Uncertainty, Learning and Growth Dynamics in Export Markets

(preliminary results only, please do not quote)

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March 8, 2017

Abstract

Learning-based trade theories provide an explanation for a large number of observed dynamics in export markets, particularly for the inverse relationship between export growth and export experience. These theories explain the age-growth dependency by suggesting that firms face uncertainty in their demand as well as destination-specific costs when they engage in export markets. This uncertainty is reduced as firms learn about their products' appeal. Analyzing Chinese panel data covering more than 100,000 firms over the period 2000-2009, this paper shows how different dimensions of a firm's experience, as well as external factors, affect the firm's export growth. The results suggest that (i) export growth decreases as the level of experience increases in the time, destination, and product dimensions; (ii) learning in export markets is a gradual rather than an abrupt process; (iii) learning takes place within and across markets of imperfectly substitutable products; (iv) uncertainty is higher in industries of more complex products; and (v) uncertainty is lower in destinations in close proximity, with better institutional quality, and with a larger diaspora.

Keywords: Learning, uncertainty, export, China.

JEL Codes: C31 I10, I12

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1 Introduction

The comprehensive information at the firm and product level collected by customs offices around the globe has equipped researchers with a growing amount of disaggregated trade data. These datasets are often merged with firm-level data that contain information from major accounting statements. The analysis of these datasets offers new insights as they include detailed characteristics of firms and their products over time. In particular, detailed data on trade costs as well as the intensive and extensive margins of exports have provided new insights into export dynamics. Empirical research shows that new exporters, despite facing high entry costs, regularly start their export activities by supplying small quantities, often to only one export destination. Many of these new exporters do not survive the first few years in foreign markets and soon exit specific destinations, or cease their export activities entirely. Albornoz et al. 2012, Eaton, J. et al. 2008, and Damijan et al. 2008 show the prevalence of exit seen amongst new exporters with Argentinian, Colombian, and Slovenian data respectively. One of the primary purposes of the current trade literature is to identify the underlying reasons for such high rates of attrition observed in the first few years of firms' overseas ventures.

Albornoz et al. (2012), Arkolakis, Papageorgiou and Timoshenko (2015) or Nguyen (2012) study potential explanations for many aspects of the aforementioned firm behavior using models of learning in highly uncertain export markets. In these studies, firms face uncertainty in their demand as well as destination-specific costs when they engage in new export markets and therefore prefer to start supplying small quantities to minimize the cost of potential withdrawal. Firms have to embrace this uncertainty at the start because they can only learn about export costs and market demand after they enter a new market. Once firms learn about the demand for their products in a given market, they adjust the quantities that they supply. For instance, learning that their export activities are profitable leads to firms having greater confidence and making bolder supply decisions, while the opposite is true if firms find that they have overestimated their market potential ex-ante. As young and less experienced exporters are likely to face higher levels of uncertainty, their adjustments are expected to be more frequent or more drastic than those of their mature counterparts. As such, the learning models usually predict an inverse relationship between export growth and the experience level of a firm.

Berthou and Vicard (2015) and Bastos, Dias, and Timoshenko (2016) have provided evidence for an inverse relationship between export experience and export growth. However, most of these analyses focus on a general dependency of growth on firm age and do not distinguish between learning within destinations and learning across destinations. Albornoz et al. (2012) is an exception in that they study export profitability and uncertainty that are correlated over time as well as across destinations. Therefore, what exporters learnt from exporting to a new market is useful not only for continuing the exporting to this market for years to come, but also for exporting to other markets in the future. Conversely this implies that the level of uncertainty faced by a firm is at its highest in the earliest periods in the firm's earliest export destinations. The empirical findings of Albornoz et al. (2012) based on Argentinian exporter data support their hypothesis that uncertainty can be at least partially uncovered by learning from previous experience in other destinations. Their findings also suggest that parts of uncertainty may require destination-specific experience to be uncovered. However, their empirical analysis focuses on firms' first year in their first export destination.[1] It, therefore, does not allow for any detailed inferences about how experience affects growth over multiple periods or destinations and hence if learning processes are abrupt or gradual. Furthermore, Albornoz et al. (2012) focus on the internal process of how firms uncover uncertainty through the accumulation of export experience. However, what has not been considered is what external factors are giving rise to uncertainty in the first place. Understanding these external factors is important because without them, information would be perfect and learning is redundant.

Against this background, the current paper aims to provide new evidence for the relevance of uncertainty and learning in export markets. It adopts the idea that learning takes place within and across destinations and aims to reveal how the dynamics of learning manifest across multiple destinations and over multiple years. Also, it extends the analysis to the product level. While the destination-specific growth rates could result from quantity changes of existing products or the addition of new products, product level growth rates result only from changes in the intensive margin. Therefore, the product level analysis can reveal how the intensive margin is affected by the firm's experience level. Ultimately, the product level analysis allows for some inferences about the role of product-specific experience and can hence shed some light on the relevance of different types of uncertainty. On the one hand, uncertainty about demand is driven by consumer preferences, and it is product-destination-specific; as a result, learning across destinations could potentially only take place for the same product. On the other hand, uncertainty regarding destination-specific factors can be learnt from any products at the same destination. A comparison of the destination level and product level analyses can reveal the relative importance of these two learning processes. Lastly, it also studies how firms' learning and associated export dynamics vary under various circumstances defined by industry groups, peer groups, institutional quality of destinations, geography, and migrant networks, respectively.

The empirical analysis in this work is based on a large, firm-level dataset of an exporting powerhouse – China. The dataset contains export information for more than 100,000 firms from the manufacturing sector and covers

[1] They have testedbut found no significant growth in the second year.

the period 2000-2009. It provides information on the volume of export sales per firm, product, and destination. To our best knowledge, this paper is the first work that empirically analyses Chinese firm and product level data in various contexts according to the degree of a firm's demand uncertainty and learning. The main findings are: (i) that export growth decrease as the level of experience increases in the time, destination or product dimensions; (ii) that learning in export markets is a gradual rather than an abrupt process; (iii) that learning takes place within and across destinations; (iv) that uncertainty is higher in industries of more complex products; and (v) that uncertainty is lower in destinations in close proximity, with better institutional quality, and with a larger diaspora.

The rest of this paper is organized as follows. Section 2 explains the methodology. Section 3 introduces the dataset. Section 4 presents the empirical results based on the extension of Albornoz et al. (2012). Section 5 examines some external factors that are related to uncertainty faced by exporters. The last section then concludes.

2 Methodology

2.1 The Baseline Model

We first estimate the baseline model of Albornoz et al. (2012) using Chinese instead of Argentinian firm data. The purpose is to examine if there are fundamental differences in the way Chinese firms behave in new export markets due to factors such as business culture and practice. The first regression is:

$$\Delta log X_{ijt} = \alpha_1 FY_{ij,t-1} + \alpha_2 FM_{ij} + \alpha_3 (FY_{ij,t-1} \times FM_{ij}) + FE + u_{ijt} \tag{1}$$

where $\Delta log X_{ijt}$ represents the growth rate of firm i's exports to destination j between periods $t-1$ and t;[2] $FY_{ij,t-1}$ is a dummy variable that takes a value of 1 if period $t-1$ is the first year that firm i exports to destination j, and a value of 0 otherwise; FM_{ij} is a dummy variable that takes a value of 1 if destination j is the first export destination for firm i, and a value of 0 otherwise; FE stands for a variety of firm, year, destination and year-destination fixed effects (FEs); and u_{ijt} is the error term. As regarding FM_{ij}, a firm can have more than one first export destination, if it starts its export activities simultaneously in multiple destinations within

[2] Note that we aggregate data over product for each firm.

the same year. In what follows, if $FY_{ij,t-1} = 1$, then we refer to $\Delta logX_{ijt}$ as the first year growth rate (after entry), the growth rate between t and $t + 1$ as the second year growth rate, and so forth.

The baseline group in this regression is the observations with $FY_{ij,t-1} = 0$ and $FM_{ij} = 0$, that is, the average growth rate for non-first years in non-first destinations. Interpreting the coefficients of eq.(1) is not straightforward because the three main terms are not mutually exclusive. To ease the task, we rewrite the regression in the following form:

$$\begin{aligned}\Delta logX_{ijt} &= \alpha_1 FY_{ij,t-1} \times (1 - FM_{ij}) + \alpha_2 FM_{ij} \times (1 - FY_{ij,t-1}) \\ &+ (\alpha_1 + \alpha_2 + \alpha_3)(FY_{ij,t-1} \times FM_{ij}) + FE + u_{ijt} \end{aligned} \tag{2}$$

Now the three terms are mutually exclusive. Here coefficient α_1 indicates the average additional growth for a firm's first export destination over non-first years compared to the baseline growth, and coefficient α_2 indicates the average additional growth for the first year across non-first destinations. Coefficient α_3 indicates the 'bonus' additional growth over and above α_1 and α_2 for the first year in the first destination; thus, $(\alpha_1 + \alpha_2 + \alpha_3)$ indicates the additional growth in the very first exporting episode of a firm relative to the baseline growth rate.

The motivation for the baseline regression is as follows. As suggested by the literature on learning in export markets, we hypothesize that firms face uncertainty when they engage in export activities. While a firm may be able to reduce some of this uncertainty by observing its competitors, a notable part of its uncertainty can only be uncovered by self-discovery and actual engagement in export activities. If a firm faces a high level of uncertainty, it engages in export markets with less confidence and is more likely to provide smaller quantities. Once the firm has uncovered this uncertainty and finds itself to be profitable, it exports with more confidence and consequently engages in additional destinations and with increasing quantities. If a firm finds itself not to be profitable, it may reduce quantities, exit selective export destinations or even cease its export activities completely. The learning process, in the context of this paper, can be summarized as follows: The higher the level of uncertainty faced by a firm, the more it can potentially learn, and thus the larger its adjustment to subsequent export quantities. For firms that are able to survive the initial years in the foreign market, they are likely to be the ones that learn that their products are profitable and therefore their quantity adjustment is likely to be positive. In other words, if firms are uncertain about the demand for their products *ex ante* but learn that it is high *ex post*, they are likely to grow quickly.

Furthermore, uncertainty - at least parts of it - is not only correlated across time but also across destinations. From here on, this paper distinguishes between two types of uncertainty, namely general uncertainty and destination-specific uncertainty. General uncertainty refers to the part of uncertainty that firms can uncover by gaining experience across destinations, and destination-specific uncertainty refers to the part of uncertainty firms can uncover through engagement within a certain destination. The baseline regression can test for the relative importance of these two types of uncertainty. Moreover, the total level of uncertainty that firms face, in the context of their export activities, should be at its highest level at the very beginning of their export activities. This is due to the fact that the firm, at this point, has not exported to another destination and has consequently not been able to partially or fully uncover any uncertainty that would require self discovery. It has finally been suggested that, the more uncertainty the firm uncovers, the larger the adjustments of its export activities should be. As a consequence, the growth rate should be at its highest level in the first year in the firm's first export destination. It is also acknowledged that uncertainty (and learning) is not directly observable. Nonetheless, the consequence of the presumed learning process does give rise to a testable hypothesis:[3]

Hypothesis 1: *Conditional on survival, the growth rate of a firm's exports is highest in the first year in its first destination.*

Hypothesis 1 requires $\alpha_1 + \alpha_2 + \alpha_3 > 0$ and $\alpha_3 > 0$. Specifically, $\alpha_1 + \alpha_2 + \alpha_3 > 0$ implies that a firm's growth in the first year in its first destination is higher than the average growth over non-first years across non-first destinations, and $\alpha_3 > 0$ implies that it is also higher than the average growth for the first year across non-first destinations as well as that for the first destination over non-first years. It should be acknowledged that in a strict sense we are not testing if growth is truly at its highest level in the first year in the first destination, since it allows only to compare this period to the average of other periods.

2.2 Extension to Multiple Years and Destinations

The baseline regression as in eq.(1) considers learning in the earliest years in a given destination and in the first export destination. A natural extension will be to investigate whether destination-specific uncertainty is fully uncovered in the earliest years, or if the learning process is rather gradual over multiple years. Albornoz et al. (2012) have also considered learning in the second year but found that learning takes place mostly in the first

[3]It is adopted from Albornoz et al. (2012).

year. Here we re-examine this issue using Chinese firm data. To that end, we extend eq.(1) to include three time periods:

$$\Delta logX_{ijt} = \alpha_1 FY_{ij,t-1} + \alpha_2 SY_{ij,t-1} + \alpha_3 TY_{ij,t-1} + \alpha_4 FM_{ij} + \alpha_5(FY_{ij,t-1} \times FM_{ij}) + \alpha_6(SY_{ij,t-1} \times FM_{ij}) + \alpha_7(TY_{ij,t-1} \times FM_{ij}) + FE + u_{ijt} \quad (3)$$

where $SY_{ij,t-1}$ ($TY_{ij,t-1}$) takes the value of 1 if period $t-1$ was the second (third) period that firm i exported to destination j, and 0 otherwise. In this regression, the baseline growth rate is the average growth rate for the fourth and subsequent years in the second and subsequent destinations. As before, the total additional growth of the first year in the first export destination compared to the baseline growth rate is equal to $\alpha_1 + \alpha_4 + \alpha_5$. The total additional growth of the second year in the first export destination is equal to $\alpha_2 + \alpha_4 + \alpha_6$, and so forth.

The second extension is the inclusion of subsequent destinations. The inclusion of multiple destinations can test if general uncertainty is relevant and if this part of uncertainty is fully uncovered in the firm's first export destination, or if it is rather gradually uncovered across markets. If general uncertainty is gradually uncovered across multiple destinations, then a larger number of previous destinations should result in a smaller level of general uncertainty. Therefore, the initial growth rate in earlier destinations should be larger than the initial growth rate in later destinations. We extend eq.(1) to including three destinations:

$$\Delta logX_{ijt} = \alpha_1 FY_{ij,t-1} + \alpha_2 FM_{ij} + \alpha_3 SM_{ij,t-1} + \alpha_4 TM_{ij,t-1} + \alpha_5(FY_{ij,t-1} \times FM_{ij}) + \alpha_6(FY_{ij,t-1} \times SM_{ij}) + \alpha_7(FY_{ij,t-1} \times TM_{ij}) + FE + u_{ijt} \quad (4)$$

where SM_{ij} (TM_{ij}) equals 1 if the corresponding observations are from the second (third) export destination and 0 otherwise. As in the case of the first destination, it is possible that a firm has multiple second or third export destinations if the firm expands its export activities to several new markets in the same year. In this regression, the baseline growth rate is the average growth rate for the second and subsequent years in the fourth and subsequent destinations. Compared to this baseline, the total additional growth of the first year in the first export destination is equal to $\alpha_1 + \alpha_2 + \alpha_5$. The total additional growth of the first year in the second export destination is equal to $\alpha_1 + \alpha_3 + \alpha_6$, and so forth.

The third extension is the combination of the previous two:

$$
\begin{aligned}
\Delta log X_{ijt} = {} & \alpha_1 FY_{ij,t-1} + \alpha_2 SY_{ij,t-1} + \alpha_3 TY_{ij,t-1} \\
& + \alpha_4 FM_{ij} + \alpha_5 SM_{ij,t-1} + \alpha_6 TM_{ij,t-1} \\
& + \alpha_7 (FY_{ij,t-1} \times FM_{ij}) + \alpha_8 (SY_{ij,t-1} \times FM_{ij}) + \alpha_9 (TY_{ij,t-1} \times FM_{ij}) \\
& + \alpha_{10} (FY_{ij,t-1} \times SM_{ij}) + \alpha_{11} (SY_{ij,t-1} \times SM_{ij}) + \alpha_{12} (TY_{ij,t-1} \times SM_{ij}) \\
& + \alpha_{13} (FY_{ij,t-1} \times TM_{ij}) + \alpha_{14} (SY_{ij,t-1} \times TM_{ij}) + \alpha_{15} (TY_{ij,t-1} \times TM_{ij}) + FE + u_{ijt} \quad (5)
\end{aligned}
$$

In this regression, the baseline growth rate is the average growth in the fourth and later destinations in the fourth and later years. The additional growth rate for the first year in the first destination in this case is equal to $\alpha_1 + \alpha_4 + \alpha_7$. Similarly, the additional growth rate for the second year in the second destination is equal to $\alpha_2 + \alpha_5 + \alpha_{11}$, and so forth.

In estimating the above regressions, we can state the following two hypotheses:

Hypothesis 2: *Conditional on survival, the growth rate of a firm's destination-specific exports decreases over time.*

If Hypothesis 2 is valid for the first export destination, it would be expected that, based on eq.(5), $\alpha_1+\alpha_4+\alpha_7 > \alpha_2 + \alpha_4 + \alpha_8 > \alpha_3 + \alpha_4 + \alpha_9$ or simply $\alpha_1 + \alpha_7 > \alpha_2 + \alpha_8 > \alpha_3 + \alpha_9$. Likewise, if Hypothesis 2 is valid for the second destination, it would be expected that $\alpha_1 + \alpha_{10} > \alpha_2 + \alpha_{11} > \alpha_3 + \alpha_{12}$, and so forth.

Hypothesis 3: *Conditional on survival, a firm's initial growth is higher in earlier destinations than in later destinations.*

If Hypothesis 3 is valid for the first year growth rate, it would be expected that, based on eq.(5), $\alpha_1+\alpha_4+\alpha_7 > \alpha_1 + \alpha_5 + \alpha_{10} > \alpha_1 + \alpha_6 + \alpha_{13}$ or simply $\alpha_4 + \alpha_7 > \alpha_5 + \alpha_{10} > \alpha_6 + \alpha_{13}$. Likewise, if the hypothesis is valid for the second year growth rate, it would be expected that $\alpha_4 + \alpha_8 > \alpha_5 + \alpha_{11} > \alpha_6 + \alpha_{14}$, and so forth.

2.3 Product Level Analysis

The third part of the empirical analysis shifts the focus from firm and destination level growth rates to the more disaggregated product level growth rates within a specific export destination. At the firm and destination level, growth can result from the addition of new products or from an increasing sales volume of an existing product. In other words, the destination-specific growth rate is a combination of the intensive and the extensive margin at the product level. Product level analysis allows us to eliminate the potential impact from the extensive margin and focus entirely on the intensive margin. As before, it is expected that the less experienced a firm is *ex ante*, the higher the growth tends to be *ex post*. Furthermore, the product level analysis allows us to explore whether there is product-specific uncertainty in addition to general uncertainty and destination uncertainty. To that end, we extend eq.1 into a product level model:

$$\begin{aligned} \Delta log X_{ijkt} &= \alpha_1 FY_{ij,t-1} + \alpha_2 FM_{ij} + \alpha_3 (FY_{ij,t-1} \times FM_{ij}) \\ &\quad + \alpha_4 FY_{ijk,t-1} + \alpha_5 FM_{ijk} + \alpha_6 (FY_{ijk,t-1} \times FM_{ijk}) + FE + u_{ijkt} \end{aligned} \tag{6}$$

where $\Delta log X_{ijkt}$ and u_{ijkt} are now product-specific; and $FY_{ijk,t-1}$ is a dummy variable that takes the value 1 if the period $t-1$ was the first period for firm i to export product k to destination j, and 0 otherwise. FM_{ijk} is a dummy variable that takes the value of 1 if destination j is the first export destination to which firm i exports product k, and 0 otherwise. As in the firm level case, a product can also have multiple first destinations if a firm starts exporting the same product to multiple destinations within the same year.

In this regression, the baseline growth rate is the average growth for observations that are (i) not from the firm's first export destination, (ii) not from the firm's first year in subsequent export destinations, (iii) not from the first export destination for a specific product, and (iv) not from the first year in subsequent destinations for the specific product. To interpret the coefficients in this more complex estimation it is important to note the relationship between the variables. For example, due to the conditioning on the survival of the product, $FY_{ij,t-1} \times FM_{ij} = 1$ implies that $FY_{ijk,t-1} \times FM_{ijk} = 1$. Therefore, $\sum_{r=1}^{6} \alpha_r$ indicates the total additional growth, compared to the baseline growth, for the very first product that a firm exports (obviously to its very first market for the very first time), while $\alpha_4 + \alpha_5 + \alpha_6$ indicates the additional growth compared to the baseline that results from introducing a new product in a given market for the first time. We refer to this effect as the "product-specific uncertainty" effect.

If product-specific uncertainty is relevant and at least in parts uncovered across destinations, then product level growth should be at its highest level in the first year in the first export destination to which the firm exports this specific product. This leads to the following hypothesis:

Hypothesis 4: *Conditional on the product's survival, product sales growth in a given destination is highest in the first year in its first destination.*

Hypothesis 4 implies that $\alpha_6 > 0$ and $\alpha_4 + \alpha_5 + \alpha_6 > 0$.

3 Data

Our dataset originates from two sources, namely the Chinese Customs Office and the Enterprise Survey for Chinese firms. It covers annual observations for more than 100,000 Chinese firms from the manufacturing sector and spans over a decade from 2000-2009. It provides information on the annual volume of export sales in USD. Because of the lack of information prior to year 2000, in the empirical analysis year 2000 is not considered as the first year of exporting in a given destination.[4] Products are classified at the 6-digit level of the Harmonized Commodity Description and Coding System (HS-6).

Out of 122,899 firms that had any sales between 2000 and 2009, 81.6% of them were at some point engaged in exporting. Table 1 summarizes the most common export destinations for these exporting firms. Of the firms that engaged in exporting, approximately half exported at some point to the U.S., which was also the most common export destination for the observed firms. The U.S. is followed by the Asian countries Hong Kong, Japan and South Korea, then by Germany as the first European country. Even though this table focuses on the number of firms that exported to a specific destination rather than on trade volumes, the ranking appears to be align with the gravity model in the sense that the most common export destinations are relatively large economies (the U.S., Germany, Japan) or geographically close economies (Hong Kong, Japan, South Korea).

[4]The accuracy in identifying firms' experience could be further improved by focusing on firms that reportedly did not export during the first few years of the dataset, e.g. 2000-2002. But doing so would reduce the number of observations. It is worthwhile to mention that China's exports started to grow and diversify dramatically only after it joined the World Trade Organization in December 2001 (IMF 2004). Therefore, the aforementioned problems associated with measurement errors of the initial years may not be that substantial in reality.

Table 2 shows the development of Chinese manufacturing exporters in the dataset during the time period 2000-2009. In the year 2000 only 15,645 firms exported any products, but by 2009 the number had more than tripled – reaching 47,005. Not only did the number of firms that exported increase during this period, but firms on average also exported to more destinations (from 6.4 to 10.3). Furthermore, the export sales of an average firm increased by a factor of roughly five and export sales at the destination level by a factor of approximately three. Due to this strong increase in multiple dimensions, the total export volume of the Chinese manufacturing firms rose tremendously from approximately $11 billion to over $160 billion.

Table 3 shows that the vast majority of the exporting firms (91.83 percent) exported to multiple destinations. However, for the very first period, only 36.7 percent of firms start with exporting multiple destinations. A similar pattern can be observed with respect to the number of products that the observed firms exported. 84.14 percent of the exporters exported more than one product, but only 39.42 percent of firms started with multiple products from the very begining. These figures suggest that a large share of exporting firms started their export activities on a small scale in terms of the number of destinations as well as the number of products.

Of particular interest in this paper are the differences in measures of export growth as the experience level of a firm increases. As shown in Figure 1, while the first year growth rate in an average destination was 17.66 percent, it decreased to 4.84 percent in the second year and then to 2.63 percent in the third year. The average growth of subsequent years was only 0.93 percent. Similarly, Figure 2 indicates that the initial growth rate decreased as firms expanded their activities to new destinations. While the initial growth rate in the first destination was 23.73 percent, it declined in the following destination to 12.81 percent and then to 10.98 percent in the third destination. The initial growth rate of the subsequent destinations was on average equal to only 0.98 percent.

Overall, the preliminary analysis of the dataset gives some first impressions on how behavior and growth patterns might differ when younger and more mature exporters are compared. The next section investigates these patterns in further detail using econometric analyses. The summary statistics for the dataset at the firm and product level can be found in Appendix A.

4 Results

4.1 Baseline Model Estimation

The results for the baseline model, eq.(1), are shown in Table 4. When interpreting these results, it is important to keep in mind that all estimations are conditional on the survival of the firm.

In column (1) we include firm, year and destination FEs. Firm FEs account for all firm specific characteristics that are time-invariant and that could influence the growth rate of a firm's export sales such as brands. Destination FEs account for standard time-invariant but country-specific factors typically entering into the gravity model such as the distance, common borders, and cultural and institutional similarities between China and its export destinations. Year FEs account for time-variant Chinese factors such as interest rates and time-varying global factors such as world commodity prices.

In column (1), the coefficients of $FY_{ij,t-1}$, FM_{ij}, and $FY_{ij,t-1} \times FM_{ij}$ are all positive and significant at the 1 percent level. The results therefore unambiguously support Hypothesis 1. Recall that the baseline growth rate in this regression is the average growth rate for non-first years in non-first destinations.

The estimated coefficient of $FY_{ij,t-1}$ means that, excluding the first destination, the average growth in the first year in other destinations is on average about 11 percentage points larger than that of subsequent years. While the results are consistent with the notion of destination-specific uncertainty and learning, it could also be an artifact from using annual observations. Firms may start exporting to a new destination at a later time of the year and sales would consequently only be generated over a few months, and thereby these firm may be more likely to register a big jump in annual sales in their full second year of exporting to the same destination. This ambiguity can be resolved by examining the growth in subsequent periods provided that learning is not completed in the first year, as we will demonstrate later.

The estimated coefficient on FM_{ij} means that, excluding the first year, the average growth in other years in the firm's first export destination is about 4 percentage points higher compared to that in subsequent destinations. The results support the notion of learning across destinations. That is, firms have less knowledge of their first export destination than of subsequent destinations, and the higher levels of uncertainty associated with the former also result in higher growth when the uncertainty is uncovered.

By combining the coefficients of FM_{ij}, $FY_{ij,t-1}$, and their interaction term $FY_{ij,t-1} \times FM_{ij}$, we can conclude that the growth rate in the first year in the first export destination is, on average about 35 percentage points higher than the baseline growth. The results are remarkably similar to the results (33 percentage points) of Albornoz et al. (2012).

China is well known for processing trade in that it imports components from other countries, processing them and then exporting the outputs to the next stop (for unfinished products) or destinations (for finished products). A well-known example is the iPad, for which Chinese firms import components from other countries and then re-export the assembled products. Firms that export processing goods as part of a much larger international supply chain may not face uncertainty compared to firms that export non-processing goods. This is because, it is the company that owns the final product (e.g. Apple Inc. for iPads) that judges the market demand and decides how many components need to be processed by their Chinese contractors. As a result, the relationship depicted between exporting experience and initial growth may not apply to firms of processing goods in the same way as to other firms. To check if the 'noise' from processing goods affects our findings, in column (2) we consider a sub-sample of firms exporting non-processing goods. A comparison of the results in columns (1) and (2) shows that our findings are very robust to the dropping of processing goods. Although the number of observations reduces by nearly 25 percent, both the qualitative and quantitative results are virtually identical. Therefore, in what follows we continue to use the whole sample.

Although we have controlled for firm, year, and destination FEs in column (1), one may argue that it still omits time-variant characteristics of export destinations, such as income growth, exchange rates, and tariffs. In column (3) we do substitute year- and destination FEs with year-destination FEs. But the results in column (3) are very similar to those in column (1), meaning that controlling for year-destination FEs adds little to the estimations.[5]

Furthermore, we have also considered controlling for firm size because the literature has indicated its importance when estimating the effect of experience on growth (Bastos, Dias & Timoshenko 2016; Berthou & Vicard 2015). Albornoz et al. (2012) use the lagged logarithm of the firm's total exports as a proxy for firm size. In this paper we use the logarithm of the simple average of total exports in the periods t and $t-1$ instead. Firms that face positive transitory shocks are more likely to face negative growth rates in the subsequent period, and this can result in a spurious correlation between growth and the firm size measure (Davis and Haltiwanger, 1992; Berthou and Vicard, 2015). Using the value for the firm size proxy from period $t-1$ would then likely lead to a

[5] It could be argued that there is also need to include year-firm FEs to account for time-variant characteristics of firms such as management plan, innovation, and production capacity. We do not consider doing so for two reasons. First, it is even more burdensome computationally than including year-destination FEs. Second, and more importantly, if firms learn over time, then including year-firm FEs could lead to underestimation of the learning effect that we try to identify.

negative correlation, while the use of the corresponding value from period t would likely result in the opposite effect. Therefore, in this paper we use the simple average from period t and $t-1$. In addition to total exports, we have also considered total sales as a proxy for firm size. Controlling for firm size using either measures has little effect on either the qualitative or quantitative results. The results are not shown here to save space.

Lastly, the impact of experience on export growth may be conditional on firms' access to credit. Albornoz et al. (2012) investigate the relevance of credit constraints but do not find any weakening effect regarding the experience effect. Our dataset does not have the relevant information to carry out a similar test. Nevertheless, it should be pointed out that in the case of China, political connection and state ownership remain key factors in accessing to credits (Cheng and Wu 2015). To the extent that these factors are not time-variant within the duration of the dataset, they have been accounted by firm FEs.

4.2 Extension to Multiple Years and Destinations

The baseline regression focuses on the first year and the first export destination of firms. However, there are no particular reasons why most of the uncertainty faced by exporters is fully or largely uncovered in the first year or in the first destination. In this section, we aim to answer the following questions: How does growth in a given destination develop over time as firms gain destination-specific experience? Does the learning effect wear out after the first year in a given destination, or is a gradual decrease of growth observable over time? How do initial growth rates differ across destinations? To address these questions, the baseline regression is expanded in both the time and the destination dimension. Given that there are only ten years of data and one year of observations is used for the lagged terms, the analysis is limited to three destinations and three years. The results are shown in Table 5.

Column (1) shows the results for including additional years only. All coefficients, except the one of $SY_{ij,t-1}$, are statistically significant at the standard levels. This finding indicates that learning is not limited to the first year - it can persist for at least three years. Furthermore, the signs and magnitudes of the coefficients indicate that for the first destination, the growth rate gradually declines from the first year to the second year and then further to the third year, consistent with the expectations the longer a firm operates in a market, the less uncertain it is about the demand for its product. Overall, the findings support Hypothesis 2.

In contrast to column (1), column (2) shows the results for including additional destinations only. All coefficients are statistically significant at the standard levels. This finding indicates that learning is not limited to the first destination - it can go on for at least the first three destinations. Again, the signs and magnitudes of the coefficients indicate that for the first year, the growth rate gradually declines from the first destination to the second destination and then further to the third destination. This is consistent with the expectations that the more markets a firm operates in a given year, the less uncertainty there is about the demand for its product. Overall, the findings support Hypothesis 3.

Finally, column (3) includes both multiple years and destinations. The coefficient of FM_{ij} is the only coefficient that is insignificant at the standard levels. $FY_{ij,t-1}$ is significant at the 10 percent level and all other coefficients are significant at the one percent level. To learn about the magnitude of learning and thus uncertainty, we compute from the estimated coefficients the additional growth for initial years and destinations as compared to later years and destinations. In Figure 3, the first set of bars on the left hand side shows the additional growth for the first, second, and third year in the first destination, as compared to the average growth for the fourth and later years in the first destination (here we label it the 'first destination baseline growth rate' as in contrast to the general baseline growth rate).[6] The first year growth rate in the first export destination is estimated to be 62.83 percentage points (= 0.5997 + 0.0286) higher than the first destination baseline. The second year growth rate in the first destination is estimated to be 31.07 percentage points (= 0.3764 − 0.0657) higher than the first destination baseline, and the third year growth rate is 14.67 percentage points (= 0.2659 − 0.1192) higher than the first destination baseline. Next, we examine the growth pattern over time in the second export destination. The results are shown in the middle set of bars in Figure 3. Now the 'second destination baseline growth' is the average growth for the fourth and later years in the second destination.[7] The results for the second export destination of the firm also indicate a decreasing growth pattern over time. Here, the additional growth compared to the baseline decreases from 41.22 percentage points in the first year, to 20.06 percentage points in the second year, to 4.92 percentage points in the third year. Likewise, the set of bars on the right hand side of Figure 3 shows the growth pattern over time in the third export destination relative the 'third destination baseline'. While the pattern is less distinct compared to the first and second destination, a decreasing growth pattern over time can still be identified. In comparison to the baseline, the growth rate is 31.60 percentage points higher in the first year, 9.47 percentage points higher in the second year, and 7.32 percentage points higher in the third year. Overall, a clear decreasing growth pattern is observable in the firm's first, second, and third export destinations, respectively, over multiple years. Therefore, the findings once again lend strong support to Hypothesis 2.

[6] The first destination baseline growth rate is equal to the coefficient of FM_{ij} plus the general baseline growth rate. Recall that the general baseline growth rate is the average growth rate for year four and later in the fourth and later destinations.

[7] Following the same logic as before, the baseline growth in this case is given by the coefficient of SM_{ij} plus the general baseline growth rate.

The focus now shifts to the growth patterns across destinations. In Figure 4, the first set of bars on the left hand side shows that the first year growth rates in the first, second, and third destinations are 59.97 percentage points, 31.33 percentage points and 18.26 percentage points, respectively, higher than the first year growth rate in the fourth and later destinations (i.e. the ’first year baseline growth’). Likewise, the middle set of bars shows the additional second year growth rates in the first three destinations as compared to the ’second year baseline growth’ (i.e. the second year growth rate in the fourth and later destinations), and the set of bars on the right hand side shows the additional third year growth rates relative to the ’third year baseline growth’. Overall, a clear decreasing growth pattern is observable in the firm’s first, second, and third year of exporting, respectively, over multiple destinations. Therefore, the findings once again lend strong support to Hypothesis 3.

To summarize, we find strong evidence that the average growth rate of a firm’s exports in a given destination decreases in both time and destination dimensions of experience. Therefore, the findings also provide strong support to the idea that firms’ uncertainty is – at least partially – correlated across destinations. Most importantly, looking at these findings from a learning perspective, the empirical results indicate that learning is a gradual rather than an abrupt process.

4.3 Product Level Analysis

In this section, the growth rate of a firm’s product-specific sales in a given destination is used as the dependent variable. This allows for the analysis of the role of experience and uncertainty in two new aspects. Firstly, the destination level growth rate analyzed in the previous sections could be driven either by changes in the quantities of a product or the addition of new products; on the contrary, product-specific growth does not have an extensive margin component[8] and allows us to pinpoint the effect of experience on the intensive margin. Secondly, by including measures of product-specific experience, the analysis allows us to test how product-specific uncertainty may affect growth. The results are shown in Table 6.

Column (1) has a similar specification to the baseline model in Table 4, except for the dependent variable. We use year and destination FEs instead of year-destination FEs here to ease the computational burden. [Note: Estimations with year-destination FEs will be added in revision.] The qualitative results are the same as those of the baseline model and the quantitive results are quite similar as well. The results suggest that growth in the second and later years in the first export destination of the firm is 4.32 percentage points higher than the

[8]Unless it happens at a more disaggregated level than the HS-6.

baseline. For the first year in the second and later destinations, the growth rate is on average 5.07 percentage points higher than the baseline. For the first year in the first export destination of the firm, the additional growth rate is in total 25.78 percentage points higher than the baseline growth rate. Therefore, it can be concluded that product-specific growth is affected by firms' level of experience.

In column (2) we add variables for product-specific experience. All the newly added variables have the expected positive signs, but FM_{ijk} is not significant at the standard levels. In column (3) we further control for product FEs, but the results change little. According to the results in column (3), the first year growth rate after a product is introduced to a destination is on average 1.35 (α_4) percentage points higher than the baseline growth rate. If it is also the first export destination for this product, the growth rate is on average 4 ($\alpha_4 + \alpha_5 + \alpha_6$) percentage points higher. If it is one of the very first products the firm exported, the initial growth rate is on average 26.48 ($\sum_{r=1}^{6} \alpha_r$) percentage points higher than the baseline growth. In addition, coefficient α_6 is positive and significant at the 1 percent level. As such, the results support Hypothesis 4. Although the findings indicate that product-specific uncertainty and thus experience (as measured by α_4, α_5 and α_6) are relevant, they also suggest that general and destination experience (as measured by α_1, α_2 and α_3) are more important and, hence, have a stronger impact on product level growth.

Lastly, it is worthwhile to compare the coefficient of FM_{ij} across the three columns. As the estimation in column (1) does not control for FM_{ijk}, the coefficient on FM_{ij} captures both product-specific and non-product-specific learning in the first destination. However, after controlling for FM_{ijk}, the estimated coefficients for FM_{ij} in columns (2) and (3) remain highly significant and become only slightly smaller, suggesting that firms can learn from markets of imperfectly substitutable products. The reason is that, as stated earlier, general and destination experience is of more importance than product experience.

5 Sources and Remedies of Uncertainty

The results presented in the previous section highlight how firms' own experience over time or across destinations can help them uncover uncertainty. However, there are internal as well as external aspects to uncertainty. Experience (or, more precisely, the lack of it) is obviously the key internal factor in determining uncertainty. However, if information is perfect and freely available to producers, then their own experience is not important at all. In other words, experience is important only because firms need it to overcome uncertainty generated by external factors. This section aims to shed light on what external factors may lead to uncertainty confronted by exporting firms. We start with factors closer to firms, including industry group and peer groups, and then look at factors pertaining to distance, including institutional quality of destinations, geography, and migrant networks.

In this section, we ease the computational burden by using year and destination FEs instead of year-destination FEs. [Note: Estimations with year-destination FEs will be added in revision.]

5.1 Industry Groups

Our dataset covers only manufacturing exports, which can be highly heterogeneous in terms of complexity. In general, the more complex a product is, the more differentiated it is from competing products, and the more difficult it is for producers to gauge market reaction based on the demand for competing products. Therefore, we would expect to see a bigger learning effect for industries with more sophisticated technologies and products. We test this hypothesis by examining the subsample of seven industries for which there are sufficiently large numbers of observations. The estimation results using the baseline model are shown in Table 7. The qualitative results remain intact as compared to those in Table 4. However, the quantitative results vary noticeably across industries. For each column the estimated coefficients represent the additional growth relative to the baseline growth of its own subsample, thereby a comparison of coefficients across columns is akin to assessing the 'difference in differences'. In Table 7 the industries are ordered based on the value of $\alpha_1 + \alpha_2 + \alpha_3$. In general, the additional growth in the first year in the first destination is larger in industries producing relatively high-tech products such as machinery and electronic equipments than those producing low-tech products such as textile and footwear. The results therefore support the hypothesis that product complexity matters in export uncertainty and learning.

5.2 Peer Groups

In the previous section we focus only on how firms learn from their own experience, either over time or across destinations. But firms can learn not only from their own experience but also from observing their peers. In particular, the more peers operating in a destination, the more sources from which a firm can potentially learn. On the other hand, however, a stronger presence of peers in a given destination also means stronger competition and thereby uncertainty. To test which of the two forces dominate, we define a variable that determines the number of firms from the same industry that exported to a specific destination in $t-1$. We then divide the observations based on the number of *same-industry* competitors in a given destination. For instance, as more Chinese firms in the textile industry export to the U.S. and far fewer in the electronic industry export to Fiji, observations associated with exporting textile products to the U.S. will be grouped into the top percentile while an observation associated with exporting electronic products to Fiji will be grouped into the bottom percentile. Then we can compare the learning experience of firms in the former group to that of firms in the latter group. The results are shown in Table 8.

In comparing the results for the top and bottom 5 percent observations in terms of peer group presence, it can be seen that the learning effect is stronger when there are fewer peers in the same destination, but the difference between the two columns is small in magnitude.[9] When we extend the comparison to top/bottom 10 percent, top/bottom 20 percent, and above/below average destinations, respectively, the effect is reversed, i.e. the learning effect is stronger when there are more peers in the same destination. Therefore, the messages from different subsamples are mixed and we cannot conclude whether the peer learning effect or the peer competition effect dominates.

5.3 Institutional Quality of Destinations

One of the foremost factors that creates economic uncertainty is poor institutional quality. For instance, markets in developing countries often have fewer clear rules and regulations, and require more local knowledge to navigate around. Therefore, the impact of experience on growth should be higher in places with poorer governance. We test this hypothesis using the World Bank's governance indicators data. To classify destinations by institutional quality, we first created an aggregated indicator as the mean of the World Bank's six governance indicators.[10] We then divide the destinations based on their index values. This allows us to estimate and compare the learning effects in destinations with different institutional quality. The results are shown in Table 9.

In Table 9, the 'Top 5 Percent' is the subsample of the roughly five percent of observations with the highest values for the institutional quality indicator, and so forth. It can been seen that, firms learn more in the bottom 5 percent destinations than in the top 5 percent ones, implying that there is more uncertainty regarding the former than the latter. The same conclusion can be reached by comparing the results for the top/bottom 10 percent,

[9] The slight differences in sample sizes between the top and bottom percentiles result from rounding the percentile thresholds when creating the subsamples.

[10] For that we dropped all observations from the main dataset where one or more of the six measures are missing.

top/bottom 20 percent, and above/below average subsamples, respectively. Admittedly, a comparison amongst close groups do not yield the same conclusion. For instance, firms learn more in the top 5 percent destinations than than top 10 or 20 percent destinations. This may be due to other uncontrolled factors. Despite that, overall, there is still clear evidence to support the hypothesis that destinations with poorer institutional quality pose higher uncertainty and therefore warrant a greater scope of learning upon entry (and survival).

5.4 Geography

Formal institutions are not the only factors that shape the environment faced by exporters. Informal institutions such as social norms and culture could also be important for trade. Empirical evidence, such as that from the gravity model, suggests that countries of closer geographic and cultural proximity trade more because of lower transaction and information costs. China's immediate neighbors in Northeast Asia are: Hong Kong, Taiwan, South Korea, and Japan. Not only are these countries/economies geographically close to China, but they also share the same Confucius culture with China.

In the first two columns on the left hand side of Table 10, we compare the learning effect for firms exporting to the Northeast Asian markets with firms exporting to the rest of the world (i.e. the world minus Northeast Asia). The results support the hypothesis that Chinese firms are more familiar with the markets in Northeast Asia and therefore have less to learn when entering those markets, compared to when entering the rest of the world. In the next two columns, we expand upon Northeast Asia to include Southeast Asian countries: Brunei, Cambodia, East Timor, Indonesia, Laos, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Vietnam. The qualitative results remain the same although the quantitative difference between the broader Asian group and the rest of the world becomes smaller. It is also interesting to notice that the learning effect is larger in North- and Southeast Asia combined than in Northeast Asia alone. This is consistent with the fact that Southeast Asia is geographically and culturally more distant from China than Northeast Asia.

5.5 Migrant Networks

There is also established evidence that migrant networks facilitate trade by reducing the information cost between the source and destination countries. To test how the Chinese diaspora might lower the uncertainty faced by Chinese exporters, we divide the sample into four quantiles using year 2000 Chinese migration data from the

World Bank.[11] We then compare the top and bottom quantile and the results are shown in Table 11. The bottom quantile destination countries took 18 or less migrants from China in year 2000, while the top quantile destination countries took 1625 or more Chinese migrants in the same year. The results indicate that the learning effect and thus uncertainty are much greater in destinations with a small network of Chinese migrants than those with a large network.

6 Conclusion

This paper aims to provide new and detailed evidence on the relationship between experience and export growth. The empirical analysis of a Chinese firm dataset has shown that the experience level of a firm appears to be an important and significant driver for the growth rate of export sales at the firm and destination level. This is generally in line with the findings of an inverse relationship between growth and experience in the previous empirical literature. A potential explanation for this inverse relationship, from a theoretical perspective, lies in a learning mechanism. The idea is that firms undergo a learning process which reduces the level of uncertainty that they face when engaging in export markets. The empirical results of this paper provide strong support for such a mechanism. However, in contrast with a large part of the previous literature, the presented analysis has extended beyond a unidimensional approach. By building upon Albornoz et al. (2012), the empirical results not only suggest that learning takes place within and across destinations, they also indicate that learning in both dimensions appears to be gradual. In each of the first three destinations, a strong pattern of decreasing growth over time is observed. Likewise, the initial growth in earlier destinations is consistently higher than in later destinations. By expanding the analysis to the product level, it is further found that product level growth in a given destination is driven by multiple measures of experience, namely general experience, destination-specific experience and product-specific experience.

Besides investigating how uncertainty is correlated over time and across destinations and, hence, how firms learn through their own experience, this paper also tries to identify what external factors could cast uncertainty in the first place. In particular, we examine the influence of industry groups, peer groups, institutional quality of destinations, geography, and migrant networks on uncertainty and, in parallel, the learning process. We have found unambiguous expected results for all factors except for peer groups. Overall, the empirical results

[11] In total 226 countries have data on Chinese migrants.

presented in this paper suggest that exporter learning is a complex process: it is gradual and bi-dimensional (over time and across destinations), as well as conditional on multiple external factors.

References

Albornoz, F, Calvo Pardo, HF, Corcos, G & Ornelas, E 2012, 'Sequential exporting', Journal of International Economics, vol. 88, no. 1, pp. 17-31.

Arkolakis, C, Papageorgiou, T & Timoshenko, O 2015, 'Firm Learning and Growth', Unpublished Manuscript.

Bastos, P, Dias, DA & Timoshenko, OA 2016, 'Learning, prices, and firm dynamics', Unpublished Manuscript.

Berthou, A & Vicard, V 2015, 'Firms' Export Dynamics: Experience Versus Size', The World Economy, vol. 38, no. 7, pp. 1130-58.

Cheng, W & Wu, Y 2015, Bank Finance for Private Firms in China: Does Political CApital Still Pay off? Discussion Paper 07/16. Department of Economics, Monash Business School.

Damijan, JP, Kostevc, C & Polanec, S, 2008. Exporter Strategies: Geographic and Product Diversification Patterns. Mimeo, University of Ljubljana.

Davis, SJ & Haltiwanger, J 1992, 'Gross Job Creation, Gross Job Destruction, and Employment Reallocation', The Quarterly Journal of Economics, vol. 107, no. 3, pp. 819-63.

Eaton, J, Eslava, M, Kugler, M & Tybout, J 2008, 'The margins of entry into export markets: evidence from Colombia', in E Helpman, D Marin & T Verdier (eds), The Organization of Firms in a Global Economy, Harvard University Press, Cambridge, MA, pp. 231-72.

Nguyen, DX 2012, 'Demand uncertainty: Exporting delays and exporting failures', Journal of International Economics, vol. 86, no. 2, pp. 336-44.

Rumbaugh, T & Blancher, N 2004. China: International Trade and WTO Accession. Working Paper WP/04/36, International Monetary Fund.

Table 1: Main Export Destinations for Chinese Firms

Export Destination	Number of Firms Which Exported to That Destination at Any Point Between 2000-2009
USA	56,858
Hong Kong	48,486
Japan	44,272
South Korea	38,899
Germany	38,509
United Kingdom	34,361
Australia	32,409
Canada	31,882
Italy	30,681
Taiwan	29,803

Table 2: Export Development of Chinese Manufacturing Firms Between 2000 and 2009

	2000	2009
Number of firms engaged in exports	15,645	47,005
Average exports per exporting firm	$0.71 million	$3.43 million
Total value of exports of all firms	$11.15 billion	$161.26 billion
Average number of destinations per exporting firm	6.41	10.27
Average exports per exporting firm and destination	$0.11 million	$0.33 million

Table 3: Multi-Desination and Multi-Product - Average vs New Exporters

	Overall	First Year
Share of multi-destination firms	91.83%	36.70%
Share of multi-product firms	84.14%	39.42%

Table 4: Estimation Results for Baseline Regression

Dependent Variable: $\Delta log X_{ijt}$			
	1	2	3
$FY_{ij,t-1}$ (α_1)	0.1116**	0.1067**	0.1132**
	(0.0052)	(0.0054)	(0.0052)
FM_{ij} (α_2)	0.0426**	0.0433**	0.0444**
	(0.0035)	(0.0038)	(0.0036)
$FY_{ij,t-1} \times FM_{ij}$ (α_3)	0.2021**	0.2034**	0.2006**
	(0.0115)	(0.0124)	(0.0115)
$\alpha_1 + \alpha_2 + \alpha_3$	0.3563	0.3534	0.3582
Firm FEs	yes	yes	yes
Year FEs	yes	yes	no
Destination FEs	yes	yes	no
Year-Destination FEs	no	no	yes
Observations	1,249,586	944,524	1,249,586
R-squared	0.2949	0.3053	0.2971

Note: * and ** denote significant at the 10 percent and 1 percent level respectively; robust standard errors clustered by firms in brackets.

Table 5: Estimation Results for Extensions to Multiple Years and Destinations

Dependent Variable: $\Delta logX_{ijt}$			
	1	2	3
$FY_{ij,t-1}$	0.1474**	0.0233*	0.0286*
	(0.0064)	(0.0102)	(0.0143)
$SY_{ij,t-1}$	0.0128		–0.0657**
	(0.0079)		(0.0190)
$TY_{ij,t-1}$	–0.0415**		–0.1192**
	(0.0086)		(0.0214)
FM_{ij}	–0.0189*	0.0317**	–0.0037
	(0.0064)	(0.0069)	(0.0139)
SM_{ij}		–0.0286**	–0.0703**
		(0.0068)	(0.0143)
TM_{ij}		–0.0454**	–0.1048**
		(0.0072)	(0.0148)
$FY_{ij,t-1} \times FM_{ij}$	0.3172**	0.3117**	0.5997**
	(0.0139)	(0.0160)	(0.0275)
$SY_{ij,t-1} \times FM_{ij}$	0.1740**		0.3764**
	(0.0142)		(0.0270)
$TY_{ij,t-1} \times FM_{ij}$	0.1094**		0.2659**
	(0.0148)		(0.0262)
$FY_{ij,t-1} \times SM_{ij}$		0.1587**	0.3836**
		(0.0162)	(0.0257)
$SY_{ij,t-1} \times SM_{ij}$			0.2663**
			(0.0269)
$TY_{ij,t-1} \times SM_{ij}$			0.1686**
			(0.0264)
$FY_{ij,t-1} \times TM_{ij}$		0.1148**	0.2874**
		(0.0167)	(0.0228)
$SY_{ij,t-1} \times TM_{ij}$			0.1604**
			(0.0252)
$TY_{ij,t-1} \times TM_{ij}$			0.1924**
			(0.0314)
Firm FEs	yes	yes	yes
Year-Destination FEs	yes	yes	yes
Observations	1,249,586	1,249,586	1,249,586
R-squared	0.2985	0.2977	0.3002

Note: * and ** denote significant at the 10 percent and 1 percent level respectively; robust standard errors clustered by firms in brackets.

Table 6: Estimation Results for Product Level Analysis

Dependent Variable: $\Delta logX_{ijtk}$			
	1	2	3
$FY_{ij,t-1}$ (α_1)	0.0507**	0.0409**	0.0397**
	(0.0059)	(0.0067)	(0.0067)
FM_{ij} (α_2)	0.0432**	0.0407**	0.0400**
	(0.0037)	(0.0042)	(0.0042)
$FY_{ij,t-1} \times FM_{ij}$ (α_3)	0.1639**	0.1467**	0.1451**
	(0.0123)	(0.0133)	(0.0133)
$FY_{ijk,t-1}$ (α_4)		0.0125*	0.0135**
		(0.0052)	(0.0052)
FM_{ijk} (α_5)		0.0040	0.0050
		(0.0036)	(0.0035)
$FY_{ijk,t-1} \times FM_{ijk}$ (α_6)		0.0199**	0.0215**
		(0.0076)	(0.0076)
$\sum_{r=1}^{6} \alpha_r$	0.2578	0.2647	0.2648
$\alpha_4 + \alpha_5 + \alpha_6$		0.0364	0.04
Firm FEs	yes	yes	yes
Year FEs	yes	yes	yes
Destination FEs	yes	yes	yes
Product FEs	no	no	yes
Observations	2,152,466	2,152,466	2,152,466
R-squared	0.3412	0.3413	0.3434

Note: * and ** denote significant at the 10 percent and 1 percent level respectively; robust standard errors clustered by firms in brackets.

Table 7: Comparison by Industry Group

Dependent Variable: $\Delta logX_{ijt}$							
	Manufacture of Articles for Culture, Education, & Sport Activities	Manufacture of Textile	Manufacture of Apparel, Footwear & Cap	Manufacture of Metal Products	Electrical Machinery & Equipment	Manufacture of General Purpose Machinery	Computers & Other Electronic Equipment
$FY_{ij,t-1}$	0.0941**	0.1439**	0.1735**	0.0895**	0.1836**	0.1424**	0.1214**
	(0.0216)	(0.0230)	(0.0192)	(0.0209)	(0.0220)	(0.0150)	(0.0209)
FM_{ij}	0.0315*	0.0406**	0.0065	0.0258*	0.0828**	0.0812**	0.0484**
	(0.0140)	(0.0145)	(0.0151)	(0.0150)	(0.0145)	(0.0140)	(0.0140)
$FY_{ij,t-1} \times FM_{ij}$	0.1071*	0.0836*	0.1602**	0.2559**	0.1475**	0.2025**	0.2769**
	(0.0523)	(0.0413)	(0.0358)	(0.0449)	(0.0411)	(0.0493)	(0.0529)
$\alpha_1+\alpha_2+\alpha_3$	0.2327	0.2681	0.3402	0.3712	0.4139	0.4261	0.4467
Firm FEs	yes	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes	yes
Destination FEs	yes	yes	yes	yes	yes	yes	yes
Observations	75,097	95,593	62,039	80,111	121,105	84,109	118,545
R-squared	0.2588	0.3055	0.3009	0.3496	0.3133	0.3416	0.3388

Note: * and ** denote significant at the 10 percent and 1 percent level respectively; robust standard errors clustered by firms in brackets.

Table 8: Comparison of Destinations by Peer Group

	Top 5 Percent	Bottom 5 Percent	Top 10 Percent	Bottom 10 Percent	Top 20 Percent	Bottom 20 Percent	Above Average	Below Average
$FY_{ij,t-1}$	0.0673	0.0972**	0.1159**	0.0939**	0.1177**	0.0995**	0.1161**	0.1058**
	(0.0411)	(0.0194)	(0.0206)	(0.0134)	(0.0116)	(0.0096)	(0.0062)	(0.0076)
FM_{ij}	0.0005	0.0486*	0.0229	0.0556**	0.0434**	0.0466**	0.0421**	0.0534**
	(0.0299)	(0.0211)	(0.0144)	(0.0136)	(0.0079)	(0.0089)	(0.0041)	(0.0066)
$FY_{ij,t-1} \times FM_{ij}$	0.2506**	0.1339**	0.2226**	0.1688**	0.2267**	0.1648**	0.2145**	0.1730**
	(0.0499)	(0.0413)	(0.0264)	(0.0291)	(0.0174)	(0.0217)	(0.0123)	(0.0177)
$\alpha_1 + \alpha_2 + \alpha_3$	0.251	0.2797	0.3614	0.3183	0.3878	0.3109	0.3758	0.3322
Firm FEs	yes	yes	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes	yes	yes
Destination FEs	yes	yes	yes	yes	yes	yes	yes	yes
Observations	58,805	55,470	119,687	112,282	241,783	224,765	778,338	400,562
R-squared	0.6524	0.4865	0.511	0.4318	0.4241	0.3852	0.3223	0.3529

Note: * and ** denote significant at the 10 percent and 1 percent level respectively; robust standard errors clustered by firms in brackets.

Table 9: Comparison of Destinations by Institutional Quality

	Top 5 Percent	Bottom 5 Percent	Top 10 Percent	Bottom 10 Percent	Top 20 Percent	Bottom 20 Percent	Above Average	Below Average
$FY_{ij,t-1}$	0.1466**	0.1271**	0.1123**	0.1254**	0.1187**	0.1226**	0.1147**	0.1186**
	(0.0208)	(0.0215)	(0.0141)	(0.0145)	(0.0102)	(0.0103)	(0.0064)	(0.0074)
FM_{ij}	0.0641**	0.0542**	0.0218*	0.0546**	0.0412**	0.0577**	0.0370**	0.0536**
	(0.0184)	(0.0183)	(0.0115)	(0.0117)	(0.0079)	(0.0080)	(0.0044)	(0.0055)
$FY_{ij,t-1} \times FM_{ij}$	0.1224**	0.1820**	0.1682**	0.2065**	0.1581**	0.2172**	0.1864**	0.2101**
	(0.0293)	(0.0360)	(0.0215)	(0.0255)	(0.0165)	(0.0210)	(0.0119)	(0.0165)
$\alpha_1 + \alpha_2 + \alpha_3$	0.3331	0.3633	0.3023	0.3865	0.318	0.3975	0.3381	0.3823
Firm FEs	yes	yes	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes	yes	yes
Destination FEs	yes	yes	yes	yes	yes	yes	yes	yes
Observations	53,983	47,309	109,683	97,910	214,628	201,686	606,980	452,382
R-squared	0.3974	0.4012	0.3902	0.3665	0.3495	0.3391	0.3110	0.3113

Note: * and ** denote significant at the 10 percent and 1 percent level respectively; robust standard errors clustered by firms in brackets.

Table 10: Comparison of Destinations by Region

	Northeast Asia	World minus Northeast Asia	Northeast and Southeast Asia	World minus Northeast and Southeast Asia
$FY_{ij,t-1}$	0.1247**	0.1140**	0.1210**	0.1137**
	(0.0147)	(0.0054)	(0.0096)	(0.0057)
FM_{ij}	0.0462**	0.0461**	0.0528**	0.0445**
	(0.0097)	(0.0038)	(0.0065)	(0.0039)
$FY_{ij,t-1} \times FM_{ij}$	0.1632**	0.2049**	0.1843**	0.2030**
	(0.0180)	(0.0123)	(0.0145)	(0.0127)
$\alpha_1 + \alpha_2 + \alpha_3$	0.3341	0.365	0.3581	0.3612
Firm FEs	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes
Destination FEs	yes	yes	yes	yes
Observations	186,345	1,063,241	314,852	934,734
R-squared	0.3622	0.297	0.3354	0.2993

Note: * and ** denote significant at the 10 percent and 1 percent level respectively; robust standard errors clustered by firms in brackets.

Table 11: Comparison of Destinations by Chinese Migrant Network

	Top 25 Percent	Bottom 25 Percent
$FY_{ij,t-1}$	0.1187**	0.1390**
	(0.0067)	(0.0275)
FM_{ij}	0.0464**	0.0839**
	(0.0046)	(0.0262)
$FY_{ij,t-1} \times FM_{ij}$	0.1885**	0.2103**
	(0.0132)	(0.0468)
$\alpha_1 + \alpha_2 + \alpha_3$	0.3536	0.4332
Firm FEs	yes	yes
Year FEs	yes	yes
Destination FEs	yes	yes
Observations	569,329	29,123
R-squared	0.3201	0.4151

Note: * and ** denote significant at the 10 percent and 1 percent level respectively; robust standard errors clustered by firms in brackets.

Figure 1: Average Firm Level Growth Rate for Earlier Years in a Given Destination

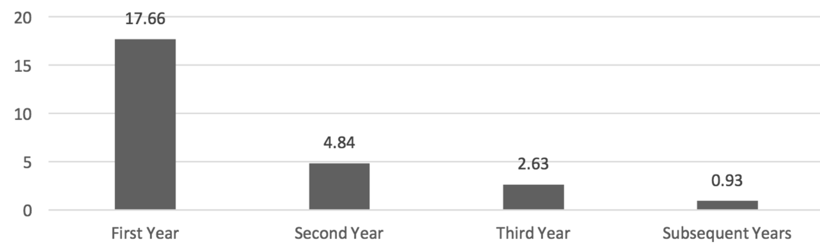


Figure 2: Average Firm Level First Year Growth Rate for Earlier Destinations

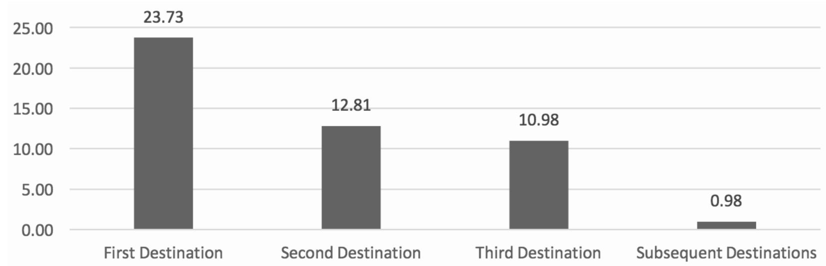
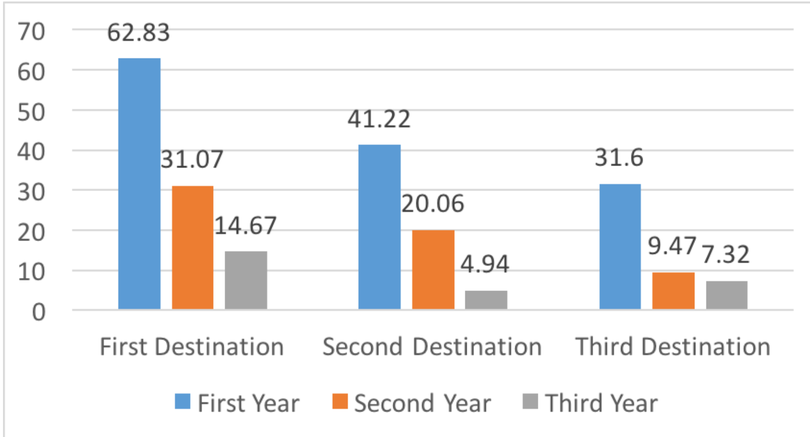
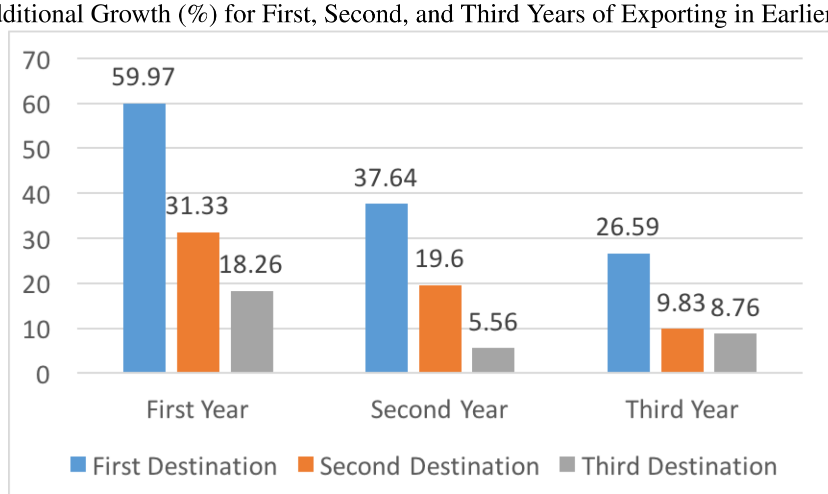


Figure 3: Additional Growth (%) Within First, Second, and Third Export Destinations in Earlier Years



Note: The baseline growth rate for the first destination is the average growth rate of the fourth and later years in the first destination, the baseline growth rate for the second destination is the average growth rate of the fourth and later years in the second destination, and so forth.

Figure 4: Additional Growth (%) for First, Second, and Third Years of Exporting in Earlier Destinations



Note: The baseline growth rate for the first year is the average growth rate of the first year in the fourth and later destinations, the baseline growth rate for the second year is the average growth rate of the second year in the fourth and later destination, and so forth.

Appendix

Table 12: Summary Statistics Destination Level

Variable:	Observations	Mean	Std. Dev.	Min	Max
$\Delta logX_{ijt}$	1533399	0.0758	0.8399	-10.02905	11.44633
$\text{FY}_{ij,t-1}$	2672905	0.1975	0.3981	0	1
$\text{SY}_{ij,t-1}$	2672905	0.1313	0.3377	0	1
$\text{TY}_{ij,t-1}$	2672905	0.0882	0.2836	0	1
FM_{ij}	3099998	0.5939	0.4911	0	1
SM_{ij}	3099998	0.1981	0.3986	0	1
TM_{ij}	3099998	0.0994	0.2992	0	1
$\text{FY}_{ij,t-1}\times\text{FM}_{ij}$	2672905	0.1088	0.3114	0	1
$\text{SY}_{ij,t-1}\times\text{FM}_{ij}$	2672905	0.0762	0.2653	0	1
$\text{TY}_{ij,t-1}\times\text{FM}_{ij}$	2672905	0.0534	0.2248	0	1
$\text{FY}_{ij,t-1}\times\text{SM}_{ij}$	2672905	0.0436	0.2043	0	1
$\text{SY}_{ij,t-1}\times\text{SM}_{ij}$	2672905	0.0289	0.1676	0	1
$\text{TY}_{ij,t-1}\times\text{SM}_{ij}$	2672905	0.0186	0.1352	0	1
$\text{FY}_{ij,t-1}\times\text{TM}_{ij}$	2672905	0.0218	0.1461	0	1
$\text{SY}_{ij,t-1}\times\text{TM}_{ij}$	2672905	0.013	0.1131	0	1
$\text{TY}_{ij,t-1}\times\text{TM}_{ij}$	2672905	0.0078	0.0878	0	1
LogX_i	1533399	14.30174	2.316242	2.381087	25.96659
LogSale_i	1430392	14.9987	2.22709	6.361808	26.32534

Table 13: Summary Statistics Product Level

Variable:	Observations	Mean	Std. Dev.	Min	Max
$\Delta logX_{ijtk}$	2812339	0.0696	0.8609	-10.05409	11.44633
FM_{ijk}	7124950	0.6241	0.4843	0	1
$\mathrm{FY}_{ijk,t-1}$	6387287	0.1812	0.3852	0	1
FM_{ij}	7124950	0.6858	0.4642	0	1
$\mathrm{FY}_{ij,t-1}$	5828301	0.2064	0.4047	0	1
$\mathrm{FY}_{ij,t-1}\times\mathrm{FM}_{ij}$	5828301	0.0819	0.2742	0	1
$\mathrm{FY}_{ijk,t-1}\times\mathrm{FM}_{ijk}$	6387287	0.1071	0.3093	0	1
LogX_i	2812339	14.8597	2.4953	2.3811	25.9666
$\mathrm{LogSale}_i$	2630227	15.4811	2.4606	6.3618	26.3253