Exporter Survival with Uncertainty and Experimentation*

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Abstract

Two facts distinctively separate exporter dynamics from firm dynamics. One is the strikingly low survival rate of new entrants into export markets. The second is that new entrants survive less than re-entrants. We argue that these two facts are critical to discipline exporter dynamics models because many sources of firm heterogeneity (e.g. fixed costs) do not affect survival rates when firms time their entry decision optimally. We extend a standard exporter dynamics model by positing that firms experiment to resolve an uncertain component in foreign-market profitability. We estimate the model using customs data from Peru. Despite its parsimony, having only four relevant parameters, the model matches the survival profile of entrants and re-entrants. It is also sufficiently rich to deliver predictions about many exporter dynamics facts highlighted in the literature. Finally, we exploit variation across products and markets to provide additional evidence supporting the model's experimentation mechanism.

JEL codes: F10, F12, F14

Keywords: Exporter dynamics, uncertainty, experimentation, foreign demand, geometric Brownian motion.

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1 Introduction

Countries worldwide dedicate considerable resources, mainly through export promotion agencies and foreign embassy services, to helping firms establish a sustained presence in foreign markets. Underlying these policies is the view that increasing the number of domestic firms capable of achieving sustained exports is vital to fostering aggregate export growth and economic development. Academic research supports this view, showing that a considerable fraction of aggregate exports is accounted for by firms not exporting a few years earlier (Eaton et al., 2008; Freund and Pierola, 2010; Lederman et al., 2011). However, the effectiveness of these policy efforts may falter as the dynamics of new exporters are still not well understood.

A growing body of literature has developed models of exporter dynamics by analogy to the closed-economy firm-dynamics literature, emphasizing sunk cost and fixed costs, learning, customer capital, and financial frictions.[1] Two facts, however, distinctively separate exporter dynamics from domestic firm dynamics. The first fact is that most new exports into a market do not become established export businesses (Eaton et al. (2008) and Ruhl and Willis (2017), among others). Indeed, in most cases, there is no export activity during the year after entry. The second fact, documented in this paper, is that re-entrants survive more than first-time entrants. This fact is a core feature of exporter dynamics given that re-entry in export markets is pervasive (Blum et al., 2013; Arkolakis, 2016).

In this paper, we argue that survival moments that condition on the time of market entry, such as these two facts, are particularly useful to discipline models of exporter dynamics. The reason is that these moments are largely insensitive to time-invariant sources of heterogeneity that are critical to match exporter cross-sectional facts, such as firm-specific demand or fixed costs in each export market (Eaton et al., 2011). One core insight is that variation in these features - e.g. lower fixed costs - would not make a firm more successful than another in a given market; instead, the firm would start exporting earlier. Thus, by focusing on survival moments upon entry, we can learn about the key *dynamic* components of the firm's profitability process while allowing for arbitrary heterogeneity in the *static* components of firm profitability. This remark extends to any extensive margin moment - i.e. moments that depend on whether the firm actively exports at any point in time - that condition solely on entry. By contrast, other exporter dynamics facts, such as export growth or moments conditional on size, require taking a stand on the relationship between profits and sales and the static components of firm profitability, respectively.

Guided by these two facts, we build a parsimonious model of exporter dynamics. The model has two key ingredients. The first is a standard persistent process for firm profitability - see, e.g. Arkolakis (2016) - with firms timing their entry into export markets optimally to maximize expected profits. The second is uncertainty about foreign market profitability that can only be resolved by actively exporting (Segura-Cayuela and Vilarrubia, 2008; Freund and Pierola, 2010; Albornoz et al., 2012; Nguyen, 2012; Cebreros, 2016; Eaton et al., 2021). In the model, this takes the form of a

[1] See Alessandria et al. (2021a) for a survey.

one-time profitability boost to export profits, whose size and timing are uncertain to the firm.

The model naturally delivers the two distinctive exporter dynamics facts mentioned above. First, firms have an incentive to export at a loss in the hope of improving their profits, i.e. they go through an "experimentation" phase. Many of them, however, receive only a small ex-post profitability boost and thus exit. This explains the low survival rates. Second, since many re-entrants have already resolved their uncertainty during their initial export spell, they do not re-enter to experiment. Hence, their re-entry decision is more conservative and, as a result, they survive longer. We provide evidence in support of the central mechanism of the model by exploiting hypothesized variation in the degree of uncertainty by product and distance to the destination. The implied predictions of uncertainty variation on survival probabilities are upheld by the data.

The model has the virtue of its simplicity. In particular, the theoretical solution of the dynamic problem boils down to the implicit solution of one equation in one unknown. This simplicity facilitates a transparent understanding of the operating forces in the model and how they shape predicted exporter behavior. The model, whose parameters are estimated by simulated method of moments (SMM) using only the two distinctive exporter survival facts, does an excellent job explaining a class of extensive-margin moments - mostly related to survival and re-entry patterns. Another virtue of the model is its modularity. The model can easily accommodate alternative assumptions to study other moments related to exporter behavior while retaining the core constitutive elements of behavior on the extensive margin. Perhaps surprisingly, we show that even under the restrictive assumptions of CES demand and homogeneity in the time-invariant components of profitability (i.e. demand shifters and fixed costs), the model does a reasonable job explaining facts related to export sales growth as well as survival and growth conditional on size. The margins of mismatch are informative about additional model features that could help improve the model's performance regarding these facts.

We model a stylized uncertainty and experimentation mechanism embedded in a theoretical framework with otherwise standard elements. A firm is initially inexperienced in a given export market, with gross profits determined by an idiosyncratic time-varying component that follows a geometric Brownian motion (GBM) and a constant and idiosyncratic market-specific component. The evolution of gross profits is independent across export markets. Operation in a market requires paying a continuous, constant, and idiosyncratic fixed cost. Firms can enter and exit the market freely, i.e. there are no sunk costs. In the absence of experimentation, the decision to export is static: firms export whenever gross profits exceed fixed costs, as in Arkolakis (2016).

With experimentation, inexperienced firms make an additional consideration: their gross profits in the market may be boosted by a multiplicative shock ψ, an event that occurs with intensity λ. After the occurrence of this event, the firm becomes experienced and remains in that state for the remainder of its lifetime (in that market). While firms have different ψ ex-post, they are assumed to be identical ex-ante and draw ψ from the same Pareto distribution (with scale parameter greater or equal to 1). In other words, they are uncertain about how much and fast their profits will jump.

In this environment, the firm enters the foreign market even when operating profits are lower than fixed costs. It initially experiments at a loss to "learn" its long-run profitability ψ, expecting this profit boost to justify the initial investment. However, once the shock is received, the firm stays active only if operating profits are higher than fixed costs, as there is no further uncertainty to resolve. The shock ψ embodies two economic forces. On the one hand, the firm knows that, by experimenting, it will eventually become better at generating profits in the market; this is a "learning-by-exporting" component. Second, as ψ is stochastic, the firm is uncertain about how much better it will become at that time. In reduced form, the ψ shock captures that some sources of uncertainty can only be resolved by exporting. This modelling device is reminiscent of the learning-about-demand idea in the seminal model by Jovanovic (1982), albeit in a stylized "one-shot-learning" version.

Using the model, we formalize the argument above that survival probabilities upon entry are the critical moments for identification. First, we show that firms' decisions are characterized by a threshold strategy such that they export if and only if their idiosyncratic profitability is above some value. Then, we obtain a key analytical result, which is that those probabilities are independent of the market-specific idiosyncratic profit component and idiosyncratic fixed costs as firms time their entry and exit decisions as a function of these heterogeneous parameters precisely in a way that offsets the parameters' potential impact on survival probabilities. As a result, the latter are identical across firms as they only depend on common parameters, which alone determine some of the most important exporter dynamic features - particularly those based on the extensive margin of export behavior - and can be estimated without any information about the myriad of firm-specific parameters or even about the probability distribution that generates them.

While static differences across firms do not matter for survival, dynamic differences do. In our model, those differences stem from experience status. By looking at the differential average behavior between firms that enter a market for the first time, which are necessarily inexperienced, and firms that re-enter the market, only some of which are inexperienced, one can infer the importance of experimentation. In addition, we show that the "uncertain", rather than the "learning-by-doing" component of experimentation, explains the result. Indeed, we show analytically that if the magnitude of the profitability boost ψ - albeit not its timing - were known in advance by the firm, inexperienced firms would enter markets more conservatively than experienced firms, which would lead to a higher survival probability for first-time entrants - a counterfactual result. By contrast, when ψ is unknown, inexperienced firms take more risks than experienced ones, disproportionately lowering survival for first-time entrants. This effect is more pronounced the larger the variance of ψ, a result we use for our validation exercise exploiting variation in this variance across markets.[2]

We estimate the model using firm-level customs data of exports from Peru for the period 1993-2008. We calculate survival rates one to five years after entry for both entrants and re-entrants. These ten moments are then used to estimate the model's parameters with SMM. Despite its

[2]Another potential dynamic difference between entrants and re-entrants involves the size of sunk costs. However, under the natural assumption that re-entrants pay a smaller sunk cost, they are predicted to survive less, which is also a counterfactual result.

parsimony, the model accurately predicts the survival rates of entrants and re-entrants. Also, our estimates indicate that firms learn fast: a firm that continuously exports has a 21.6% probability of receiving the multiplicative shock within a month. The shock also has a considerable dispersion, which justifies the willingness of firms to experiment in foreign markets in the hope of benefiting from a good realization of this random variable.

A concern with the centrality played by experimentation in our model is that it is not an observed component of exporter behavior. Since we do not have direct evidence of experimentation, we take a two-pronged approach to argue for its empirical relevance.[3] First, we exploit variation in the type of products exported and the distance to the destination. If uncertainty is a key driver of the low survival rates of new entrants, then we would expect survival to be lower in differentiated products (relative to homogeneous products) and destinations farther away, both cases where we expect a higher degree of uncertainty about market profitability. These predictions hold in the data.[4] Second, we show that the model also performs well when fitting other standard untargeted moments often studied in the literature. In particular, it fits conditional survival and re-entry moments well, which, as those we use for estimation, are also determined by the "extensive margin". In addition, by making some restrictive auxiliary assumptions about model features over which we do not need to take a stand to generate our main predictions, we show that the model fits other moments used in the literature related to export growth and survival and growth conditional on size reasonably well. Here, however, there is sufficient mismatch to suggest the need to enrich the model, relaxing those restrictive auxiliary assumptions.

Related Literature This paper belongs to an extensive literature on exporter dynamics, surveyed in Alessandria et al. (2021a). In particular, it is most closely connected to a strand of the literature that argues that demand uncertainty is a defining feature of export markets (Albornoz et al., 2012; Nguyen, 2012; Akhmetova and Mitaritonna, 2013; Cebreros, 2016; Li, 2018; Berman et al., 2019; Eaton et al., 2021). Similar to these papers, our model includes a market-specific uncertain component that can only be resolved by exporting. We contribute to this literature in three ways. First, we develop a new framework that is tractable enough to deliver novel analytical results while at the same time being sufficiently rich to generate quantitative predictions about the main exporter dynamics facts highlighted in the literature. In particular, we identify a large class of relevant moments in the data that only depend on four model parameters and are robust to time-invariant sources of heterogeneity à la Eaton et al. (2011). In this regard, our framework complements complex structural models in this literature - notably Eaton et al. (2021) - with an alternative approach that prioritizes parsimony. Second, we document a novel fact on the difference between the survival rates of entrants and re-entrants. Our model implies that this fact provides critical evidence supporting an experimentation mechanism that helps resolve foreign market uncertainty.

[3] There is also evidence from exporter case studies emphasizing the lack of knowledge about export markets as a key hurdle to exporting (Artopoulos et al., 2013; Domínguez et al., 2023).

[4] Albornoz et al. (2016) show that firms survive more when they have experience in similar markets. While our model features independent markets, a simple extension of our model would naturally rationalize this result.

Third, we provide additional empirical evidence on the relevance of experimentation in exporter dynamics by exploiting differences in survival rates across markets and products.

Another strand of the literature studies economies with a learning-by-doing mechanism where exporters get better during the first years of their export experience (Schmeiser, 2012; Timoshenko, 2015; Ruhl and Willis, 2017; Alessandria et al., 2021b). Our model also features this channel, but it differs from these papers in that the size of the profitability improvement is uncertain. Importantly, we show analytically that a model where the size of improvement is deterministic has the opposite implications for survival probabilities. If firms get better by exporting but the size of the improvement is not stochastic, re-entrants would survive more, which is counterfactual.

Finally, we contribute to the literature on time-aggregation biases in export data by uncovering an additional source of bias on top of the well-understood partial-year effect (Bernard et al., 2017). Since survival rates are low, many exporters are close to the profitability threshold that makes exporting optimal, and thus spend part of the year - even years that are not the incursion ones - out of the export market. As a result, the fraction of the year the firm is "active" in the export market varies substantially across firms, especially among small and young ones. We show that this margin is quantitatively relevant for many moments of exporter dynamics. For example, early in their exporting experience, firms display a larger variance in their growth rates due to significant variation in the "fraction of time" within a given year that their profitability is above the export threshold.[5] Finally, we also show that the partial-year effect is also quantitatively relevant for other exporter dynamics moments beyond growth rates (Bernard et al., 2017), such as survival rates.

Outline The rest of the paper is organized as follows. Section 2 describes the two distinguishing facts about exporter survival that we emphasize in this paper. Section 3 sets up the model and derives predictions on survival probabilities. Section 4 discusses identification, describes the data and estimates the model. Section 5 tests for the uncertainty and experimentation mechanism of the model by looking at its implications across products and markets. Section 6 tests the model's predictions for untargeted moments commonly used in the exporter dynamics literature. Section 7 provides concluding remarks.

2 Two central facts about exporter survival

A vast amount of literature has established a number of facts about patterns of firm dynamics related to their survival (Mansfield, 1962; Evans, 1987; Dunne et al., 1988, 1989), growth rates (Hart and Prais, 1956; Mansfield, 1962; Evans, 1987; Hall, 1987; Dunne et al., 1989; Davis and Haltiwanger, 1992), and size distribution (Simon and Bonini, 1958; Cabral and Mata, 2003; Luttmer, 2007). A

[5] This new partial-year effect, which operates on the extensive margin, is closely connected to the decomposition of the intensive margin between number of shipments and sales per shipment (Alessandria et al., 2010; Kropf and Sauré, 2014; Hornok and Koren, 2015; Békés et al., 2017). Indeed, if the number of shipments is related to the amount of time a firm spends above the threshold, our model also has implications for this decomposition. See Appendix H for a formalization of this idea.

growing strand of literature has uncovered analogous patterns in the dynamics of firm exports. For example, smaller and younger exporters, like smaller and younger domestic firms, are less likely to survive and display higher growth rates conditional on survival (Eaton et al., 2008; Berthou and Vicard, 2015; Arkolakis, 2016). Also, the upper tail of the size distribution of export sales resembles a Pareto (Eaton et al., 2011; Arkolakis, 2016). Despite the notable similarities, two facts uniquely distinguish exporter dynamics. The first is that the survival profile (i.e. the line connecting survival rates at different horizons) of export entrants is low and flat. The second is that the survival profile of export re-entrants is higher than the survival profile of entrants. This section describes these two facts and discusses how they guide our search for a parsimonious model of exporter dynamics that can explain them.

First, we briefly discuss some definitions and basic data issues. We employ firm-level customs data from Peru for the period 1993-2008 graciously provided to us by the Trade and Integration Unit of the World Bank Research Department.[6] Our dataset covers all export shipments from Peru between 1993 and 2008 by firm and destination country (i.e. export market). We define an export "incursion" as the first entry of a firm in a given export market. The "survival rate" S_T is the proportion of incursions that are active in the corresponding export market T years after entry. We follow an incursion for up to five years. Hence, the "survival profile" is composed of the set of survival rates $\{S_T\}_{T=1,..,5}$. Since we do not observe data before 1993, we only consider incursions starting in 1997 to minimize the chances of falsely identifying as incursions export instances with an antecedent before 1993.[7] Also, since we track survival up to five years after entry, we restrict the sample to incursions starting no later than 2003. Our definition of survival does not impose consecutive activity as an exporter up to T. Thus, an incursion that exited at $T = 2$ but is active at $T = 3$ after re-entering the market is considered a survivor in the latter horizon.[8]

To deal with partial-year effects, we define firm-market-specific years. For every firm-market pair, we define the entry year starting with the date of the first shipment. For example, if a firm first exported to a market in June 3rd 1997, then the entry year is June 3rd 1997 - June 2nd 1998, the first year where we study survival is June 3rd 1998 - June 2nd 1999, and so on. In Appendix B, we present this paper's empirical results alternatively using annual data based on calendar years. The results are qualitatively similar; the main quantitative difference occurs in the first year, which becomes subject to the well-known partial-year effect (Bernard et al., 2017).

If the firm does not maintain a continuous presence in the market during all consecutive (firm-market-specific) years after the incursion, subsequent entries are defined as "re-entries". We define an export re-entry as the start of a new spell of exports to a destination by a firm that has exported

[6]The dataset was collected by this unit as part of their efforts to build the Exporter Dynamics Database. Details of its construction are described in the Annex of Cebeci et al. (2012).

[7]For example, incursions in 1997 would be false if the firm exported in the past but not in the last four years. Using the latest years in our database, we find the proportion of incursions that have exported in the past but not in the last four years to be 8.4%. As we consider incursions in later years, false incursions will arise only after a longer period of inactivity. For example, the proportion of false incursions is 3%(1%) when we firms are inactive for 7(10) years. Averaging across incursions in all years, we estimate the proportion of false incursions to be 3.3%.

[8]We consider alternative definitions of survival, e.g. continuous survival, in Section 6.1.

to that destination in the past but has not done so in the previous year. When studying the survival of the re-entrant firm, we consider years specific to that re-entry. That is, if the re-entry happened on November 30th 2001, then the re-entry year is November 30th 2001 - November 29th 2002, the first year where we study survival is November 30th 2002 - November 29th 2003, and so on. Note that, given our definition of survival, re-entries may also be instances of survival for the original incursion.[9]

A potential concern with our re-entrant definition is that some firms may be re-entrants not because of profitability but because of the natural frequency of shipments. In Appendix C, we exploit our shipment-level data to construct alternative definitions of re-entry based on the minimum time period elapsed between consecutive shipments (12 months, 18 months, 24 months). We find that the results presented below are robust to these alternative definitions.

Fact 1: The exporter survival profile is low and flat

Figure 1a shows the survival profile of export incursions in our dataset (solid-blue line). A striking feature of this profile is how low survival rates are. Only 29.4% of Peruvian export incursions are still active one year after entry. Five years after entry, the survival rate is 16.9%.[10] Another salient feature of the survival profile is the flat slope after $T = 1$. In contrast to the vast fraction of firms that exit just after entering the export market, further exit at longer horizons is considerably more gradual. As a reference, Figure 1a displays the survival profile of U.S. domestic firms as production units (dashed-red line).[11] Compared to exporter survival rates, domestic survival rates are substantially higher. The first year after entry, 77.9% of U.S. firms in an entry cohort are still in operation. Five years after entry, the survival rate is 49.1%.[12]

The slope of the exporter survival profile depicted in Figure 1a is not driven by compositional effects. Alternatively to the raw data used to display fact 1 in the figure, we can obtain the survival profile by controlling for other covariates in a regression framework. The results are displayed in Table A.1. First, we regress the survival status of incursions in each of the first five horizons on horizon dummies (column 1).[13] This exercise is equivalent to simply calculating the survival rate

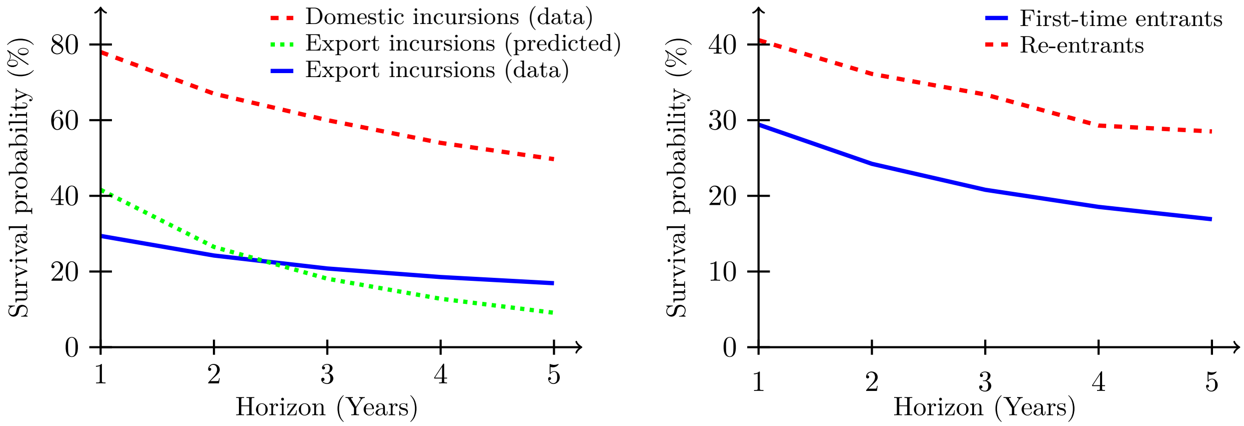
[9] Here, we focus on the first re-entry of an exporter whose incursion we observe. We do this for consistency with the estimation in Section 4. The results are very similar using all re-entrants and with alternative definitions of re-entry, including those based on calendar years (see Appendix B and C, respectively).

[10] Low survival rates are not specific to Peru. Using data from the Exporter Dynamic Database, Cebeci et al. (2012) report that the average and median one-year survival rates across 38 countries are both 43%. Splitting the sample into developed and developing countries, the average survival rate is 43% for each of the two groups. For Peru, they find a survival rate of 44%. Their reported rates are higher because they are calculated by merging all destinations into one aggregate export market.

[11] Domestic survival rates are computed using the number of firms by entry cohorts reported in the Business Dynamics Statistics (BDS) constructed by the Bureau of the Census. For comparison with export survival rates, we only consider tradable-firm producers (agriculture, mining, and manufacturing) in entry cohorts 1997-2004. The survival profile is almost unaffected if we include only manufacturing firms or firms in all remaining sectors. Note that these data are yearly, so we cannot correct for the partial-year effect.

[12] Domestic and exporter survival rates are not strictly comparable. While domestic survival rates capture persistence as an employer, exporter survival rates capture persistence as a seller in a specific market.

[13] Standard errors are computed by clustering at the firm level, allowing for arbitrary correlation between the survival status of incursions and re-incursions of a firm at any horizon and across markets.



(a) Survival profile: Domestic vs. exporter

(b) Survival profile: First entry vs. re-entry

Figure 1: Two key facts of exporter dynamics

per horizon, as we did in the figure.[14] Then, we add a set of fixed effects by product (2-digit Harmonized System) and destination-year (i.e. the country and year corresponding to the survival status).[15] We can see in column 2 that adding these flexible controls has a negligible impact on the estimated survival rates.

The fact that exporter survival rates are notoriously low has already been emphasized in the literature.[16] Freund and Pierola (2010), Albornoz et al. (2012), Nguyen (2012), and Eaton et al. (2021) provide a plausible explanation for this fact. If export profitability has an uncertain component that can only be resolved by actively exporting, firms have incentives to export as an experiment to resolve this uncertainty. Thus, export entry is consistent with low survival rates to the extent that firms do it as a bet on a relatively unlikely outcome. This is also the core mechanism in our model. As long as firms resolve their uncertainty sufficiently fast, this mechanism can explain both features of the exporter survival profile. It is low at early horizons because many firms exit soon after they find that exporting is not profitable. It is flat because firms that have received a favorable shock are less likely to exit afterwards.

As an additional reference, Figure 1a also displays the survival profile predicted by a special case of our model – *the benchmark model* – where this source of uncertainty is removed (dotted-green line).[17] As we can see in the figure, the benchmark model cannot predict the exporter survival profile observed in the data as it predicts survival rates that are too high early upon entry but too low at longer horizons. Despite the specificity of this special case, its inability to fit the exporter

[14]Year 1 is the base group, so to compute the numbers in the figure, one needs to add the constant and the corresponding horizon dummy.

[15]Since years are firm-market-specific, they involve more than one calendar year. Thus, for each firm-market incursion, we attribute the calendar year with the largest overlap, e.g. if the firm-market-specific year is May (October) 1st 1997 - April (September) 30th 1998, then we attribute the year 1997 (1998) for the purpose of the year fixed effect.

[16]See, among others, Eaton et al. (2008), Volpe Martincus and Carballo (2009), Nguyen (2012), and Ruhl and Willis (2017).

[17]Section 4.4 discusses the estimation of the benchmark model.

survival profile represents the implications of a broader family of firm and exporter dynamics models where profitability follows a persistent process. These models struggle to explain low survival rates at early horizons without also predicting a counterfactual steep survival profile.

Fact 1 has been key to motivating recent work on uncertainty and experimentation in models of exporter dynamics. Nevertheless, it is the novel fact we present next that, combined with fact 1, makes a substantially stronger case for the relevance of such models.

Fact 2: The survival profile is higher for re-entrants than for (first-time) entrants

Firms often temporarily cease to export only to re-enter the same market later. In our dataset, 20% of the incursions that exit a market re-enter that market within five years. Figure 1b compares the survival profile of re-entrants (dashed-red line) with the profile for (first-time) entrants (solid-blue line). Re-entrants have uniformly higher survival rates. Most of the difference already occurs in the first year after entry, when the survival rate is 40.6% for re-entrants versus 29.4% for entrants. Over longer horizons, this gap is preserved with only slight changes. Like fact 1, fact 2 is not driven by composition either. Columns 3 and 4 of Table A.1 display analogous results including re-incursions. In column 3, we include horizon dummies for re-entrants, which delivers the survival rates depicted in Figure 1b. In column 4, we include a full set of dummies by product and destination-year. Again, we find that these controls for composition do not substantially affect the survival profiles depicted in the figure.

Fact 2 has no corresponding analogue in the firm dynamics literature. As a matter of fact, we are not aware of any study that has computed re-entrant domestic survival rates. A likely reason is that instances of domestic re-entry are much more infrequent than in the case of exports and are typically either dismissed as a nuisance or tinkered with assuming them as measurement error.[18]

An appealing explanation for the higher survival rates of re-entrants arises naturally from the experimentation mechanism described above. Firms that exit and re-enter could have already resolved their uncertainty and, hence, do not enter to experiment. As their (re-)entry decisions are made with more accurate information about their potential profitability, they are more conservative about entering and, hence, tend to survive longer. Next, we build a model to formalize this idea.

3 The model

In this section, we develop a partial equilibrium model of firm export behavior. For tractability, we assume that firms' export decisions are independent across markets.[19] Next, we study the firm's

[18] Due to how "entry" is defined in standard firm dynamic databases (Baldwin et al., 2002), recorded re-entry instances might be spurious. For example, the BDS reports that re-entry instances represent 7% of incursions. However, since the database only includes firms with at least one employee in its payroll, a large fraction of this percentage probably comes from transitions in and out of employer status (Jarmin and Miranda, 2002).

[19] In our model, this can be microfounded using CES demand, linear variable costs, no interdependence in fixed costs across markets, and independence across markets in the market-firm-specific shifter ψ introduced below. Interdependence in export decisions substantially increases the theoretical and computational complexity of the problem (see Albornoz et al., 2016 for an analytical example and Alfaro-Urena et al., 2023 for a quantitative model).

problem in a given market. To economize on notation, we avoid firm and market subindexes.

3.1 Set up

Firms go through two stages in their lifetime as exporters in a given market. At first, they are *inexperienced* (i) and earn flow profits

$$\pi_i(\theta_t) = \left\{ \begin{array}{c} \kappa\theta_t - F \text{ if export at } t \\ 0 \text{ otherwise} \end{array} \right\}$$

where θ_t is a time-varying index of profitability, $\kappa > 0$ is a constant profitability parameter, and $F > 0$ is a fixed cost. These three determinants of export potential are firm-market specific. Time-varying profitability follows a geometric Brownian motion (GBM),[20]

$$d \log \theta_t = \mu dt + \sigma dZ_t. \tag{1}$$

Firms are born with profitability $\bar{\theta} > 0$. $\mu, \bar{\theta}$ and σ are common across firms.[21]

Since all firms are born with $\bar{\theta}$, κ is an index of initial profitability in the market. For example, a high value of κ may capture a better ability to make product adaptations that match export market idiosyncrasies based on a prior understanding of the market's demand features (Artopoulos et al., 2013). This parameter may also capture an advantage in communicating or conducting transactions with foreign agents at lower variable trade costs, e.g. due to family ties. The fixed expenses F represent the costs incurred in activities such as sustaining a distribution network and conducting marketing efforts in the foreign market, which are paid on a continual basis while exporting.[22]

For inexperienced firms, exporting yields additional benefits beyond receiving flow profits. Inexperienced firms know that their current profitability level in the export market is only transient and that they will eventually become *experienced* if they keep exporting. More specifically, while exporting, inexperienced firms become experienced (e) with intensity λ. An experienced firm earns flow profits

$$\pi_e(\theta_t; \psi) = \left\{ \begin{array}{c} \psi\kappa\theta_t - F \text{ if export at } t \\ 0 \text{ otherwise} \end{array} \right\}$$

where ψ is a firm-specific profitability shifter that is absent in the case of an inexperienced firm.[23]

[20] The profitability parameter θ_t can be microfounded as the combination of random processes for demand and productivity jointly determined by a multivariate GBM in a stationary competition environment with CES preferences. See Luttmer (2007).

[21] We assume that the firm's discount factor satisfies $r > \mu + \frac{1}{2}\sigma^2$ so that expected profits are finite, which is satisfied by our estimated values. Furthermore, to guarantee the existence of a stationary distribution, we follow Arkolakis (2016) and assume that the mass of firms that are born at each instant grows at rate $g_B > 0$. We could also assume an exogenous death rate $\delta > 0$. However, δ would directly affect survival probabilities while g_B does not.

[22] Note that we do not include entry sunk costs in the model, so firms may exit and re-enter markets freely. While this is an assumption made for simplicity, we argue in Section 4.4 that sunk costs are not necessary to obtain the qualitative predictions of the model, nor do they help improve its quantitative predictions.

[23] Alternatively, we could have modelled ψ affecting fixed costs rather than operating profits. This decision is

We assume $\psi \sim$ Pareto(ψ_m, α). The scale parameter ψ_m governs the potential for profit scaling up when the firm becomes experienced. We assume $\psi_m \geq 1$, which implies that being experienced is always desirable. The shape parameter α is the critical parameter in our model, as it governs the extent of uncertainty the firm faces. A lower value of α implies the distribution has a higher variance and fatter tails.

A key feature of our model is that ψ is unknown ex-ante by inexperienced firms. This captures the fact some sources of uncertainty are hard to unravel without actively participating in the targeted export market. For example, firms may be uncertain about the appeal of their products at the destination or their ability to engage the right distributors to push them in those markets (Eaton et al., 2021).

3.2 Entry and exit decisions

We assume the firm is rational and maximizes the present-discounted sum of its expected profits. The problem has three state variables: profitability θ_t, experience status $x \in \{i, e\}$, and, conditional on being experienced, the shifter ψ. Henceforth, it will be convenient to work with normalized profitability, defined as $\tilde{\theta}_t \equiv \frac{\kappa\theta_t}{F}$. By Ito's Lemma, $\tilde{\theta}_t$ is a GBM with the same parameters as θ_t.

The firm's problem is choosing an exporting policy $\{y_e(\tilde{\theta};\psi), y_i(\tilde{\theta})\}_{\psi,\tilde{\theta}}$ to maximize profits, where $y_e(\tilde{\theta};\psi)$ and $y_i(\tilde{\theta})$ are indicator variables that take a value of one if the firm exports and zero otherwise. We solve this problem in two steps. Since $x = e$ is an absorbing state, we first solve for the optimal policy of an experienced firm $\{y_e^*(\tilde{\theta};\psi)\}_{\psi,\tilde{\theta}}$. Then, we solve for the optimal policy $\{y_i^*(\tilde{\theta})\}_{\tilde{\theta}}$ of an inexperienced firm, taking into account that once it becomes experienced it will follow policy $\{y_e^*(\tilde{\theta};\psi)\}_{\psi,\tilde{\theta}}$.

The experienced firm In Appendix D.1, we show that the experienced firm's problem can be written as the solution to following Hamilton-Jacobi-Bellman (HJB) equation,

$$rV_e(\tilde{\theta};\psi)dt = \max_{y\in\{0,1\}} \left\{F\left(\psi\tilde{\theta} - 1\right)y\right\}dt + \mathbb{E}\left(dV_e(\tilde{\theta};\psi)\right) \tag{2}$$

This equation says that the return of the firm is the sum of the instantaneous profit flow plus the expected appreciation. Since future profitability is independent of the firm's actions and there are no exit or re-entry costs, the exporting decision only depends on whether current profits are non-negative. Thus, the firm's optimal policy is simply $y_e^*(\tilde{\theta};\psi) = 1$ if $\tilde{\theta} \geq \frac{1}{\psi}$ and $y_e^*(\tilde{\theta};\psi) = 0$ if $\tilde{\theta} < \frac{1}{\psi}$.

inconsequential in explaining facts related to exporter survival.

The inexperienced firm In Appendix D.1, we show that the inexperienced firm's problem can be written as the solution to the following HJB equation,

$$rV_i(\tilde{\theta})dt = \max_{y\in\{0,1\}} \left\{ F\left(\tilde{\theta} - 1\right) + \lambda\left(\mathbb{E}_\psi V_e(\tilde{\theta};\psi) - V_i(\tilde{\theta})\right)\right\} ydt + \mathbb{E}\left(dV_i(\tilde{\theta})\right). \tag{3}$$

The term in brackets in equation (3) clarifies the potential trade-off involved in the firm's exporting decision. On the one hand, by exporting, there is a chance that the firm will become experienced. Accordingly, the term $\lambda(\mathbb{E}_\psi V_e(\tilde{\theta};\psi) - V_i(\tilde{\theta}))$ captures the benefits of experimentation, which are always positive since profits are higher for an experienced firm. Thus, inexperienced firms unambiguously prefer to export when $\tilde{\theta}^* \geq 1$. On the other hand, when $\tilde{\theta} < 1$ the first term becomes negative, i.e. $F(\tilde{\theta} - 1) < 0$. In this case, the firm faces a trade-off: by exporting it earns the possibility of becoming experienced at the cost of incurring a contemporaneous loss. The following proposition shows that there exists a region $(\tilde{\theta}^*, 1)$ where firms choose to experiment.[24]

Proposition 1. *(a) The unique piecewise-continuous optimal policy is characterized by a threshold $\tilde{\theta}^* \in [0,1)$ such that if $\tilde{\theta} < \tilde{\theta}^*$, the firm does not export while if $\tilde{\theta} > \tilde{\theta}^*$, the firm exports; (b) $\tilde{\theta}^*$ solves*

$$F\left(\tilde{\theta}^* - 1\right) + \lambda\left(\mathbb{E}_\psi V_e(\tilde{\theta}^*;\psi) - V_i(\tilde{\theta}^*)\right) = 0. \tag{4}$$

Proof. See Appendix D.2.

In Appendix D.3, we show that (4) can be solved to obtain

$$\begin{aligned} \tilde{\theta}^* - 1 + \lambda\left(\frac{2}{J+\tilde{J}}\right)\Bigg\{ \int_{\tilde{\theta}^*}^{\infty} \left(\frac{\tilde{\theta}^*}{z}\right)^{\tilde{\beta}_1} \left(\mathbb{E}_\psi\left(\max\left(\psi z - 1, 0\right)\right) - (z-1)\right)\frac{dz}{z} \\ + \int_0^{\tilde{\theta}^*} \left(\frac{\tilde{\theta}^*}{z}\right)^{\beta_2} \mathbb{E}_\psi\left(\max\left(\psi z - 1, 0\right)\right)\frac{dz}{z} \Bigg\} = 0. \end{aligned} \tag{5}$$

where $J = \sqrt{\mu^2 + 2r\sigma^2}$, $\tilde{J} = \sqrt{\mu^2 + 2\left(r+\lambda\right)\sigma^2}$, $\tilde{\beta}_1 = \frac{-\mu+\tilde{J}}{\sigma^2} > 1$ and $\beta_2 = \frac{-\mu-J}{\sigma^2} < 0$.

The intuition for (5) is as follows. First, note that, for any GBM, we can write the solution as an integral of the flow profits over states z multiplied by a "weight" for that state.[25] The weight

[24]This result does not rely on the fact that θ_t follows a GBM and ψ is a multiplicative Pareto shock. In Appendix D.2, we provide a more general set of sufficient conditions that guarantee that the firm follows a single-threshold strategy. The key condition, which is satisfied in our setup, is:

$$\frac{d\lambda\mathbb{E}_\psi\left(\max\left\{\pi_e\left(\theta_t;\psi\right),0\right\}\right)}{d\theta_t} > \frac{d\lim_{dt\to 0}\left\{\mathbb{E}(e^{-rdt}\pi_i(\theta_{t+dt})) - \pi_i\left(\theta_t\right)\right\}}{d\theta_t}.$$

This condition says that the expected flow benefits of becoming experienced should increase faster than the costs of experimenting today rather than tomorrow (recall $\pi_i < 0$ in the relevant region). This rules out cases in which there is a region for θ where experienced-firm profits are relatively high, but inexperienced-firm losses from exporting are strongly decreasing in θ, inducing firms to wait, and another region in which inexperienced-firm losses from exporting are flat in θ and experienced-firm profits are low but high enough that firms want to export. In addition, we show for arbitrary distributions of ψ that, as long as $\mathbb{E}\psi \geq 1$, $\tilde{\theta}^* < 1$, i.e. firms experiment at a loss.

[25]The weight here is $\left(\frac{2}{J+\tilde{J}}\right)\left(\frac{\tilde{\theta}^*}{z}\right)^{\tilde{\beta}_1}\frac{1}{z}$ for $\tilde{\theta} > \tilde{\theta}^*$ and $\left(\frac{2}{J+\tilde{J}}\right)\left(\frac{\theta^*}{z}\right)^{\beta_2}\frac{1}{z}$ for $\tilde{\theta} < \tilde{\theta}^*$. This is a property of GBM

represents the length of time the process spends in each state, taking into account the proper discounting. For states with $z > \tilde{\theta}^*$, the correct discount – which is reflected in $\tilde{\beta}_1$ – is $r + \lambda$ since the inexperienced firm becomes experienced at rate λ. Since the inexperienced firm exports in that region, the integrand is the difference between the (expected) flow profits of an experienced firm and that of an inexperienced firm. Note $\tilde{\beta}_1 > 0$ since larger z are less likely and, therefore, more heavily discounted. For states $z < \tilde{\theta}^*$, only some experienced firms export. Hence, we only have the (expected) flow profits of an experienced firm. The proper discount, reflected in β_2, is now r since an inexperienced firm remains inexperienced in this region. Note that $\beta_2 < 0$, reflecting that when $z < \tilde{\theta}^*$ lower states are less likely and, thus, more heavily discounted.

Equation (5) shows a very convenient feature of our uncertainty and experimentation model: only one equation in one unknown needs to be solved to characterize the whole strategy of the firm. This property will enable us to understand more transparently, as discussed in later sections, how the model works and how the different features of exporters' observed behavior discipline the model.[26] Furthermore, note that F and κ do not appear in (5). This is a key property of the model, as it implies that $\tilde{\theta}^*$ does not depend on these parameters. In other words, θ^* is proportional to κ and to $\frac{1}{F}$. Intuitively, the firm "undoes" the effect of κ and F by timing its entry decision: a low-κ firm will wait longer until θ is large enough to perfectly offset the effect of κ. This property of the model is going to be very important in the next section and the empirical exercise.

The left and right panels of Figure 2 plot two sample paths of operating profits normalized by fixed costs (solid-orange line). In both panels, the history of time-varying profitability $\{\tilde{\theta}_t\}_{t=0}^{\infty}$ and whether the firm learns conditional on exporting are identical. However, the magnitude of the shock ψ differs. Firms are originally inexperienced and stay away from the market as long as normalized profits are below $\tilde{\theta}^*$ (dashed-blue line). As soon as $\tilde{\theta}_t$ exceeds $\tilde{\theta}^*$ they start to export. At this point, firms are experiencing losses since $\tilde{\theta}^*$ is lower than one. Nevertheless, firms are willing to experiment and incur losses to resolve the uncertainty concerning their profitability shifter ψ. In the figure, as profitability drifts down, firms exit the market before ψ is realized. Eventually, firms' profitability improves again, and they re-enter the market. This is the first type of re-entrant in our model: inexperienced re-entrants, who are identical to first-time entrants. During the second export spell, firms become experienced. When they do, the relevant threshold for normalized operating profits becomes 1 (dashed-blue line). In the left panel, the ψ shock is too small and the firm exits. In the right panel, the ψ shock is sufficiently large and the firm continues exporting. Profitability subsequently worsens, so even the high-ψ firm exits the export market after a while. Later, profitability improves again, and the firm re-enters the export market. This is the second type of re-entrant in our model: the experienced re-entrant.

Understanding survival upon entry for this type of re-entrant, an experienced firm, vis-à-vis a

processes (see Stokey, 2009).

[26] π_i and π_e being both linear in θ (or, equivalently, ψ being multiplicative) is not essential for this result. In Appendix D.3 we show that with general profit functions $\pi_i(\theta)$ and $\pi_e(\theta;\psi)$ the problem can still be reduced to one equation in one unknown.

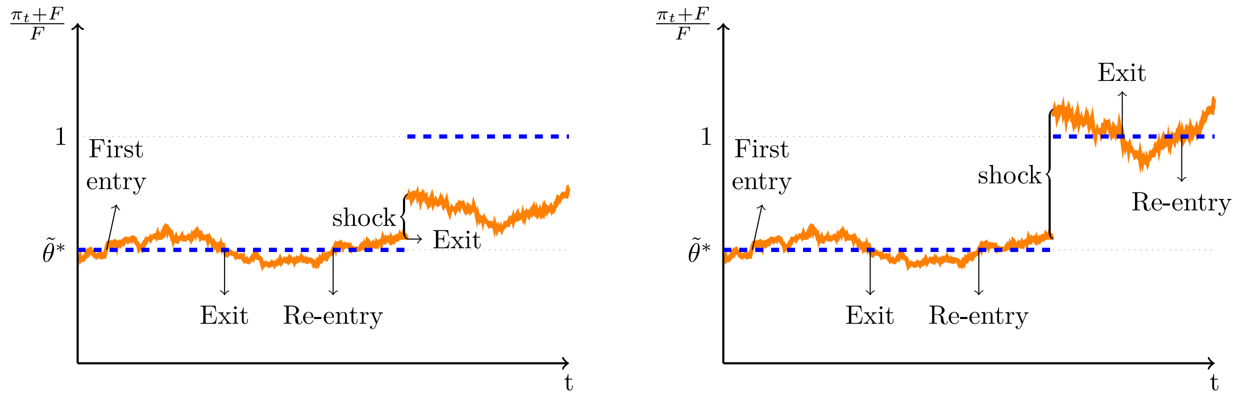


Figure 2: Sample paths.

first-time entrant, an inexperienced firm, is the key to explaining fact 2. We study this next.

3.3 Survival upon entry: Key properties

Henceforth, we assume that all firms are born inactive in the export market, i.e. $\frac{\kappa\bar{\theta}}{F} < \tilde{\theta}^*$. Normalizing the entry time to $t = 0$, an inexperienced firm enters the foreign market with $\tilde{\theta}_0 = \tilde{\theta}^*$. Since $\tilde{\theta}_t$ is a GBM,

$$\ln \tilde{\theta}_t = \ln \tilde{\theta}^* + \mu t + \sigma Z_t$$

where Z_t is distributed $\mathcal{N}(0, t)$. Defining $k_t \equiv \frac{\ln \tilde{\theta}_t - \ln \tilde{\theta}^*}{\sigma}$,

$$k_t = \frac{\mu}{\sigma} t + Z_t.$$

First, note that an inexperienced firm is active iff

$$\ln \tilde{\theta}_t > \ln \tilde{\theta}^* \Leftrightarrow k_t > 0 \Leftrightarrow Z_t > -\frac{\mu}{\sigma} t. \tag{6}$$

Thus, the likelihood of this event happening at any time t depends only on $\frac{\mu}{\sigma}$. In other words, the variance of the process does not matter once the drift is scaled appropriately. Since entry and exit thresholds coincide conditional on remaining inexperienced, a larger variance amplifies the profitability trajectory, but it does not affect whether it is above or below the initial entry point. Furthermore, since an exporter becomes experienced with intensity λ, the likelihood of becoming experienced depends only on $\frac{\mu}{\sigma}$ and λ.

Second, define $\tilde{\psi} \equiv \left(\frac{\psi}{\psi_m}\right)^{\frac{1}{\sigma}}$, which is distributed Pareto$(1, \alpha\sigma)$. When a firm is experienced, it is active iff

$$\ln \tilde{\theta}_t + \ln \psi > 0 \Leftrightarrow \ln k_t + \ln \tilde{\psi} > -\frac{\ln(\psi_m \tilde{\theta}^*)}{\sigma} \Leftrightarrow Z_t + \ln \tilde{\psi} > -\frac{\mu}{\sigma} t - \frac{\ln(\psi_m \tilde{\theta}^*)}{\sigma} \tag{7}$$

Thus, the likelihood of this event depends only on $\frac{\mu}{\sigma}$, $\frac{\ln(\psi_m\tilde{\theta}^*)}{\sigma}$ and $\alpha\sigma$. Like before, the variance of the process, σ, does not matter if everything else is scaled appropriately. In this case, we need to adjust not only the drift μ but also the size of the required profitability boost to survive, $-\ln(\psi_m\tilde{\theta}^*)$, and the shape parameter of the Pareto distribution, α.

Let $y(t)$ be an indicator function that takes the value of 1 if the firm is an exporter at t. Using the results in the preceding paragraphs, we conclude that knowing $\Upsilon = \left\{\frac{\mu}{\sigma}, \lambda, \frac{\ln(\psi_m\tilde{\theta}^*)}{\sigma}, \alpha\sigma\right\}$ is sufficient to determine the likelihood of any given trajectory of $\{y(t)\}_{t=0}^{\infty}$ upon entry. In other words, any combination of parameters that delivers the same Υ implies the same probability of a firm being an exporter at any given instant. Henceforth, we call this aspect of an export trajectory the "extensive margin" of exporter dynamics.

To contrast the model with the data, we study a variety of moments that are different aggregations of events over multiple instants. Among these moments, we can identify a class, M_1, comprised of moments that only aggregate over the extensive margin. Formally, let us define a function $g : \{y(t)\}_{t=0}^{\infty} \to \mathbb{R}$ that maps a given survival trajectory - i.e. a series of zeros and ones - onto a number. For example, as will be later discussed, when we study survival at horizon T, for any trajectory $\{y(t)\}_{t=0}^{\infty}$, the function g returns a value of 1 or 0 depending on whether the firm in the model survives (exports) at least one instant between T and $T+1$. The moment of interest m is then the average of this dichotomous function across firms, i.e. $m = \mathbb{E}g$. In this example, the resulting moment is the model prediction for a point in Figure 1b.

Any moment m that belongs to this class, M_1, depends only on Υ, as shown in Proposition 2 below. This is important, as it implies that these moments are robust to assumptions on any other parameters of the problem or unspecified features of the environment, e.g. the mapping between profitability and sales. Particular cases are the survival-upon-entry moments that constitute fact 1 and fact 2, which we use to discipline our model. In Section 6.1, we study other common survival and re-entry moments belonging to this class.

Proposition 2. *We say that a moment m belongs to a class of moments M_1 if it can be written as $m = \mathbb{E}(g)$ for some function $g : \{y(t)\}_{t=0}^{\infty} \to \mathbb{R}$. Any moment $m \in M_1$ depends only on Υ. In particular, the survival moments that constitute facts 1 and 2 in Section 2 belong to M_1 and, therefore, depend only on Υ.*

Proof. In the text, we show that the probability of any individual event $y(t) \in \{0,1\}$ only depends on Υ. We only need to show the same is true for the argument of g: a trajectory, which is comprised of individual instants. Equations (6) and (7) and the fact that the firm becomes experienced with intensity λ imply that the likelihood of a given trajectory $\{y(t)\}_{t=0}^{\infty}$ is determined by $\frac{\ln(\psi_m\tilde{\theta}^*)}{\sigma}$, and λ, which are the first two elements that comprise Υ, and random variables $\tilde{\psi}$ and $\{k_t\}_{t=0}^{\infty}$. $\tilde{\psi}$ is distributed Pareto$(1, \alpha\sigma)$. By Ito's Lemma, k_t is a GBM with drift $\frac{\mu}{\sigma}$ and unitary variance. Therefore, the likelihood of any given trajectory $\{k_t\}_{t=0}^{\infty}$ only depends on $\frac{\mu}{\sigma}$. This concludes the proof. $\square$

Another important consequence of Proposition 2 is the following:

Corollary 1. *Any moment m in class M_1 is independent of κ and F. In particular, as the moments that constitute facts 1 and 2 in Section 2 belong to M_1, they are independent of κ and F.*

Proof. By Proposition 2, m only depends on Υ. From equation (5) it follows that $\tilde{\theta}^*$ is independent of κ and F. Thus, m is also independent of κ and F. $\square$

Corollary 1 is a key result. It establishes that the probability of survival of an export incursion is independent of κ and F and hence only depends on parameters that are common across firms.[27] The main implication of this result is that all firms entering a given market have the same probability of survival T periods after entry. The strength of this prediction is achieved despite a substantial amount of heterogeneity in the model allowed for by heterogeneous profit shifters (κ) and fixed costs (F) across firms and markets. Heterogeneity in κ allows the model to affect the likelihood of any entry sequence into foreign markets. This parameter, however, does not provide any information about the probability of survival in the market once it has entered it.

Since entry profits are given by $\pi_0 \propto F$ (the common factor of proportionality is $\tilde{\theta}^*$), heterogeneity in F also implies heterogeneous sales at the time of entry. For example, if sales are a constant proportion of profits, entry sales will also be proportional to fixed costs. Thus, the model has a degree of freedom left to rationalize the shape of the firm size distribution by adjusting the distribution of fixed costs accordingly. Most results in this paper do not depend on specific assumptions about this distribution, which we do not need to impose. The two implications of Corollary 1 highlight an advantage of focusing on entrant survival since we can obtain sharp predictions on observables without sacrificing flexibility over firm-specific parameters we know little about.

Next, we provide a sharper characterization of the facts described in Section 2. The probability of survival upon entry of first-time entrants in horizon T is given by:[28]

$$p^{ft}(T) = \Pr(\exists t \in (T, T+1) | y(t) = 1, \tilde{\theta}_0 = \tilde{\theta}^*). \tag{8}$$

The probability of survival for a re-entrant is defined similarly, except that we need to take into account whether they are experienced or not,

$$\begin{aligned} p^{re}(T) = & \Pr(x_{re} = e) \Pr(\exists t \in (T, T+1) | y(t) = 1, \tilde{\theta}_0 = 1) + \\ & \Pr(x_{re} = i) \Pr(\exists t \in (T, T+1) | y(t) = 1, \tilde{\theta}_0 = \tilde{\theta}^*) \end{aligned} \tag{9}$$

[27] An analogous result concerning heterogeneous market-specific profitability shifters is obtained in Albornoz et al. (2016) in a framework without experimentation.

[28] Previous research often focuses on "instantaneous" survival probabilities, e.g. $\Pr(y(T) > 1)$. We find that, in the context of our paper, these instantaneous measures are useful abstractions to build intuition, but they provide a poor quantitative approximation to the objects we can measure in the data. The reason is that firms spend a good share of their time close to the threshold, and there is an important margin of variation given by the amount of time a firm decides to export within a year. We discuss these time-aggregation issues in Section 6 and Appendix B.

where $\Pr(x_{re} = i)$ and $\Pr(x_{re} = e)$ are the probability of being inexperienced and experienced at the moment of re-entry, respectively. In the special case without experimentation ($\lambda = 0$), there is no difference between the survival probabilities of first-time entrants and re-entrants. With experimentation ($\lambda > 0$), inexperienced and experienced firms behave differently. While all first-time entrants are inexperienced firms, only a share of re-entrants are. Thus, their survival probabilities differ. Since λ is the key parameter controlling this composition effect, it is crucial to match the size of the survival gap between entrants and re-entrants.

The other key parameter that allows the model to explain facts 1 and 2 is α, which controls the uncertainty surrounding the firm's future profitability in the export market, ψ. As α decreases, the mean and variance of ψ increase. Because of the possibility of inaction, firms like taking a gamble in this model: they reap the benefits from a high ψ, but they can exit if ψ turns out to be low.[29] Thus, when the shock's variance is larger, firms have incentives to enter earlier in the export market in the hope that a good realization of the shock will substantially boost profits. Formally, Proposition 3 establishes that the threshold $\tilde{\theta}^*$ increases with α.

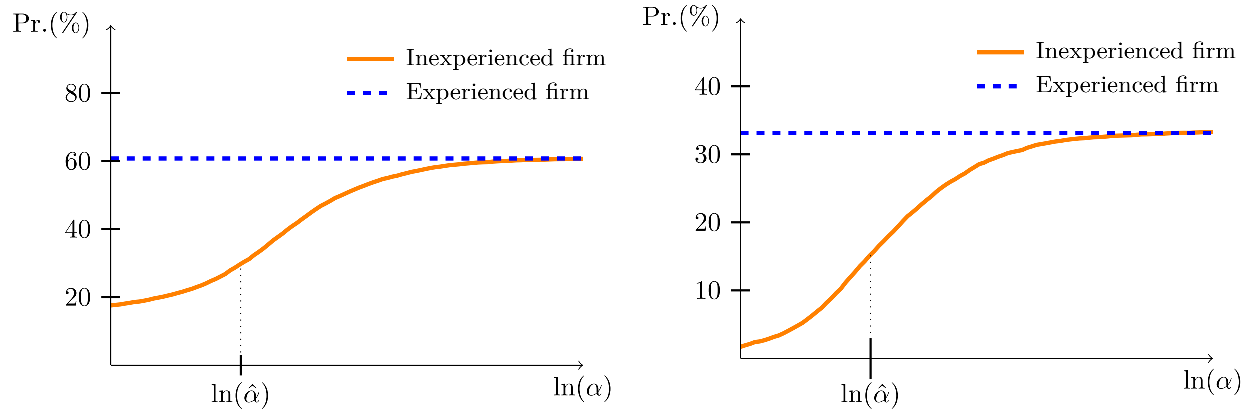
Proposition 3. *The normalized threshold $\tilde{\theta}^*$ increases with α.*

Proof. See Appendix D.4. □

Although it is intuitive to think that entering the export market earlier would lead to a lower survival probability, this need not always be the case. A lower α also implies higher chances of experiencing large realizations of ψ, placing the firm well above the exit threshold and making it more likely to survive. This is the reason why no general proposition can be obtained regarding a lower survival probability in response to a lower α. Nevertheless, firms experiment aggressively at our estimated parameter values, so the intuitive result holds: inexperienced firms' survival probability is smaller than that of experienced firms at all horizons, and the gap between them increases with uncertainty. This implication of a lower α can be seen in Figures 3a and 3b, which plot the survival probability (solid-orange line) as a function of α at one-year and five-year horizons, respectively, with the remaining parameters at their estimated values. Note that, as $\alpha \to \infty$, the gains from experimentation vanish and the model's predictions converge to the survival rate of experienced firms (dashed-blue line).

An avid reader may wonder to what extent these results are driven by uncertainty since α also changes the mean of the distribution. A clean exercise to address this concern is to modify the scale parameter ψ_m, which changes the mean of the distribution while keeping its shape intact. Proposition 4 shows that a more attractive distribution, i.e. one with a higher ψ_m, leads to firms surviving more, not less.

[29]Formally, this risk-loving behavior is captured in equation (5) by the term $\mathbb{E}_\psi(\max\{\psi z - 1\})$, which decreases with α.



(a) Probability of survival (one year)

(b) Probability of survival (five years)

Figure 3: The effect of uncertainty (α)

Proposition 4. *The probability of survival of a first-time entrant at any horizon increases with* ψ_m.[30]

Proof. See Appendix D.5. □

To understand this result, it is useful to compare changes in ψ_m and κ of the same size. Recall that the normalized threshold $\tilde{\theta}^* = \frac{\kappa\theta^*}{F}$ is independent of κ, which implies that if κ increases then the threshold θ^* decreases exactly such that $\kappa\theta^*$ stays constant. An increase in ψ_m raises profits for any realization of the shock, similar to an increase in κ. The key difference is that ψ_m does not increase profits during the experimentation period. As a result, relative to an equivalent change in κ, a change in ψ_m makes the experimentation phase more costly, implying that $\psi_m\tilde{\theta}^*$ increases with ψ_m. In other words, the firm does not fully offset the higher future profits by entering earlier. Hence, after ψ is realized, the inexperienced firm finds itself farther away from the threshold, with higher chances of surviving.

Proposition 4 is also crucial to understand the role of uncertainty about ψ to generate lower survival. Consider a firm that knew its ψ beforehand. In our model, this would imply setting $\psi_m = \psi$ and $\alpha \to \infty$ (i.e., a deterministic jump size). We know that, if $\psi_m = 1$, being experienced is the same as being inexperienced. Therefore, by Proposition 4, if $\psi_m > 1$, this firm would survive on average less as an experienced firm than as an inexperienced firm. Thus, since $\psi \geq 1$ for all firms, a model where ψ is known ex-ante would be unable to explain fact 2.

In sum, a model with an experimentation phase subject to uncertainty can explain facts 1 and 2. High uncertainty (i.e., a low α) induces inexperienced firms to experiment aggressively, explaining high early exit rates. Furthermore, since low survival probabilities at short horizons are obtained without resorting to a very negative trend, the model has a degree of freedom in $\frac{\mu}{\sigma}$ to match the flat

[30]This is valid for any family of distributions linked by a scale parameter, i.e. if we have two distributions ψ_1, ψ_2 such that $\psi_1 = \psi_m\psi_2$, then the result carries over.

slope of the survival profile in fact 1. Finally, fact 2 is explained by a composition effect: first-time entrants are 100% inexperienced, whereas only a fraction of re-entrants are. The remaining fraction of experienced re-entrants do not engage in risky experimentation and, therefore, survive more.

4 Estimation

4.1 Parameter identification

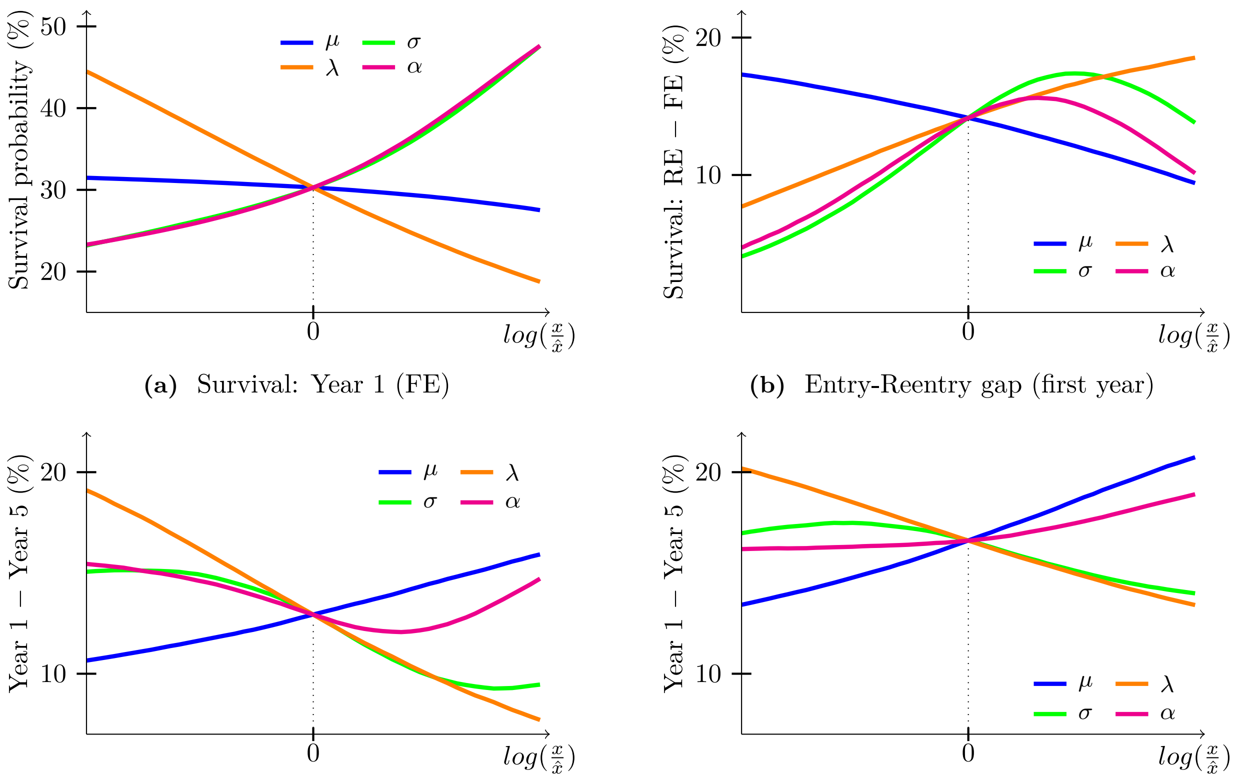
We discipline the model parameters using the moments underlying facts 1 and 2 in Section 2. An immediate implication of Proposition 2 is that our model has only four degrees of freedom to match these moments. That is, any combination of parameters $\{\mu, \sigma, \lambda, \alpha, \psi_m, r\}$ that yields the same $\Upsilon = \{\frac{\ln(\psi_m \tilde{\theta}^*)}{\sigma}, \frac{\mu}{\sigma}, \sigma\alpha, \lambda\}$ will imply the same extensive-margin moments.[31] To make progress, we set $r = 0.1$ and make the natural assumption that $\psi_m = 1$, which implies that the firm learns nothing under the worst possible realization of ψ. This value for ψ_m also has the appealing property of converging to a standard model without experimentation as uncertainty decreases, i.e. as $\alpha \to \infty$. We are thus left with $\varphi = \{\mu, \sigma, \lambda, \alpha\}$, which we estimate via simulated method of moments (SMM). Our SMM estimator chooses φ to minimize $m(\varphi)'m(\varphi)$, where $m(\varphi)$ are the ten survival moments in Section 2 (details in Appendix E).

The four parameters affect all ten moments, so providing intuition for the individual identification of each parameter is not straightforward. However, some insight can be obtained by analyzing the influence of each parameter on some key features of the survival profiles described in Section 2. Consider first the main feature of fact 1: the high exit rate early upon entry. Figure 4a plots the first-year survival probability of a first-time entrant as we vary each of the four parameters from 0.5 to 2 times its estimated value. A higher λ and a lower α increase, respectively, the speed and magnitude of the potential prize, making firms experiment more aggressively and thus survive less. Regarding the parameters of the GBM process, a larger, more negative, drift μ or a smaller variance σ imply, as in the benchmark model, a more negative normalized drift $\frac{\mu}{\sigma}$, which also leads to lower survival rates.[32]

Second, consider fact 2, i.e. the gap between the survival profile of entrants and re-entrants. Since re-entrants survive more than first-time entrants, the experimentation mechanism must be active, i.e. $\lambda > 0$ and $\alpha < \infty$. Figure 4b plots the first-year survival-rate gap between entrants and re-entrants, also varying one parameter at a time. The effect of λ is straightforward: (i) it lowers survival among first-time entrants by making them more eager to enter and, (ii), it increases re-entrant survival relative to first-time entrants since firms are more likely to be experienced when they re-enter. Both effects increase the gap. By contrast, the effect of α is more subtle. On the one hand, as discussed in Section 3, a lower α (higher uncertainty) should decrease survival among inexperienced firms and thus increase the gap in early years. However, α also affects the composition

[31]Note that the normalized threshold $\tilde{\theta}^*$ is a function of these six parameters - see equation (5).

[32]The fact that this effect dominates is a non-trivial numerical result since μ and σ also affect the threshold $\tilde{\theta}^*$.



(a) Survival: Year 1 (FE)

(b) Entry-Reentry gap (first year)

(c) Survival: Year 1 vs Year 5 (FE)

(d) Survival: Year 1 vs Year 5 (RE)

Figure 4: Parameter identification

Notes: In each figure, the horizontal axis denotes the ratio of model parameter $x \in \{\mu, \sigma, \lambda, \alpha\}$ to its estimated value $\hat{x} \in \{\hat{\mu}, \hat{\sigma}, \hat{\lambda}, \hat{\alpha}\}$, expressed in logarithmic scale. The range of variation is from $\frac{x}{\hat{x}} = 0.5$ to $\frac{x}{\hat{x}} = 2$; -0.69 to 0.69 in logs. Note that $\hat{\mu} < 0$ (see Section 4.3), so μ becomes more negative to the right. The vertical axes in each panel are, respectively: (a) first-year survival probability of a first-time entrant; (b) first-year re-entrant survival probability minus first-time entrant survival probability; (c) five-year minus first-year survival rates of a first-time entrant; (d) five-year minus first-year survival rates of a re-entrant.

of re-entrants. When α is low, firms bet on a small probability yet very profitable outcome. As most firms receive negative news (i.e. an insufficient ψ) and are very unlikely to re-enter, there are few experienced re-entrants. Thus, in this case, most re-entrants tend to be inexperienced, which reduces the gap. In our simulations, the effect of α on the gap is hump-shaped and the estimated value is near the peak of the hump, so that variation in uncertainty does not have a large effect on the gap.[33] Finally, note that the other parameters, μ and σ, are not innocuous to the gap size. A more negative μ lowers survival for every firm, but it does so relatively more for re-entrants as a fraction of them are experienced. The effect of σ is more complicated since it also affects the relative importance of the shock, i.e. $\alpha\sigma$ matters in Υ. Like α, the overall effect of σ on the gap depends on the region of the parameter space.

[33]Our estimate for α is 5.43 and the peak is at 6.71. Furthermore, the gap tends to zero not only when $\alpha \to \infty$ (no uncertainty), but also when uncertainty becomes very large, more precisely when $\alpha \to 1$ from above.

Finally, consider the second key feature of fact 1: survival profiles that are too flat. To capture this feature, Figures 4c and 4d plot the difference between first- and fifth-year survival rates among first-time entrants and re-entrants, respectively. A larger λ and a smaller μ make the profile flatter by "killing" more firms early and by making $\frac{\mu}{\sigma}$ smaller, respectively. μ matters more for re-entrants, who are less affected by the shock. The effects of α and σ are more subtle and depend on their location in the parameter space. Notably, while α and σ seem to have similar effects on the outcome variables in panels (a) through (c), their impact on the slope of the re-entrant profile in panel (d) is different in a neighborhood of our estimated values.

4.2 Descriptive statistics

Table 1 provides descriptive statistics about exporters and incursions in our dataset (left panel) and about the macroeconomic environment in Peru (right panel) during the sample period, using annual data. The first column details the number of exporters each year. The second and third columns display the number of incursions and re-entries, respectively. In total, during the sample period (1997-2002) we identify $24,855$ incursions by $10,071$ unique firms and $1,659$ re-incursions by $1,017$ unique firms. The first four columns in the left panel show growing exporting activity in Peru during the sample period. The last column shows the survival rate for each cohort of incursions in a two-year horizon. The survival rate hovers around an average of 24.2%.

Table 1: Descriptive Statistics

	Firms and Entries				Macro Variables		
Year	Firms	Incursions	Re-entries	Incursions: 2-year surv. (%)	Exports (US$ mill.)	GDP growth (%)	RER (%)
1997	3,775	4,081	0	23.6	6,825	6.5	2.3
1998	3,563	3,522	0	26.3	5,757	-0.4	4.1
1999	3,895	4,249	141	24.7	6,088	1.5	14.1
2000	4,017	4,537	348	22.3	6,955	2.7	2.7
2001	4,347	4,244	491	24.2	7,026	0.6	1.4
2002	4,685	4,222	679	24.7	7,714	5.5	1.7
2003					9,091	4.2	-1.1
2004					12,809	5.0	-2.8
2005					17,368	6.3	-1.8
2006					23,830	7.5	0.5
2007					28,094	8.5	-3.4
2008					31,018	9.1	-8.2
Total	28,098	24,855	1,659	24.2			

Notes: Left panel based on Peruvian customs dataset (World Bank). First two columns of right panel based on INEI. The real exchange rate (RER) multiplies nominal exchange rate by US PPI (BLS) and divides it by Peruvian CPI (INEI). GDP growth and RER are expressed in annual variation (%). A higher RER means a more depreciated Peruvian currency.

The right panel of the table displays summary indicators of the macroeconomic performance of Peru. The information is provided for an expanded period that includes both the sample years used to identify incursions (1997-2002) and the additional years used to compute survival (2003-2008). The first column of this panel shows a strong positive trend for aggregate exports in Peru. Similarly, the second column shows a strong positive trend in the evolution of GDP, particularly in the later years of the sample. The last column displays the evolution of the real exchange rate, which exhibits an accumulated depreciation of 29% during the period 1996-2002, followed by an accumulated appreciation of 16% during the period 2002-2008. While our model does not account for changes over time in potential export profitability due to changes in the real exchange rate, by focusing on averages over a period that includes both appreciation and depreciation of the domestic currency we hope to capture patterns in the data that approximate those that would arise in a fully stable macroeconomic environment.

4.3 Results

The top part of Table 2 displays the estimation results. The parameters of the GBM are $\hat{\mu} = -0.017$ and $\hat{\sigma} = 0.081$. These values imply that the normalized drift of the GBM is $\frac{\hat{\mu}}{\hat{\sigma}} = -0.212$, which is considerably smaller than the method-of-moments estimates of -0.279 and -0.270 obtained by Luttmer (2007) and Arkolakis (2016), respectively, for this ratio. Under the light of our model, a normalized drift $\frac{\mu}{\sigma}$ closer to zero is required to explain the "flatness" of the survival profile, especially for re-entrants, who are more sensitive to the GBM drift, as they include experienced firms. The low survival rates are explained instead by the experimentation mechanism, which is governed by α and λ.[34] The estimate for the parameter of the Poisson process is $\widehat{\lambda} = 2.92$. This estimate implies that a firm that continuously exports has a 21.6% probability of becoming experienced within a month. Finally, $\widehat{\alpha} = 5.427$, which implies a standard deviation of 0.28 for the profitability shifter ψ. Taken together, the four parameters determine a value of 0.68 for the normalized threshold, $\tilde{\theta}^*$. This entry value implies that if the firm became experienced the instant it starts exporting, the probability that it would decide to continue exporting the next instant would only be $\tilde{\theta}^{*\alpha} = 12\%$.[35] Furthermore, they imply that only around 40% of re-entrants are experienced. Having a substantial share of inexperienced firms among re-entrants is necessary to explain that even re-entrants have a low and flat survival profile.

The second part of Table 2 compares the data with the model predictions. Figure 5 provides a visual representation of the same information. The model does an excellent job. In particular, it predicts a low and flat survival profile for both entrants and re-entrants and an average gap of about 12 percentage points between both, as in the data. The average absolute discrepancy between data

[34]Indeed, in Section 4.4 we show that, in the absence of experimentation, $\frac{\mu}{\sigma}$ needs to be twice as large to match the low survival rates of exporters.

[35]This is an "instantaneous" probability of survival. However, some firms may exit the instant the shock hits them but re-enter the market within the next year. When we aggregate instants into years, survival probabilities become substantially larger than this "instantaneous" measure.

Table 2: SMM Estimation results

	Fixed parameters	
r	0.1	
ψ_m	1	
	Estimated parameters	
μ	-0.017	
σ	0.081	
λ	2.920	
α	5.427	
	Survival probabilities	
	Panel A: Entrants	
	Model	Data
Year 1	0.304	0.294
Year 2	0.219	0.242
Year 3	0.193	0.208
Year 4	0.182	0.185
Year 5	0.174	0.169
	Panel B: Re-entrants	
Year 1	0.446	0.406
Year 2	0.359	0.361
Year 3	0.320	0.334
Year 4	0.297	0.292
Year 5	0.279	0.285

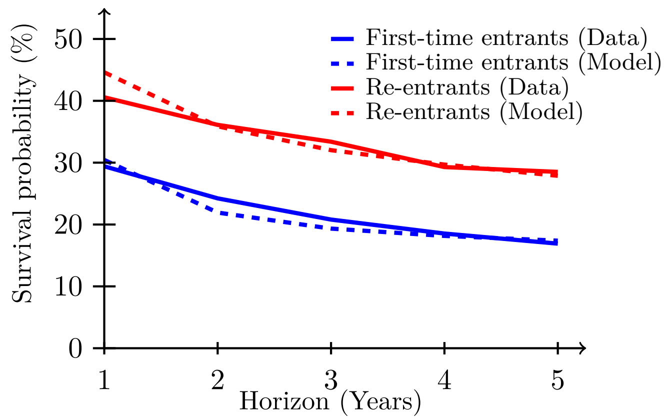


Figure 5: Survival profiles predicted by the model

and predictions is slightly above a percentage point, with the largest discrepancy in the first year for re-entrants (44.4% in the model versus 40.6% in the data).

4.4 Sunk costs of exporting

Our baseline model allows firms to enter and exit export markets freely. By contrast, a large body of theoretical and empirical work on exporter dynamics assumes that becoming an exporter involves incurring a sunk cost as a costly investment decision (Baldwin and Krugman, 1989; Dixit, 1989; Roberts and Tybout, 1997; Alessandria and Choi, 2007; Das et al., 2007; Impullitti et al., 2013; Dickstein and Morales, 2018; Morales et al., 2019). Like experimentation, sunk costs introduce dynamic differences across firms that depend on their past export history. In this section, we argue that they only worsen the model's predictions on survival probabilities.

We make two changes to our baseline model to study the role of sunk costs. First, we assume that firms must pay a sunk cost every time they enter or re-enter an export market, as in Das et al. (2007). In the first entry, the firm pays S^i. In subsequent entries, it pays S^e. We allow sunk costs to decline with export experience, i.e. $S^e \leq S^i$.[36] Second, to isolate the role of sunk costs, we shut down the experimentation mechanism by setting $\lambda = 0$.

As a stepping stone, it is useful to study a "benchmark" model without experimentation or sunk costs, as in Arkolakis (2016). The shortcomings of this model are apparent. Since there are no dynamic differences across firms, export history has no impact on survival probabilities, so the model cannot explain fact 2. More interestingly, the benchmark model is also unable to explain fact 1. The green-colored dashed line in Figure 1a (discussed in Section 2) corresponds to the best prediction of the benchmark model. This prediction is obtained by estimating the model with the SMM using only the survival profile of entrants $\{S_t\}_{t=1,\ldots,5}$.[37] In this case, the only object to estimate is the ratio $\widetilde{\mu} = \frac{\mu}{\sigma}$. Table 3 shows that the estimate of this parameter ($\widehat{\widetilde{\mu}} = -0.71$) is

[36]See Appendix F for details and derivations.

[37]We could alternatively use the ten survival moments - five for entrants and five for re-entrants - to estimate but prefer to focus only on the first five to give the benchmark model more flexibility to fit fact 1.

Table 3: SMM estimation results
(Benchmark model)

	Estimated parameter	
μ/σ	-0.71	
	Survival probabilities: Entrants	
	Model	Data
Year 1	0.420	0.358
Year 2	0.265	0.266
Year 3	0.181	0.223
Year 4	0.128	0.196
Year 5	0.091	0.177

much more negative than the one obtained in the full model and also presents predicted survival rates using this estimate. These predictions are depicted in Figure 1a. We can see that the model overpredicts survival rates at short horizons while underpredicting them at longer horizons.

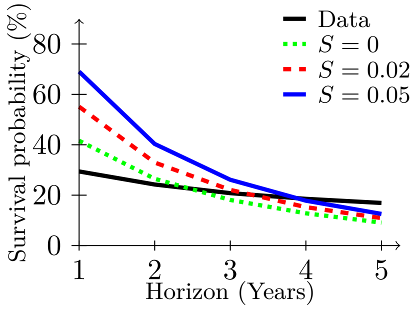
Allowing for positive sunk costs does not improve the benchmark model's ability to explain fact 1. Figure 6a shows how the survival profile changes when we add a positive sunk cost.[38] The larger the sunk cost, the more conservatively firms enter to improve their odds of recovering the initial losses - and thus, the larger the difference between their entry and exit thresholds. Hence, they survive more. In fact, firms survive more especially in early periods, when the implications of their conservative entry - i.e. still being far from the exit threshold - gain prominence to explain survival relative to the natural drift and volatility of the profitability process. However, this is the opposite of what was needed to improve the benchmark model's fit to fact 1: flattening the survival profile. Indeed, Figure 6b shows that the survival profile becomes steeper when we re-estimate the drift μ, as the model needs an even more negative drift to counter the higher survival.

The implications of introducing sunk costs are even more at odds with the fact that re-entrants survive more than first-time entrants (fact 2). Figure 6c plots the difference between the survival profile of first-time entrants and re-entrants under two alternative assumptions on the re-entry cost: half repayment and free re-entry (notice that in the full repayment case maintained so far, this difference is zero). As re-entrants face lower sunk costs, they enter less conservatively and thus survive less. This is the opposite of what is needed to explain fact 2.

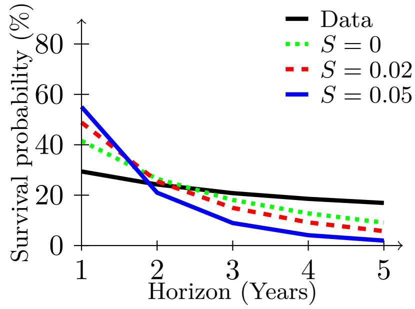
5 Mechanisms

We have presented two facts about exporter survival and developed a model with uncertainty and experimentation in export markets that naturally explains them. In this section, we provide further evidence of the relevance of uncertainty and experimentation in the dynamics of firm exports by associating variation in the parameter α to observed characteristics of products and markets.

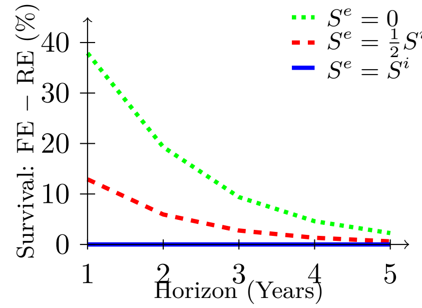
[38] For this figure, we assume $S^e = S^i$, which provides the best fit for fact 2 (see discussion below).



(a) Varying S



(b) Varying S, μ re-estimated



(c) Entry-Reentry gap varying S^e

Figure 6: The effect of sunk costs on survival probabilities

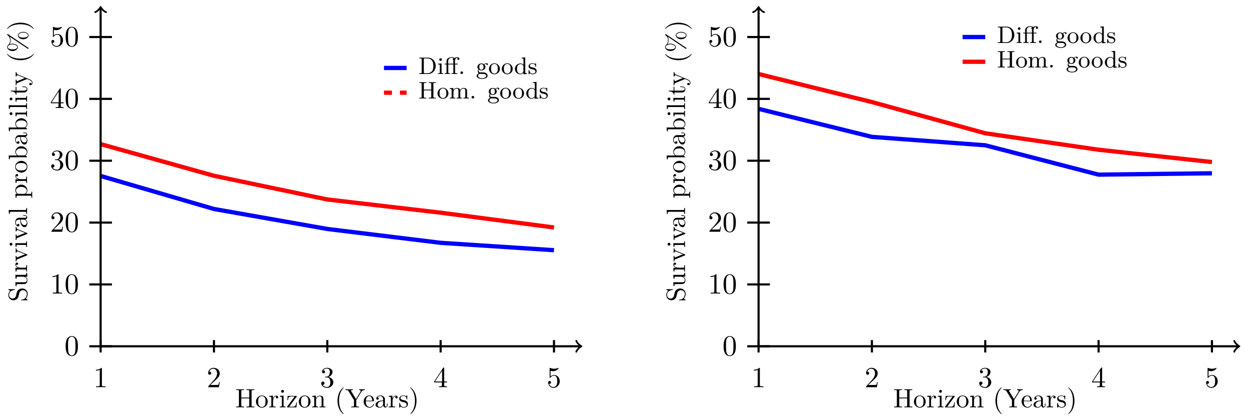
Notes: Panels (a) and (b) plot survival for varying sunk costs. $S = 0.02$ means that the sunk cost is 2% of the fixed cost paid by a firm that is active during an entire year. Fixing $\sigma = 0.1$, in panel (a) $\mu = -0.071$ while in panel (b) it is estimated to fit fact 1 ($\hat{\mu} = -0.086$ and $\hat{\mu} = -0.112$ for $S = 0.02$ and $S = 0.05$, respectively). Panel (c) plots the difference in survival probabilities between first-time entrants and re-entrants for varying re-entrant sunk costs S^e, keeping first-entrant sunk costs fixed at $S^i = 0.05$.

We do not observe α. However, the magnitude of this parameter can be linked to observable characteristics of products and export destinations. Since α governs the variance and positive skewness of the shock, its magnitude captures the degree of uncertainty about the component of export market profitability that can be resolved by experimenting. As discussed in Section 3, possible sources are the need to adapt products to satisfy foreign demand idiosyncrasies and to match with distributors who will push product sales. It is reasonable to assume that these sources of uncertainty are more relevant for differentiated products than for homogeneous products. Thus, we expect a lower α and, hence, a lower survival probability for the former.

To test this implication, we classify all incursions in our database in either of two categories, differentiated or homogeneous, following Rauch (1999).[39] We first map export data classified at the Harmonized System 10-digit level into Rev.2 SITC 4-digit categories using the United Nations Statistics Division Conversion Tables. Then, we map the latter categories into one of our two categories.[40] Finally, we identify the category with the largest value of exports in the year of entry and assign the incursion to that category. There are $14,533$ differentiated incursions and $9,701$ homogeneous incursions in our database. Figure 7a displays the survival profile for each category. Consistent with the hypothesis that α is lower for differentiated products, these products display uniformly lower survival rates. For example, the survival rate is more than six percentage points lower in the first year after entry and more than four percentage points lower in the fifth year. Similar results are obtained in a regression framework, where we can perform inference and control for other covariates. We regress the survival status of each incursion-horizon combination on

[39]We merge homogeneous and referenced-priced categories in Rauch (1999) into only one "homogeneous" category.

[40]The mapping from SITC to Rauch leaves 5.82% of the incursions unclassified. We reduce this proportion to 2.61% by assigning to unclassified SITC 4-digit categories the classification of similar SITC 4-digit categories. Of the remaining unclassified instances, 52.47% are transactions without a reported HS code.



(a) First-time entrants

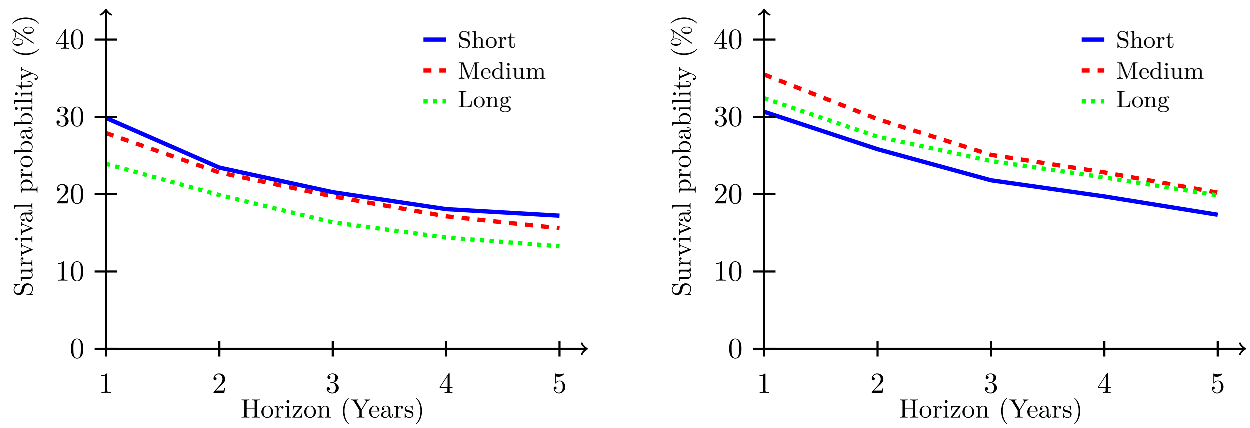
(b) Re-entrants

Figure 7: Survival profile by type of product

dummies for horizon and a dichotomous variable for differentiated products. The results, displayed in column 1 of Table A.2, show that the survival rate of differentiated products is significantly lower than for homogeneous products. We also interact the differentiated dummy with horizon dummies. Column 2 shows that the survival rate of incursions in differentiated products is lower at all horizons. Columns 3 and 4 show that these results are not an artifact of composition effects. The results are very similar when we replicate the regressions in the first two columns by adding a full set of destination-year fixed effects.

The survival profile for exporters of differentiated goods relative to exporters of homogeneous goods should also display the effects of uncertainty and experimentation in the case of re-entrants. Although many of them have already learned the realization of α, a fraction of re-entrants still behave as entrants and thus are subject to similar chances of early termination of their export experiences. Consistent with this prediction, Figure 7b shows that the survival profile is uniformly lower for exporters of differentiated goods than for exporters of homogeneous goods. Columns 5 to 8 in Table A.2 replicate these results in a regression framework. The difference in survival rates between differentiated and homogeneous goods is also statistically significant for re-entrants, although the relationship is weaker at longer horizons. These results are not an artifact of composition effects either, as including destination-year fixed effects yields very similar results.

The uncertainty surrounding export market profitability could also be hypothesized to vary according to the distance to the destination. In the first place, neighboring countries are more likely to have similar income levels and thus share similar consumption patterns. In the second place, even controlling for income levels, demand idiosyncrasies are more likely to coincide the closer the exporter and the importer are. In the third place, less distant countries are more likely to have a more similar business culture that facilitates communication with distributors and anticipation of their actions. As a result, we could expect a higher degree of uncertainty about export market profitability in more distant destinations. Setting a smaller α for those destinations, the model predicts lower



(a) Differentiated goods

(b) Homogeneous goods

Figure 8: Survival profile by distance (First-time entrants)

survival probabilities in those cases. To assess this prediction, we divide export destinations into three groups according to their distance from Peru. Short-distance destinations are those with a distance smaller than $3,424$ km. Medium-distance destinations are those with a distance between $3,424$ km. and $10,040$ km. Long-distance destinations are those with a distance above $10,040$ km. The cut-offs are chosen so that each distance group has an equal number of incursions. Figure 8a displays the survival profile for each distance group in the case of differentiated goods. We can see that the profile is uniformly lower the farther away is the destination. For example, one year after entry, the survival rate for the long-distance group is six percentage points lower than for the short-distance group, while five years after entry, the survival rate for the former group is four percentage points lower. Figure 8b displays analogous information in the case of homogeneous products, where it is unclear whether distance should matter. In this case, we do not see lower survival rates in more distant destinations. If anything, the opposite seems to be the case.

These results also arise in a regression framework where we can also control for distance as a continuous variable, in addition to controlling for other covariates. The results are displayed in Table A.3. In column 1, we regress survival on interactions of (log)distance with dummies indicating whether the product is differentiated or homogeneous. Similar to the graphical results, the longer the distance, the lower the survival rate for differentiated products. For homogeneous products, by contrast, the result is just the opposite. Column 2 includes horizon-specific interactions with the differentiated and homogeneous dummies, with similar results. These results barely change when we include year fixed effects (columns 3 and 4).

In sum, the results of this section show that reasonable assumptions about how α varies across products and destinations yield predictions consistent with the data. These results support the notion that uncertainty and experimentation are crucial features in the dynamics of firm exports.

6 Other relevant exporter dynamics moments

While we have focused so far on facts 1 and 2, a specific collection of survival moments, the literature has highlighted many other relevant moments that characterize exporter behavior. This section studies our model's ability to explain those other moments. We organize them into three classes. The first class includes additional moments related to exporter survival and re-entry. The second class comprises moments related to export growth. The third class contains moments pertaining to survival and growth conditional on size. For each of these classes, we assess (a) the model's ability to explain the moments and (b) the additional assumptions, if any, required to make predictions about them.

6.1 Survival and re-entry moments

Although our model was designed to explain facts 1 and 2, Proposition 2 implies that it should also be able to predict any moment that belongs to class M_1, which includes all those that aggregate over subsets of the "extensive margin" of exporter behavior (see the discussion in Section 3.3). Many survival and re-entry moments used in the literature belong to this class. Thus, to the extent the model's ability to match our facts stems from a more profound ability to explain the entire extensive margin, it should also match those other moments.

A common practice in the literature is to define "continuous survival" measures based on uninterrupted export experiences (e.g. Eaton et al. (2008) and Ruhl and Willis (2017), among others). For example, a firm that exports to a market for the first time at $t = 0$, does not export at $t = 1$, and exports again at $t = 2$ is not considered a survivor at $t = 2$ under this alternative definition while it is a survivor under the definition used in this paper. The top panel in Table 4 computes continuous survival probabilities (i.e. imposing the additional requirement of uninterrupted export spells). Columns 1 and 2 compare the probability of continuously surviving until year t given that the firm entered at $t = 0$ in the model and in the data. The model does an excellent job matching these moments, with an average discrepancy of one percentage point. Columns 3 and 4 similarly compare "conditional survival" probabilities, which capture the probability of surviving at t conditional on continuous survival until $t - 1$ (i.e. the complement of the hazard rate). Although conditional survival is just a function of continuous survival, which is matched quite accurately, the discrepancies are larger as this measure involves divisions by small numbers.[41]

Pervasive re-entry in export markets is a crucial feature of exporter dynamics. Like survival, re-entry is entirely determined by the extensive margin. That is, once we know the export status of a firm incursion along its trajectory, we also know the probability of re-entering the market over any period after exit. We compute two re-entry moments. First, we compute the share of firms that ever re-enter up to year $t_X + T$, where t_X is the time of the first exit (note $T \geq 2$ by definition

[41] In Appendix G, we provide an alternative estimation of the model that adds these conditional survival moments to the estimation strategy. The model's ability to explain these moments improves considerably at the expense of slightly worsening the fit for the re-entrant survival profile (from a 1.3 percentage point average deviation to 2.7).

of exit). The first two columns in the bottom panel of Table 4 report the results. In the data, about 10% of exiters have re-entered the market within two years, with that number increasing to 20% within five years. The model matches these numbers very well. It slightly underestimates the extent of re-entry by two percentage points, mainly driven by too little early re-entry. Second, we compute the probability of exporting in period $t_X + T$ and report the model and data results in the last two columns of the table. In the data, the share of exiters at t_X that export in any of the next five years hovers around 9%. The model also matches this feature of the data well, with the main discrepancy for $T = 2$, where, by definition, this share coincides with the previous re-entry measure.

Taken together, these facts suggest that despite the parsimony of the model, it does a very good job explaining an important class of moments related to survival and re-entry, which only depend on the extensive margin of exporter behavior.[42]

6.2 Export growth moments

Another class of moments (M_2) studied in the exporter dynamics literature relates to growth in export sales. As opposed to moments based on the extensive margin, predictions on export growth require additional assumptions. In particular, we need assumptions that allow us to map profitability (θ) onto export sales. This can be done easily by assuming CES demand and interpreting θ as productivity or quality (see footnote 20), which is our approach in this section. More sophisticated models may imply a richer mapping between profitability and sales and, thus, a better ability to explain export growth moments. However, our purpose here is to assess how far this restricted version of the model can go in explaining the moments in M_2.

Setting t_0 as the entry year of the first-time entrant, we define growth rates as the log-difference in accumulated export sales during one year, i.e. $\ln(\text{sales}_{t_0+T}) - \ln(\text{sales}_{t_0+T-1})$, and compute its mean, median and standard deviation for all firms that are alive at both $t_0 + T$ and $t_0 + T - 1$.[43] Panel A in Table 5 reports the results. Let us focus on the model predictions first. Although known results from the firm and exporter dynamics literature predict larger growth rates in earlier periods due to strong selection forces, here a countervailing "exiting partial-year" effect arises because a large fraction of surviving firms - i.e. those for whom export growth can be computed - exit the market sometime along the exiting year accumulating fewer sales. This countervailing effect appears to dominate the unconditional export growth prediction in year 1 for the mean, albeit not for the

[42] One caveat is that the literature typically focuses on annual data based on calendar years instead of defining firm-market specific years as we do here. In Appendix B.2, we show the results using this alternate way of aggregating shipments. They are similar, except that (both in the model and the data) survival rates are larger because of time-aggregation issues, especially in the first year.

[43] In Appendix B.3, we present all the results in this section using annual data based on calendar years. Since our model is set in continuous time, it provides a natural lab to think about time-aggregation issues. To compare with calendar-year data, we simulate a random variable in our model that determines the entry moment of a firm in a given calendar year. The results are similar, except that in the first year (from year 0 to year 1) we observe, both in the model and in the data, the standard partial-year effect pointed out by Bernard et al. (2017): growth rates are abnormally high since, everything else equal, firms export during a shorter amount of time in year 0.

Table 4: Other moments: Extensive margin

	A: Other survival measures (entry: year 0)			
	Continuous survival		Conditional survival	
Horizon	Model	Data	Model	Data
Year 2	0.169	0.185	0.558	0.629
Year 3	0.124	0.133	0.736	0.718
Year 4	0.105	0.104	0.851	0.784
Year 5	0.094	0.086	0.893	0.825
	B: Moments conditional on exit (exit: year 0)			
	Re-entry		Survival	
Horizon	Model	Data	Model	Data
Year 2	0.075	0.097	0.075	0.097
Year 3	0.120	0.147	0.089	0.097
Year 4	0.153	0.179	0.090	0.092
Year 5	0.178	0.200	0.090	0.089

median. For the mean, we can see in the table that, contrary to the standard prediction, the model predicts the lowest growth rate for that year - a negative one. From year 2 onwards, however, the standard effect prevails. To explore this issue further, in panel B we report the growth rate in the number of shipments, which we take as a proxy for the model counterpart of the "amount of time" a firm spends over the threshold.[44] Consistent with this explanation, panel B shows a large negative growth in the mean number of shipments during the first year.

The countervailing exiting partial-year effect also holds in the data for both mean and median growth rates. In fact, in the data this is true for both the mean and median (panel A), and also appears to be driven by the unconditional shipments growth rates (panel B). Nevertheless, in contrast to the theoretical predictions, in the data this effect appears to prevail not only in year 1 but also in all subsequent years. This mismatch points to the restricted model's limits and suggests the need for richer demand features to fit better export growth data.[45]

The model correctly predicts the decline in the standard deviation of growth rates as the horizon lengthens (the last two columns in panel A). This result uncovers a novel mechanism affecting the volatility of firms' growth rates, especially for young and small firms, who are close to the export threshold. While in continuous time selection implies smaller volatility for *instantaneous* growth rates, a point forcefully made by Arkolakis (2016), annual growth rates feature a countervailing force due to time aggregation: firms close to the threshold have a large volatility because they are

[44]More precisely, in the model we compute $\ln(\int_{t_0+T+1}^{t_0+T+2} y(t)dt) - \ln(\int_{t_0+T}^{t_0+T+1} y(t)dt)$ and in the data $\ln(\sum_{t=t_0+T+1}^{t_0+T+2} \text{shipments}_t) - \ln(\sum_{t=t_0+T}^{t_0+T+1} \text{shipments}_t)$.

[45]Alternatively, the model could be enriched with other features. Appendix H, for example, discusses an extension with lumpiness in shipments (discussed later in footnote 46). Table G.2 shows that introducing this extension greatly improves the model fit.

Table 5: Other moments: Growth rates

	A: Unconditional sales growth rates (entry: year 0)					
	Mean		Median		Std. deviation	
Horizon	Model	Data	Model	Data	Model	Data
Year 1	0.030	−0.228	0.121	−0.178	1.815	1.732
Year 2	0.095	−0.008	0.018	0.030	1.458	1.532
Year 3	0.074	0.021	0.010	0.038	1.354	1.565
Year 4	0.052	0.058	0.005	0.075	1.263	1.501
Year 5	0.031	0.105	0.003	0.116	1.224	1.453
	B: Unconditional shipment growth rates (entry: year 0)					
	Mean		Median		Std. deviation	
Horizon	Model	Data	Model	Data	Model	Data
Year 1	−0.071	−0.189	0.018	−0.0727	1.781	0.990
Year 2	0.055	−0.039	0	0	1.431	0.969
Year 3	0.055	−0.024	0	0	1.330	0.952
Year 4	0.040	−0.018	0	0	1.242	0.900
Year 5	0.023	0	0	0	1.204	0.896
	C: Sales growth rates conditional on surviving at least until year 5 (entry: year 0)					
	Mean		Median		Std. deviation	
Horizon	Model	Data	Model	Data	Model	Data
Year 1	0.539	0.145	0.302	0.122	1.260	1.381
Year 2	0.262	0.216	0.036	0.201	1.019	1.315
Year 3	0.066	0.103	0.009	0.127	0.810	1.289
Year 4	0.007	0.129	−0.001	0.117	0.746	1.286
Year 5	−0.118	0.016	−0.010	0.084	0.867	1.185

not active during the entire year. This force introduces a new “intra-year” extensive margin effect that increases the volatility of their total sales. This effect is stronger at shorter horizons, when more firms are close to the threshold, but it also increases volatility levels in general. Whereas in panel A the model predicts quite well the standard deviations observed in the data, it strongly overpredicts them in panel B. In Appendix H, we show that the latter is due to the continuous-time formulation, which exaggerates the quantitative importance of the intra-year extensive margin.[46]

Panel C reports sales growth rate moments conditional on surviving at least five years after entry, in the spirit of Bernard et al. (2017). In the model, sales growth rates decrease over time because of selection. In the data, however, the trend is much less clear, with the second year (and the fourth year in the case of the mean) featuring a higher growth rate than the preceding year. In Appendix I, we also compute, more generally, growth rate moments conditional on export-spell length, e.g. firms surviving exactly for T years, following Fitzgerald et al. (2023). The results are fairly similar: the model predicts strong growth at the beginning and a significant drop in the last period of export activity, leading to hump-shapes for $T > 3$ (see Figure H.1 in Appendix I). In the data, the strong growth at the beginning is absent.[47]

Overall, the results for the class of moments M_2 suggest that, while the restricted model can capture some broad features of exporter’s growth rates, the data rejects the joint assumption of CES demand and θ representing productivity or quality. Instead, the results suggest that one should entertain theories that make sales and shipments lag behind profitability. For example, barriers to how fast agents may find new customers, as in Fitzgerald et al. (2023) and Eaton et al. (2021), or how fast firms can adjust their production process to satisfy demand in export markets, as in Rho and Rodrigue (2016). We leave such extensions for future research.

6.3 Moments conditional on size

Finally, a third class of moments we consider (M_3) includes survival and growth moments conditional on size. This class of moments requires specifying, on top of the baseline model, not only a specific mapping between sales and profitability (necessary to obtain the moments in M_2) but also the distribution of the heterogeneous parameters κ and F in the population of firms. In other words, our model does not deliver predictions about this class of moments unless we are willing to make these additional distributional assumptions, which are not required to yield predictions about M_1 or M_2. In this section, we keep the assumption of CES demand and assume, in addition, that both κ and F are common across firms. As in Section 6.2, this exercise aims to assess how far this restricted version of the model can go in explaining the moments in M_3.

[46]More precisely, we enrich the model by assuming firms cannot export at every instant; rather, they can only export when they are hit by an “export opportunity” shock, which occurs with intensity η. By choosing η to get a reasonable number of shipments per year, the standard deviation of shipment growth rates becomes much closer to the data. Naturally, the modified model now comes short of explaining the overall volatility of sales. This suggests that another economic force may be at play in the intensive margin, e.g. marketing costs as in (Arkolakis, 2010).

[47]With annual data based on calendar years, we get a hump shape driven by the well-known partial-year effect, both in the model and the data (see Appendix I).

Table 6: Moments conditional on size

	A: First-year (first-time entrants)					
	Survival		Sales growth: mean		Sales growth: std. dev.	
Quartile	Model	Data	Model	Data	Model	Data
1	0.185	0.118	2.161	1.256	2.004	2.620
2	0.189	0.220	0.242	−0.123	1.650	1.518
3	0.241	0.320	−0.513	−0.343	1.634	1.562
4	0.602	0.520	−0.474	−0.538	1.310	1.469
	B: Steady state					
	Survival		Sales growth: mean		Sales growth: std. dev.	
Quartile	Model	Data	Model	Data	Model	Data
1	0.412	0.314	2.248	1.116	1.994	2.145
2	0.423	0.486	0.254	0.182	1.659	1.423
3	0.699	0.620	−0.374	−0.033	1.395	1.377
4	0.999	0.797	−0.092	−0.218	0.378	1.208

Table 6 shows survival and growth moments conditional on size (quartiles of the firm size distribution) for the first-year of first-time entrants (panel A) and for all firms at the steady state (panel B).[48] Even this restricted version of the model - again, with CES demand, θ representing productivity or quality, and homogeneous κ and F - captures some broad qualitative features of the data. First, survival increases with size for first-time entrants and firms at the steady state. Second, both mean and standard deviation of sales growth rates decrease with size.[49]

Quantitatively, despite a few specific instances where mismatches are considerable, even this version of the model where we shut down heterogeneity in κ and F delivers predictions that are not far from the data, particularly in the case of survival and the standard deviation of growth rates. However, consistent with the results in the previous section, the predictions of this restricted model for mean growth rates are the least accurate. In particular, the model predicts a stronger relationship with size than the data, where this relationship could be weaker as size quartiles are also determined by other firm characteristics that correlate with size but are unrelated to profitability, e.g. fixed-cost heterogeneity or firm-destination demand shifters κ.[50]

[48]For the steady-state computation, we assume that every year N_t firms are born and that $N_{t+1} = g_B N_t$ where g_B is chosen to match the average growth rate in the number of exporters we see in our database (4.32%), as in Arkolakis (2016). We simulate firms for $T = 20$ years. Since we do not know the time of the year for the first entry, we simulate a random variable that determines it for each firm. In the data counterpart, incumbents' survival and growth moments are computed using annual data based on calendar years.

[49]There is an exception in that mean growth rates are slightly larger in the fourth quartile than in the third. In unreported results, we verify that the top decile drives the non-monotonicity. The reason is related to time aggregation: as firms become very large, they are far from the threshold and, therefore, are unlikely to display fewer shipments in the year due to exit.

[50]The literature often interprets the statistical significance of both size *and* age as explanatory variables for survival and export growth as evidence of experimentation or other forms of demand learning (see, e.g. Arkolakis et al. (2018)). Our results here suggest this class of moments should be interpreted with caution. Even in a benchmark model without

Overall, taken together, the results of this section support the idea of a hierarchy of moments, according to which it makes sense to focus first on survival probabilities upon entry (as well as any other moments based on the extensive margin of survival). These survival moments are more "robust" in that they only restrict the dynamics of the profitability process while allowing for substantial flexibility in other model features we know little about. In particular, by focusing on survival, we do not need to take a stand on demand characteristics that determine the mapping between sales and profitability or on firm-destination fixed characteristics, such as demand-shifters (e.g. quality) or fixed costs, which have been shown to be relevant dimensions of heterogeneity in earlier work (Eaton et al., 2011).

7 Concluding remarks

This paper develops a model of exporter dynamics with uncertainty and experimentation. The model is parsimonious and has tractable features that allow us to characterize the solution to the firm's problem sharply. The model can rationalize two central facts about export survival in foreign markets. The first fact is that the survival profile of export entrants is low and flat. The second is that re-entrants to foreign markets display higher survival rates than first-time entrants. We estimate the model, show that it can explain these facts qualitatively and quantitatively, and study its implications for a rich set of exporter dynamics facts. The importance of uncertainty and experimentation in exporter dynamics is further supported by evidence that exploits hypothesized variation in the degree of uncertainty about foreign market profitability across products and distance to the destination.

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experimentation, if size is an imperfect proxy for firm profitability $\tilde{\theta}$ due to variation in static parameters such as F and κ, exporter age will pick up the residual variation coming from $\tilde{\theta}$.

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Appendix (for online publication)

A Facts in regression framework

In this section, we present the main empirical results of the paper in regression form to show that the results do not rely on composition effects. Note that since years are firm-market-specific, they involve more than one calendar year. In each case, we attribute the calendar year with the largest overlap, e.g. if the firm-market-specific year is May (October) 1st 1997 - April (September) 30th 1998, then we attribute the year 1997 (1998) for the purpose of the year fixed effect. All regressions have standard errors clustered at the firm level to allow for correlation over time (i.e. different export experiences of a firm) and across markets.

Table A.1: Facts 1 and 2 controlling for composition

	(1)	(2)	(3)	(4)
	Entrants		Re-entrants	
Constant	0.294***		0.294***	
	(0.00455)		(0.00455)	
Year 2	-0.052***	-0.051***	-0.052***	-0.051***
	(0.00282)	(0.00355)	(0.00282)	(0.00354)
Year 3	-0.086***	-0.083***	-0.086***	-0.083***
	(0.00330)	(0.00520)	(0.00330)	(0.00520)
Year 4	-0.109***	-0.104***	-0.109***	-0.105***
	(0.00368)	(0.00670)	(0.00368)	(0.00669)
Year 5	-0.125***	-0.120***	-0.125***	-0.120***
	(0.00380)	(0.00827)	(0.00380)	(0.00821)
Year 1*Re-ent.			0.112***	0.100***
			(0.01358)	(0.01365)
Year 2*Re-ent.			0.119***	0.108***
			(0.01346)	(0.01348)
Year 3*Re-ent.			0.126***	0.115***
			(0.01334)	(0.01344)
Year 4*Re-ent.			0.108***	0.092***
			(0.01279)	(0.01313)
Year 5*Re-ent.			0.116***	0.102***
			(0.01322)	(0.01358)
Destination-year fixed effect	No	Yes	No	Yes
Product fixed effect	No	Yes	No	Yes
Observations	124275	123934	132570	132233
R^2	0.012	0.057	0.016	0.060

Notes: Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Effect of type of product on survival

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Entrants				Re-entrants			
Differentiated	-0.048***		-0.056***		-0.038*		-0.048**	
	(0.00868)		(0.00836)		(0.02164)		(0.02322)	
Year 1*Diff.		-0.051***		-0.060***		-0.056**		-0.084***
		(0.00929)		(0.00890)		(0.02649)		(0.02859)
Year 2*Diff.		-0.054***		-0.062***		-0.056**		-0.056*
		(0.00950)		(0.00910)		(0.02687)		(0.02902)
Year 3*Diff.		-0.048***		-0.055***		-0.019		-0.031
		(0.00951)		(0.00927)		(0.02768)		(0.02967)
Year 4*Diff.		-0.049***		-0.057***		-0.040		-0.049*
		(0.00950)		(0.00939)		(0.02736)		(0.02890)
Year 5*Diff.		-0.037***		-0.045***		-0.018		-0.018
		(0.00957)		(0.00953)		(0.02808)		(0.02932)
Destination-year fixed effect	No	No	Yes	Yes	No	No	Yes	Yes
Observations	121270	121270	120931	120931	8175	8175	8032	8032
R^2	0.015	0.015	0.034	0.034	0.011	0.011	0.089	0.089

Notes: All regressions include horizon dummies. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Effect of distance on survival

	(1)	(2)	(3)	(4)
Log(dist)*Diff.	-0.024***		-0.024***	
	(0.00449)		(0.00450)	
Log(dist)*Homog.	0.015**		0.015**	
	(0.00610)		(0.00613)	
Year 1*Diff.*Log(dist)		-0.033***		-0.033***
		(0.00565)		(0.00566)
Year 2*Diff.*Log(dist)		-0.021***		-0.021***
		(0.00549)		(0.00550)
Year 3*Diff.*Log(dist)		-0.022***		-0.022***
		(0.00514)		(0.00514)
Year 4*Diff.*Log(dist)		-0.021***		-0.021***
		(0.00519)		(0.00520)
Year 5*Diff.*Log(dist)		-0.023***		-0.023***
		(0.00502)		(0.00503)
Year 1*Homog.*Log(dist)		0.016**		0.016**
		(0.00706)		(0.00709)
Year 2*Homog.*Log(dist)		0.013*		0.014**
		(0.00704)		(0.00709)
Year 3*Homog.*Log(dist)		0.016**		0.017**
		(0.00724)		(0.00728)
Year 4*Homog.*Log(dist)		0.015**		0.015**
		(0.00674)		(0.00677)
Year 5*Homog.*Log(dist)		0.015**		0.015**
		(0.00687)		(0.00689)
Year fixed effect	No	No	Yes	Yes
Observations	120030	120030	120030	120030
R^2	0.017	0.017	0.017	0.017

Notes: All regressions include horizon dummies, a differentiated good dummy, and the interaction between a differentiated good dummy and horizon dummies (omitted). Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B Annual data based on calendar years

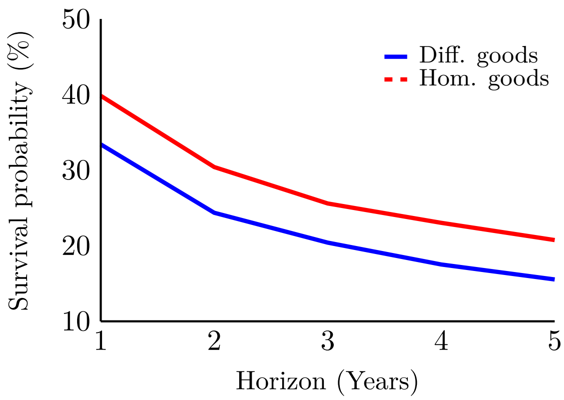
In this section, we replicate the main facts of our paper using annual data based on calendar years instead of our firm-specific definition of years based on the moment of the first shipment. We consider entries (firm-market level) between 1997 and 2003. An entry in year t is considered a "re-entry" if the firm has exported at least one year to the market under consideration since 1993 and did not export at $t-1$. This alternative measure is subject to time-aggregation issues (e.g. firms may enter in different months), but it has the benefit that it can be defined for incumbents as well, increasing sample size.

Table B.1: Descriptive Statistics

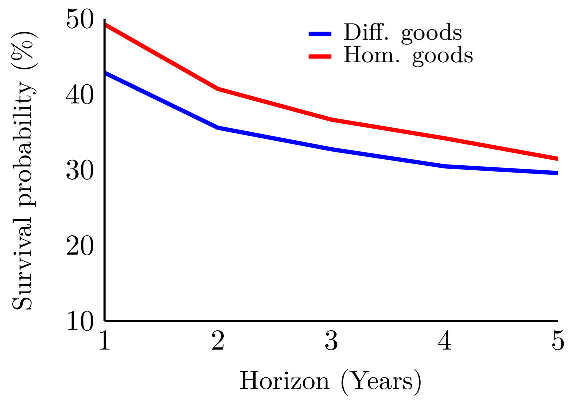
Year	Firms	Incursions	Re-entries	Incursions: 2-year surv. (%)
1997	3,775	4,081	700	25.7
1998	3,563	3,522	729	29.0
1999	3,895	4,249	1,102	27.5
2000	4,017	4,537	1,106	24.2
2001	4,347	4,244	1,175	25.9
2002	4,685	4,222	1,338	27.3
2003	5,094	4,836	1,458	27.4
Total	28,098	29,691	7,608	26.6

Notes: Based on Peruvian customs dataset (World Bank).

In the model predictions, we take into account partial year effects by simulating a random variable that determines the time of the year that the firm enters. We assume this random variable is uniformly distributed over the year. Overall, we find that the partial-year effect substantially affects all moments, including survival probabilities, especially during the first year. Our partial-year correction moves moments in the same direction as in the data in all cases, but it exaggerates the magnitude of these movements in the first year.

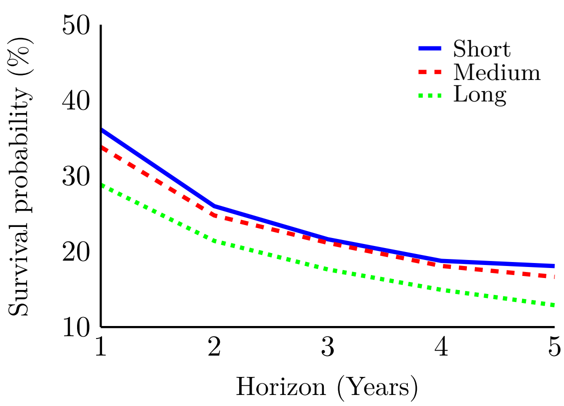


(a) First-time entrants

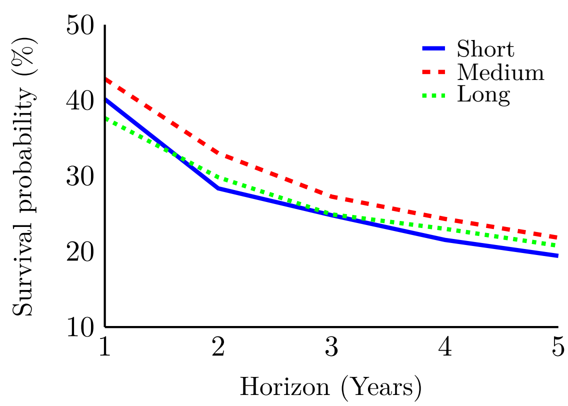


(b) Re-entrants

Figure E.1: Survival profile by type of product



(a) Differentiated goods



(b) Homogeneous goods

Figure E.2: Survival profile by distance (First-time entrants)

B.1 Main Facts

Tables B.2 to B.4, presented below, replicate tables A.1 to A.3 using annual data based on calendar years and all re-entrants, regardless of whether we observe their first-time entry.

Table B.2: Facts 1 and 2 controlling for composition

	(1)	(2)	(3)	(4)
	Entrants		Re-entrants	
Constant	0.357***		0.357***	
	(0.00402)		(0.00402)	
Year 2	-0.091***	-0.094***	-0.091***	-0.095***
	(0.00294)	(0.00342)	(0.00294)	(0.00338)
Year 3	-0.134***	-0.137***	-0.134***	-0.140***
	(0.00338)	(0.00468)	(0.00338)	(0.00448)
Year 4	-0.161***	-0.163***	-0.161***	-0.168***
	(0.00364)	(0.00590)	(0.00364)	(0.00555)
Year 5	-0.178***	-0.181***	-0.178***	-0.188***
	(0.00384)	(0.00740)	(0.00384)	(0.00682)
Year 1*Re-ent.			0.097***	0.084***
			(0.00722)	(0.00733)
Year 2*Re-ent.			0.111***	0.099***
			(0.00758)	(0.00754)
Year 3*Re-ent.			0.120***	0.108***
			(0.00777)	(0.00775)
Year 4*Re-ent.			0.124***	0.111***
			(0.00809)	(0.00804)
Year 5*Re-ent.			0.123***	0.111***
			(0.00822)	(0.00811)
Destination-year fixed effect	No	Yes	No	Yes
Product fixed effect	No	Yes	No	Yes
Observations	148455	148099	186495	186145
R^2	0.022	0.066	0.030	0.068

Notes: Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: Effect of type of product on survival

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Entrants				Re-entrants			
Differentiated	-0.055***		-0.065***		-0.042***		-0.048***	
	(0.00788)		(0.00767)		(0.01300)		(0.01317)	
Year 1*Diff.		-0.064***		-0.078***		-0.064***		-0.077***
		(0.00801)		(0.00791)		(0.01341)		(0.01361)
Year 2*Diff.		-0.061***		-0.070***		-0.051***		-0.059***
		(0.00875)		(0.00853)		(0.01461)		(0.01500)
Year 3*Diff.		-0.052***		-0.061***		-0.039**		-0.044***
		(0.00900)		(0.00880)		(0.01528)		(0.01551)
Year 4*Diff.		-0.055***		-0.063***		-0.037**		-0.039**
		(0.00899)		(0.00888)		(0.01610)		(0.01640)
Year 5*Diff.		-0.045***		-0.053***		-0.019		-0.021
		(0.00904)		(0.00896)		(0.01643)		(0.01668)
Destination-year fixed effect	No	No	Yes	Yes	No	No	Yes	Yes
Observations	144910	144910	144555	144555	37145	37145	36903	36903
R^2	0.026	0.026	0.045	0.045	0.015	0.015	0.050	0.051

Notes: All regressions include horizon dummies. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: Effect of distance on survival

	(1)	(2)	(3)	(4)
Log(dist)*Diff.	-0.026***		-0.026***	
	(0.00414)		(0.00414)	
Log(dist)*Homog.	0.009		0.009	
	(0.00559)		(0.00561)	
Year 1*Diff.*Log(dist)		-0.037***		-0.036***
		(0.00527)		(0.00528)
Year 2*Diff.*Log(dist)		-0.024***		-0.024***
		(0.00502)		(0.00502)
Year 3*Diff.*Log(dist)		-0.021***		-0.021***
		(0.00504)		(0.00505)
Year 4*Diff.*Log(dist)		-0.020***		-0.020***
		(0.00480)		(0.00481)
Year 5*Diff.*Log(dist)		-0.028***		-0.028***
		(0.00467)		(0.00467)
Year 1*Homog.*Log(dist)		-0.006		-0.006
		(0.00645)		(0.00643)
Year 2*Homog.*Log(dist)		0.017***		0.018***
		(0.00665)		(0.00669)
Year 3*Homog.*Log(dist)		0.007		0.007
		(0.00660)		(0.00663)
Year 4*Homog.*Log(dist)		0.012*		0.012*
		(0.00650)		(0.00653)
Year 5*Homog.*Log(dist)		0.012*		0.012*
		(0.00664)		(0.00666)
Year fixed effect	No	No	Yes	Yes
Observations	143345	143345	143345	143345
R^2	0.028	0.028	0.028	0.028

Notes: All regressions include horizon dummies, a differentiated good dummy, and the interaction between a differentiated good dummy and horizon dummies (omitted). Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In Table B.5, we show the annualized version of the ten moments that constitute facts 1 and 2 (restricted to first-time re-entrants to isolate the implications of partial-year effects) and the corresponding model predictions using our baseline estimates.

While the partial-year effect is often discussed in relationship with growth rates (Bernard et al., 2017), we show that survival rates are also substantially affected. Indeed, first-year survival rates in the first year are about 5 percentage points higher both for first-time entrants and for re-entrants, as it is easier to survive after a month than it is to survive after an entire year. The effect gets smaller, but it is still present on longer horizons. The model also predicts higher survival

Table B.5: Survival probabilities: Annual data

	Panel A: Entrants	
	Model	Data
Year 1	0.498	0.357
Year 2	0.252	0.266
Year 3	0.203	0.223
Year 4	0.186	0.196
Year 5	0.177	0.179
	Panel B: Re-entrants	
	Model	Data
Year 1	0.563	0.454
Year 2	0.370	0.373
Year 3	0.322	0.332
Year 4	0.292	0.302
Year 5	0.273	0.285

probabilities but substantially overstates the partial-year effect during the first year. Since our model is cast in continuous time and firms make decisions instant-by-instant, the model does not include any reason why shipments may be spread out over time, such as inventory management by importers (Alessandria et al., 2010). This makes firms entering late into the year extremely likely to survive. Indeed, in the model, a firm entering in December has an 87% probability of surviving, while a firm entering in January survives with 31% probability. Our model is better suited for moments aggregated at a frequency where the natural delay in shipments matters less, which is why we constructed firm-market-specific years in our main analysis.[51] The model does an excellent job at horizons from year 2 onwards.

B.2 Other extensive-margin moments

We re-do here the analysis in Section 6.1 with annual data. The results are similar, except that continuous survival and the extent of re-entry are slightly larger, both in the model and in the data. The conditional survival in year 2 is farther from the data, but this mainly reflects that our model exaggerates the partial-year effect, which leads us to overestimate survival in year 1 (the denominator used to compute conditional survival).

[51] See also Appendix H for a model with lumpiness.

Table B.6: Other moments: Extensive margin. Annual data.

	A: Other survival measures (entry: year 0)			
	Continuous survival		Conditional survival	
Horizon	Model	Data	Model	Data
Year 2	0.2072	0.208	0.416	0.582
Year 3	0.1348	0.146	0.651	0.701
Year 4	0.1092	0.111	0.810	0.763
Year 5	0.0957	0.091	0.877	0.818
	B: Moments conditional on exit (exit: year 0)			
	Re-entry		Survival	
Horizon	Model	Data	Model	Data
Year 2	0.083	0.108	0.083	0.108
Year 3	0.131	0.159	0.095	0.104
Year 4	0.165	0.192	0.093	0.099
Year 5	0.190	0.215	0.092	0.096

B.3 Growth rate moments

We re-do the analysis in Section 6.2 with calendar-year annual data. The results are similar, except for a sizeable partial year effect in year 1. Similar to the results on survival, our model also predicts a partial-year effect that is too large for growth. The fit to the survivors (i.e. those surviving at least six years) is now closer to the data, which is also monotonically decreasing on the horizon.

Table B.7: Other moments: Growth rates. Annual data.

	A: Unconditional sales growth rates (entry: year 0)					
	Mean		Median		Std. deviation	
Horizon	Model	Data	Model	Data	Model	Data
Year 1	0.870	0.357	0.789	0.303	2.049	1.811
Year 2	0.032	-0.025	0.038	0.021	1.609	1.566
Year 3	0.082	0.010	0.012	0.049	1.406	1.500
Year 4	0.057	0.023	0.007	0.057	1.294	1.419
Year 5	0.029	0.090	0.004	0.108	1.249	1.496
	B: Unconditional shipment growth rates (entry: year 0)					
	Mean		Median		Std. deviation	
Horizon	Model	Data	Model	Data	Model	Data
Year 1	0.793	0.301	0.693	0.154	2.015	1.053
Year 2	-0.038	-0.035	0.000	0.000	1.578	0.979
Year 3	0.054	-0.030	0.000	0.000	1.380	0.946
Year 4	0.042	-0.027	0.000	0.000	1.272	0.916
Year 5	0.019	-0.003	0.000	0.000	1.230	0.881
	C: Sales growth rates conditional on surviving at least until year 5 (entry: year 0)					
	Mean		Median		Std. deviation	
Horizon	Model	Data	Model	Data	Model	Data
Year 1	1.576	0.799	1.240	0.704	1.728	1.600
Year 2	0.350	0.267	0.084	0.214	1.118	1.304
Year 3	0.122	0.147	0.015	0.151	0.904	1.225
Year 4	0.022	0.073	0.001	0.096	0.798	1.101
Year 5	-0.123	0.008	-0.010	0.079	0.910	1.186

B.4 Moments conditional on size

We re-do here the analysis in Section 6.3 with calendar-year annual data. The effect of size on survival is smaller, potentially because many small firms are now firms that enter late into the year and are very likely to survive. Indeed, according to the model, firms in the lowest quartile survive more than firms in the second quartile. The relationship with size is also weaker in the data, but the ranking is not reversed. As argued before, our partial-year-effect correction in the model for annual data based on calendar years seems to overcorrect this problem. As expected, the partial year effect also shifts upwards growth rates, which are now monotonic even in the model. In both model and data, the relationship between standard deviation and size becomes weaker, as firms may now be small because they enter late into the year.

Table B.8: Moments conditional on size. Annual data.

	First-year (first-time entrants)					
	Survival		Sales growth: mean		Sales growth: std. dev.	
Quartile	Model	Data	Model	Data	Model	Data
1	0.459	0.207	3.000	1.662	1.894	2.507
2	0.440	0.305	1.005	0.443	1.600	1.470
3	0.461	0.383	0.155	0.252	1.568	1.518
4	0.630	0.534	-0.251	-0.124	1.454	1.595

C Robustness: Other re-entrant definitions

In this section, we show the robustness of our main fact - that re-entrants survive less than first-time entrants - to several definitions of re-entrants. One worry is that the fact that shipments are discrete may lead us to falsely consider "re-entrants" firms that were not observed to export for longer than a year, but rather than having exited the market, the reason for their apparent inactivity is that they performed concentrated shipments. To address this concern, we study an alternative definition of re-entrants based on the time elapsed between re-entry and the last shipment before exit. Specifically, we call a shipment a "re-entry" if more than X months have passed since the previous shipment, where $X = 12, 18, 24$ (we also present results with annual data based on calendar years in Section B.1).

Tables C.1, C.2 and C.3 show the results with raw data. We have also verified that the results controlling for composition are similar (analogously to Table A.1). We conclude that it is very unlikely that the infrequent nature of shipments drives fact 2.

Table C.1: Survival Probabilities (Raw Data, 12 Months)

Horizon	First-time entrants	Re-entrants
1	0.2941	0.4294
2	0.2423	0.3722
3	0.2080	0.3416
4	0.1854	0.3146
5	0.1691	0.2975

Table C.2: Survival Probabilities (Raw Data, 18 Months)

Horizon	First-time entrants	Re-entrants
1	0.2941	0.4029
2	0.2423	0.3496
3	0.2080	0.3205
4	0.1854	0.2999
5	0.1691	0.2845

Table C.3: Survival Probabilities (Raw Data, 24 Months)

Horizon	First-time entrants	Re-entrants
1	0.2941	0.3845
2	0.2423	0.3338
3	0.2080	0.3108
4	0.1854	0.2897
5	0.1691	0.2716

D General model, proofs and derivations

D.1 Derivation of HJB equations

The inexperienced firm An experienced firm receives profits given by $\pi_e(\theta_t;\psi) = \psi\kappa\theta_t - F = F\left(\psi\tilde{\theta}_t - 1\right)$ if it exports and 0 otherwise. The value of an experienced firm (V_e) at $t = 0$ is the solution to the following problem:

$$V_e(\tilde{\theta}_0;\psi) = \sup_{\{y_e(\tilde{\theta}_t)\}_{t=0}^{\infty}} \mathbb{E}\left(\int_0^{\infty} e^{-rt} F\left(\psi\tilde{\theta}_t - 1\right) y_e(\tilde{\theta}_t)dt\right)$$

subject to (1) with $\tilde{\theta}_0$ given, where r is the discount rate.

Suppose a firm follows any constant policy $y_e \in \{0,1\}$ during an interval of time $[t, t+\tau]$. Exploiting the stationarity of the problem, we can write the problem recursively as

$$V_e(\tilde{\theta}_t;\psi) = \max_{y_e\in\{0,1\}} \mathbb{E}\left(\int_0^{\tau} e^{-rs} F\left(\psi\tilde{\theta}_{t+s} - 1\right) y_e ds + e^{-r\tau}V_e(\tilde{\theta}_{t+\tau};\psi)\right).$$

Taking the limit $\tau \to 0$ and rearranging yields (2).

The inexperienced firm First, we make a technical assumption so that the inexperienced firms' problem is well-defined: we assume that the distribution of ψ is such that $\mathbb{E}_{\psi}V_e(\tilde{\theta};\psi)$ satisfies a polynomial growth condition.[52] Let t denote the (random) time at which a firm becomes experienced. Given that this event occurs with intensity λ only if the firm exports, the probability density function (p.d.f) of t depends on the export policy. At time $t = 0$, this density is given by $\lambda y_i(\tilde{\theta}_t)e^{-\int_0^t \lambda y_i(\tilde{\theta}_s)ds}$, where the exponent term captures the probability that the shock did not take place until t and $\lambda y_i(\tilde{\theta}_t)$ is the instantaneous arrival rate. Then, the inexperienced firm's problem can be written as

$$V_i(\tilde{\theta}_0) = \sup_{\{y_i(\tilde{\theta}_t)\}_{t=0}^{\infty}} \mathbb{E}\int_0^{\infty}\left[\int_0^t e^{-ru}F\left(\tilde{\theta}_u - 1\right)y_i(\tilde{\theta}_u)du + e^{-rt}\mathbb{E}V_e(\tilde{\theta}_t;\psi)\right]\lambda y_i(\tilde{\theta}_t)e^{-\int_0^t \lambda y_i(\tilde{\theta}_s)ds}dt \tag{A.1}$$

subject to (1) with $\tilde{\theta}_0$ given. Fixing a time t at which the firm receives the shock, the term in square brackets in (A.1) captures the expected discounted profits, which consist of the discounted stream of net profit flows $F\left(\tilde{\theta}_u - 1\right)du$ accumulated during export periods up to t and the discounted expected value of being an experienced firm. Note that by exporting the firm may become experienced sooner, which is always desirable because it implies a higher profit flow on average.

[52]We say that $f : [0,\infty) \to$ satisfies a polynomial growth condition if there exist $M > 0$ and $\nu > 0$ such that $|f(\theta)| \leq M(1+\theta^{\nu})$. Since $\tilde{\theta}$ is a GBM, it is easy to see that V_e is a power function. Thus, when ψ is Pareto, this is akin to a lower bound on α to guarantee that the expectation is finite.

Manipulating (A.1), we can rewrite the inexperienced firm's problem as[53]

$$V_i(\tilde{\theta}_0) = \sup_{\{y_i(\tilde{\theta}_t)\}_{t=0}^{\infty}} \mathbb{E}\int_0^{\infty} e^{-rt-\lambda\int_0^t y_i(\tilde{\theta}_s)ds}\left\{F\left(\tilde{\theta}_t - 1\right) + \lambda\mathbb{E}_{\psi}V_e(\tilde{\theta}_t)\right\} y_i(\tilde{\theta}_t)dt \tag{A.2}$$

subject to (1) and $\tilde{\theta}_0$ given. Consider a firm that follows any constant policy $y_i \in \{0,1\}$ during an interval of time $[t, t+\tau]$. Exploiting the stationarity of problem (A.2) we can write it recursively as

$$V_i(\tilde{\theta}_t) = \max_{y_i\in\{0,1\}} \mathbb{E}\left(\int_0^{\tau} e^{-(r+\lambda y_i)s}\left\{F\left(\tilde{\theta}_{t+s} - 1\right) + \lambda\mathbb{E}_{\psi}V_e(\tilde{\theta}_{t+s};\psi)\right\} y_i ds + e^{-(r+\lambda y_i)\tau}V_i(\tilde{\theta}_{t+\tau})\right). \tag{A.3}$$

Taking the limit $\tau \to 0$ and rearranging yields (3).

D.2 Proof of Proposition 1

We prove the result under the general conditions on the profit function $\pi(\cdot)$, the law of motion of profitability, θ_t, and distribution ψ stated below:

Assumption 1. *$\mathbb{E}_{\psi}\pi_e(\psi,\theta) \geq \pi_i(\theta)\,\forall\theta\pi_e$ is continuous, π_i belongs to C^2 and both are weakly increasing in $\theta\forall\psi$. ψ and θ are independent.*

Assumption 2. *Let $h \equiv \lambda\mathbb{E}_{\psi}\left(\max\left\{\pi_e\left(\theta;\psi\right),0\right\}\right) - \lim_{dt\to 0}\left\{\mathbb{E}(e^{-rdt}\pi_i(\theta_{t+dt})) - \pi_i(\theta_t)\right\}$. If $\lambda > 0$, $h\left(\theta\right)$ is weakly increasing in θ. Furthermore, $E\left[\int_0^{\infty} e^{-rt}h(\theta_t)d\theta_t|\theta_0\right]$ satisfies a polynomial growth condition.*[54]

Assumption 3. *There exists $\bar{\theta}$ such that $\forall\theta > \bar{\theta}$, flow profits are positive even for inexperienced firms, $\pi_i(\theta) \geq 0$.*

Assumption 4. *The profitability process $\{\theta_t\}_{t=0}^{\infty}$ is assumed to follow a diffusion,*

$$d\theta_t = \mu_{\theta}dt + \sigma_{\theta}dZ_t \tag{A.4}$$

where Z_t is a standard brownian motion. We assume μ_{θ} and σ_{θ} are continuous functions of θ that satisfy Lipschitz and growth conditions on μ and σ.[55] *Furthermore, if $\theta'' > \theta'$, then $F\left(\theta|\theta''\right) \succsim_{FOSD} F\left(\theta|\theta'\right)$.*

[53] Distribute the term $\lambda y_i(\tilde{\theta}_t)e^{-\lambda\int_0^t y_i(\tilde{\theta}_s)ds}$ inside the parenthesis and note that $\int_0^{\infty}\int_0^t e^{-ru-\lambda\int_0^t y_i(\tilde{\theta}_s)ds}\lambda y_i(\tilde{\theta}_t)F\left(\tilde{\theta}_u - 1\right)y_i(\tilde{\theta}_u)dudt = \int_0^{\infty}\int_s^{\infty} e^{-ru-\lambda\int_0^t y_i(\tilde{\theta}_s)ds}\lambda y_i(\tilde{\theta}_t)dtF\left(\tilde{\theta}_u - 1\right)y_i(\tilde{\theta}_u)du = \int_0^{\infty} e^{-ru-\lambda\int_0^u y_i(\tilde{\theta}_s)ds}F\left(\tilde{\theta}_u - 1\right)y_i(\tilde{\theta}_u)du$.

[54] We say that $f : [0,\infty) \to \mathbb{R}$ satisfies a polynomial growth condition if there exist $M > 0$ and $\nu > 0$ such that $|f\left(\theta\right)| \leq M\left(1+\theta^{\nu}\right)$.

[55] We say that μ satisfies a Lipschitz condition if there exists $k > 0$ such that

$$\left|\mu\left(\theta\right) - \mu\left(\theta'\right)\right| \leq k\left|\theta - \theta'\right|.$$

This ensures the existence of a strong solution to (A.4).

Assumption 5. *$\mathbb{E}_\psi V_e$ satisfies a polynomial growth condition $\forall\theta$.*

Assumption 1 is satisfied in the model in the text because $\mathbb{E}(\psi) \geq 1$. Applying Ito's Lemma to Assumption 2 we get

$$h \equiv \lambda \mathbb{E}_\psi \pi_e(\theta;\psi) + r\pi_i(\theta) - \mu_\theta \frac{d\pi_i(\theta)}{d\theta} - \frac{1}{2}\sigma_\theta^2 \frac{d^2\pi_i}{d\theta^2}$$

In the model in the text,

$$h \equiv \mathbb{E}_\psi\left[\max\left\{\psi\tilde{\theta} - 1, 0\right\}\right] + \frac{r}{\lambda}\left(\tilde{\theta} - 1\right) - \frac{\tilde{\theta}}{\lambda}\left(\mu + \frac{1}{2}\sigma^2\right)$$

which is clearly increasing in $\tilde{\theta}$ (recall $r > \mu + \frac{1}{2}\sigma^2 > 0$). Furthermore, Assumption 3 is satisfied by taking $\bar{\theta} = \frac{F}{\kappa}$ and Assumption 4 is satisfied by the GBM assumption ($\mu_\theta = (\mu + \frac{1}{2}\sigma^2)\theta$ and $\sigma_\theta = \sigma\theta$). Finally, when ψ is distributed Pareto, one can show that

$$\mathbb{E}_\psi V_e(\tilde{\theta}) = F \begin{cases} \frac{2}{(\alpha-1)(\beta_1-\alpha)(\alpha-\beta_2)\sigma^2}\tilde{\theta}^\alpha - \frac{A_{e1}\alpha}{\beta_1-\alpha}\tilde{\theta}^{\beta_1} & \text{if } \tilde{\theta} < 1 \\ \frac{\alpha A_{e2}}{\alpha-\beta_2}\tilde{\theta}^{\beta_2} + \frac{\alpha}{(r-\mu')(\alpha-1)}\tilde{\theta} - \frac{1}{r} & \text{if } \tilde{\theta} \geq 1 \end{cases},$$

for some constants A_{e1} and A_{e2}. This expression satisfies a polynomial growth condition, i.e. Assumption 5 is satisfied.

First, we prove the following result,

Lemma 1. *Exporting is optimal for an inexperienced firm when $\theta > \bar{\theta}$.*

Proof. Exporting while $\theta > \bar{\theta}$ yields flow profits $\pi_i(\theta) \geq 0$ in $[\bar{\theta}, +\infty)$ if the firm remains inexperienced and introduces the possibility of becoming experienced, which, by assumption 1, increases expected profits. Hence, exporting is optimal in this region. □

Define $\pi^{EE}(\theta) \equiv \mathbb{E}_\psi(\max\{\pi_e(\theta,\psi), 0\})$. Note that the flow benefits of exporting (W) are given by

$$W = \pi_i + \lambda(\mathbb{E}_\psi V_e - V_i).$$

Since y_i is piecewise continuous, V_i is continuous. Given that π_i and V_e are continuous, this implies W is continuous. Assuming an indifferent firm exports, a firm will export iff $W \geq 0$. By Assumption 1 and the possibility of inaction, we know that $0 \leq V_i(\theta) \leq V_e(\theta) < \infty \ \forall\theta$. Moreover, since W is continuous and π_e and π_i are continuous, by the Feynman-Kac Theorem we know that $V_i, V_e \in C^2$ and, thus, $W \in C^2$. Hence, V_e and V_i satisfy the following Hamilton-Jacobi-Bellman equations,

$$r\mathbb{E}_\psi V_e = \pi^{EE} + \mu_\theta \frac{d\mathbb{E}_\psi V_e}{d\theta} + \frac{1}{2}\sigma_\theta^2 \frac{d^2\mathbb{E}_\psi V_e}{d\theta^2} \ \forall\theta \quad \text{(A.5)}$$

$$\begin{aligned} (r+\lambda) V_i &= \pi_i + \lambda \mathbb{E}_\psi V_e + \mu_\theta \frac{dV_i}{d\theta} + \frac{1}{2}\sigma_\theta^2 \frac{d^2 V_i}{d\theta^2} \text{ when } W(\theta) \geq 0 && \text{(A.6)} \\ rV_i &= \mu_\theta \frac{dV_i}{d\theta} + \frac{1}{2}\sigma_\theta^2 \frac{dV_i}{d\theta} \text{ when } W(\theta) < 0 && \text{(A.7)} \end{aligned}$$

Next, subtract (A.6) and (A.7) from (A.5) to obtain,

$$\begin{aligned} (r+\lambda)(\mathbb{E}_\psi V_e - V_i) &= \pi^{EE} - \pi_i + \mu_\theta \left(\frac{d\mathbb{E}_\psi V_e}{d\theta} - \frac{dV_i}{d\theta} \right) + \frac{\sigma_\theta^2}{2} \left(\frac{d^2 \mathbb{E}_\psi V_e}{d\theta^2} - \frac{d^2 V_i}{d\theta^2} \right) \text{ when } W(\theta) \geq 0 && \text{(A.8)} \\ r(\mathbb{E}_\psi V_e - V_i) &= \pi^{EE} + \mu_\theta \left(\frac{d\mathbb{E}_\psi V_e}{d\theta} - \frac{dV_i}{d\theta} \right) + \frac{\sigma_\theta^2}{2} \left(\frac{d^2 \mathbb{E}_\psi V_e}{d\theta^2} - \frac{d^2 V_i}{d\theta^2} \right) \text{ when } W(\theta) < 0 && \text{(A.9)} \end{aligned}$$

Rewrite (A.8) and (A.9) in terms of W to obtain

$$\begin{aligned} \left(\frac{r+\lambda}{\lambda}\right)(W - \pi_i) &= \pi^{EE} - \pi_i + \frac{\mu_\theta}{\lambda} \left(\frac{dW}{d\theta} - \frac{d\pi_i}{d\theta} \right) + \frac{1}{2}\frac{\sigma_\theta^2}{\lambda} \left(\frac{d^2 W}{d\theta^2} - \frac{d^2 \pi_i}{d\theta^2} \right) \text{ when } W(\theta) \geq 0 \\ \left(\frac{r}{\lambda}\right)(W - \pi_i) &= \pi^{EE} + \frac{\mu_\theta}{\lambda} \left(\frac{dW}{d\theta} - \frac{d\pi_i}{d\theta} \right) + \frac{1}{2}\frac{\sigma_\theta^2}{\lambda} \left(\frac{d^2 W}{d\theta^2} - \frac{d^2 \pi_i}{d\theta^2} \right) \text{ when } W(\theta) < 0 \end{aligned}$$

where we used the fact that $\pi_i \in C^2$. Rearranging,

$$\begin{aligned} \left(1 + \frac{r}{\lambda}\right) W &= \pi^{EE} + \frac{r}{\lambda}\pi_i - \frac{\mu_\theta}{\lambda}\frac{d\pi_i}{d\theta} - \frac{1}{2}\frac{\sigma_\theta^2}{\lambda}\frac{d^2\pi_i}{d\theta^2} + \frac{\mu_\theta}{\lambda}\frac{dW}{d\theta} + \frac{1}{2}\frac{\sigma_\theta^2}{\lambda}\frac{d^2 W}{d\theta^2} \text{ when } W(\theta) \geq 0 \\ \left(1 + \frac{r}{\lambda}\right) W &= W + \pi^{EE} + \frac{r}{\lambda}\pi_i - \frac{\mu_\theta}{\lambda}\frac{d\pi_i}{d\theta} - \frac{1}{2}\frac{\sigma_\theta^2}{\lambda}\frac{d^2\pi_i}{d\theta^2} + \frac{\mu_\theta}{\lambda}\frac{dW}{d\theta} + \frac{1}{2}\frac{\sigma_\theta^2}{\lambda}\frac{d^2 W}{d\theta^2} \text{ when } W(\theta) < 0. \end{aligned}$$

Define $h \equiv \pi^{EE} + \frac{r}{\lambda}\pi_i - \frac{\mu_\theta}{\lambda}\frac{d\pi^I}{d\theta} - \frac{1}{2}\frac{\sigma_\theta^2}{\lambda}\frac{d^2\pi_i}{d\theta^2}$, which is exactly Assumption 2 after applying Ito's Lemma. We can rewrite this as

$$\left(1 + \frac{r}{\lambda}\right) W = W \mathbf{1}_{W<0} + h + \frac{\mu_\theta}{\lambda}\frac{dW}{d\theta} + \frac{1}{2}\frac{\sigma_\theta^2}{\lambda}\frac{d^2 W}{d\theta^2}. \tag{A.10}$$

By assumptions 2 and 5, we know that W and h satisfy a polynomial growth condition. Furthermore, we know that W is continuous. Hence, by Feynman-Kac theorem (Duffie, Appendix E, p.344), the unique solution that satisfies a polynomial growth condition to (A.10) is given by

$$W(\theta_0) = \mathbb{E}\left(\int_0^\infty e^{-\left(1+\frac{r}{\lambda}\right)t} \left\{ W(\theta_t) \mathbf{1}_{W(\theta_t)<0} + h(\theta_t) \right\} d\theta_t | \theta_0 \right). \tag{A.11}$$

We still need to show such a solution exists. We do this next.

Lemma 2. *There is a unique continuous solution W to the functional equation* (A.11)*.*

Proof. By Lemma 1, the solution satisfies $W(\theta) \geq 0$ for $\theta_t > \bar{\theta}$. Since only $W(\theta) < 0$ appears on the RHS of the functional equation (A.11), we can focus our attention on the set $[0, \bar{\theta}]$. Define the

operator $T : C(X) \rightarrow C(X)$ as the RHS on (A.11) restricted to $\left[0,\bar{\theta}\right]$, where C is the space of continuous and bounded functions. Note that T is well-defined in the sense that if $f \in C$, $Tf \in C$. Next, we show that T satisfies monotonicity and discounting:
(i) Monotonicity. Take $f \geq g$. Then,

$$\begin{aligned}
Tf(\theta_0) &= \mathbb{E}[\int_0^\infty e^{-(1+\frac{r}{\lambda})}\{f(\theta_t)\mathbf{1}_{f(\theta_t)<0\cap\theta_t<\bar{\theta}} + h(\theta_t)\}d\theta_t|\theta_0] \\
&\geq \mathbb{E}[\int_0^\infty e^{-(1+\frac{r}{\lambda})}\{g(\theta_t)\mathbf{1}_{f(\theta_t)<0\cap\theta_t<\bar{\theta}} + h(\theta_t)\}d\theta_t|\theta_0] \\
&\geq \mathbb{E}[\int_0^\infty e^{-(1+\frac{r}{\lambda})}\{g(\theta_t)\mathbf{1}_{g(\theta_t)<0\cap\theta_t<\bar{\theta}} + h(\theta_t)\}d\theta_t|\theta_0] = Tg(\theta_0).
\end{aligned}$$

The first step uses $f \geq g$, while the second step uses the fact that if $f(z) < 0 \Rightarrow g(z) < 0$ so $g(z)\,1_{g(z)<0} = g(z)\,1_{f(z)<0} + g(z)\,1_{f(z)\geq 0\cap g(z)<0} \leq g(z)\,1_{f(z)<0}$.
(ii) Discounting. Take $a > 0$. Then,

$$\begin{aligned}
T(f(\theta_0)+a) &= \mathbb{E}[\int_0^\infty e^{-(1+\frac{r}{\lambda})}\{(f(\theta_t)+a)\mathbf{1}_{f(\theta_t)+a<0\cap\theta_t<\bar{\theta}} + h(\theta_t)\}d\theta_t|\theta_0] \\
&= \mathbb{E}[\int_0^\infty e^{-(1+\frac{r}{\lambda})}\{(f(\theta_t)+a)\mathbf{1}_{f(\theta_t)<0\cap\theta_t<\bar{\theta}} + h(\theta_t) - (f(\theta_t)+a)\mathbf{1}_{-a\leq f(\theta_t)<0\cap\theta_t<\bar{\theta}}\}d\theta_t|\theta_0] \\
&\leq Tf(\theta_0) + a\mathbb{E}[\int_0^\infty e^{-(1+\frac{r}{\lambda})}\mathbf{1}_{f(\theta_t)<0\cap\theta_t<\bar{\theta}}d\theta_t|\theta_0] \\
&\leq Tf(\theta_0) + \frac{a}{1+\frac{r}{\lambda}}.
\end{aligned}$$

Since $r > 0$ by Assumption 5, the result follows. Thus, by Blackwell's theorem $T : C(X) \rightarrow C(X)$ is a contraction. Since $W_{[0,\bar{\theta}]} \in C(X)$, by the contraction mapping theorem, there exists a unique continuous $W : [0,\bar{\theta}] \rightarrow$ that solves (A.11). Given this, $W(\theta)$ for $\theta > \bar{\theta}$ is uniquely defined from (A.11). □

Lemma 3. *W is weakly increasing.*

Proof. Take some weakly increasing function f and apply T for $\theta \in [0,\bar{\theta}]$,

$$Tf(\theta) = \mathbb{E}\left(\int_0^\infty e^{-\left(1+\frac{r}{\lambda}\right)}\left\{f(\theta_t)\,\mathbf{1}_{f(\theta_t)<0\cap\theta_t<\bar{\theta}} + h(\theta_t)\right\}d\theta_t|\theta_0\right).$$

Since $f(z)\,1_{f(z)<0\cap\theta<\bar{\theta}} + h(z)$ is weakly increasing and θ has the FOSD property, Tf is also weakly increasing. Since the space of bounded, continuous and weakly increasing functions is complete, W is also weakly increasing in $\left[0,\bar{\theta}\right]$. This result, together with $h(z)$ being weakly increasing and θ having the FOSD property, imply that W is also weakly increasing for $\theta \geq \bar{\theta}$. □

Now we are ready to prove the main result,

Proposition. *The unique piecewise continuous optimal strategy features a threshold θ^* such that for $\theta < \theta^*$ not exporting is optimal while for $\theta \geq \theta^*$ exporting is optimal.*

Proof. Suppose $W(0) > 0$. Then, since W is weakly increasing, exporting is optimal $\forall\theta$, i.e. $\theta^* = 0$. Suppose $W(0) < 0$. Since W is continuous, weakly increasing and satisfies $W(\bar{\theta}) > 0$, there exists θ^* such that not exporting is optimal $\forall\theta < \theta^*$ ($W(\theta) < 0$), $W(\theta^*) = 0$, and exporting is optimal $\forall\theta > \theta^*$ ($W(\theta) \geq 0$). $\square$

Finally, note that in the particular case discussed in the paper, $\bar{\theta} = \frac{F}{\kappa}$ and, as long as $\alpha < \infty$, $\mathbb{E}_\psi V_e(\frac{F}{\kappa};\psi) - V_i(\frac{F}{\kappa}) > 0$. It follows that $\theta^* < \frac{F}{\kappa}$ or, equivalently, $\tilde{\theta}^* < 1$.

D.3 Derivation of the threshold equation (5)

In the GBM case, the HJB equations become

$$r\mathbb{E}_\psi V_e = \pi^{EE}(\theta_t) + (\mu + \frac{1}{2}\sigma^2)\frac{d\mathbb{E}_\psi V_e}{d\theta} + \frac{1}{2}\sigma^2\frac{d^2\mathbb{E}_\psi V_e}{d\theta^2} \tag{A.12}$$

for the experienced firm and

$$\begin{aligned}(r+\lambda)V_i &= \pi_i + \lambda E_\psi V_e + (\mu + \frac{1}{2}\sigma^2)\frac{dV_i}{d\theta} + \frac{1}{2}\sigma^2\frac{d^2V_i}{d\theta^2} \text{ when } \theta > \theta^* && \text{(A.13)}\\ rV_i &= (\mu + \frac{1}{2}\sigma^2)\frac{dV_i}{d\theta} + \frac{1}{2}\sigma^2\frac{dV_i}{d\theta} \text{ when } \theta < \theta^* && \text{(A.14)}\end{aligned}$$

for the inexperienced firm. Define $\Delta V \equiv E_\psi(V_e) - V_i$. Subtracting (A.13) and (A.14) from (A.12) yields

$$\begin{aligned}(r+\lambda)\Delta V &= \pi^{EE}(\theta) - \pi_i + (\mu + \frac{1}{2}\sigma^2)\frac{d\Delta V}{d\theta} + \frac{1}{2}\sigma^2\frac{d^2\Delta V}{d\theta} \text{ when } \theta > \theta^* && \text{(A.15)}\\ r\Delta V &= \pi^{EE}(\theta) + (\mu + \frac{1}{2}\sigma^2)\frac{d\Delta V}{d\theta} + \frac{1}{2}\sigma^2\frac{d^2\Delta V}{d\theta} \text{ when } \theta < \theta^* && \text{(A.16)}\end{aligned}$$

When $\theta > \theta^*$, the solution to (A.15) is given by[56]

$$\begin{aligned}\Delta V(\theta) = \frac{1}{\tilde{J}}&\left[\int_\theta^\infty \left(\frac{\theta}{z}\right)^{\tilde{\beta}_1}\left(\pi^{EE}(z) - \pi_i(z)\right)\frac{dz}{z} + \int_{\theta^*}^\theta \left(\frac{\theta}{z}\right)^{\tilde{\beta}_2}\left(\pi^{EE}(z) - \pi_i(z)\right)\frac{dz}{z}\right]\\ &+ C_{1U}\theta^{\tilde{\beta}_1} + C_{2U}\theta^{\tilde{\beta}_2}\end{aligned}$$

where

$$\begin{aligned}\tilde{J} &= \sqrt{\mu^2 + 2(r+\lambda)\sigma^2} \geq |\mu|\\ \tilde{\beta}_1 &= \frac{-\mu + \tilde{J}}{\sigma^2} > 1\\ \tilde{\beta}_2 &= \frac{-\mu - \tilde{J}}{\sigma^2} < 0\end{aligned}$$

[56]See formula 5.24. in Stokey (2008).

and C_{1U} and C_{2U} are unknown constants. Using the transversality condition, $C_{1U} = 0$.

Note the derivative wrt θ is

$$\frac{d\Delta V}{d\theta} = \frac{1}{\theta}\begin{bmatrix} \tilde{\beta}_1 \frac{1}{\tilde{J}} \int_\theta^\infty \left(\frac{\theta}{z}\right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z)\right) \frac{dz}{z} \\ +\tilde{\beta}_2 \frac{1}{\tilde{J}} \int_{\theta^*}^\theta \left(\frac{\theta}{z}\right)^{\tilde{\beta}_2} \left(\pi^{EE}(z) - \pi_i(z)\right) \frac{dz}{z} \\ +\tilde{\beta}_2 C_{2U} \theta^{\tilde{\beta}_2} \end{bmatrix}$$

When $\theta < \theta^*$, the solution to (A.16) is given by

$$\Delta V(\theta) = \frac{1}{J}\left[\int_\theta^{\theta^*} \left(\frac{\theta}{z}\right)^{\beta_1} \pi^{EE}(z) \frac{dz}{z} + \int_0^\theta \left(\frac{\theta}{z}\right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z}\right] + C_{1D}\theta^{\beta_1} + C_{2D}\theta^{\beta_2}$$

where

$$\begin{aligned} J &= \sqrt{\mu^2 + 2r\sigma^2} \geq |\mu| \\ \beta_1 &= \frac{-\mu + J}{\sigma^2} > 1 \\ \beta_2 &= \frac{-\mu - J}{\sigma^2} < 0 \end{aligned}$$

and C_{1D} and C_{2D} are unknown constants. Using the initial condition $\Delta V(0) = 0$, $C_{2D} = 0$.

Note the derivative wrt θ

$$\frac{d\Delta V}{d\theta} = \frac{1}{J}\frac{1}{\theta}\begin{bmatrix} \beta_1 \int_\theta^{\theta^*} \left(\frac{\theta}{z}\right)^{\beta_1} \pi^{EE}(z) \frac{dz}{z} \\ +\beta_2 \int_0^\theta \left(\frac{\theta}{z}\right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z} \\ +\beta_1 C_{1D} \theta^{\beta_1} \end{bmatrix}$$

We have three unknowns, C_{1D}, C_{2U} and θ^*. Using the fact that ΔV is C^1 at θ^*,

$$\begin{aligned} \frac{1}{\tilde{J}}\left[\int_{\theta^*}^\infty \left(\frac{\theta^*}{z}\right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z)\right) \frac{dz}{z}\right] + C_{2U}\theta^{*\tilde{\beta}_2} &= \frac{1}{J}\left[\int_0^{\theta^*} \left(\frac{\theta^*}{z}\right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z}\right] \\ &\quad + C_{1D}\theta^{*\beta_1} \\ \frac{1}{\tilde{J}}\left[\tilde{\beta}_1 \int_{\theta^*}^\infty \left(\frac{\theta^*}{z}\right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z)\right) \frac{dz}{z}\right] + \tilde{\beta}_2 C_{2U}\theta^{*\tilde{\beta}_2} &= \frac{1}{J}\left[\beta_2 \int_0^{\theta^*} \left(\frac{\theta^*}{z}\right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z}\right] \\ &\quad + \beta_1 C_{1D}\theta^{*\beta_1}. \end{aligned}$$

Next, multiply the first equation by β_1 and subtract the second equation to obtain,

$$\begin{aligned} &\left(\frac{\beta_1 - \tilde{\beta}_1}{\tilde{J}}\right) \int_{\theta^*}^\infty \left(\frac{\theta^*}{z}\right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z)\right) \frac{dz}{z} \\ &\qquad + \left(\beta_1 - \tilde{\beta}_2\right) C_{2U}\theta^{*\tilde{\beta}_2} = \left(\frac{\beta_1 - \beta_2}{J}\right) \int_0^{\theta^*} \left(\frac{\theta^*}{z}\right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z} \end{aligned}$$

Rearranging,

$$C_{2U} = \frac{\theta^{*-\tilde{\beta}_2}}{\beta_1 - \tilde{\beta}_2} \Bigg\{ \left(\frac{\beta_1 - \beta_2}{J} \right) \int_0^{\theta^*} \left(\frac{\theta^*}{z} \right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z} + \left(\frac{\tilde{\beta}_1 - \beta_1}{\tilde{J}} \right) \int_{\theta^*}^{\infty} \left(\frac{\theta^*}{z} \right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z) \right) \frac{dz}{z} \Bigg\} \tag{A.17}$$

Since $\pi^{EE} - \pi_i \geq 0$ and $\tilde{\beta}_1 \geq \beta_1$, it follows that $C_{2U} \geq 0$. Next, multiply the first equation by $\tilde{\beta}_2$ and subtract the second equation to obtain,

$$\left(\frac{\tilde{\beta}_2 - \tilde{\beta}_1}{\tilde{J}} \right) \int_{\theta^*}^{\infty} \left(\frac{\theta^*}{z} \right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z) \right) \frac{dz}{z} = \left(\frac{\tilde{\beta}_2 - \beta_2}{J} \right) \int_0^{\theta^*} \left(\frac{\theta^*}{z} \right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z} + \left(\tilde{\beta}_2 - \beta_1 \right) C_{1D} \theta^{\beta_1}$$

Rearranging,

$$C_{1D} = \frac{\theta^{*-\beta_1}}{\beta_1 - \tilde{\beta}_2} \Bigg\{ \left(\frac{\tilde{\beta}_1 - \tilde{\beta}_2}{\tilde{J}} \right) \int_{\theta^*}^{\infty} \left(\frac{\theta^*}{z} \right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z) \right) \frac{dz}{z} + \left(\frac{\tilde{\beta}_2 - \beta_2}{J} \right) \int_0^{\theta^*} \left(\frac{\theta^*}{z} \right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z} \Bigg\} \tag{A.18}$$

The remaining equation is the fact that, by continuity, at the threshold the firm is indifferent between exporting and not exporting, i.e. $\pi_i(\theta^*) + \lambda \Delta V(\theta^*) = 0$,

$$\pi_i(\theta^*) + \frac{1}{\tilde{J}} \lambda \left[\int_{\theta^*}^{\infty} \left(\frac{\theta^*}{z} \right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z) \right) \frac{dz}{z} + C_{2U} \theta^{*\tilde{\beta}_2} \right] = 0$$

Substituting in (A.17),

$$\pi_i(\theta^*) + \lambda \left[\begin{array}{c} \frac{1}{\tilde{J}} \int_{\theta^*}^{\infty} \left(\frac{\theta^*}{z} \right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z) \right) \frac{dz}{z} + \left(\frac{1}{J} \right) \left(\frac{\beta_1 - \beta_2}{\beta_1 - \tilde{\beta}_2} \right) \int_0^{\theta^*} \left(\frac{\theta^*}{z} \right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z} \\ + \left(\frac{1}{\tilde{J}} \right) \left(\frac{\tilde{\beta}_1 - \beta_1}{\beta_1 - \tilde{\beta}_2} \right) \int_{\theta^*}^{\infty} \left(\frac{\theta^*}{z} \right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z) \right) \frac{dz}{z} \end{array} \right] = 0$$

Simplifying,

$$\pi_i(\theta^*) + \frac{\lambda}{\beta_1 - \tilde{\beta}_2} \left[\begin{array}{c} \left(\tilde{\beta}_1 - \tilde{\beta}_2 \right) \frac{1}{\tilde{J}} \int_{\theta^*}^{\infty} \left(\frac{\theta^*}{z} \right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z) \right) \frac{dz}{z} \\ + \frac{1}{J} (\beta_1 - \beta_2) \int_0^{\theta^*} \left(\frac{\theta^*}{z} \right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z} \end{array} \right] = 0. \tag{A.19}$$

Next, note

$$\begin{aligned}
\beta_1 - \beta_2 &= \frac{2J}{\sigma^2} \\
\tilde{\beta}_1 - \tilde{\beta}_2 &= \frac{2\tilde{J}}{\sigma^2} \\
\beta_1 - \tilde{\beta}_2 &= \frac{J + \tilde{J}}{\sigma^2}
\end{aligned}$$

Thus,

$$\pi_i\left(\theta^*\right) + \lambda\left(\frac{2}{J+\tilde{J}}\right)\left[\int_{\theta^*}^{\infty}\left(\frac{\theta^*}{z}\right)^{\tilde{\beta}_1}\left(\pi^{EE}\left(z\right) - \pi_i\left(z\right)\right)\frac{dz}{z} + \int_0^{\theta^*}\left(\frac{\theta^*}{z}\right)^{\beta_2}\pi^{EE}\left(z\right)\frac{dz}{z}\right] = 0.$$

As suggested in the main body, this equation shows that the model boils down to one equation in one unknown even if ψ is not multiplicative. In our baseline model, $\pi^{EE} = \mathbb{E}_{\psi}\left[\max\left\{\psi\frac{\kappa\theta}{F} - 1, 0\right\}\right]$ and $\pi_i = \kappa\theta - F$. Replacing,

$$\begin{aligned}
\kappa\theta - F + \lambda\left(\frac{2}{J+\tilde{J}}\right)\Bigg\{\int_{\theta^*}^{\infty}\left(\frac{\theta^*}{z}\right)^{\tilde{\beta}_1}\left(\mathbb{E}_{\psi}\left(\max\left\{\psi\kappa z - F, 0\right\}\right) - \left(\kappa z - 1\right)\right)\frac{dz}{z} \\
+ \int_0^{\theta^*}\left(\frac{\theta^*}{z}\right)^{\beta_2}\mathbb{E}_{\psi}\left(\max\left\{\psi\kappa z - F, 0\right\}\right)\frac{dz}{z}\Bigg\} = 0.
\end{aligned}$$

In terms of $\tilde{\theta}$ and redefining $z = \frac{\kappa z}{F}$:

$$\begin{aligned}
\tilde{\theta} - 1 + \lambda\left(\frac{2}{J+\tilde{J}}\right)\Bigg\{\int_{\tilde{\theta}^*}^{\infty}\left(\frac{\tilde{\theta}^*}{z}\right)^{\tilde{\beta}_1}\left(\mathbb{E}_{\psi}\left(\max\left\{\psi z - 1, 0\right\}\right) - \left(z - 1\right)\right)\frac{dz}{z} \\
+ \int_0^{\tilde{\theta}^*}\left(\frac{\tilde{\theta}^*}{z}\right)^{\beta_2}\mathbb{E}_{\psi}\left(\max\left\{\psi z - 1, 0\right\}\right)\frac{dz}{z}\Bigg\} = 0.
\end{aligned}$$

D.4 Proof of Proposition 3

First, let us compute $\mathbb{E}_{\psi}(\max\{\psi z - 1, 0\})$. When $z > \psi_m^{-1}$,

$$\mathbb{E}_{\psi}(\max(\psi z - 1, 0) = (\frac{\alpha}{\alpha - 1})\psi_m z - 1, \tag{A.20}$$

which is decreasing in α. When $z < \psi_m^{-1}$,

$$\mathbb{E}_{\psi}(\max(\psi z - 1, 0) = (\frac{1}{\alpha - 1})\psi_m^{\alpha} z^{\alpha}, \tag{A.21}$$

which is decreasing in α since $\ln\left(\psi_m^{\alpha} z^{\alpha}\right) < 0$ in this region. Thus, $\mathbb{E}_{\psi}\max\{\psi z - 1, 0\}$ decreases with α $\forall z$ and, thus, the LHS of equation (5) decreases with α.

Next, define $m = \frac{z}{\tilde{\theta}^*}$ and rewrite equation (5) as

$$\tilde{\theta}^* - 1 + \lambda\left(\frac{2}{J+\tilde{J}}\right)\left[\begin{array}{c} \int_1^\infty m^{-\tilde{\beta}_1}\left(E_\psi\left(\max\left(\psi\tilde{\theta}^* m - 1, 0\right)\right) - \left(\tilde{\theta} m - 1\right)\right)\frac{dm}{m} \\ + \int_0^1 m^{-\beta_2} E_\psi\left(\max\left(\psi\tilde{\theta}^* m - 1, 0\right)\right)\frac{dm}{m} \end{array}\right] = 0 \qquad \text{(A.22)}$$

Solving the second integral in the first line of the bracket,

$$\begin{array}{c} \tilde{\theta}^*\left(1 - \frac{2\lambda}{(J+\tilde{J})(\tilde{\beta}_1 - 1)}\right) - \left(1 - \frac{2\lambda}{(J+\tilde{J})\tilde{\beta}_1}\right) \\ +\lambda\left(\frac{2}{J+\tilde{J}}\right)\left[\begin{array}{c} \int_1^\infty m^{-\tilde{\beta}_1} E_\psi\left(\max\left(\psi\tilde{\theta}^* m - 1, 0\right)\right)\right)\frac{dm}{m} \\ + \int_0^1 m^{-\beta_2} E_\psi\left(\max\left(\psi\tilde{\theta}^* m - 1, 0\right)\right)\frac{dm}{m} \end{array}\right] = 0 \end{array}$$

Since $1 - \lambda\frac{2}{J+\tilde{J}}\frac{1}{\tilde{\beta}-1} \geq 0$, the LHS decreases with $\tilde{\theta}^*$. Thus, by the implicit function theorem, $\tilde{\theta}^*$ increases with α.

D.5 Proof of Proposition 4

Define $\hat{\theta} = \psi_m\tilde{\theta}$ and $\tilde{\psi} = \frac{\psi}{\psi_m}$ and rewrite equation (5),

$$\frac{1}{\psi_m}\hat{\theta} - 1 + \lambda\left(\frac{2}{J+\tilde{J}}\right)\left[\begin{array}{c} \int_{\frac{1}{\psi_m}\hat{\theta}^*}^{:\infty}\left(\frac{\hat{\theta}^*}{\psi_m z}\right)^{\tilde{\beta}_1}\left(E\max\left\{\psi_m\tilde{\psi}z - 1\right\} - (z-1)\right)\frac{dz}{z} \\ + \int_0^{\frac{1}{\psi_m}\hat{\theta}^*}\left(\frac{\hat{\theta}^*}{\psi_m z}\right)^{\beta_2} E\max\left\{\psi_m\tilde{\psi}z - 1\right\}\frac{dz}{z} \end{array}\right] = 0$$

Let $\hat{z} \equiv \psi_m z$. Then,

$$\begin{array}{rcl} \frac{1}{\psi_m}\hat{\theta} - 1 & & \\ +\lambda\left(\frac{2}{J+\tilde{J}}\right)\left[\begin{array}{c} \int_{\hat{\theta}^*}^{:\infty}\left(\frac{\hat{\theta}^*}{\hat{z}}\right)^{\tilde{\beta}_1}\left(E\max\left\{\tilde{\psi}\hat{z} - 1, 0\right\} - \frac{1}{\psi_m}\hat{z} + 1\right)\frac{d\hat{z}}{\hat{z}} \\ + \int_0^{\hat{\theta}^*}\left(\frac{\hat{\theta}^*}{\hat{z}}\right)^{\beta_2} E\max\left\{\tilde{\psi}\hat{z} - 1\right\}\frac{d\hat{z}}{\hat{z}} \end{array}\right] & = & 0 \\ \frac{1}{\psi_m}\left(\hat{\theta} - \lambda\left(\frac{2}{J+\tilde{J}}\right)\int_{\hat{\theta}^*}^{:\infty}\left(\frac{\hat{\theta}^*}{\hat{z}}\right)^{\tilde{\beta}_1} d\hat{z}\right) - 1 & & \\ +\lambda\left(\frac{2}{J+\tilde{J}}\right)\left[\begin{array}{c} \int_{\hat{\theta}^*}^{:\infty}\left(\frac{\hat{\theta}^*}{\hat{z}}\right)^{\tilde{\beta}_1}\left(E\max\left\{\tilde{\psi}\hat{z} - 1, 0\right\} + 1\right)\frac{d\hat{z}}{\hat{z}} \\ + \int_0^{\hat{\theta}^*}\left(\frac{\hat{\theta}^*}{\hat{z}}\right)^{\beta_2} E\max\left\{\tilde{\psi}\hat{z} - 1\right\}\frac{d\hat{z}}{\hat{z}} \end{array}\right] & = & 0 \\ \frac{1}{\psi_m}\hat{\theta}\left(1 - \lambda\frac{2}{J+\tilde{J}}\frac{1}{\tilde{\beta}_1 - 1}\right) - 1 & & \\ +\lambda\left(\frac{2}{J+\tilde{J}}\right)\left[\begin{array}{c} \int_{\hat{\theta}^*}^{:\infty}\left(\frac{\hat{\theta}^*}{\hat{z}}\right)^{\tilde{\beta}_1}\left(E\max\left\{\tilde{\psi}\hat{z} - 1, 0\right\} + 1\right)\frac{d\hat{z}}{\hat{z}} \\ + \int_0^{\hat{\theta}^*}\left(\frac{\hat{\theta}^*}{\hat{z}}\right)^{\beta_2} E\max\left\{\tilde{\psi}\hat{z} - 1\right\}\frac{d\hat{z}}{\hat{z}} \end{array}\right] & = & 0 \end{array}$$

Since $1 - \lambda\frac{2}{J+\tilde{J}}\frac{1}{\tilde{\beta}-1} \geq 0$, the LHS decreases with ψ_m.

Changing the dummy of integration to $m = \frac{z}{\hat{\theta}^*}$,

$$\frac{1}{\psi_m}\hat{\theta}\left(1-\lambda\frac{2}{J+\tilde{J}}\frac{1}{\tilde{\beta}_1-1}\right)-1+\lambda\left(\frac{2}{J+\tilde{J}}\right)\left[\begin{array}{c}\int_1^{:\infty} m^{-\tilde{\beta}_1}\left(E\max\left\{\tilde{\psi}m\hat{\theta}^*-1,0\right\}+1\right)\frac{dm}{m} \\ +\int_0^1 m^{-\beta_2}E\max\left\{\tilde{\psi}m\hat{\theta}^*-1\right\}\frac{dm}{m}\end{array}\right]=0$$

The first derivative wrt $\hat{\theta}^*$ yields

$$\frac{1}{\psi_m}\left(1-\lambda\frac{2}{J+\tilde{J}}\frac{1}{\tilde{\beta}_1-1}\right)+\lambda\left(\frac{2}{J+\tilde{J}}\right)\left[\begin{array}{c}\int_1^{\infty} m^{-\tilde{\beta}_1+1}\frac{dE\left[\max\left\{\psi m\tilde{\theta}^*-1\right\}\right]}{dm\tilde{\theta}^*}\frac{dm}{m} \\ +\int_0^1 m^{-\beta_2+1}\frac{dE\left[\max\left\{\psi m\tilde{\theta}^*-1\right\}\right]}{dm\tilde{\theta}^*}\frac{dm}{m}\end{array}\right]>0.$$

Hence, the LHS increases with $\hat{\theta}^*$. Thus, by the implicit function theorem, $\frac{d\hat{\theta}^*}{d\psi_m} > 0$.

E Estimation details

E.1 SMM estimator

The firms in our sample that are used for estimation may enter a market j twice: once as first-time entrants and once as re-entrants. For each entry, we let $y_{ij\tau r} \in \{0,1\}$ denote the export participation decision τ years after entry of firm i, with the subindex r denoting whether it is a first-time entrant ($r=0$) or a re-entrant ($r=1$). Recall that years are redefined according to the time of the first shipment to avoid partial-year effects.

Our SMM estimator uses ten moments. The first five moments are survival probabilities of first-time entrants:

$$\frac{1}{N}\sum_{i=1}^{N}\Big\{\frac{1}{J_i}\sum_{j=1}^{J_i}\{y_{ij\tau 0}^{obs} - \frac{1}{S}\sum_{s=1}^{S} y_{ij\tau 0}^{s}(\varphi)\}\Big\} = 0 \qquad \text{for} \qquad \tau = 1,\ldots,5. \tag{A.23}$$

where $\varphi = \{\mu,\sigma,\lambda,\alpha\}$ is the vector of model parameters, $y_{ij\tau 0}^{obs}$ denotes the observed export-participation decision, $y_{ij\tau 0}^{s}(\varphi)$ is the analogous model-implied export participation decision, N is the number of firms that are first-time entrants at least in one market, J_i the number of such entry markets for firm i, and S is the number of model simulations.

The last five moments are survival probabilities of re-entrants,

$$\frac{1}{N}\sum_{i=1}^{N}\Big\{\frac{1}{J_i}\sum_{j=1}^{J_i}\{\sum_{r=0,1}(y_{ij\tau r}^{obs} - \frac{1}{S}\sum_{s=1}^{S} y_{ij\tau r}^{s}(\theta, z_{ij}))\mathbf{1}_{r=1}\}\Big\} = 0 \qquad \text{for} \qquad \tau = 1,\ldots,5. \tag{A.24}$$

where $\mathbf{1}_{r=1}$ is an indicator function for the event $r=1$, so that only re-entrant observations contribute to these moments and z_{ij} is the amount of time that passed between the date of the first entry and the date of the first re-entry. Unlike first-time entrants, who all enter as inexperienced firms (equation 8), re-entrants may enter experienced or inexperienced (equation 9). The probability of being each type of re-entrant depends on the age of the exporter: if a firm spent a long time active in the market, then the likelihood of being experienced when it re-enters it increases. Importantly, the share of experienced re-entrants affects the expected re-entry survival rate. Given that the sample covers the period 1997-2008 and that we only consider re-entrants who we also observe as first-time entrants, the latest year in which the firm could re-enter is year 6 in the export experience (the firm should have exited and then re-entered again with five years left to study survival). The latest possible re-entrant with five years to study survival is a firm that enters on January 1st 1997, exits in 2001, and re-enters on December 31st 2002 (year 6). [57] In other words, our sample is biased towards young, inexperienced re-entrants. To capture this effect, we write our re-entry survival moment as the expected survival rate for re-entrants conditional on the firm-market specific "age" z_{ij} and then sum over the observed z_{ij}. We define z_{ij} in years for computational tractability. More

[57] We could also include firms that, having entered on January 1st 1997, exited in 2002 and re-entered on January 1st 2003, but we do not see such a firm in our sample.

precisely, we create three groups: firms with a re-entry shipment between 2 and 3 years after the first-entry shipment, between 3 and 4 years, and more than 4 years later (up to year 6).

Let $m_k(\varphi)$, with $k = 1, \ldots, 10$, denote the ten moments above and $m(\varphi)$ a vector with these ten moments. Our SMM estimator chooses φ to minimize $m(\varphi)'Wm(\varphi)$. Since all our moments are survival probabilities, we choose an identity matrix as the weighting matrix W.

Furthermore, given that the objective function is non-smooth, we took a three-step approach. First, we fixed μ and estimated the remaining parameters: μ was fixed alternatively at 0, -0.025, -0.05, -0.075, -0.1, -0.15 and -0.2. The model performance clearly decreased for values larger than -0.1. Thus, in a second step, we estimated the model using the genetic algorithm *ga* in MATLAB with a population size of 1000 within a narrower set of parameters guided by the best points in the previous grid (μ between 0 and -0.1). Finally, we refined the solution with a local optimizer, fminsearch.

E.2 Simulation details

Our goal is to simulate equations (8) and (9). Thus, there are three objects that we need to simulate: (i) the survival rate of an inexperienced firm, (ii) the survival rate of an experienced firm, and (iii) the probability of being an experienced re-entrant for each of the three possible values of z_{ij}. We simulate $S = 200,000$ firms for $T = 6$ years with a time interval of $dt = 0.001$.[58] Since all firms and markets are identical (except for κ and F, but those are irrelevant for survival, see Proposition 2), we use the same simulations for all firm-markets. Since the interval is of size dt, there are $1/dt$ "instants" per year. In the data, we define firm-market-specific years according to the time of first entry. Accordingly, in the model, instants between $\tau/dt + 1$ and $(\tau + 1)/dt$ correspond to year τ of the firm's export experience (letting 0 denote the entry year). In each simulation, there is a random draw for the GBM process, i.e. $T/dt = 6000$ random draws of dZ_t - one per instant, a random draw for whether the firm becomes experienced in each instant if it decides to export - also one per instant so 6000 additional draws, and a random draw of ψ.

Consider first the survival rate of inexperienced firms. Since the GBM is continuous, firms enter exactly at the threshold, $\tilde{\theta}_0 = \tilde{\theta}^*$. Using this result and the random draws of the GBM, we construct the path for $\tilde{\theta}_t$. Whenever $\tilde{\theta}_t \geq \tilde{\theta}^*$, we check whether the firm becomes experienced according to the corresponding random draw. If so, we modify the firm's (normalized) operating profits from the next instant onwards from $\tilde{\theta}_t$ to $\psi\tilde{\theta}_t$. While inexperienced, the firm is active in any given instant if $\tilde{\theta}_t \geq \tilde{\theta}^*$. Once it becomes experienced, which is an absorbing state, it is only active if $\psi\tilde{\theta}_t \geq 1$. If the firm is active in any instant $t \in [\tau/dt + 1, (\tau + 1)/dt]$, then the firm is active in year τ. The firm is always active by definition in the first year ($\tau = 0$). The subsequent five years $\tau = 1, \ldots, 5$ are used to construct the required survival probabilities of inexperienced firms, which are also the survival probabilities of first-time entrants (the first five moments).

Next, we compute the survival rate of experienced firms. These firms also enter exactly at their

[58] In Section H, we need to simulate more years since firms do not enter exactly at the threshold.

relevant threshold, i.e. $\psi\tilde{\theta}_0 = 1$. Since entry and exit thresholds coincide for experienced firms, and the GBM is memoryless, we do not need to keep track of ψ to compute this survival rate. That is, we start the process at any value, e.g. $\tilde{\theta} = 1$, we construct the path for $\tilde{\theta}_t$ using the random draws of the GBM, and then we check in every instant whether the process is above the initial value, e.g. whether $\tilde{\theta}_t \geq 1$. If the firm is active in any instant $t \in [\tau/dt + 1, (\tau + 1)/dt]$, then the firm is active in year τ. The fact that the GBM is memoryless implies that this computation is independent of the chosen value to start the process (e.g. $\tilde{\theta}_0 = 1$).

Finally, we need to compute the share of firms that enter experienced vs. inexperienced for each of the z_{ij} values. To do so, for each of the $S = 200,000$ firms that we simulate starting as inexperienced firms, we check whether they become re-entrants (only for the first time, as in the data).[59] If so, we keep track of their experience status at the moment of re-entry, we check the date of the first shipment as a re-entrant and using this we compute the amount of time that has passed since the first shipment of the first entry. Using this, we classify the re-entry into one of the three possible values of z_{ij}. Then, we compute the share of the firms in each category of z_{ij} that are experienced. Armed with the three pieces, we can calculate the predicted re-entry probability for each z_{ij} using equation (9).

[59] Note that since the maximum value of z_{ij} is year 6, we do not need to simulate extra years.

F Sunk cost model

There are two types of firms: “experienced” firms, who have entered the market at least once in the past, and “inexperienced” firms, who have not. The difference between these firms is that experienced firms pay a lower sunk cost to enter the market: $0 \leq S_e \leq S_i$. We shut down the experimentation mechanism by setting $\lambda = 0$. We assume that all firms have the same ratio of sunk to fixed costs, which allows us to preserve a large degree of firm heterogeneity that does not affect survival (Albornoz et al., 2016).

Experienced firms The analysis in this region is the same as the model in Appendix 2 of (Albornoz et al., 2016), which we repeat here for convenience. Within this region, there are two subregions. Firms with $\tilde{\theta} > \underline{\tilde{\theta}}_e$, export if they exported the previous instant. We call these firms “active” exporters and denote their value function with a subindex 1. Firms with $\tilde{\theta} < \bar{\tilde{\theta}}_e$ do not export if they did not export the previous instant. We call these firms “inactive” exporters and denote their value function with a subindex 0. As we will verify later, $\underline{\tilde{\theta}}_e \leq \bar{\tilde{\theta}}_e$, strictly so if $S_e > 0$.

Inactive exporters do not generate any income flow in market k while they are outside the market. Their value function satisfies the HJB equation

$$rV_{0e}(\tilde{\theta})dt = \mathbb{E}\big(dV_{0e}(\tilde{\theta})\big).$$

Applying Ito’s Lemma,

$$rV_{0e}(\tilde{\theta})dt = (\mu + \frac{1}{2}\sigma^2)\frac{dV_{0e}(\tilde{\theta})}{d\tilde{\theta}} + \frac{1}{2}\sigma^2\frac{d^2V_{0e}(\tilde{\theta})}{d\tilde{\theta}^2}.$$

Guess and verify that the solution is of the form

$$V_{0e}(\tilde{\theta}) = A_{0e}\tilde{\theta}_1^{\beta} + \tilde{A}_{0e}\tilde{\theta}_2^{\beta}$$

where the roots β_1 and β_2 are given by

$$\beta_{1,2} = -\frac{\mu}{\sigma^2} \pm \sqrt{(\frac{\mu}{\sigma^2})^2 + 2\frac{r}{\sigma^2}}.$$

Using the fact that $\mu + \frac{1}{2}\sigma^2 < r$ (otherwise profits are infinite), one can establish that $\beta_1 > 1$ and $\beta_2 < 0$. Since the value of the firm is zero when $\tilde{\theta} = 0$, $\tilde{A}_{0e} = 0$. Therefore, we obtain

$$V_{0e}(\tilde{\theta}) = A_{0e}\tilde{\theta}_1^{\beta}.$$

Active exporters generate an income flow of $F(\tilde{\theta} - 1)dt$. Their value function satisfies the HJB equation

$$rV_{1e}(\tilde{\theta})dt = F(\tilde{\theta} - 1)dt + \mathbb{E}\big(dV_{1e}(\tilde{\theta})\big).$$

Applying Ito's Lemma,

$$rV_{1e}(\tilde{\theta})dt = F(\tilde{\theta}-1)dt + (\mu + \frac{1}{2}\sigma^2)\frac{dV_{1e}(\tilde{\theta})}{d\tilde{\theta}} + \frac{1}{2}\sigma^2\frac{d^2V_{1e}(\tilde{\theta})}{d\tilde{\theta}^2}.$$

Guess and verify that the solution is of the form

$$V_{0e}(\tilde{\theta}) = \tilde{A}_{1e}\tilde{\theta}_1^{\beta} + A_{1e}\tilde{\theta}_2^{\beta} + (\frac{F}{r-\mu-\frac{1}{2}\sigma^2})\tilde{\theta} - \frac{F}{r}$$

where the roots β_1 and β_2 are given by

$$\beta_{1,2} = -\frac{\mu}{\sigma^2} \pm \sqrt{(\frac{\mu}{\sigma^2})^2 + 2\frac{r}{\sigma^2}}.$$

When $\tilde{\theta} \to \infty$, the value of inaction should go to zero and profits should converge to $(\frac{F}{r-\mu-\frac{1}{2}\sigma^2})\tilde{\theta} - \frac{F}{r}$ so $\tilde{A}_{1e} = 0$. Therefore, we obtain

$$V_{1e}(\tilde{\theta}) = A_{1e}\tilde{\theta}_2^{\beta} + (\frac{F}{r-\mu-\frac{1}{2}\sigma^2})\tilde{\theta} - \frac{F}{r}.$$

There are still four unknowns left: $A_{0e}, A_{1e}, \underline{\tilde{\theta}}_e, \bar{\tilde{\theta}}_e$. To find them we use the value-matching and smooth pasting conditions at the thresholds:

$$\begin{aligned}
V_{0e}(\bar{\tilde{\theta}}_e) &= V_{1e}(\bar{\tilde{\theta}}_e) - S_e \\
\frac{dV_{0e}(\bar{\tilde{\theta}}_e)}{d\tilde{\theta}} &= \frac{dV_{1e}(\bar{\tilde{\theta}}_e)}{d\tilde{\theta}} \\
V_{0e}(\underline{\tilde{\theta}}_e) &= V_{1e}(\underline{\tilde{\theta}}_e) \\
\frac{dV_{1e}(\underline{\tilde{\theta}}_e)}{d\tilde{\theta}} &= \frac{dV_{0e}(\underline{\tilde{\theta}}_e)}{d\tilde{\theta}}
\end{aligned}$$

Plugging in:

$$\begin{aligned}
A_{0e}\bar{\tilde{\theta}}_e^{\beta_1} &= A_{1e}\bar{\tilde{\theta}}_e^{\beta_2} + (\frac{F}{r-\mu-\frac{1}{2}\sigma^2})\bar{\tilde{\theta}}_e - \frac{F}{r} - S_e \\
\beta_1 A_{0e}\bar{\tilde{\theta}}_e^{\beta_1-1} &= \beta_2 A_{1e}\bar{\tilde{\theta}}_e^{\beta_2-1} + (\frac{F}{r-\mu-\frac{1}{2}\sigma^2}) \\
A_{0e}\underline{\tilde{\theta}}_e^{\beta_1} &= A_{1e}\underline{\tilde{\theta}}_e^{\beta_2} + (\frac{F}{r-\mu-\frac{1}{2}\sigma^2})\underline{\tilde{\theta}}_e - \frac{F}{r} \\
\beta_1 A_{0e}\underline{\tilde{\theta}}_e^{\beta_1-1} &= \beta_2 A_{1e}\underline{\tilde{\theta}}_e^{\beta_2-1} + (\frac{F}{r-\mu-\frac{1}{2}\sigma^2})
\end{aligned}$$

Note that in these equations it is immediate that only S_e/F matters. We solve this system of equations numerically.

Inexperienced firms This is very similar, except that the sunk cost is different. Value-matching and smooth-pasting are:

$$V_{0i}(\bar{\bar{\tilde{\theta}}}_i) = V_{1e}(\bar{\bar{\tilde{\theta}}}_i) - S_i$$
$$\frac{dV_{0i}(\bar{\bar{\tilde{\theta}}}_i)}{d\tilde{\theta}} = \frac{dV_{1e}(\bar{\bar{\tilde{\theta}}}_i)}{d\tilde{\theta}}$$

Plugging in:

$$A_{0i}\bar{\bar{\tilde{\theta}}}_i^{\beta_1} = A_{1e}\bar{\bar{\tilde{\theta}}}_i^{\beta_2} + (\frac{F}{r-\mu-\frac{1}{2}\sigma^2})\bar{\bar{\tilde{\theta}}}_i - \frac{F}{r} - S_i$$
$$\beta_1 A_{0i}\bar{\bar{\tilde{\theta}}}_i^{\beta_1-1} = \beta_2 A_{1e}\bar{\bar{\tilde{\theta}}}_i^{\beta_2-1} + (\frac{F}{r-\mu-\frac{1}{2}\sigma^2})$$

This is a system of two equations in two unknowns (A_{0i} and $\bar{\bar{\tilde{\theta}}}_i$). It's an easier to solve since we already know the value of becoming an exporter (governed by A_1e), which goes together with becoming experienced in this model. We solve this numerically.

G Alternative estimation

In this appendix, we re-estimate the model by including the four conditional survival moments of Table 4 (Panel A, last columns) in the set of moments to match (in addition to the ten moments of the baseline estimation). Table F.1 shows the results. The model does an excellent job at matching continuous conditional survival probabilities and even improves the fit to the first-time entrant survival profile (fact 1). By contrast, the fit for re-entrants worsens, but it is still very good: the average discrepancy is 2.7 percentage points instead of 1.3. The model overestimates the first-year re-entrant survival rate by more and predicts a profile that is too steep. To understand why, note that this alternative estimation strategy delivers faster learning (i.e. higher $\hat{\lambda}$). This implies that a larger share of re-entrants are experienced, which raises their survival rate (58% of re-entrants are experienced vs 40% in the main estimation). Furthermore, to match better continuous conditional survival probabilities, the estimation picks a more negative $\frac{\hat{\mu}}{\hat{\sigma}}$ (-0.35). This makes the slope of the survival profile steeper, especially for experienced firms and, thus, for re-entrants. Regarding the other moments analyzed in Section 6, these new estimates neither substantially improve nor worsen the model's fit (results available upon request).

Table F.1: SMM Estimation results: Alternative targets

	Fixed parameters	
r	0.1	
ψ_m	1	
	Estimated parameters	
μ	-0.0569	
σ	0.1622	
λ	4.518	
α	4.711	
	Survival probabilities	
	Panel A: Entrants	
	Model	Data
Year 1	0.298	0.294
Year 2	0.235	0.242
Year 3	0.205	0.208
Year 4	0.185	0.185
Year 5	0.167	0.169
	Panel B: Re-entrants	
Year 1	0.467	0.406
Year 2	0.375	0.361
Year 3	0.320	0.334
Year 4	0.281	0.292
Year 5	0.245	0.285
	Panel C: Conditional survival	
Year 2	0.604	0.629
Year 3	0.734	0.718
Year 4	0.800	0.784
Year 5	0.826	0.825

H A simple model with lumpy exports

Our continuous-time model has the advantage of facilitating time-aggregation corrections. However, since re-entry is pervasive and many exporters spend significant time close to the threshold, one may worry that (i) we may get in the model spurious entry and re-entry of firms that barely spent any time above the threshold and, (ii), this may exaggerate the intra-period extensive margin by including even very small intervals above the threshold for firms close to it. To address these concerns, we develop an extension of our model that introduces discrete shipments. This extension keeps all features of the original model except that firms can no longer export at every instant. Instead, firms receive an "export opportunity" shock with intensity $\eta > 0$. If there is no shock, then firms do not export and get zero instantaneous profits regardless of their potential profitability. If there is a shock, then firms decide whether to export or not. If they do, they obtain a discrete amount of export profits $\pi_i(\theta_t)$ if inexperienced and $\pi_e(\theta_t, \psi)$ if experienced:

$$\pi_i(\theta_t) = \frac{1}{\eta}\left\{ \begin{array}{c} \kappa\theta_t - F \text{ if export at } t \\ 0 \text{ otherwise} \end{array} \right\}$$

$$\pi_e(\theta_t;\psi) = \frac{1}{\eta}\left\{ \begin{array}{c} \psi\kappa\theta_t - F \text{ if export at } t \\ 0 \text{ otherwise} \end{array} \right\}.$$

We scale profits with η such that changing η does not change the average profits in a time period. The HJB equation of an inexperienced firm is, then,

$$\begin{aligned} rV &= \underbrace{\eta^{-1}\left(\kappa\theta_t - F\right) + \eta^{-1}\lambda(\mathbb{E}V_e - V_i)}_{\text{profits conditional on exporting}} \qquad \underbrace{\eta dt}_{\text{probability of exporting}} \\ &\quad + (\mu + \frac{1}{2}\sigma^2)\theta\frac{dV^1}{d\theta} + \frac{1}{2}\sigma^2\theta\frac{d^2V^1}{d\theta^2}\text{for}\kappa\theta > F \\ rV &= (\mu + \frac{1}{2}\sigma^2)\theta\frac{dV}{d\theta} + \frac{1}{2}\sigma^2\theta\frac{d^2V}{d\theta^2}\text{for } \kappa\theta < F. \end{aligned}$$

An analogous equation holds for the experienced firm. Since firms are risk neutral, η does not affect any value functions, hence, nor the threshold. However, it will affect the time of entry (it will now be above θ^*). It will also affect survival predictions: firms may not only exit because they are bad but also because they did not get lucky with the export opportunity shock. This matters more for firms close to the threshold. For reasonable values of η, firms that spend the entire period above the threshold are extremely likely to export.

H.1 Moments with $\eta < \infty$

Next, we compare the model predictions for different values of η. Note that a lower η tends to decrease survival probabilities: firms not only need to be above the threshold but also be hit by the export-opportunity shock to survive.[60] For this reason, we re-estimate the model for each value of η. We consider $\eta \in \{0.005, 0.01, 0.025, 0.05\}$, implying that if firms are above the threshold for an entire year, the expected number of shipments are 5, 10, 25, and 50, respectively. The average number of shipments by first-time entrants is 12.5 in the data, but this presumably includes firms that only spend a fraction of the time above the threshold. Conditioning on firms that survived for five years and looking at their average number of shipments in year 3 of their export experience yields 25.8 shipments.

Panels A and B in Table G.1 show the estimated values for $\{\mu, \sigma, \lambda, \alpha\}$ and predicted survival probabilities, respectively, for different values of η. Clearly, η is not identified by survival moments: as we change η, the remaining parameters change to deliver the same survival probabilities. In other words, adding lumpiness does not hurt or improve the model's performance to match survival moments.

As argued before, η is also very important for the intra-period extensive margin and the growth-rates implications. For this reason, we replicate Table 5 at our preferred value: $\eta = 0.025$. The model fit for shipments (panel B) is substantially improved. In particular, the standard deviation is much closer to that in the data. As a result, however, the overall volatility of sales (panel A) is now smaller than in the data, suggesting that other forces may increase the variance of small and young firms, e.g. marketing costs (Arkolakis, 2016).

[60] There is a countervailing force: firms enter above the threshold and, therefore, are more likely to be above the threshold in the future. We find this effect to be weaker in our simulations.

Table G.1: SMM Estimation results

	Fixed parameters				
r	0.1	0.1	0.1	0.1	
η	0.005	0.01	0.025	0.05	
	Estimated parameters				
μ	-0.014	-0.018	-0.014	-0.018	
σ	0.052	0.085	0.052	0.075	
λ	1.478	1.666	2.350	2.451	
α	6.136	4.170	7.632	5.612	
	Survival probabilities				
	Panel A: Entrants				
	Model				Data
Year 1	0.297	0.309	0.297	0.300	0.294
Year 2	0.228	0.225	0.222	0.220	0.243
Year 3	0.202	0.198	0.199	0.195	0.211
Year 4	0.188	0.186	0.185	0.182	0.189
Year 5	0.178	0.179	0.175	0.173	0.174
	Panel B: Re-entrants				
	Model				Data
Year 1	0.437	0.435	0.444	0.445	0.394
Year 2	0.363	0.362	0.363	0.366	0.351
Year 3	0.318	0.323	0.323	0.323	0.325
Year 4	0.291	0.294	0.294	0.293	0.282
Year 5	0.272	0.280	0.275	0.273	0.276

Table G.2: Other moments: Growth rates. $\eta = 0.025$

	A: Unconditional sales growth rates (entry: year 0)					
	Mean		Median		Std. deviation	
Horizon	Model	Data	Model	Data	Model	Data
Year 1	-0.108	-0.228	-0.000	-0.178	1.126	1.732
Year 2	0.011	-0.008	0.006	0.030	0.929	1.532
Year 3	0.002	0.021	0.002	0.038	0.861	1.565
Year 4	-0.010	0.058	-0.003	0.075	0.827	1.501
Year 5	-0.012	0.105	-0.003	0.116	0.796	1.453
	B: Unconditional shipment growth rates (entry: year 0)					
	Mean		Median		Std. deviation	
Horizon	Model	Data	Model	Data	Model	Data
Year 1	-0.186	-0.189	-0.051	-0.077	1.091	0.990
Year 2	-0.012	-0.039	0	0	0.908	0.969
Year 3	-0.006	-0.024	0	0	0.845	0.952
Year 4	-0.001	-0.018	0	0	0.812	0.900
Year 5	-0.001	0.000	0	0	0.783	0.896
	C: Sales growth rates conditional on surviving at least until year 5 (entry: year 0)					
	Mean		Median		Std. deviation	
Horizon	Model	Data	Model	Data	Model	Data
Year 1	0.272	0.145	0.181	0.122	0.803	1.381
Year 2	0.146	0.216	0.059	0.201	0.687	1.315
Year 3	0.028	0.103	0.010	0.127	0.575	1.289
Year 4	-0.008	0.129	-0.006	0.117	0.547	1.186
Year 5	-0.092	0.016	-0.034	0.084	0.627	1.185

I Sales by spell duration

In this section, we follow Fitzgerald et al. (2023) and present facts related to firm sales depending on the duration of an export spell. More specifically, we take our first-time entrants and define a dummy $\mathbf{1}_s$ that is equal to one if the firm's export experience (i.e. without any exits in between) lasts for exactly $s \in \{1, \ldots, 5, 6\}$ periods.[61] Then, we run a regression of $\ln(\text{sales}_t)$ on these dummies, with the one-year spells being the base group. Thus, each coefficient has the interpretation of how much more a firm of spell s exports in horizon h relative to the sales of a firm that did not survive any periods. We consider specifications adding destination-year, product, and firm-year fixed effects.

Table H.1: Log(sales)

	(1)	(2)	(3)
Year 0, 1-year spell	-	-	-
Year 0, 2-year spell	1.188***	1.083***	0.896***
	(0.05406)	(0.04832)	(0.05206)
Year 1, 2-year spell	0.600***	0.547***	0.414***
	(0.05206)	(0.04815)	(0.05190)
Year 0, 3-year spell	1.680***	1.627***	1.367***
	(0.07170)	(0.06450)	(0.06988)
Year 1, 3-year spell	1.421***	1.373***	1.194***
	(0.07403)	(0.06803)	(0.07445)
Year 2, 3-year spell	0.976***	0.942***	0.853***
	(0.07428)	(0.07322)	(0.07817)
Year 0, 4-year spell	1.946***	1.751***	1.414***
	(0.09558)	(0.08409)	(0.08410)
Year 1, 4-year spell	1.930***	1.783***	1.536***
	(0.09518)	(0.08448)	(0.08363)
Year 2, 4-year spell	1.901***	1.745***	1.577***
	(0.09770)	(0.08716)	(0.08845)
Year 3, 4-year spell	1.310***	1.169***	1.101***
	(0.09570)	(0.09412)	(0.09843)
Year 0, 5-year spell	1.948***	1.785***	1.471***
	(0.11755)	(0.10294)	(0.10702)
Year 1, 5-year spell	1.867***	1.738***	1.524***
	(0.12117)	(0.11208)	(0.11672)
Year 2, 5-year spell	2.089***	1.961***	1.839***
	(0.11423)	(0.10447)	(0.11039)
Year 3, 5-year spell	2.017***	1.904***	1.827***

[61] Firms that survive 7 or more years are excluded from the regression. We also exclude right-censored export spells, i.e. those where we cannot determine how many years they survived.

	(0.11448)	(0.11040)	(0.11329)
Year 4, 5-year spell	1.414***	1.282***	1.271***
	(0.11272)	(0.12079)	(0.12202)
Year 0, 6-year spell	2.494***	2.224***	1.983***
	(0.15069)	(0.12596)	(0.13582)
Year 1, 6-year spell	2.441***	2.270***	2.112***
	(0.14140)	(0.11851)	(0.12030)
Year 2, 6-year spell	2.485***	2.319***	2.239***
	(0.14839)	(0.12866)	(0.12675)
Year 3, 6-year spell	2.478***	2.327***	2.320***
	(0.14900)	(0.14357)	(0.14027)
Year 4, 6-year spell	2.471***	2.258***	2.362***
	(0.13792)	(0.14126)	(0.14007)
Year 5, 6-year spell	1.877***	1.683***	1.899***
	(0.13311)	(0.15327)	(0.16822)
Destination-year fixed effect	No	Yes	Yes
Product fixed effect	No	Yes	Yes
Firm-year fixed effect	No	No	Yes
Observations	33675	33391	26986
R^2	0.104	0.316	0.629

Table H.1 shows the results. Overall, we see that firms that survive longer sell more, but that their sales are relatively flat over the life-cycle, except for the last year, where they sell substantially less - likely an artifact of time-aggregation (i.e. during the last period, firms exit, so that year is shorter). This result is robust across all specifications; only the levels of sales seem to be affected by the fixed effects. Figure H.1 plots the results in the case with product and destination-year fixed effects activated, as well as the model predictions under the assumptions of CES demand and equal κ and F (which is required to compare sales levels across firms with different spell durations). As argued in the main text, because of selection, the model predicts strong growth in the beginning, which is counterfactual, and a large drop in the exit year due to a partial-year effect upon exit. The former is not present in the data, suggesting that even profitable firms find it difficult to increase sales, even after learning they are very profitable in that market.

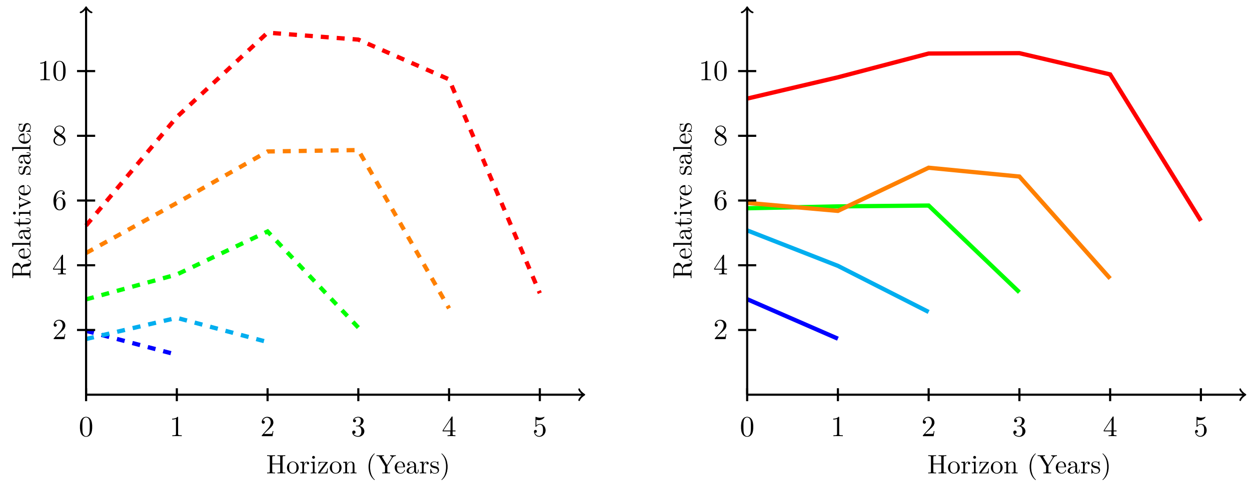
Table H.2: Log(sales) (Annual data)

	(1)	(2)	(3)
Year 0, 1-year spell			
Year 0, 2-year spell	0.865***	0.804***	0.617***
	(0.04197)	(0.03857)	(0.04470)
Year 1, 2-year spell	0.840***	0.801***	0.641***

	(0.04097)	(0.03998)	(0.04444)
Year 0, 3-year spell	1.212***	1.109***	0.934***
	(0.06014)	(0.05507)	(0.05781)
Year 1, 3-year spell	1.623***	1.531***	1.384***
	(0.06201)	(0.05889)	(0.05860)
Year 2, 3-year spell	1.109***	1.029***	0.888***
	(0.06276)	(0.06377)	(0.06447)
Year 0, 4-year spell	1.354***	1.274***	1.068***
	(0.08083)	(0.07069)	(0.07595)
Year 1, 4-year spell	1.898***	1.813***	1.647***
	(0.08365)	(0.07605)	(0.07939)
Year 2, 4-year spell	1.968***	1.904***	1.754***
	(0.08478)	(0.07615)	(0.08022)
Year 3, 4-year spell	1.396***	1.318***	1.176***
	(0.08654)	(0.08369)	(0.09075)
Year 0, 5-year spell	1.531***	1.400***	1.203***
	(0.08971)	(0.08422)	(0.08704)
Year 1, 5-year spell	2.234***	2.126***	1.958***
	(0.08785)	(0.07815)	(0.08324)
Year 2, 5-year spell	2.239***	2.137***	2.000***
	(0.10243)	(0.09674)	(0.10243)
Year 3, 5-year spell	2.230***	2.123***	1.985***
	(0.09875)	(0.09764)	(0.10185)
Year 4, 5-year spell	1.636***	1.549***	1.363***
	(0.09841)	(0.10230)	(0.11817)
Year 0, 6-year spell	1.934***	1.703***	1.539***
	(0.13314)	(0.10588)	(0.11511)
Year 1, 6-year spell	2.425***	2.246***	2.114***
	(0.12744)	(0.10968)	(0.11659)
Year 2, 6-year spell	2.569***	2.428***	2.297***
	(0.12062)	(0.10763)	(0.11301)
Year 3, 6-year spell	2.472***	2.306***	2.218***
	(0.12339)	(0.11891)	(0.11896)
Year 4, 6-year spell	2.341***	2.185***	2.112***
	(0.12505)	(0.12319)	(0.12106)
Year 5, 6-year spell	1.833***	1.704***	1.580***
	(0.13266)	(0.12993)	(0.14649)
Destination-year fixed effect	No	Yes	Yes
Product fixed effect	No	Yes	Yes
Firm-year fixed effect	No	No	Yes

Observations	42783	42476	35264
R^2	0.099	0.299	0.615

We repeat the exercise with annual data based on calendar years, as in the original analysis of Fitzgerald et al. (2023) (Table H.2). Figure H.2 shows that the fit looks better: now the data also exhibits a hump, which is also a feature in our model. The difference between the results with annual data and firm-specific years suggests that the partial-year effect entirely drives the hump. As discussed before, our uniform-entry and pure continuous-time model seems to overcorrect for this partial-year effect, leading to an exacerbated growth rate between the first two years of the export experience.

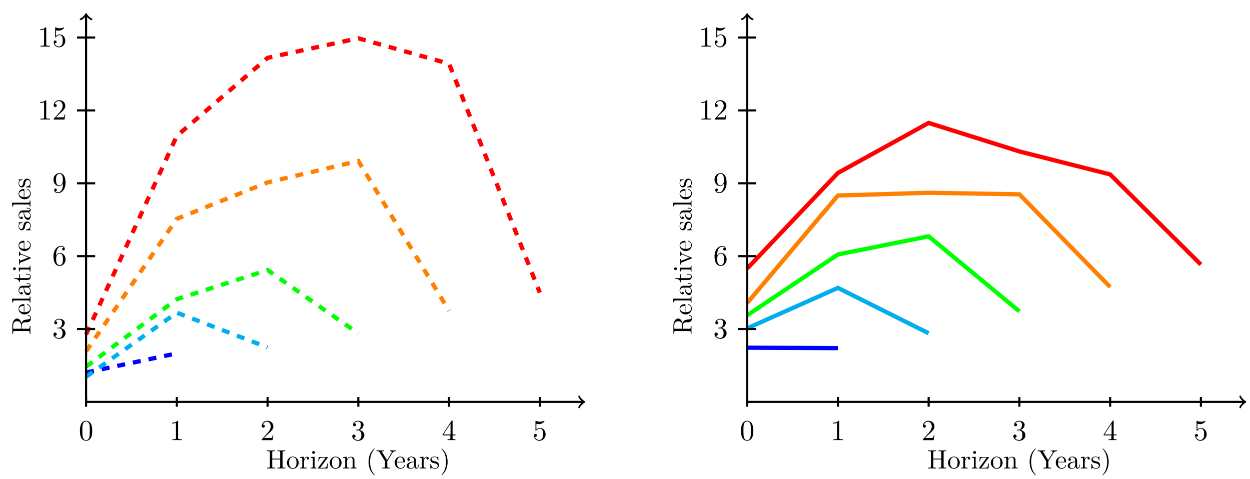


(a) Sales by export spell, model

(b) Sales by export spell, data

Figure H.1: Sales by export spell, model vs. data

Notes: To construct the model predictions, we first classify first-time entrants according to the length of their export spell, i.e. the number of firm-specific years of uninterrupted exports. We compute the mean log sales in each year of their export experience, conditional on being a firm that survives for exactly $x \in \{1, 2, 3, 4, 5, 6\}$ years. We then plot these average sales in levels for firms that last for $x = 2$ (blue), $x = 3$ (cyan), $x = 4$ (green), $x = 5$ (orange) and $x = 6$ (red) divided by the average sales in levels of firms that do not export after the entry year.



(a) Sales by export spell, model

(b) Sales by export spell, data

Figure H.2: Sales by export spell, model vs. data. Annual data.

Notes: To construct the model predictions, we first classify first-time entrants according to the length of their export spell, i.e. the number of calendar years of uninterrupted exports. We compute the mean log sales in each year of their export experience, conditional on being a firm that survives for exactly $x \in \{1, 2, 3, 4, 5, 6\}$ years. We then plot these average sales in levels for firms that last for $x = 2$ (blue), $x = 3$ (cyan), $x = 4$ (green), $x = 5$ (orange) and $x = 6$ (red) divided by the average sales in levels of firms that do not export after the entry year.