+1$)	-0.68	-0.05	0.46	0.97	1.60	0.46	1.08	40565

Source: Authors' calculation based on China's transaction-level trade data (2001-2005). All variables are city-country-year specific. Definition of new entry = 0 for all markets that were served by some firms in China. Subscript m denotes same market and $(-m)$ other markets.

Table A3: Correlations between Key Regressors

	$\triangle\ln(x_{cmt})$	$\triangle\ln(x_{c(-m)t})$	$\ln(x_{cmt})$	$\ln(x_{c(-m)t})$	$\ln(n_{cm,t-1}/Area_c)$	$\ln(n_{c(-m),t-1}/Area_c)$
$\triangle\ln(x_{cmt})$	1					
$\triangle\ln(x_{c(-m)t})$	0.187	1				
$\ln(x_{cmt})$	0.045	0.019	1			
$\ln(x_{c(-m)t})$	0.001	0.034	0.150	1		
$\ln(n_{cm,t-1}/Area_c)$	0.010	0.043	0.258	0.214	1	
$\ln(n_{c(-m),t-1}/Area_c)$	-0.001	0.036	-0.053	0.286	0.666	1

Table A4: Using Number of Neighboring Firms as a Measure of Spillover

Dependent Variable	Entry		Initial Sales		Survival		Post-entry Growth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(n_{cm,t-1})\times\triangle\ln(x_{cmt})$	0.108***	0.102***	0.0295***	0.0297***	0.326**	0.391**	-0.0403***	-0.0401***
	(8.40)	(8.21)	(4.80)	(4.78)	(2.15)	(2.55)	(-4.03)	(-3.97)
$\triangle\ln(x_{cmt})$ (signal)	-0.0503***	-0.0466***	0.00812	0.00787	-0.314	-0.408	-0.0887***	-0.0888***
	(-5.19)	(-4.93)	(0.71)	(0.68)	(-1.06)	(-1.37)	(-4.45)	(-4.42)
$\ln(n_{cm,t-1})$	0.0509***	-0.00536	0.00597	-0.000288	-4.99***	-4.56***	-0.0411**	-0.0111
	(2.87)	(-0.24)	(0.48)	(-0.02)	(-14.58)	(-11.54)	(-1.96)	(-0.47)
Controls		yes		yes		yes		yes
Firm-year Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
City-country Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Nb of Obs.	14,756,513	14,756,442	513,433	513,402	513,433	513,402	248,424	248,411
R-squared	.102	.102	.546	.546	.588	.588	.512	.512

See eq. (12) for the estimation specification. Coefficients in the Entry and Survival regressions (columns (1), (2), (5), (6)) are multiplied by 100 for clearer reporting. The sample excludes outliers (in terms of signal) and transactions to Hong Kong. The source of spillover in the same city-market is measured by ln(number exporters). All columns include firm-year and city-country fixed effects. Even columns include Spillover from neighbors exporting to other countries as additional controls. See notes to Tables 3, 6, 7 and 8 for more details. 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 A5: Using Average Sales as a Measure of Signal

Dependent Variable	Entry		Initial Sales		Survival		Post-entry growth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(n_{cm,t-1}/Area_c)\times \ln(x_{cmt})$	0.0707***	0.0858***	-0.00242	-0.00127	-0.268***	-0.194*	-0.0105**	-0.0172**
	(9.67)	(10.12)	(-0.71)	(-0.27)	(-3.22)	(-1.66)	(-1.99)	(-2.17)
$\ln(x_{cmt})$ [signal]	0.585***	0.588***	-0.0481*	-0.0528**	-1.60***	-1.32**	-0.0847**	-0.0712*
	(9.83)	(9.61)	(-1.91)	(-2.02)	(-2.64)	(-2.11)	(-2.30)	(-1.88)
$\ln(n_{cm,t-1}/Area_c)$	-0.762***	-0.966***	0.0458	0.0243	-1.99**	-2.44*	0.0717	0.172*
	(-9.03)	(-10.16)	(1.15)	(0.47)	(-2.00)	(-1.85)	(1.14)	(1.93)
Controls		yes		yes		yes		yes
Firm-year Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
City-country Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Nb of Obs.	14,596,820	14,596,749	513,433	513,402	513,433	513,402	248,424	248,411
R-squared	.102	.102	.546	.546	.588	.588	.511	.511

See eq. (12) for the estimation specification. Coefficients in the Entry and Survival regressions (columns (1), (2), (5) and (6)) are multiplied by 100 for clearer reporting. The sample excludes outliers (in terms of signal$_t$) and transactions to Hong Kong. The source of spillover is measured by the (log) number of "same-market" neigboring firms divided the area of the city, $\ln(n_{cm,t-1}/Area_c)$, and the signal is measured by average sales. All columns include firm-year and city-country fixed effects. Even-numbered columns include spillover from neighbors exporting to other countries as additional controls. See notes to Tables 3, 6, 7 and 8 for more details. 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 A6: New Exporters' Performance and Learning (Textile Firms Only with 3-way Fixed Effects)

Dependent Variable	Entry	Initial Sales	Survival	Post-Entry Growth
	(1)	(2)	(3)	(4)
$\ln(n_{cm,t-1}/Area_c) \times \triangle \ln(x_{cmt})$	0.109***	0.0230**	0.268	-0.0622***
	(3.64)	(2.24)	(1.05)	(-2.98)
$\triangle \ln(x_{cmt})$ [signal]	0.914***	0.220***	2.29	-0.631***
	(3.75)	(2.92)	(1.21)	(-4.17)
$\ln(n_{cm,t-1}/Area_c)$	-0.00662	0.0211	-6.50***	0.0444
	(-0.08)	(0.56)	(-7.16)	(0.60)
$\ln(n_{c(-m),t-1}/Area_c) \times \triangle \ln(x_{c(-m)t})$	3.19	-0.573	1.99	-0.556
	(1.05)	(-0.93)	(0.13)	(-0.64)
$\triangle \ln(x_{c(-m)t})$	20.7	0.0933	-9.25	-1.099
	(0.31)	(0.00)	(-0.01)	(-0.01)
$\ln(n_{c(-m),t-1}/Area_c)$	2.76	0.295	1.01	0.446
	(1.48)	(0.84)	(0.12)	(0.73)
City-country Fixed Effects	yes	yes	yes	yes
Firm-year Fixed Effects	yes	yes	yes	yes
Country-year Fixed Effects	yes	yes	yes	yes
Nb Obs.	1,915,727	87,965	87,965	37,823
R-squared	.133	.623	.635	.583

All coefficients for the Entry and Survival regressions (cols (1) and (3)) are already multipled by 100 for clearer reporting. The sample excludes outliers (in terms of signal) and transactions to Hong Kong. The source of spillover in the same city-market is measured by ln(density of exporters). All columns include firm-year, city-country and country-year 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 A7: Controlling for the Source of Spillover in the Same Province

Dependent Variable	Entry	Initial Sales	Survival	Post-Entry Growth
	(1)	(2)	(3)	(4)
$\ln(n_{cm,t-1}/Area_c)\times \triangle\ln(x_{cmt})$ (city)	0.0435***	0.0153***	0.180	-0.0254***
	(5.64)	(3.07)	(1.46)	(-3.15)
$\ln(n_{pm,t-1}/Area_p)\times \triangle\ln(x_{pmt})$ (province)	0.124***	0.0169**	0.455**	0.00753
	(10.15)	(2.22)	(2.17)	(0.63)
$\triangle\ln(x_{cmt})$ (city)	0.371***	0.161***	0.0147	-0.333***
	(5.77)	(4.40)	(1.63)	(-5.75)
$\triangle\ln(x_{pmt})$ (province)	1.35***	0.187**	4.99**	0.0864
	(10.61)	(2.53)	(2.48)	(0.76)
$\ln(n_{cm,t-1}/Area_c)$ (city)	0.0194	-0.00779	-5.12***	-0.00989
	(0.96)	(-0.52)	(-12.54)	(-0.39)
$\ln(n_{pm,t-1}/Area_p)$ (province)	-0.0376	0.0579**	3.56***	-0.0252
	(-1.46)	(2.31)	(5.32)	(-0.60)
Controls	yes	yes	yes	yes
Firm-year Fixed Effects	yes	yes	yes	yes
City-country Fixed Effects	yes	yes	yes	yes
Nb. of Obs.	14349889	508325	508325	246348
R-squared	.103	.546	.587	.511

All coefficients for the Entry and Survival regressions (cols (1) and (3)) are already multipled by 100 for clearer reporting. The source of spillover is measured by the (log) number of "same-market" neigboring firms divided the area of the city, $\ln(n_{cm,t-1}/Area_c)$. Controls include the (ln) density of exporters serving other destinations in the same city, the (ln) density of exporters serving other destinations in the same province; and their interactions with the corresponding shocks. 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 A8: Learning Effects to and from Different Ownership Types

Dependent Variable	Entry	Initial Sales	Survival	Post-Entry Growth	Entry	Initial Sales	Survival	Post-Entry Growth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(n_{cm,t-1}/Area_c)_{(D)} \times \triangle\ln(x)_{cmt(D)}$	0.087***	0.0154***	0.073	-0.0113				
	(6.44)	(2.84)	(0.56)	(-1.39)				
$\ln(n_{cm,t-1}/Area_c)_{(F)} \times \triangle\ln(x)_{cmt(F)}$	0.033***	0.00839	0.033	-0.0243***				
	(2.77)	(1.51)	(0.25)	(-2.91)				
$\triangle\ln(x)_{cmt(D)}$	0.714***	0.141***	0.514	-0.160***	0.702***	0.140***	0.479	-0.159***
	(6.61)	(3.59)	(0.55)	(-2.73)	(6.64)	(3.59)	(0.52)	(-2.72)
$\triangle\ln(x)_{cmt(F)}$	0.276***	0.0830**	0.721	-0.239***	0.271***	0.0838**	0.693	-0.239***
	(2.84)	(2.01)	(0.74)	(-3.94)	(2.79)	(2.03)	(0.71)	(-3.93)
$\ln(n_{cm,t-1}/Area_c)_{(D)}$	0.00701	0.0245	-2.04***	-0.0266	0.00901	0.0269	-2.01***	-0.0274
	(0.22)	(1.50)	(-4.60)	(-1.03)	(0.29)	(1.64)	(-4.52)	(-1.05)
$\ln(n_{cm,t-1}/Area_c)_{(F)}$	-0.0239	0.0250	-2.07***	0.000502	-0.0232	0.0222	-2.10***	0.00157
	(-0.68)	(1.56)	(-4.96)	(0.02)	(-0.67)	(1.39)	(-5.04)	(0.06)
$Rec_D \times \ln(n_{cm,t-1}/Area_c)_{(D)} \times \triangle\ln(x)_{cmt(D)}$					0.0840***	0.0154***	0.0447	-0.0103
					(6.35)	(2.79)	(0.34)	(-1.24)
$Rec_F \times \ln(n_{cm,t-1}/Area_c)_{(D)} \times \triangle\ln(x)_{cmt(D)}$					0.0878***	0.0154***	0.0978	-0.0124
					(6.56)	(2.80)	(0.75)	(-1.49)
$Rec_D \times \ln(n_{cm,t-1}/Area_c)_{(F)} \times \triangle\ln(x)_{cmt(F)}$					0.0339***	0.00967*	0.0215	-0.0241***
					(2.81)	(1.70)	(0.16)	(-2.82)
$Rec_F \times \ln(n_{cm,t-1}/Area_c)_{(F)} \times \triangle\ln(x)_{cmt(F)}$					0.0312***	0.00788	0.0348	-0.0244***
					(2.63)	(1.41)	(0.26)	(-2.90)
Controls				yes				
Firm-year Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
City-country Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Nb of Obs.	10012875	447282	447282	220475	10012875	447282	447282	220475
R-squared	.112	.553	.6	.518	.112	.553	.6	.518

All coefficients for the Entry and Survival regressions are already multipled by 100 for clearer reporting. Controls include the (ln) density of domestic exporters serving other destinations, (ln) density of foreign-owned exporters serving other destinations, and their interactions with the corresponding signals. Subscripts (D) and (F) denote domestic and foreign firms, respectively. *Rec* denotes the receipients of spillover. 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.