

Exporter Dynamics: Entry and Learning Across Destinations

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Abstract

This paper explores the dynamics of Mexican exporters upon entry to foreign markets. Exporters tend to make greater sales adjustments in their first export destination than in subsequent destinations. I develop a model of demand learning where knowledge can be carried over across destinations according to their market similarity, which rationalizes the heterogeneity in sequential versus simultaneous entry observed in the data. When foreign markets are similar, firms learn more about their foreign demand by exporting simultaneously to multiple destinations. However, if entry costs are large enough, firms find it optimal to "test the waters" in one destination before expanding to similar markets.

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1 Introduction

Documentation on the patterns of firms' foreign sales have increasingly focused on the dynamics of firm's exporting strategies (Roberts and Tybout, 1997; Buono et al., 2008; Eaton et al., 2008; Bernard et al., 2009). New exporters start small and experience low survival rates. Those who survive experience an average growth that is declining in their age. Eaton et al. (2008) show this behavior for Colombian firms and document an expansion strategy where firms enter different destinations sequentially. These patterns involve two features studied in the trade literature during the last decade: (i) The age dependence of both the growth rate and survival rate and (ii) the timing of exports¹. However, little attention was paid to the intersection of these two. Age dependence is hard to reconcile with the standard models of firm dynamics where firms' decisions are guided by size rather than age, such as Hopenhayn (1992) or Klette and Kortum (2004). The timing of exports conflicts with models of firm heterogeneity in trade like Melitz (2003) in which a firm that exports would do it to every destination at the same time. Even stochastic productivity evolution would only explain the timing of exports, but not the age dependence of the growth rate.

I use data on Mexican exports from 1995 to 2017 to introduce a series of novel facts that are consistent with previous findings in the literature on the dynamics of new exporters. First, I document a decline in growth and failure rates as exporters reach new destinations sequentially. This is, the first growth episode in a new market exhibits a lower average growth than in previous destinations. The same is true for the exit probability. This pattern suggests that the knowledge that a firm acquires in a market, leading to less adjustment as it grows older, can be carried to subsequent destinations. This possibility opens a new door for the analysis of new exporter dynamics by letting the knowledge transfer across destinations affect decisions such as: a) How many and which destinations should an exporter start selling to. b) How long should an exporter wait before expanding. c) Which country should an exporter expand to. Triggered by these considerations, the second fact I present is that of the characteristics of the destinations chosen by the firms to begin their exporting operations and those that are reached in their subsequent expansion. I will provide evidence that the first destination chosen by exporters is typically familiar in the sense that it is a close destination in terms of distance, and most of the times it shares a language or a border

¹For studies on age dependence of firm growth see Haltiwanger et al. (2013), Foster et al. (2016), Cooley and Quadrini (2001), Clementi and Hopenhayn (2006), Ruhl and Willis (2017), Arkolakis et al. (2018) and Berman et al. (2018). For studies on the timing of exports and survival see Evenett and Venables (2002), Eaton et al. (2008), Buono et al. (2008), Alborno et al. (2012), Nguyen (2012), Lawless (2013), Alborno et al. (2016) and Morales et al. (2017)

with Mexico. The last fact involves the expansion to new destinations. Categorizing new destinations into those that share attributes (border, language, continent) with previous destinations and those which do not, allows me to assess that firms that expand to the former type of markets have a stronger decline in their growth and exit rates. Consistent with the knowledge transfer across destinations, markets that are "more similar" are more likely to benefit from past experience.

I present a model of multi-market demand learning in the spirit of Jovanovic (1982) that is consistent with the findings described above. In particular, the model can rationalize the dynamics of new exporters without introducing sunk costs of exporting. Firms engage in monopolistic competition and consumers have a constant elasticity of substitution demand for each variety which is uncertain to the firm. Each period, the demand realizations are determined by an unobserved component which is variety-market specific and time invariant and a noise shock. Moreover, I allow the variety specific component of demand to be correlated across markets. Firms revise their beliefs based on the observed realizations using Bayes' rule. Hence, for firms with few observed shocks, uncertainty is mostly guided by noise and beliefs are revised in larger magnitudes. Higher volatility of beliefs about demand, combined with the profit structure of the model, yields larger expected growth rates for less informed firms. The model generates two types of behavior that reconcile the early failure and the sequential entry patterns documented for exports in the literature. First, entry to many destinations results in more learning, since firms observe more demand realizations per period. Firms with low appeal find out earlier if they are not profitable, resulting in early failure. A feature of the learning mechanism is that firms might bear (expected) losses in the current period if their continuation value is large enough to compensate them in the future. Firms that enter several destinations simultaneously might do so because either they find it profitable in the current period or they can bear larger losses. Hence, simultaneous entry is more likely to be performed only by the most productive firms. This is consistent with the finding by Eaton et al. (2008) that the frequency of firms selling to multiple markets declines with the number of destinations. The second type of behavior generated by the model is the sequential entry to export markets. Firms can infer their profitability in new destinations from what they learn in the markets they currently operate. Firms that experience losses in order to learn about demand might prefer to delay their entry to new markets and learn in the current ones until they find it profitable to enter a new destination.

For simplicity I model an economy with two symmetric destinations, without entry costs and in which there is perfect correlation between the time-invariant components of a variety's demand across markets. This simple environment can reproduce the empirical facts documented in the literature for age dependence of the growth rate and the timing of exports. I use a simulation of firms in this economy to shed light on two novel margins of heterogeneity on the dynamics of firms' growth rate generated by the model: i) The decline in the expected growth rate of a firm is larger as the number of destinations increases, conditional on size. ii) The expected growth rate of a firm in a given destination declines in the age of the firm in other destinations, conditional on size. I take this outcomes to the data and find evidence that supports these mechanisms. I document that firms that export to more destinations simultaneously experience a larger decline on their average growth rate. On the other hand, I explore the impact of past experience on the initial growth rate on a new destination by focusing on a subset of exporters: Those that begin their operations in a single market and later expand to other destinations. The size of the decline in the initial growth rate between the first and second destinations is not significantly larger for firms with a longer delay before expansion. However, I find that firms that delay more exhibit a larger initial growth rate in their first destination. This finding is consistent with the idea that firms may pursue an expansion strategy that involves gathering knowledge until they are ready to incorporate further markets, and there are heterogeneous learning capabilities to reach such threshold.

Models of demand learning have found empirical support for the age dependence of firms' growth. Arkolakis et al. (2018) introduce demand learning as in Jovanovic (1982) in a single market. They find that age is an important determinant of firms' growth using Colombian firm-level data and study the effect of age-dependent subsidies to avoid early exit by young firms. In a similar environment, Berman et al. (2018) develop a methodology to identify the firm's belief about demand using quantities and prices from international trade data for French firms. They find that belief updating is stronger for younger firms, where age is defined at the firm-market level. Cebreros (2016) uses a learning mechanism to explore the dynamics of Mexican exporters and performs a positive evaluation of export promotion policies. Here, in contrast, I study the possibility of information spillovers across markets. The mechanism that triggers the age dependence of growth is the same, but the definition of age at the firm-market level does not reflect the amount of observed demand shocks used for the belief updating. As a consequence, the age of firms in other markets and the number of markets they supply become key determinants of growth as well.

Models where demand is correlated across destinations have also found empirical support. Alborno et al. (2012) consider a model where demand is uncertain and correlated across foreign markets. Entry to one of this markets resolves the uncertainty in all of them, reconciling the rapid growth in the first export destination and the delayed expansion to other markets. Using firm-level data for Argentina, they document that controlling whether a market is a firm's first export destination is crucial to study growth and survival. Closer to the mechanism in my model, Nguyen (2012) introduces imperfect correlation of demand across destinations to the Melitz (2003) environment. Firms can forecast their profitability in new destinations based on their observations in current markets. The uncertainty in each market is resolved upon entry, but the forecasting ability of the firm towards unknown markets improves. The model is able to reproduce sequential entry patterns documented by Eaton et al. (2008). However, in these models, the early resolution of the uncertainty about demand is at odds with the age dependence of the growth rates. Upon entry to a new market, firms initially supply a quantity based on their belief about demand and later adjust it after they resolve the uncertainty. The adjustment is done only once and depends on the number of destinations the firm operates in, since it determines the accuracy of the forecast. Instead, I let the uncertainty persist even after entry, so that older firms are better informed. This generates the age dependence, while maintaining the forecasting ability that generates the sequential entry pattern.

Other mechanisms have been used in the literature to generate age dependence of firms' growth. From the supply side, models that introduce heterogeneity through financial constraints as in Cooley and Quadrini (2001) or Clementi and Hopenhayn (2006) are able to recreate the decline in the mean and variance of growth rates as firms become older. While these models focus on the time dependence of growth through borrowing, I introduce a multi-market economy where the number of destinations also plays an important role on the determination of firm dynamics. For instance, an expansion to an additional destination that alleviates borrowing constraints² can explain a larger decline in the growth rate of a successful firm, but not the early exit of those firms who fail. The learning mechanism is able to reconcile both facts at the same time. From the demand side, models of demand accumulation through market-specific investments or customer base expansion strategies generate an age dependence

²In Clementi and Hopenhayn (2006), the borrowing constraints relax as the value of the borrower's claim to future cash flows increases, which is the case by operating an additional market.

of growth. Fitzgerald et al. (2016) and Arkolakis et al. (2016) model the investment on marketing and penetration costs respectively. Fishman and Rob (2005) and Foster et al. (2016) use models of reputation to build a customer base. In these models, pricing behavior is such that demand accumulation will allow the firms to increase their prices. With learning, selection induces firms that underestimate their demand to stay in the market, so that prices fall as firms learn. Berman et al. (2018) show that prices are decreasing with age, which is hard to reconcile with pure demand accumulation. However, the interaction of both mechanisms cannot be completely ruled out.

Regarding the impact of learning and information spillovers on trade, this paper follows the line of research that studies the interdependence of trade across destinations. Lawless (2013) finds that for Irish firms, exporting experience in geographically nearby markets increases the probability of entry to a market and reduces the probability of exit. Moreover, reducing the fixed costs of exports allows lower-sales firms to access the market. Morales et al. (2017) use data from Chilean exporters to show that exports in a market may depend on how similar is that market to previous export destinations. In particular, similarities in location and language have the largest effects. From the demand side, Evenett and Venables (2002) document for 23 developing countries that importing a product from a certain country is more likely if the origin country is supplying the same product in nearby markets. I do not endogenize the correlation of demand across markets, but the evidence of such correlation supports the contribution of learning to rationalize these findings.

Lastly, modeling an environment with demand correlation across markets is suitable to speak to the literature of real business cycle comovements across countries. A recent study by di Giovanni, Levchenko and Mejean (2018) documents that the impact of direct trade and multinational linkages on comovement at the micro level has significant impact at the macro level. My model provides a framework to study the reverse causality, where comovement allows the firms to learn about the state of demand in the other country and determine the trade volume. Awareness of such concern might be useful to guide the empirical exercise to check the robustness of this finding.

The rest of the paper is organized as follows: Section 2 introduces the main empirical facts that guide the analysis. Section 3 presents the model. Section 4 contains the predictions and simulations of the model regarding firms' growth and expansion timing patterns and their data counterparts. Section 5 concludes.

2 Main Facts

I use data on Mexican exports from 1995 to 2017. The source of the data is the Bank of Mexico’s Laboratory for Microdata which accounts for a hundred percent of the exports reported to UN Comtrade by Mexico, making this analysis representative of the whole set of exporting firms, except for when it is explicitly told that a particular subset is analysed. The dataset covers a total of 244,973 firms, selling 6,332 distinct products. The main focus of this analysis is on the dynamics of new exporters, regarding their entry and subsequent expansion. Table 1 shows that entrants are typically a large share of total exported varieties, but their contribution to the total export value is very small. However, 11% of the varieties that continue in the exports market (including the newest and older exporters) expand to new destinations. These varieties account for a large share of total exports, suggesting that studying their growth dynamics is useful to understand a process that gradually transforms small entrants into powerful components of aggregate exports.

Table 1: Average proportions by type of exporter

	Entrants	Continuers	Expanding
Avg % of Varieties	42.50%	57.50%	11.51%
Avg % of Export Value	5.65%	94.35%	37.66%

In light of this gradual expansion, I will study the dynamics of a set of variables that allow me to shed light on the possibility that firms are undergoing a learning process. In particular, one in which they accumulate knowledge about their appeal and the demand conditions that shapes their export profitability. Exploring the dynamics of the growth rate and its variance, as well as the exit probability in foreign markets will be informative on whether such a mechanism can explain the outcomes that we observe for new exporters. A firm that is uncertain about its demand conditions in a market, might have to adjust its sales frequently until such uncertainty is resolved and the market can be accurately served. With little information in hand, a conjecture about the actual market conditions can be very volatile, resulting in a larger adjustment on average. Thus, accumulating knowledge leads to a decline in the average growth rate. Moreover, if this knowledge can be carried across destinations, this decline should persist in new markets that are reached sequentially. To bring this logic to the data I focus on the order of sequential entry to new markets. I define this order chronologically based on the year of entry to a new destination.

The first two facts I document are about the dynamics of the growth rate and its variance as well as the exit probability at each initial period for a new destination reached by the firms. I characterize the dynamics according to the chronological order mentioned above

Fact 1: The first period growth rate at a new destination and its variance decline with the order of entry.

Fact 2: Exit probability decreases with the order of entry to new destinations.

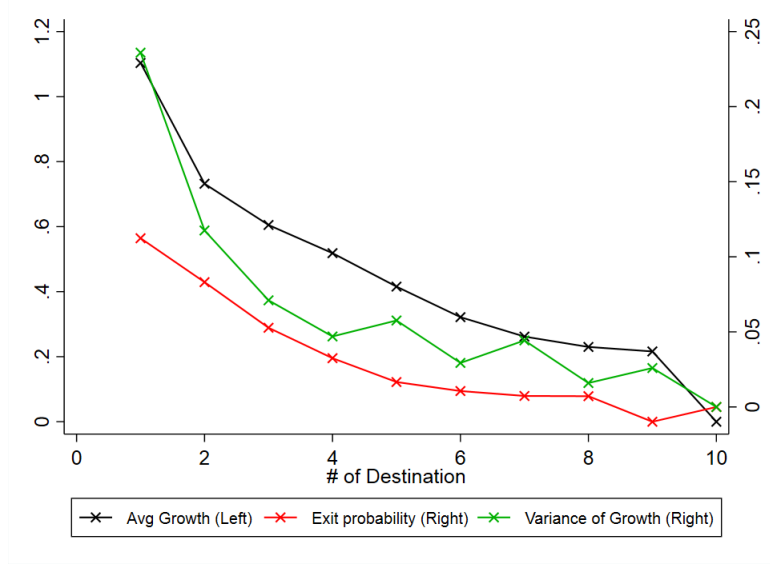
To assess the growth and survival behavior of new varieties as they enter new destinations, I estimate the following equation:

$$y_{ikjt} = \alpha + \sum_n \beta_n \times order_{ikjt}^n + \gamma_t + \gamma_{ik} + \gamma_{jk} + \delta_{size(kjt)} + \delta_{hs2(k)} + \varepsilon_{ikjt} \quad (1)$$

Where y_{ikjt} is either $\Delta \log(sales_{ikjt})$ or $I(exit_{ikjt})$. The dummy $order_{ikjt}^n = 1$ if j is the n th destination. I control for a set of fixed effects, including: γ_t , year fixed effects, γ_{ik} , variety fixed effects (only for growth), γ_{jk} , destination-product fixed effects (only for growth), $\delta_{size(kjt)}$, size category fixed effects and $\delta_{hs2(k)}$, sector fixed effects. The variance of growth is computed within a product-year category for each destination order and residualized from year and average size effects. Standard errors are clustered at the firm level.

Figure 1 plots the coefficients for the estimation of equation (1), which are expressed relative to the value of each of the dependent variables in the 10th destination. The results reveal that the initial growth rate is about 40% larger in a variety's first destination than that of the second destination. It is worth that these results are conditional on size categories. Moreover, variety fixed effects control for characteristics that are common across all markets to filter out part of the supply side effects that could be driving the results. Finally, market specific fixed effects control for the variation in growth rates that can be explained by the fact that some products are stronger in particular destinations. The decline is particularly stronger for the growth rate than for the variance and exit rates. Studies that focus on the impact of age in the dynamics of the growth rate (Arkolakis et. al (2018), Berman et. al. (2019) and Cebreros (2016)) show that the largest decline is between the second and third year of tenure in a market. Here the comparison is between the initial growth for two different markets to which a variety enters sequentially. In those studies, each year represents one observation of demand. In this case, firms can observe multiple realizations in a single year, depending on how many destinations they serve. On average, Mexican varieties reach their second destination having observed 2.25 realizations and served 1.56 destinations. These numbers grow rapidly, hinting to

Figure 1: Dynamics of growth and exit rates with sequential order of entry



Plot of the coefficients estimated from equation (1) for the growth rate and exit probability, and the coefficients of a regression of within product-year variances on order dummies, residualized from year and size effects. Coefficients are expressed relative to the omitted dummy for the 10th destination.

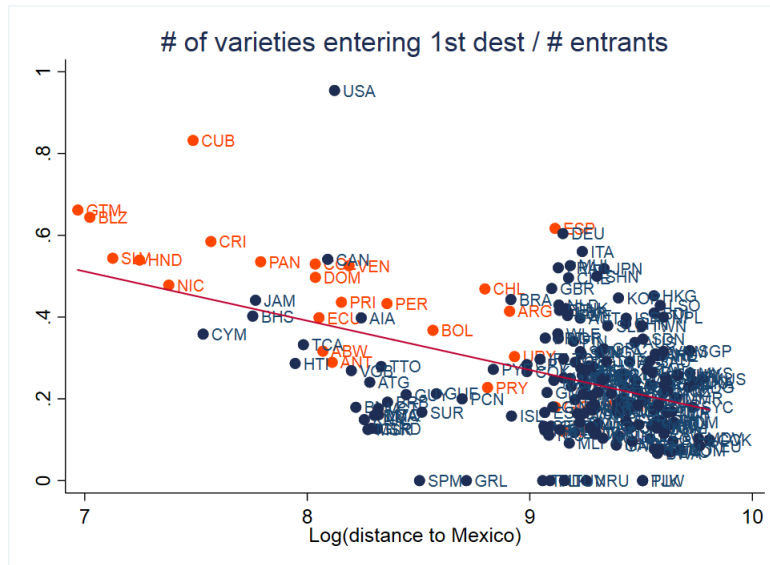
the magnitude of the the decline in growth rates across destinations.

The following fact aims to provide some understanding of the firm's entry strategy, documenting characteristics of the destinations chosen as the first market and compared to destinations targeted by the subsequent expansion.

Fact 3: Entrants choose familiar destinations as their first market.

Figure 2 shows a negative relation between a destination's distance to Mexico and the share of all entrants to that destination that chose it as their first market. There is a clear patten indicating that countries that are closer to Mexico are reached by most of the entrants as their first destination. Spanish speaking countries, highlighted in red also exhibit a higher share on average that those with other languages. In the presence of learning and knowledge accumulation, this behavior might result from the fact that uncertainty about demand might be costly to resolve, in terms of losses or forgone profits, and reaching destinations with fewer barriers attenuates such concern. Table 2 introduces the characteristics of export destinations by the order they where reached. Average distance shows a pecking order where destinations that are reached once a variety continues to export are more distant than those chosen as their first market. I also introduce the proportion of all varieties reaching their nth

Figure 2: Closer countries host a higher share of firms as their first destination



Plot of the share of entrants to a country that chose it as their first destination as a function of distance. More distant countries' entrants usually go there as part of their expansion rather than as a first destination. Spanish speaking countries are highlighted in red.

market that chose a destinations which shares a border, language or continent with Mexico (Gravity), as well as those that do not share a characteristic but a previous destination does (Extended Gravity)³. Most of the varieties choose a bordering destination as their first market but less varieties do so for post-entry expansion. A shared language is less so the case, since United States attracts most of the entrants, which later on expand to Spanish speaking destinations. Moreover, new destinations show an increasing proportion of varieties expanding to markets that share some characteristic with their previous choices. Part of this pattern is mechanical, since accumulating destinations increases the probability of sharing a characteristic, but it is highly consistent with a framework where firms learn and carry their knowledge across markets. I explore the variation in first destination characteristics across deciles of size distribution. Table 3 shows that these proportions are similar across the distribution, with exception of the first and last decile. The existence of sunk costs might explain the fact the largest varieties have a lower proportion choosing "familiar" destinations. However, the small variation across the rest of the distribution, is consistent with the fact that for a wide range of sizes the decision to enter a familiar market is not just a matter of capacity or ability to cover the cost, but also that there is some advantage on reaching such destinations and

³Extended Gravity was introduced by Morales et. al. (2019)

Table 2: Characteristics of exports' destinations

Order	Distance	Gravity			Extended Gravity			
		Border	Language	Continent	Border	Language	Continent	Some
1	100	66%	25%	63%
2	139	20%	48%	19%	16%	17%	29%	45%
3	147	12%	53%	10%	27%	19%	53%	67%
4	154	9%	53%	7%	35%	21%	64%	78%
5	161	7%	51%	5%	41%	23%	72%	85%

For the pool of destinations reached in a given order, Distance represents the average distance to Mexico, where the outcome for first destinations is normalized to 100. Gravity characteristics are those shared by a destination and Mexico and Extended Gravity is defined by not sharing a characteristic with Mexico but sharing it with a previous destination, as introduced by in Morales et. al. (2019). Gravity and Extended Gravity show the proportion of varieties that chose a destination which exhibits a given characteristic.

Table 3: Characteristics of first destination across deciles of size distribution

	1	2	3	4	5	6	7	8	9	10
Distance	100.00	101.21	101.34	101.84	101.83	101.71	102.20	102.80	102.98	106.32
Border	77.61%	75.44%	75.82%	75.20%	74.69%	76.27%	75.43%	74.38%	74.17%	68.07%
Language	18.98%	20.57%	20.05%	20.41%	20.93%	19.47%	19.92%	20.75%	20.82%	25.14%
Continent	75.33%	73.02%	73.54%	72.97%	72.37%	74.14%	73.36%	72.20%	72.13%	65.91%

accumulate knowledge and carry it to others later in their exporting life.

The last fact is about how firms carry their knowledge across destinations in their post-entry expansion.

Fact 4: Knowledge is more easily carried to countries that share attributes with known destinations.

Using the definition of extended gravity, I analyse the dynamics of the growth and failure rates in destinations that share some attribute with previous markets served by a variety. I estimate the following specification to quantify the differences:

$$y_{ikjt} = \alpha + \sum_n \beta_n \times order_{ikjt}^n \times ExtGrav_{ikjt} + \sum_n \phi_n \times order_{ikjt}^n + \gamma_t + \delta_{size(kjt)} + \delta_{hs2(k)} + \varepsilon_{ikjt} \quad (2)$$

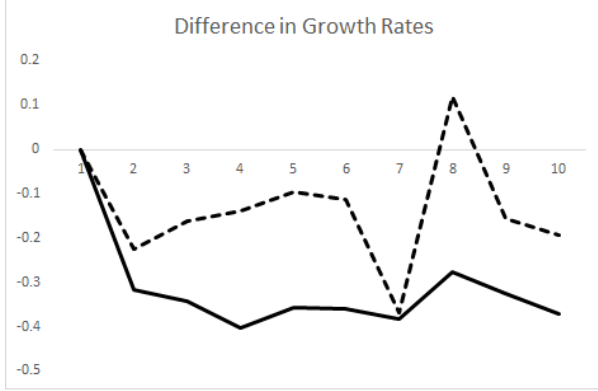
where now the order dummy is interacted with a dummy that equals one if the destination exhibits extended gravity. This way, the coefficient β_n captures the difference between both groups. Figure 3 plots the coefficients from equation (2). Panels (a) and (b) present the series of growth for destinations with and without extended gravity. Panels (c) and (d) plot the difference between groups, including the confidence intervals for the coefficients. The results of this exercise suggest that there is a larger decline in growth rates and exit probability as varieties expand to destinations that share some characteristics with their previous destinations. The noisier outcome for latter destinations is probably driven by the fact that it is very unlikely to enter a 6th or 7th destination and not exhibit extend gravity whatsoever. The impact of extended gravity in the ease to carry knowledge seems much more robust for the dynamics of the exit probability. This might be the case due to knowledge accumulation, which as time goes by, leaves less room for further learning and dynamics of sequential entry are driven solely by entry and exit decisions.

To further explore the difference in the dynamics of these groups, I use a decomposition of the contribution of new destinations to exports' yearly growth rate to shed light on such heterogeneity.

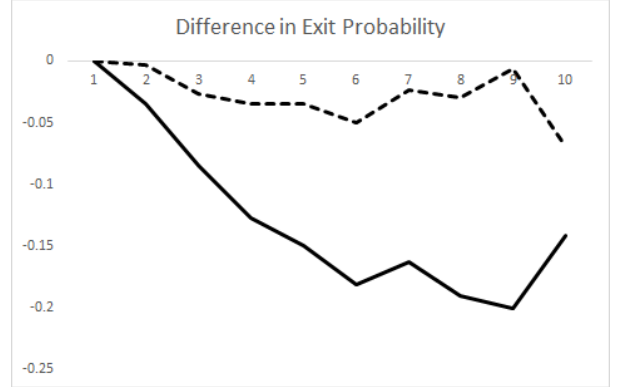
$$\frac{\sum_{ikj \in EXP} X_{ikjt}}{X_t + X_{t-1}/2} = \frac{\sum_{kj \in EXP} \sum_i (X_{ikjt} - \bar{x}_{kjt})}{X_{t+1} + X_t/2} + \frac{\sum_{kj \in EXP} N_{jk}^{exp} \bar{x}_{kjt}}{X_{t+1} + X_t/2} \quad (3)$$

The left hand side of equation (3) represents the contribution of exports by continuing varieties in new destination in the midpoint growth. The decomposition consists of two terms. The first is the sum of the differences between what a variety exports to a new destination and the average exports of incumbent firms selling the same product in that market. This way, this term can be regarded as the relative contribution these expanding varieties. The second term is a counterfactual contribution, which would happen if these expanding varieties sold as much as what incumbents do. I compute these components for varieties expanding to destinations that exhibit extended gravity and those that don't. A comparison of the term $X_{ikjt} - \bar{x}_{kjt}$ for both groups reveals that on average, varieties that expand to destinations with extended gravity export initial values that are closer to those of incumbents. Tables 4

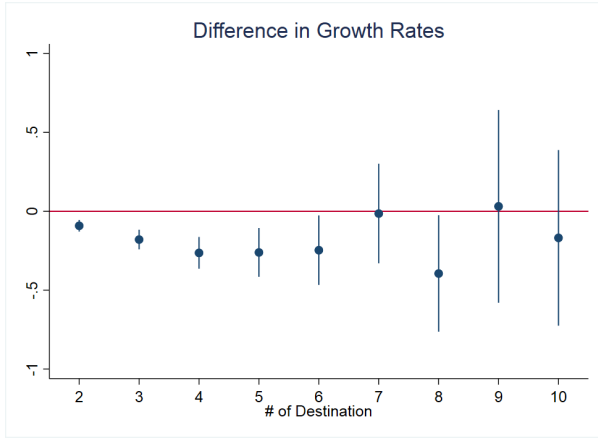
Figure 3: Impact of extended gravity on the dynamics of growth and failure rates



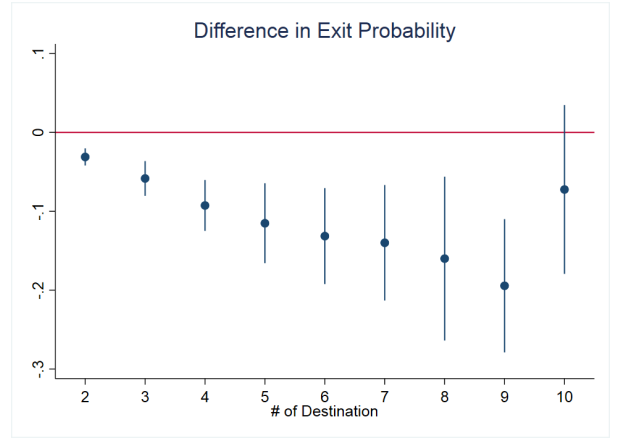
(a)



(b)



(c)



(d)

Plot of the coefficients estimated from equation (2) for the growth rate and exit probability. Coefficients are expressed relative to the omitted dummy for the 1st destination. Panels (a) and (b) present the series of growth for destinations with and without extended gravity. Panels (c) and (d) plot the difference between groups, including the confidence intervals for the coefficients.

Table 4

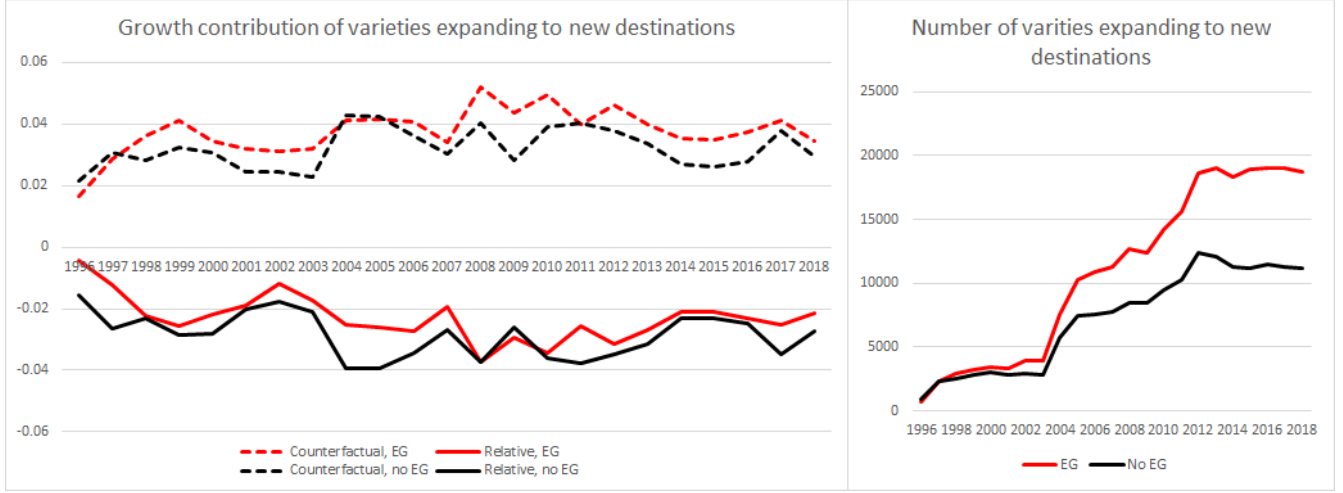
	$X_{ikjt} - \bar{x}_{kjt}$
<i>ExtGrav</i> _{<i>ikjt</i>}	220,414.5*** (55,059)
Constant	-641,294.6*** (34,486.4)
Obs	417,103
FE	<i>Firm</i> \times <i>Prod</i> \times <i>Year</i>
R^2	0.793

Table 5

Percentiles	No EG	EG	\bar{x}
1%	-10,800,000	-7,058,918	295
5%	-2,508,950	-1,271,702	1,580
10%	-1,039,633	-486,769	4,037
25%	-216,532	-94,781	19,863
50%	-29,212	-15,240	121,413
75%	-2,644	-1,247	589,301
90%	5,821	8,263	2,047,924
95%	34,365	40,883	4,054,824
99%	443,435	456,806	16,800,000
Mean	-695,413	-384,969	1,216,929

shows the results of a regression of the relative exports on a dummy for extended gravity and firm-product-year fixed effects. The outcome suggests that the initial exported value of firms that reach a new destination are closer to the incumbents' exports when the destination shares some characteristic with that variety's previous markets. Table 5 contains various percentiles of the distribution of relative exports for both groups and that for incumbents' average exports. The distribution for those with extended gravity is to the right of those destinations without. On average, the former enter new destinations exporting two thirds of what incumbents sell, while the latter do it at half the value. Figure 4 plots the result of the decomposition. The relative contribution is negative for both groups, but it is larger in absolute terms for destinations that don't have extended gravity, even when the amount of varieties adding destinations is smaller for this group. This comparison suggests there is room for a larger post-entry adjustment, which is consistent with the idea that knowledge is more easily carried to destinations that share some attribute with previous markets.

Figure 4



3 Model

This section describes a model of demand learning for an open economy in a monopolistic competition environment. A firm's demand level is subject to preference shocks that consist of a time-invariant variety-specific component and a noise component. The learning mechanism allows firms to learn about their unobserved demand level in a similar way to that in Jovanovic (1982). For a closed economy, the model was introduced by Arkolakis et al. (2018). I describe the model for an open economy where I allow a firm to carry its knowledge across export destinations. This is, what a firm learns about its unobserved demand in a given market is informative of its unobserved demand in other markets. Given the monopolistic competition environment, I do not allow firms to learn from other varieties than their own. To simplify, I will assume that there are only two destinations. In what follows I describe the environment, the consumer's decision and the firm's static and dynamic problems.

3.1 Environment

Time is discrete and denoted by t . The economy consists of two symmetric countries denoted by $i = 1, 2$. Each country is populated by a continuum of consumers of mass L . Consumers derive utility from the consumption of a

continuum of varieties which aggregate to a total consumption C_{it} . Their utility function is

$$U_i = \sum_{t=0}^{+\infty} \beta^t \ln(C_{it}) \quad (4)$$

where β is the discount factor. Varieties $c_{it}(\omega)$ are aggregated using a constant elasticity of substitution aggregator with elasticity of substitution $\sigma > 1$

$$C_{it} = \left(\int_{\omega \in \Omega_{it}} (e^{a_{it}(\omega)})^{\frac{1}{\sigma}} c_{it}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}} \quad (5)$$

where Ω_{it} is the continuum of varieties available in country i at time t ; $a_{it}(\omega)$ is a preference shock for variety $\omega \in \Omega_{it}$ at time t in country i . The realization of the preference shock for each variety is determined by a time invariant component, $\theta_i(\omega)$, and a white noise shock, $\varepsilon_{it}(\omega)$ given by

$$a_{it}(\omega) = \theta_i(\omega) + \varepsilon_{it}(\omega), \quad \varepsilon_{it}(\omega) \sim N(0, \sigma_\varepsilon^2) \quad i.i.d$$

The time invariant component of the preference shock is what firms seek to learn about. It can be interpreted as an unobserved demand parameter that is subject to shocks $\varepsilon_{it}(\omega)$. This shocks are independent over time and across varieties. Moreover, to preserve the symmetry, the shocks are independent and identically distributed across countries. Upon entry, firms draw their unobserved demand parameter, $\theta_i(\omega)$ from a normal distribution with mean $\bar{\theta}$ and variance σ_θ^2 .

Firms maximize the expected present value of their profits. All firms have the same discount factor equal to that of consumers, β . There are no sunk costs of entry to neither market. Firms are heterogeneous in their productivity level, $\varphi(\omega)$, which is drawn upon entry and is time-invariant. As incumbent firms learn about demand, each period they make a decision of whether to stay in the market or exit endogenously based on the sum of the expected discounted profits that corresponds to their current belief about demand. Exogenous exit occurs with probability δ . A firm that stays, decides whether to supply in the domestic market only or to supply both domestic and export markets, again based their current belief about demand. Firms decide the quantity produced monopolistically, $q_{it}(\omega)$. Output is produced with a constant returns to scale technology where labor is the only input and there is

a fixed cost of production that depends on which market is production destined to; f for the domestic market and f_x for the export market, with $f < f_x$ ⁴.

I let the time invariant component of the preference shocks for a certain variety, $\theta_i(\omega)$, to be correlated across countries. Firms are assumed to know this correlation, and leverage their learning about the demand in one destination to be informative of what the demand is in the other country. For simplicity, I assume that $\theta_1(\omega) = \theta_2(\omega) = \theta(\omega)$.

The timing is as follows: Potential entrants draw their productivity and unobserved demand parameter and decide whether to enter or exit. Incumbents decide whether to stay, which markets to sell in and what quantities or exit endogenously. Firms exit the market exogenously with probability δ . Firms pay the fixed costs, produce and deliver the goods to the market. The demand shock realizes and the price adjusts to clear the good's market. Firms learn about demand from the realized price and update their belief about their unobserved demand parameter.

The structure for the model allows for two intuitive types of behavior. The first is that firms might enter two markets in order to learn faster, as they observe an additional demand realization. The second is that firms might wait until they learn enough in the domestic market to begin selling in the foreign market, since demand in the former is informative about demand in the latter. These decisions rely on a firm's ability to bear losses in order to learn about demand, which in the dynamic framework are compensated by the "value of learning".

3.2 Consumers

Consumers are endowed with one unit of labor, which is inelastically supplied and receive a wage, w_t . Each consumer owns an equal share of domestic firms. Utility maximization subject to their budget constraint consists of choosing the consumption levels, $c_{it}(\omega)$ to maximize equation (4), taking prices as given. The demand for each variety is

$$q_{it}(\omega) = e^{a_{it}(\omega)} p_{it}(\omega)^{-\sigma} \frac{Y_{it}}{P_{it}^{1-\sigma}} \quad (6)$$

⁴Since the only difference between markets is the fixed cost of production and production is CRS, firms will never find it optimal to sell in the export market only. Hence, firms decision is between selling in domestic only, or in both markets, as previously stated.

where Y_{it} is the aggregate expenditure level and P_{it} is the aggregate price index given by

$$P_{it}^{1-\sigma} = \int_{\omega \in \Omega_{it}} e^{a_{it}(\omega)} p_{it}(\omega)^{1-\sigma} d\omega \quad (7)$$

3.3 Firms

Firms that decide to sell in a given period decide how much to produce before the demand shock is realized. Hence, the quantity decision is based on the belief a firm has about demand, which is formed from past observed shocks. Since the quantity supplied does not affect the extent to which firms learn about demand, the quantity choice is a static one. On the other hand, the choices of whether to stay or exit and which markets to sell in, are dynamic. For this decision, firms take into account profits in the current period and the expected discounted profits which are affected by the learning process. These dynamic considerations give rise to the value of learning by observing demand realizations. In other words, a firm might find it optimal to make a loss in the current period in order to learn about demand and make profit in the future, which will more than compensate the loss (in expectation).

To describe the firm's problem I will first introduce the belief updating process and describe the state variables that determine which information is available to the firms when they make their decisions. Then I will describe the static problem of the quantity choice and lastly the entry and exit decision. In what follows, I will drop the variety index ω .

3.3.1 Belief updating

Given the structure of the preference shock, $a_{it} = \theta + \varepsilon_{it}$, the mean of the observed shocks, denoted by \bar{a} , contains all the relevant information in order for a firm to form a belief about its unobserved demand parameter, θ . Each period, the information available to a firm at the time to make a decision consists of three variables: (i) The productivity level φ , (ii) the mean of the observed shocks, \bar{a} , and (iii) the number of observed shocks, denoted by n . In both, the static and the dynamic problems, the firm has to take expectation over the preference shock that is about to realize, conditional on what is currently known. In the static problem since the demand includes the term $e^{a_{it}}$, and in the dynamic problem since it must consider what the state variable, \bar{a}' , will be the next period. Using Bayes'

rule, the distribution of the unobserved demand parameter, conditional on the state variables of a firm is

$$\theta|\bar{a}, n \sim N(\mu_n, \nu_n^2)$$

where

$$\mu_n = \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + n\sigma_\theta^2} \bar{\theta} + \frac{n\sigma_\theta^2}{\sigma_\varepsilon^2 + n\sigma_\theta^2} \bar{a}$$

$$\nu_n^2 = \frac{\sigma_\varepsilon^2 \sigma_\theta^2}{\sigma_\varepsilon^2 + n\sigma_\theta^2}$$

Note that, as the number of observed shocks goes to infinity, the posterior belief converges to a degenerate distribution centered in \bar{a} which by the law of large numbers converges in probability to the true value of θ .

3.3.2 Quantity decision

The profit maximization problem of the firm selling is

$$\max_{q_t^i} \sum_i E_{a_t^i|\bar{a}, n} [p_t^i(a_t^i) q_t^i] - q_t^i \frac{w}{\varphi} - w f^i \quad (8)$$

subject to

$$p_t^i(a_t^i) = \left(\frac{e^{a_t^i} Y^i}{q_t^i} \right)^{\frac{1}{\sigma}} P^i \frac{\sigma - 1}{\sigma} \quad (9)$$

Under the assumptions about the correlated demands and the symmetry of the noise distributions, the optimal quantities in both markets are identical and given by

$$q_t^e(\varphi, \bar{a}, n) = q_t(\varphi, \bar{a}, n) = \left(\frac{\sigma - 1}{\sigma} \right)^\sigma (b(\bar{a}, n))^\sigma \left(\frac{\varphi}{w} \right)^\sigma \frac{Y}{P^{1-\sigma}} \quad (10)$$

where

$$b(\bar{a}, n) \equiv E_{a_t^i | \bar{a}, n} [e^{\frac{a_t}{\sigma}}] = \exp \left\{ \frac{\mu_n}{\sigma} + \frac{1}{2} \frac{\nu_n^2 + \sigma_\varepsilon^2}{\sigma^2} \right\} \quad (11)$$

Note that the size of a firm depends not only on its productivity level, but also on its belief about demand. This will become an important feature when analyzing the growth rate of a firm. In particular, it will generate age dependence.

The market clearing prices are given by

$$p_t^i(a_t^i, \varphi, \bar{a}, n) = \frac{\sigma}{\sigma - 1} \frac{w}{\varphi} \frac{e^{\frac{a_t^i}{\sigma}}}{b(\bar{a}, n)} \quad (12)$$

and the expected per period profits in each market are

$$E\pi(\varphi, \bar{a}, n) = \frac{(\sigma - 1)^{\sigma-1}}{\sigma^\sigma} (b(\bar{a}, n))^\sigma \left(\frac{\varphi}{w} \right)^{\sigma-1} \frac{Y}{P^{1-\sigma}} - wf \quad (13)$$

3.3.3 Entry and exit decision

The dynamic problem faced by the firms is to decide which markets to sell in, if they decide to stay, or to endogenously exit. The value of a firm consists of the per period expected profits and the expected discounted value of the firm in the following period. For a firm that observed n demand shock realizations with mean \bar{a} and has a productivity level φ , this value is given by

$$V(\varphi, \bar{a}, n) = \max \left\{ \begin{aligned} &E\pi(\varphi, \bar{a}, n) + \beta(1 - \delta)E_{\bar{a}' | \bar{a}, n} V(\varphi, \bar{a}', n + 1), \\ &E\pi(\varphi, \bar{a}, n) + E\pi^e(\varphi, \bar{a}, n) + \beta(1 - \delta)E_{\bar{a}'' | \bar{a}, n} V(\varphi, \bar{a}'', n + 2), \\ &0 \end{aligned} \right\} \quad (14)$$

The first term is the value of choosing to sell in the domestic market only. The firm earns the per period expected profit $E\pi_1$ and the discounted expected value of making the same decision with an additional demand observation

that results in a mean \bar{a}' of observed shocks. The second term is the value of choosing to sell in the domestic and export markets. The firm earns the per period expected profit in both markets, $E\pi_1$ and $E\pi_2$ and the discounted expected value of making the same decision with two additional demand observations that result in a mean \bar{a}'' of observed shocks. Finally, the third term is the value of exit which is normalized to zero. An important feature of the learning process is that a firm can stay even if the expected profits are negative. This option gives rise to outcomes where firms export for a small amount of periods and quits even though its productivity does not change over time. Learning in just one market can lead to outcomes where a firm expands only after a number of periods, again without productivity growth. Moreover, a firm might have incentives to explore a market just because there is a possibility of expanding in the future that will make up for the loss incurred to learn.

The solution to the dynamic problem of the firm is characterized by a set of thresholds for the state variables. For incumbents the thresholds are for the mean of the observed demand shocks, \bar{a} . A firm with productivity level φ and n observed shocks stays in the domestic market if $\bar{a} \geq \bar{a}^*(\varphi, n)$ and exports if $\bar{a} \geq \bar{a}_x^*(\varphi, n)$. These thresholds obtained by comparing the value of selling in the domestic market to that of exit and to the value of selling in both markets. This is,

$$0 = E\pi_1(\varphi, \bar{a}^*(\varphi, n), n) + \beta(1 - \delta)E_{\bar{a}'|\bar{a}^*(\varphi, n), n}V(\varphi, \bar{a}', n + 1) \quad (15)$$

$$0 = E\pi_2(\varphi, \bar{a}_x^*(\varphi, n), n) + \beta(1 - \delta)\left[E_{\bar{a}''|\bar{a}_x^*(\varphi, n), n}V(\varphi, \bar{a}'', n + 2) - E_{\bar{a}'|\bar{a}_x^*(\varphi, n), n}V(\varphi, \bar{a}', n + 1)\right] \quad (16)$$

On the other hand, entrants do not have observed shocks when they make their decision. Since all entrants draw their unobserved demand parameter from the same distribution, they all start with the same prior belief that θ is distributed normal with mean $\bar{\theta}$ and variance σ_θ^2 . Hence, entrants expectation of $e^{\frac{a}{\sigma}}$ is

$$b_0 \equiv E_{a|\bar{\theta}, 0}[e^{\frac{a}{\sigma}}] = E_{a^e|\bar{\theta}, 0}[e^{\frac{a^e}{\sigma}}] = \exp\left\{\frac{\bar{\theta}}{\sigma} + \frac{1}{2}\frac{\sigma_\theta^2 + \sigma_\varepsilon^2}{\sigma^2}\right\} \quad (17)$$

Since entrants are heterogeneous in their productivity level, there are two thresholds, φ_1^* and φ_2^* , that determine entry to markets 1 and 2 respectively. In the absence of sunk entry costs, all potential entrants draw their productivity

and those with a draw below φ_1^* exit immediately. These thresholds are characterized by

$$0 = E\pi(\varphi_1^*, \bar{\theta}, 0) + \beta(1 - \delta)E_{\bar{a}'|\bar{\theta},0}V(\varphi_1^*, \bar{a}', 1) \quad (18)$$

$$0 = E\pi^e(\varphi_2^*, \bar{\theta}, 0) + \beta(1 - \delta) \left[E_{\bar{a}''|\bar{\theta},0}V(\varphi_2^*, \bar{a}'', 2) - E_{\bar{a}'|\bar{\theta},0}V(\varphi_2^*, \bar{a}', 1) \right] \quad (19)$$

3.4 Endogenous exit

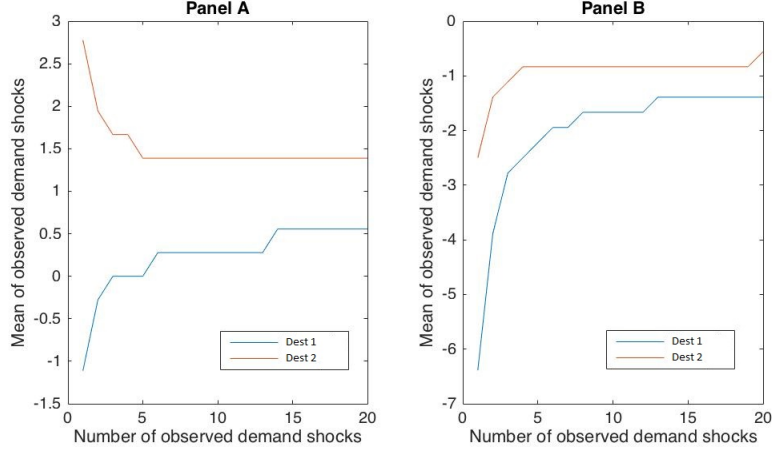
In this section I describe the endogenous exit policy functions. Given the nature of the dynamic problem of entry and exit, the model cannot be solved in a closed form. Instead, I simulate a sample of firms and analyse the implications of the model numerically. Figure 5 shows the exit thresholds of a firm as a function of the number of observed demand shocks. Panel A plots the policy functions of a firm with productivity $\varphi < \varphi_2^*$ and panel B plots those of a firm with productivity $\varphi \geq \varphi_2^*$. By definition, all incumbent firms have a productivity above φ_1^* , the threshold for entry to the domestic market. As firms observe more demand shocks, their belief about the time invariant parameter θ becomes more accurate. When firms have few observations, a low mean can be driven by the noise shock, and it is not very informative of the true demand. When the number of observations increases, low values for the mean of observed shocks imply that most likely the true demand is low. As a result, the threshold for exit in the domestic market is increasing. A firm with a low productivity (Fig.5 Panel A), that enters one market only, must observe large demand realizations to believe that it is worth to expand. As the number of observations increases, the noise washes off and the threshold decreases, meaning that high values of the observed demand result in expansion. Firms with high productivity level (Fig.5 Panel B) are incumbents in both markets, so that the threshold behaves in the same way described for the exit.

4 Predictions of the model

In this section I describe the predictions of the model. The first is about the patterns that the model generates for the growth rate of the firms. The second prediction is about the patterns of entry and survival.

Proposition 1. *The expected growth rate of a firm declines in the number of observed demand shocks, conditional on size.*

Figure 5: Exit thresholds. Source: Model simulation

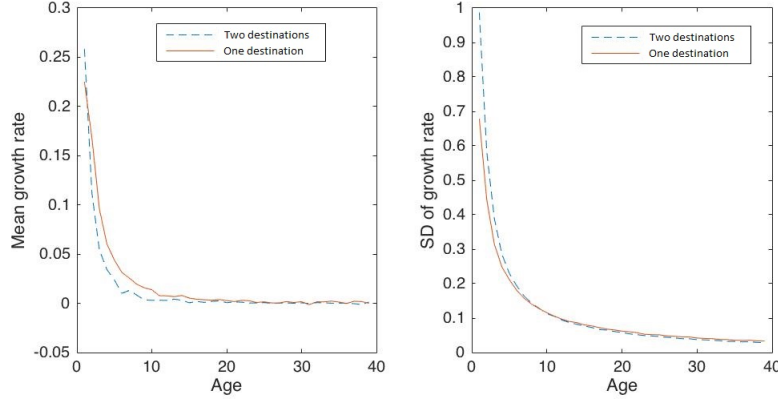


Proof. Appendix □

To understand this result note that ν_n^2 , the variance of the belief about the demand parameter, declines in the number of observed shocks. As a result, the function $b(\varphi, n)$, defined in equation (10), changes by a larger amount for small n than for large n . Since the optimal quantity (eq. 9) chosen by the firms is convex in this function (i.e. b^σ), the expectation about future output puts more weight on large increases of the function $b(\varphi, n)$ than on large declines. Hence, a highly volatile belief translates into a large growth rate.

The result in Proposition 1 implies that the growth rate of a firm declines in age, since firms in this model cannot become older without observing demand shocks. In this framework however the possibility to learn from many markets allow for different combinations of age and number of observe shock. This heterogeneity is suitable to test for the implications of this model and contrast them with the data as a validation of the mechanisms that drive the dynamics of the growth rate described in the main facts. The first prediction is based on the fact that firms can enter the exports market in order to learn more. If this is the case, the number of observed shocks will increase twice as fast as the age of the firm. This implies that a young firm can still experience a rapid decline of its growth rate. This effect is stronger if there are more destinations from which learning can be leveraged. The second prediction is based on the firms that lag their entry to the exports market and learn about demand selling in the domestic market before expanding. Upon entry to the exports market, this firms are technically young in

Figure 6: Mean and Standard Deviation of the growth rate. Source: Model simulation



the new destination but their growth rate should be lower the longer they waited to enter.

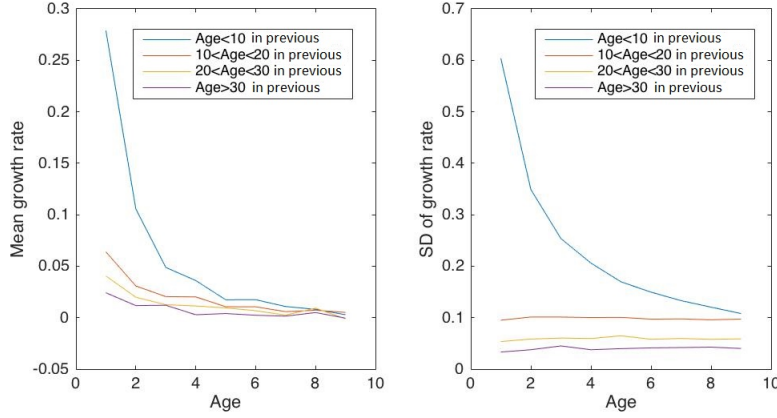
In figure 6 I split the simulated sample into firms that operate in one market only and those who export to both markets and calculate the mean and standard deviation of the growth rate across the tenure in these markets.

Figure 7 plots the mean and standard deviation of the growth rate in the second market across the simulated firms for different bins of ages in the first market. Firms that are older in previous markets have lower growth rates in the current market. The results suggest that, in the presence of multi-market demand learning, different expansion strategies should translate into the patterns shown in figures 6 and 7 on the evolution of growth rates. These patterns are consistent with those found in the empirical literature: the growth rate declines in age. The novelty lies in the new margin of heterogeneity introduced by looking at (i) the number of destinations a firm sells to and (ii) the age of the firms in other destinations.

These mechanisms represent heterogeneous strategies that might be contributing to the occurrence of the patterns documented in my empirical assessment on knowledge accumulation. Since the model was written to address the decline in growth, I can contrast the outcomes of these simulations with the data on Mexican exporters to validate the model.

I explore the possibility that learning from multiple destinations results in a larger decline of the growth rate from one period to the next using the following empirical specification

Figure 7: Mean and Standard Deviation of the growth rate. Source: Model simulation



$$g_{ikjt} = \alpha + \sum_n \beta_n \times dest_{ikjt}^n \times 2nd_{ikjt} + \sum_n \phi_n \times dest_{ikjt}^n + \gamma_t + \delta_{size(kjt)} + \delta_{hs2(k)} + \varepsilon_{ikjt} \quad (20)$$

where $dest_{ikjt}^n = 1$ if a firm exports to n destinations and $2nd_{ikjt} = 1$ if a firm is experiencing its 2nd growth episode. Table 6 shows that the estimated coefficients follow a pattern where observing more observations induces a larger decline in the growth rate from one period to the next. The coefficients for one, two and three observations are not significantly different, but learning from four and five destinations does generate a significant difference. These results suggest that the mechanism from the model can potentially play a role in the dynamics of new exporters as their entry and expansion strategy regarding the number of destination that they learn from is likely to affect the amount of knowledge they acquire. In this context, heterogeneous firms can decide to learn from less sources if it results too costly, but if they can afford a larger amount of signals, they might want to front-load the knowledge accumulation by entering several destinations simultaneously.

To assess whether increased past experience results in a lower first period growth rate when new destinations are reached, I will focus on a particular set of exporters: Those that begin by exporting to one country only and later expand. I will consider a specification to compare the initial growth rates between the first and second destination:

Table 6

	$\Delta \log(Exports)$	Test	P-value
β_1	-0.435*** (0.007)		
β_2	-0.441*** (0.014)	$\beta_1 = \beta_2$	0.6776
β_3	-0.442*** (0.020)	$\beta_1 = \beta_3$	0.7172
β_4	-0.490*** (0.026)	$\beta_1 = \beta_4$	0.0412
β_5	-0.528*** (0.030)	$\beta_1 = \beta_5$	0.0027
Observations	760410		
R^2	0.024		

$$g_{ikjt} = \alpha + \sum_n \beta_n \times past_obs_{ikjt}^n \times 2nd_{ikjt} + \sum_n \phi_n \times past_obs_{ikjt}^n + \gamma_t + \delta_{size(kjt)} + \delta_{hs2(k)} + \varepsilon_{ikjt} \quad (21)$$

where $past_obs_{ikjt}^n = 1$ if a firm enters the second destination with n past observations and $2nd_{ikjt} = 1$ if j is the firm's 2nd destination. Table 7 shows that a decreasing pattern arises for this exercise as well. However, the comparison of the coefficients suggests that varieties that accumulate a larger amount of observations does not necessarily have a larger decline in the initial growth rate when comparing its first and second destination. This finding is at odds with the simulation from the model. A possible explanation is that firms do not learn at the same rate, or that there are different degrees of uncertainty. In the model, all entrants have the same prior, so their adjustment in the first period is on average the same, conditional on exporting to the same amount of destinations and being of the same size. A glance at the first growth episode for firms with heterogeneous delays reveals that firms that took longer to expand to subsequent destinations exhibit larger growth rates. Table 8 contains the estimates for this growths as picked up by the ϕ coefficients in equation (21). These coefficients are expressed relative to the initial growth rate of the firms that took one year to expand. The significance of this estimates suggests that firms that without necessarily planning that their expansion would take longer, had an actual larger growth rate upon entry and survival. Even though this is at odds with the prediction of the model, this is because of the assumption

Table 7

	$\Delta \log(Exports)$	Test	P-value
β_1	-0.331*** (0.022)		
β_2	-0.357*** (0.038)	$\beta_1 = \beta_2$	0.561
β_3	-0.305*** (0.055)	$\beta_1 = \beta_3$	0.6693
β_4	-0.332*** (0.070)	$\beta_1 = \beta_4$	0.9835
β_5	-0.476*** (0.085)	$\beta_1 = \beta_5$	0.0994
β_6	-0.299** (0.107)	$\beta_1 = \beta_6$	0.7686
β_7	-0.419*** (0.126)	$\beta_1 = \beta_7$	0.49
β_8	-0.521*** (0.144)	$\beta_1 = \beta_8$	0.1914
Observations	49553		
R ²	0.115		

Table 8

$\Delta \log(Exports)$	ϕ_2	ϕ_3	ϕ_4	ϕ_5	ϕ_6	ϕ_7	ϕ_8
	0.0249 (0.0233)	0.0680* (0.0295)	0.0730* (0.0353)	0.208*** (0.0413)	0.229*** (0.0503)	0.231*** (0.0585)	0.196** (0.0661)
Observations	49553						
R ²	0.115						

that there is no heterogeneity in the learning process. Alternatives such as the possibility that expansion requires certain amount of learning are consistent with both, this finding and the empirical facts that motivated the model in the first place.

5 Conclusion

I explore the dynamics of Mexican exporters upon entry to foreign markets using a strategy where they enter destinations sequentially. First, I document that the decline in average growth and failure rates also holds across

destinations, suggesting that the knowledge that a firm acquires in a market can be carried to subsequent destinations. The first destination chosen by new exporters is typically familiar in the sense that it shares a border or a language with Mexico and the knowledge is more easily carried to destinations that share such attributes with previous markets.

I present a model of multi-market demand learning in the spirit of Jovanovic (1982) for an open economy to simultaneously reconcile the age dependence of firms' growth and the patterns of sequential entry to export destinations documented in the literature. Each of these facts has been studied in the past decade, but little attention was paid to their intersection. The introduction of demand accumulation that can be carried across markets allows me to give a separate treatment to a firm's age and the number of demand realizations a firm has observed in the past. I use a simulation of the economy in this environment to analyse the outcome of the model regarding i) the accumulation of knowledge in multiple destinations and ii) the delay in expansion to new destinations. Contrasting these results with the data allows me to validate and discuss the mechanisms that suggest there might be some degree of knowledge accumulation guiding the dynamics of new exporters.

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Appendix

A Proof of Proposition 1

Without endogenous exit, the expected growth rate of a firm conditional on its size q_t is

$$E_{\bar{a}'|\bar{a}}\left(\frac{q_{t+1}(\varphi, \bar{a}', n+j)}{q_t(\varphi, \bar{a}, n)}\right) \quad for \quad j = 1, 2 \quad (22)$$

where j is determined by the decision to enter either the domestic market only or both domestic and foreign. Using the optimal quantities in equation (9), we can substitute to get

$$E_{\bar{a}'|\bar{a}}\left(\frac{b(\bar{a}', n+j)^\sigma}{b(\bar{a}, n)^\sigma}\right) \quad for \quad j = 1, 2$$

Using the definition of the belief $b(\cdot)$ from equation (10), the growth rate can be written as

$$E_{\bar{a}'|\bar{a}}\left(\frac{\exp\left\{\mu_{n+j} + \frac{1}{2}\frac{\nu_{n+j}^2 + \sigma_\varepsilon^2}{\sigma}\right\}}{\exp\left\{\mu_n + \frac{1}{2}\frac{\nu_n^2 + \sigma_\varepsilon^2}{\sigma}\right\}}\right) \quad for \quad j = 1, 2$$

Using the properties of the conditional normal distribution, and the Bayesian updating process for the belief, we have that

$$\begin{aligned} E_{\bar{a}'|\bar{a}}(\mu_{n+j}) &= \mu_n \\ Var_{\bar{a}'|\bar{a}}(\mu_{n+j}) &= \frac{\sigma_\theta^4 j(j\nu_n^2 + \sigma_\varepsilon)}{(\sigma_\varepsilon + (n+j)\sigma_\theta^2)^2} \end{aligned}$$

where

$$\nu_n^2 = \frac{\sigma_\varepsilon^2 \sigma_\theta^2}{\sigma_\varepsilon^2 + n\sigma_\theta^2}$$

Hence, the expected growth rate can be written as

$$E_{\bar{a}'|\bar{a}}\left(\frac{q_{t+1}(\varphi, \bar{a}', n+j)}{q_t(\varphi, \bar{a}, n)}\right) = \frac{\exp\left\{\mu_n + \frac{1}{2} \frac{\sigma_\theta^4 j(j\nu_n^2 + \sigma_\varepsilon)}{(\sigma_\varepsilon + (n+j)\sigma_\theta^2)^2} + \frac{1}{2} \frac{\nu_{n+j}^2 + \sigma_\varepsilon}{\sigma}\right\}}{\exp\left\{\mu_n + \frac{1}{2} \frac{\nu_n^2 + \sigma_\varepsilon}{\sigma}\right\}} = \exp\left\{\frac{1}{2} \frac{\sigma_\theta^4 j(j\nu_n^2 + \sigma_\varepsilon)}{(\sigma_\varepsilon^2 + (n+j)\sigma_\theta^2)^2} + \frac{1}{2} \frac{\nu_{n+j}^2 - \nu_n^2}{\sigma}\right\}$$

Using the definition for ν_n , the expression for the growth rate can be rewritten as

$$E_{\bar{a}'|\bar{a}}\left(\frac{q_{t+1}(\varphi, \bar{a}', n+j)}{q_t(\varphi, \bar{a}, n)}\right) = \exp\left\{\frac{(\sigma-1)\sigma_\varepsilon^2\sigma_\theta^4}{2\sigma(\sigma_\varepsilon^2 + (n+j)\sigma_\theta^2)(\sigma_\varepsilon^2 + n\sigma_\theta^2)}\right\}$$

It is straightforward from the expression above that the expected growth rate decreases with the number of observed shocks n .