How Exporters Grow*

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Abstract

We use customs data for Irish firms to show that in successful episodes of export market entry, there are statistically and economically significant post-entry dynamics of quantities, but not of markups. To match these moments, we structurally estimate a model where firms can invest in future customer base through two channels: by selling more today, and by spending on marketing and advertising. Our estimates suggest that customer base is insensitive to lagged sales, so firms have no incentive to engage in dynamic pricing to accumulate customers. Instead, investment in customer base through marketing and advertising explains the dynamics of quantities. The ratio of advertising and marketing expenditures to sales implied by the model is consistent with data from other sources. Our estimated model generates long run export responses to permanent tariff changes that are bigger than short run responses, as well as responses that are increasing in the expected persistence of tariff shocks, contributing to our understanding of the International Elasticity Puzzle.

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*Appendix available at www.doireann.com. This work makes use of data from the Central Statistics Office, Ireland, which is CSO copyright. The possibility for controlled access to confidential micro data sets on the premises of the CSO is provided for in the Statistics Act 1993. The use of CSO data in this work does not imply the endorsement of the CSO in relation to the interpretation or analysis of the data. This work uses research data sets that may not exactly reproduce statistical aggregates published by the CSO. We thank the staff of the CSO for making this project possible. Expert research assistance was provided by Adrian Corcoran, Matt Shapiro and Anthony Priolo. Doireann Fitzgerald is grateful for financial support from the NSF under grant number 0647850. Yaniv Yedid-Levi is grateful for financial support from the Social Sciences and Humanities Research Council of Canada. We thank Manuel Amador, Costas Arkolakis, Russ Cooper, Tim Kehoe, Jeremy Lise, Jo Mullins, Kim Ruhl, James Tybout, Daniel Xu, and participants in the 2015 and 2016 NBER Summer Institute for comments and suggestions. The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

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1 Introduction

Recent research makes customer base central to the analysis of firm dynamics, business cycles, and international trade.[1] Although much has been learned, there is as yet no consensus on what firms do to expand customer base after entry into a market. Theories of customer base accumulation in the literature fall into two categories: (1) firms reach more customers by engaging in non-price activities such as marketing and advertising (we refer to this as the "marketing and advertising model"), and (2) future customer base is increasing in today's sales, so firms expand in a market by first charging markups below the statically optimal level. They then gradually increase markups as customer base rises towards its steady state (we refer to this as the "customer markets model").

We use customs data for Ireland for the period 1996-2009, and a combination of reduced form and structural estimation to confirm the role of customer base in export growth, and to ask whether it is possible to distinguish between these two theories. Customs data are well-suited to this exercise, because we observe quantities and prices for the same firm selling the same product in multiple segmented markets. We first show that in the years following successful entry by a firm into a new market, export quantities grow steadily in the new market relative to old markets, while prices in the new relative to old markets are flat. Assuming that marginal cost is the same for all markets the firm serves, this appears consistent with gradual accumulation of customer base in new markets that takes place primarily through marketing and advertising rather than intertemporal distortion of markups.

To test this hypothesis more formally, we estimate a model of the exporting firm's problem where we nest the two theories. In our model, customer base shifts demand conditional on prices. It may not fully depreciate between one period and the next. The firm decides whether to participate in a given export market, knowing that it can add to future customer base by spending today on marketing and advertising (which may be subject to an adjustment cost), and by increasing current sales by depressing markups today below their statically optimal level. The relative effectiveness of these two types of investment in contributing to future customer base is governed by a parameter.

We estimate the model using simulated method of moments. We do this for a series of different values of the parameter governing the relative effectiveness of the two types of

[1] See, among others, Arkolakis (2016), Drozd and Nosal (2012) Eaton et al. (2011), Eaton et al. (2021), Einav et al. (2022), Foster et al. (2008, 2016), Gilchrist et al. (2017), Gourio and Rudanko (2014), Hottman et al. (2016), Ravn et al. (2006), Ruhl and Willis (2017).

investment spanning the relevant range. The moments we match are the post-entry behavior of normalized quantities and markups, as well the exit hazard and the export entry rate. The estimated model is also constrained to match a long-run trade elasticity of 3, consistent with values estimated in the literature, as well as evidence in Fitzgerald and Haller (2018) for the Irish customs data we use.

Our model fits the data best when customer base is insensitive to lagged sales, so firms invest in customer base through marketing and advertising, but do not make use of intertemporal markup distortion. In this case we find that marketing and advertising is subject to costs of adjustment which slow down convergence to steady state. In contrast, if we impose that marketing and advertising is ineffective, so customer base depends only on lagged sales, the model cannot match the dynamics of quantities in the data given the absence of price dynamics. Between these two polar cases, model fit, and in particular, the ability to match the behavior of quantities, improves as the parameter governing the sensitivity of future customer base to current sales declines.

Our best estimates of the model (i.e. when customer base is insensitive to lagged sales) imply that selling expenses account for 18.5% of revenue in the latter years of export spells which last 7 or more years. Although we do not have data on marketing and advertising expenditures for our Irish firms with which to compare this estimate, it is within the range of what the empirical literature on selling expenses finds.[2] Our findings are also consistent with evidence in Patault and Lenoir (2022) of a positive relationship between number of sales managers and number of foreign customers for French exporters.

In an application of our estimated structural model, we calculate impulse-responses of exports to tariff shocks for incumbent exporters. The model implies long-run elasticities of export revenue and export quantities with respect to permanent tariff changes that are higher than short-run elasticities. It also implies elasticities with respect to mean-reverting shocks that are increasing in shock persistence. However the elasticity of export prices with respect to tariff changes is equal to zero at all horizons, irrespective of the persistence of the shock. These comparative statics are consistent with findings in the empirical literature using macro data,[3] and complement explanations which rely on the export participation margin. In contrast, our best estimates of the customer markets model imply smaller differences between short- and long-run trade elasticities, and responses of export prices to tariffs which

[2]Using Compustat data from the U.S. for 1971-2006, Gourio and Rudanko (2014) find that firms for which "Selling, General, and Administrative Expenses" (SG&A) are above the industry median have an average share of SG&A in sales of 27%, while firms for which SG&A are below the industry median have an average share of SG&A in sales of 17%.

[3]See Amiti, et al. (2020), Boehm et al. (2022) and Ruhl (2008).

counterfactually differ from zero.

Our contribution is related to a number of other papers which investigate quantity and price dynamics using manufacturing census and customs data. For example, Foster et al. (2008, 2016) use plant census data for the US and focus on implications for productivity measurement. Bastos et al. (2018), Berman et al. (2019) and Piveteau (2021) use customs data for Portugal and France and focus on export dynamics. In contrast to other work in this area, we use a comprehensive set of quantity, price and exit moments to structurally estimate competing models of customer base accumulation, and show which model the data favors.

Our work is also related to a literature in macroeconomics that posits that current sales affect future demand. Models with this feature are used extensively in work that focuses on flexible-price markup-based explanations for the countercyclicality of the labor wedge in business cycles. The idea is that booms are times when there are many potential new customers, and to attract these customers, firms choose low markups (e.g. e.g. Bils (1989), Ravn et al (2006) and Gilchrist et al. (2017)). While we cannot rule out that firms use dynamic markups to attract customers at a business cycle frequency, our results do not provide support for use of this mechanism over a longer horizon.

Our findings have potential implications for the many areas of macroeconomics and international economics where models with demand and customer base are used. Gourio and Rudanko show that sluggish adjustment of customer base matters for firm responses to shocks, and for the relationship between investment and Tobin's Q. Einav et al. (2022) argue that the customer margin has implications for growth. In a direct application of our findings, Fitzgerald et al. (2019) show that the marketing and advertising model we estimate here has the potential to rationalize the very different responses of exports to movements in exchange rates and changes in tariffs that we see in the data.

The paper is organized as follows. In Section 2, we lay out our model. In Section 3 we describe our data. In Section 4 we describe our reduced form empirical strategy. In Section 5, we describe our reduced form results. In Section 6 we structurally estimate the model to match these results. In Section 7 we illustrate the implications of our estimated model for incumbent exporter responses to tariff changes. The final section concludes.

2 A model of customer base accumulation

Our model generalizes the exporter problem in Arkolakis (2010). Arkolakis presents a static model in the tradition of informative advertising, where a firm can shift current demand in a market by engaging in marketing and advertising in that market. Marketing and advertising effort has decreasing returns, and does not affect the price elasticity of demand.

We generalize in two ways. First, we make the model dynamic through less than full depreciation of customer base between one period and the next. Second, we allow future customer base to depend on current sales in addition to current marketing and advertising effort. In allowing future customer base to depend on current sales, we follow a long tradition of "customer markets" models in macroeconomics (e.g. Bils (1989), Ravn et al (2006)), as well as more recent work by Foster, Haltiwanger and Syverson (2016) on firm dynamics.[4]

When future customer base depends on lagged sales, the transition to steady state customer base is gradual by assumption. We allow for adjustment costs of advertising and marketing investment in the model, so transitions may be gradual even in the limiting case where future customer base is unaffected by lagged sales.[5]

We nest this model of demand within a parsimonious model of export entry and exit in mutiple markets due to stochastic fixed and sunk costs of exporting.

More formally, firms are indexed by i, and markets are indexed by k. Markets are segmented, so the firm is able to price discriminate. Analogously, marketing and advertising effort and sales in market k affect future customer base in market k, but not other markets. The firm's decisions across different markets are linked only through common exogenous marginal cost of production, C_t^i.[6] In each export market k, the firm faces iid sunk (S_t^{ik}) and fixed (F_t^{ik}) costs of participation. Sunk costs lead to selection on entry, while fixed costs lead to selection on entry and exit.

Demand conditional on participation is assumed isoelastic:

$$Q_t^{ik} = Q_t^k \left(\frac{P_t^{ik}}{P_t^k} \right)^{-\theta} \left(D_t^{ik} \right)^{\alpha} \exp\left(\nu_t^{ik} \right). \tag{1}$$

Here, Q_t^k is aggregate demand in market k and P_t^k is an index of competitors' prices. Going

[4] Our preferred interpretation of this specification is that new customers may learn about a firm by observing the purchases of current customers, as well as through its marketing and advertising activities.

[5] This aspect of our setup is related to Drozd and Nosal (2012) who build a two-country dynamic general equilibrium model with firms which accumulate customer base through marketing expenditures.

[6] In Appendix A, we lay out a model with firm-level heterogeneity in quality as well as cost.

forward, we write $Y_t^k = Q_t^k \left(P_t^k\right)^\theta$, and refer to Y_t^k as market size.[7] Under monopolistic competition, market size is exogenous to the firm. Demand also depends on the exogenous idiosyncratic demand shifter ν_t^{ik}.

The firm affects the quantity sold in market k by choosing the price, P_t^{ik}, and by taking actions which affect customer base, D_t^{ik}. If $\alpha \in (0,1)$, demand is increasing in customer base, but at a diminishing rate. If $\alpha = 0$, demand does not depend on customer base. The intuition for diminishing returns is as in Arkolakis (2010). If investment cannot be targeted, it becomes more difficult to reach uninformed customers the higher is the share of customers that are currently informed. Note that customer base shifts demand, but does not affect the price elasticity of demand, consistent with an information story.

Let $X_t^{ik} = \{0,1\}$ be an indicator for participation. Firms entering market k start with customer base $\underline{D}^k > 0$. Customer base in market k accumulates according to:

$$D_{t+1}^{ik} = \left(1 - X_t^{ik}\right) \underline{D}^k + X_t^{ik} \left(\left(1-\delta\right) D_t^{ik} + \psi A_t^{ik} + \left(1-\psi\right) P_t^{ik} Q_t^{ik}\right) \tag{2}$$

Customer base depreciates at rate δ conditional on continued participation. There is full depreciation on exit. $\psi \in [0,1]$ governs the relative effectiveness of marketing and advertising and current sales in adding to future customer base. When $1-\psi > 0$, and customer base is below its steady state level, the firm has an incentive to set a below-steady-state markup. In doing so it trades off lower profit today in return for higher customer base and higher profits in the future. This tradeoff is governed by θ, the price elasticity of demand, and by $1-\psi$, the responsiveness of future customer base to current sales. The higher is θ, the smaller is the reduction in today's markup necessary to generate a given shift in future demand, while the higher is $1-\psi$, the greater the shift in future demand for a given increase in sales today. We show in Appendix B that the assumption that the weights on A_t^{ik} and lagged sales in the accumulation equation sum to one is without loss of generality.[8]

The cost of marketing and advertising is given by $c\left(D_t^{ik}, A_t^{ik}\right)$, where $c(\cdot, 0) = 0$, and $c(\cdot,\cdot)$ is differentiable in both arguments, with $c_A > 0$, $c_{AA} \geq 0$ and $c_D \leq 0$. Since customer base is intangible, it is natural to assume irreversibility, i.e. $A_t^{ik} \geq 0$.

There are three sources of potentially persistent heterogeneity in the model: C_t^i, Y_t^k, and ν_t^{ik}. The firm knows the processes for these variables, as well as the processes for fixed and

[7] In Appendix A we show that iceberg trade costs and tariffs enter the firm's problem in the same way as market size, but with elasticity $-\theta$.

[8] We use the Foster et al. (2016) formulation of dependence on past sales rather than past quantity for comparability with the previous literature.

sunk costs, and observes current realizations of all shocks before making decisions.[9]

Let $Z_t^{ik} = \left\{S_t^{ik}, F_t^{ik}, C_t^i, Y_t^k, \nu_t^{ik}\right\}$ denote the vector of exogenous state variables. Flow profit conditional on participation at t is:

$$\pi\left(Z_t^{ik}, X_{t-1}^{ik}, D_t^{ik}, A_t^{ik}, P_t^{ik}\right) = \left(P_t^{ik} - C_t^i\right) Y_t^k \left(P_t^{ik}\right)^{-\theta} \left(D_t^{ik}\right)^{\alpha} \exp\left(\nu_t^{ik}\right) \tag{3}$$

$$-c\left(D_t^{ik}, A_t^{ik}\right) - F_t^{ik} - \left(1 - X_{t-1}^{ik}\right) S_t^{ik}$$

Current participation (X_t^{ik}), marketing and advertising effort (A_t^{ik}), and current prices (P_t^{ik}) affect future as well as current profits. Assuming that firms discount the future at rate β, the Bellman equation for the firm's problem is:

$$V\left(Z_t^{ik}, X_{t-1}^{ik}, D_t^{ik}\right) = \max_{\substack{X_t^{ik} \in \{0,1\} \\ A_t^{ik} > 0 \\ P_t^{ik} > 0}} \left\{ \begin{array}{c} X_t^{ik} \pi\left(Z_t^{ik}, X_{t-1}^{ik}, D_t^{ik}, A_t^{ik}, P_t^{ik}\right) + \\ \\ \beta \mathbb{E}\left\{V\left(Z_{t+1}^{ik}, X_t^{ik}, D_{t+1}^{ik}\right) | Z_t^{ik}\right\} \end{array} \right\}$$

subject to the accumulation of customer base.

2.1 Model predictions

By making assumptions about functional forms and the statistical processes for the exogenous variables, we can prove a series of propositions for the polar cases where $\psi = 1$ (marketing and advertising model) and $\psi = 0$ (customer markets model). We prove three propositions showing that markups behave differently in these two polar cases. This suggests that markup behavior can be used to distinguish between these cases empirically. We prove a fourth proposition to provide support for our approach to dealing with unobserved heterogeneity in idiosyncratic demand in our empirical strategy.

Assume that marginal cost is constant for each firm ($C_t^i = C^i$), market size is constant for each market ($Y_t^k = Y^k$), and ν_t^{ik} remains fixed within an export spell (i.e. an episode of continuous participation by a firm in a particular market). On exit, the firm loses its draw of ν_t^{ik}, and receives a new draw in every subsequent period of non-participation. Assume that F_t^{ik} can take only two values, zero and infinity (so exit is exogenous), and the adjustment cost

[9] Berman et al (2019) propose that learning about idiosyncratic demand may induce post-entry export dynamics. In Appendix C we describe a model where learning about ν_t^{ik} rather than customer base accumulation induces dynamics in quantities and prices. We structurally estimate this model (see Appendix K), and find it provides a poor fit to the data.

function for marketing and advertising takes the form $c(D,A) = A + \phi(A^2/D)$.[10] Assuming the resulting value functions are differentiable and concave, we prove the following:

Proposition 1. When $\psi = 1$ (marketing and advertising model), the markup is *independent* of C^i, Y^k and ν_t^{ik}.

Proof See Appendix D.

The intuition for Proposition 1 is straightforward. When $\psi = 1$, current sales do not affect future customer base. The optimal price is a static decision, and is given by the standard CES markup over marginal cost, $\theta/(\theta-1)$.[11]

Proposition 2. When $\psi = 0$ (customer markets model), the markup on entry is *increasing* in C^i and *decreasing* in Y^k and ν_t^{ik}.

Proof See Appendix D.

Proposition 3. When $\psi = 0$ (customer markets model), if customer base on entry is below steady state customer base, then (a) the markup converges to the steady state markup from below, and (b) growth in the markup on entry (i.e. growth between the first and second periods of participation) is *decreasing* in C^i, and *increasing* in Y^k and ν_t^{ik}.

Proof See Appendix D.

The intuition for Propositions 2 and 3 is that below-steady-state markups are an investment in customer base. Steady state customer base is decreasing in marginal cost and increasing in market size and idiosyncratic demand. Holding fixed customer base on entry, the greater is steady state customer base, the greater the incentive to invest.

We verify in model simulations that the behavior of markups in Propositions 1-3 carries over to the case of endogenous exit. In Appendix D, we also prove a series of propositions characterizing the behavior of quantities, and show that in both polar cases ($\psi = 1$ and $\psi = 0$), quantities on entry and quantity growth depend on costs, market size, and idiosyncratic demand.

Our last proposition allows us to use duration i.e. how long a firm survives in a particular market, as a proxy for unobserved idiosyncratic demand in our reduced form empirical analysis. The following holds under endogenous exit, both when $\psi = 1$ and when $\psi = 0$:

[10] We use this functional form in the structural estimation.

[11] This is obviously true under much more general assumptions.

Proposition 4. Fix C^i, Y^k, and D_t^{ik}. Let $\bar{\nu}^{ik}$ be the current draw of ν_t^{ik}. Then the probability of survival is increasing in $\bar{\nu}^{ik}$.

Proof See Appendix D.

The intuition is straightforward. On exit, the firm loses its current draw of the permanent component of idiosyncratic demand. The value of exit is therefore independent of this draw, while the value of continued participation is increasing in this draw. Hence, the probability that the firm will continue to participate is increasing in its current draw of the permanent component of idiosyncratic demand. This implies that duration, which is an increasing function of the survival probability, is also increasing in $\bar{\nu}^{ik}$. In Appendix D.3, we verify numerically that as long as customer base is above customer base on entry (i.e. $D > \underline{D}$), the probability of survival is also decreasing in costs and increasing in market size at our baseline estimates of the structural model.

3 Data

We make use of two sources of confidential micro data made available to us by the Central Statistics Office (CSO) in Ireland: the Irish Census of Industrial Production (CIP), and customs records for merchandise exports. The data are described in detail in Appendix E.

3.1 Census of Industrial Production

The CIP is an annual census of manufacturing, mining, and utilities. Firms with three or more employees are required to file returns.[12] We make use of data for the years 1996-2009 and for NACE Revision 1.1 sectors 10-40 (manufacturing, mining, and utilities). Of the variables collected in the CIP, those we make use of in this paper are total revenue, employment, and country of ownership.

In constructing our sample for analysis, we drop firms with a zero value for total revenue or zero employees in more than half of their years in the sample. We perform some recoding of firm identifiers to maintain the panel dimension of the data, for example, in cases in which ownership changes.

[12] We work with firm- rather than plant-level data, since this is the level at which the match with customs records can be performed.

3.2 Customs records

Our main source of data is customs records of Irish merchandise exports for the years 1996-2014. The f.o.b. value (euros) and quantity (tonnes)[13] of exports are available at the level of the VAT number, the Combined Nomenclature (CN) eight-digit product, and the destination market (country), aggregated to an annual frequency. These data are matched by the CSO to CIP firms using a correspondence between VAT numbers and CIP firm identifiers, along with other confidential information. Appendix E provides additional information on this match and on other details of the data. We make use of all matched records.

An important feature of the customs data is that the eight-digit CN classification system changes every year. In order to make time-series comparisions, we concord the product-level data over time at the most disaggregated level possible following the approach of Pierce and Schott (2012) and Van Beveren et al. (2012).[14] The breakdown of exports by HS 2-digit classification over the sample period is reported in Appendix E (Table 6).

For our baseline analysis, we restrict attention to the period 1996-2009, for which we have CIP data in addition to customs data, and for this analysis we make use only of customs data that matches to a CIP firm. In some robustness checks, we make use of the full sample period, 1996-2014. When we do so, we do not condition on a CIP match. We perform the product concordance separately for the two different sample periods, as dictated by the Pierce and Schott approach.

As a result, we have annual panel data on the value and quantity of exports at the firm-product-market level, where the product is defined at the eight-digit (concorded) level, and the market refers to the destination country. We use this to construct a price (unit value) by dividing value by quantity, where available. In aggregate trade statistics, unit value data at the product level are notoriously noisy. However, conditioning on the exporting firm as well as the product considerably reduces this noise.[15]

3.3 Summary statistics

Table 1 shows summary statistics on exporting behavior in our data. Export participation is high, export intensity conditional on participation is high, and more than half of exporters

[13] The value is always available, but quantity is missing for about 10% of export records. For a limited set of observations, an additional quantity measure (besides tonnes) is available. We make use of this in a robustness check.

[14] We examine robustness to conditioning on products for which the concordance is 1-1 for all pairs of years in the sample.

[15] We check that our results are robust to dropping unit value outliers.

export to more than one market (we observe 141 distinct export markets over the course of the panel). These facts are typical of small open European economies (see ISGEP (2008)).

There is a good deal of churn in export participation at the firm-market level, and entry and exit are not synchronized across different export markets within a given firm.[16] This is illustrated in Table 2, which reports the distribution of exporter-level changes in the number of export markets from year to year. In any given year, on average 49% of exporters change the *number* of markets they participate in. This is a lower bound on churn, as firms may keep the total number of export markets constant, while switching between markets. This churn is consistent with stochastic fixed and sunk costs of the type we include in our model. Fitzgerald and Haller (2018) document additional facts about entry and exit in these data.

4 Reduced form empirical strategy

Our reduced form analysis has three goals. First, we want to confirm that customer base accumulation is an important source of post-entry dynamics in our data. Second, we want to see whether there are post-entry dynamics in markups. Third, the moments we construct will be used as inputs into our simulated method of moments estimation in Section 6. Before describing exactly what we do, we define some useful variables, and give an overview of how our approach achieves these three goals.

4.1 Definitions and measurement

As explained in Section 3.2, an observation in our data is a firm-product-market-year.

An *export spell* is a continuous episode of market participation, i.e. an episode in which there are positive exports for that firm-product-market in every consecutive year. A spell is left-censored if we see exports in the first year of our sample.[17] It is right-censored if we see exports in the last year of the sample. If we observe zero exports for one or more years after some positive exports, any reentry is counted as part of a distinct export spell.[18]

Export *age* is set equal to 1 in the first year of exporting after not exporting in the previous year, i.e. in the first year of an export spell. Age is incremented by 1 in each subsequent year of continuous participation. Age is censored if the spell is left-censored.

[16] This is consistent with Lawless (2009), who uses a different data set for a selected sample of Irish firms.

[17] Our sample starts in 1996, but due to issues with the match between customs data and firms in 1996, we also consider spell entry to be censored if it takes place in 1997.

[18] In our baseline analysis we treat these reentry spells the same as first spells.

Duration is defined as age in the last year prior to exit. Duration is observed only if the export spell is neither left- nor right-censored. However for right-censored spells, we know that duration is at least as great as age at the end of the sample. By top-coding duration, we can make use of this information. We topcode both age and duration at 7 years.[19]

4.2 Overview

To confirm that customer base accumulation is an important source of post-entry quantity dynamics, we need to isolate variation in quantities that is not driven by changes in marginal cost. To examine the dynamics of markups, we must similarly purge changes in marginal cost from prices. Under the assumption that marginal cost is the same for all markets served by a particular firm-product pair, we achieve both of these aims by differencing quantities and prices across markets within a firm-product i.e. by regressing logs of these variables on firm-product-year fixed effects.

We are not interested in dynamics that are due purely to exogenous changes in market size. So for both quantities and prices, we control for time-varying market size by differencing quantities and prices across firms selling the same product in the same market, i.e. by regressing logs of these variables on product-market-year fixed effects. This is valid under monopolistic competition, where all market participants face the same market size.

We are concerned that selection on persistent unobserved idiosyncratic demand may give the appearance of a relationship between relative quantities and age and relative markups and age, even when there are no true underlying dynamics. This may happen if firm-product-market spells which survive for a long time have higher idiosyncratic demand than the average entrant. Regressing, say, quantities on age may therefore lead us to infer dynamics even when there are none. So motivated by Proposition 4, we control for persistent idiosyncratic demand by conditioning on duration, i.e. how long a firm-product pair survives in a particular market.[20]

Dynamics in relative quantities and markups are then identified by examining how the residual variation in quantities and prices after these controls evolves with a firm-product pair's age in a market.

To allow dynamics to vary with the factors that drive the return to investment, we interact age with proxies for these variables (i.e. marginal cost, market size, and idiosyncratic

[19]Using our full panel of customs data, which lasts for 19 years, we show that our key results are robust to top-coding at levels up to 10 years.

[20]This follows Abraham and Farber (1987), who use duration to proxy for unobserved heterogeneity in the quality of worker-firm matches in order to obtain an unbiased estimate of returns to job tenure.

demand) motivated by Proposition 4 and related conjectures. We obtain estimates of the dynamic behavior of relative quantities and markups for fixed marginal cost, market size and idiosyncratic demand by evaluating at fixed values of these proxies.

We proxy marginal cost using the number of distinct markets a firm exports to over the entire sample period. We proxy market size using the number of distinct firms which export to a market over the entire sample period. As already noted, we proxy idiosyncratic demand using duration. For our empirical strategy to identify dynamics conditional on marginal cost, market size, and permanent heterogeneity in idiosyncratic demand, our proxies must fully span variation in these variables. In Appendix D.3.4 we verify in model simulations that these proxies are indeed correlated with marginal cost, market size, and idiosyncratic demand as hypothesized.

In addition to examining dynamics in relative quantities and markups, we also characterize the behavior of the exit hazard, verifying that it is downward-sloping conditional on firm- and market-specific factors, consistent with the hypothesis that there is selection on idiosyncratic demand. This supports our use of duration as a proxy for idiosyncratic demand, and is useful for quantifying heterogeneity in idiosyncratic demand in the structural estimation.

4.3 Implementation

Let w_t^{ijk} denote log quantity, or log price at the firm-product-market level, where i indexes firms, j indexes products, and k indexes markets. Let c_t^{ij} be a a set of firm-product-year fixed effects. Let d_t^{jk} be a set of product-market-year fixed effects. Let $\mathbf{a}_t^{ijk}$ be a vector of indicator variables for firm i's age in market k with product j. Let $\mathbf{l}_t^{ijk}$ be a vector of indicators for the duration of the relevant spell. This indicator does not vary within a spell. Let $\mathbf{cens}^{ijk}$ be a vector of indicators for spells that are left-censored ($cens_l^{ijk}$), and right-censored but not left-censored ($cens_r^{ijk}$). Then let:

$$\mathbf{s}_t^{ijk} = \begin{bmatrix} \mathbf{l}_t^{ijk} \otimes \mathbf{a}_t^{ijk} \\ \mathbf{cens}^{ijk} \end{bmatrix}$$

where the symbol $\otimes$ indicates the Kronecker product. We do not observe age of greater than l for a spell that lasts l years, so the redundant interactions are dropped. We code $\mathbf{s}_t^{ijk}$ such that the dependent variable (log quantity or price) is normalized to 0 for 1-year export spells.

Let m^i and f^k be the number of markets per firm and the number of firms per market as described above. Our baseline estimating equation is:

$$w_t^{ijk} = c_t^{ij} + d_t^{jk} + \boldsymbol{\beta}' \left(\mathbf{s}_t^{ijk} \otimes \begin{pmatrix} 1 \\ m^i \\ f^k \end{pmatrix} \right) + \epsilon_t^{ijk}. \tag{4}$$

We include all observations with positive exports in estimating this equation.

Because $\mathbf{s}_t^{ijk}$ includes all possible combinations of age and duration, our specification is fully non-parametric with respect to age and duration, and semi-parametric with respect to m^i and f^k. By controlling nonparametrically for duration and age, we allow for nonlinearities induced by entry or exit part-way through a year. In interpreting our results, we take these effects into account, and we explicitly incorporate them into our structural model.[21]

We can then use the estimated coefficients $\boldsymbol{\beta}$ to evaluate

$$E\left(w_t^{ijk} - c_t^{ij} - d_t^{jk} | a, l, m^i, f^k\right) - E\left(w_t^{ijk} - c_t^{ij} - d_t^{jk} | 1, 1, m^i, f^k\right)$$

for values of $\left\{a, l, m^i, f^k\right\}$. Assuming our proxies span the underlying unobserved heterogeneity, this gives us estimates of the dynamics of relative quantities and relative markups conditional on marginal cost, market size, and idiosyncratic demand.

To characterize the conditional exit hazard at the firm-market level, we estimate the following linear probability model:

$$\Pr\left[X_{t+1}^{ik} = 0 | X_t^{ik} = 1\right] = c_t^i + d_t^k + \boldsymbol{\beta}' \left(\begin{pmatrix} \mathbf{a}_t^{ik} \\ cens_l^{ik} \end{pmatrix} \otimes \begin{pmatrix} 1 \\ m^i \\ f^k \end{pmatrix} \right) + \epsilon_t^{ik} \tag{5}$$

We include all observations where exit is not censored by the end of the sample. The terms c_t^i, d_t^k, $\mathbf{a}_t^{ik}$ and $cens_l^{ik}$ are defined as above. We code $\mathbf{a}_t^{ik}$ and $cens_l^{ik}$ such that the exit hazard is normalized to zero for for the first year of an export spell. Based on our estimates of this expression, we can trace out

$$E\left(\Pr\left[X_{t+1}^{ik} = 0 | X_t^{ik} = 1\right] - c_t^i - d_t^k | a, m^i, f^k\right) - E\left(\Pr\left[X_{t+1}^{ik} = 0 | X_t^{ik} = 1\right] - c_t^i - d_t^k | 1, m^i, f^k\right)$$

[21] Some authors who have access to high-frequency data correct for part-year effects by dating the beginning of an export spell e.g. from its first month, and aggregating to an annual frequency starting each "year" in the entry month. Our data do not allow us to do this, and it would in any case invalidate the use of calendar year fixed effects to control for marginal cost and market size.

for values of $\{a, m^i, f^k\}$. This gives us estimates of the exit hazard conditional on marginal cost and market size, providing insight into selection on idiosyncratic demand. We also estimate this equation at the firm-product-market level.

Because they are useful as target moments in the structural estimation, we also regress entry rates and one-year exit rates at the firm-market level on m^i and f^k. This allows us to calculate entry and 1-year exit rates conditional on values of m^i and f^k.

5 Reduced form results

We first confirm that our proxies for marginal cost, market size and idiosyncratic demand have desirable properties.

Table 3 shows that the number of markets per firm (m^i) is positively correlated with log employment, sales per worker and TFP, giving us confidence that it captures an important dimension of the firm's underlying cost advantage. Meanwhile, the number of firms per market (f^k) is strongly positively correlated with market k's share in world GDP and negatively correlated with market k's distance from Ireland, giving us confidence that it summarizes the attractiveness of market k to Irish firms.[22]

Table 3 also reports the correlations of the firm- and market-level proxies with each other. At the export spell level, m^i and f^k are negatively correlated, consistent with "bad" firms exporting only to "good" markets, and conversely, only "good" firms exporting to "bad" markets. This is in line with what we expect based on our model.

In Table 4, we report the distribution of duration across export spells and export observations. Short-duration spells account for a large fraction of spells, but a substantially smaller fraction of export observations. In Table 5, we regress duration on m^i and f^k. As we expect, the coefficients on m^i and f^k are positive and strongly significant. However the R-squared of the regression is less than 1%. Conditional on entry, firm- and market-specific heterogeneity does not account for much of the variation in duration. Unlike m^i and f^k, we do not have alternative proxies for idiosyncratic demand with which to compare duration. But the fact that there is a good deal of residual variation in duration conditional on m^i and f^k is consistent with an important role for selection on idiosyncratic demand.

[22]See Appendix E for more information on data sources and construction.

5.1 Baseline results

We now present the results from estimating our baseline specification, equation (4). We report the results in the form of figures which show the (exponential of the) fitted values of the dependent variables, evaluated at the mean values of our proxies for costs and market size, i.e. $\left\{\bar{m}^i, \bar{f}^k\right\}$, for all possible combinations of age and duration. These fitted values are graphed against age. The omitted category in all regressions is export spells which last one year. The log of the dependent variable for these spells is therefore normalized to 0, and the exponential is normalized to 1. Figure 1 shows the results for quantities, and Figure 2 shows the results for prices. Full results from estimating our baseline specification are reported in Appendix Tables 9-11.[23]

Figures 1 and 2 illustrate average trajectories of relative quantities and relative prices (i.e. quantities and prices net of the relevant the firm-product-year and market-product-year fixed effects) for export spells of different duration, for a firm of type $\bar{m}^i$ in a market of type $\bar{f}^k$. Note that these means (i.e. $\bar{m}^i$ and $\bar{f}^k$) are taken across all firm-product-market-year observations: $\bar{m}^i$ is at the 96th percentile in terms of exporting firms, at the 57th percentile in terms of export spells, and at the 55th percentile in terms of export observations. Meanwhile $\bar{f}^k$ is at the 95th percentile of export markets, at the 63rd percentile of export spells, and at the 59th percentile of export observations. So these are average trajectories for low-cost firms in large markets.[24]

Four key findings emerge from Figures 1 and 2. First, relative quantity on entry is increasing in duration. Second, there is no statistically significant relationship between relative markups on entry and duration. Third, relative quantity grows fourfold between years one and five of export spells that last at least seven years. This growth is statistically significant up to a horizon of four years and is not driven purely by part-year effects in the first year i.e. there is economically and statistically significant growth between years two and four. Fourth, within export spells that last at least seven years, there are no statistically significant dynamics in (relative) markups up to a horizon of six years.

Next we confirm that there is a decreasing hazard of exit conditional on firm- and market-specific heterogeneity. Figure 3 graphs the fitted values of the firm-product-market and firm-market export hazards, evaluated at $\left\{\bar{m}^i, \bar{f}^k\right\}$. The omitted category is observations in

[23] We include exponentials of standard errors in the quantity figure. To make the price figure easier to read, we include only standard errors for the longest spell.

[24] Relative quantity on entry is increasing in f^k. Relative markups on entry are unrelated to either m^i or f^k. We do not see evidence of a systematic relationship between dynamics in either relative quantity or markups and m^i or f^k.

their first year of export participation, so in both cases the exit probability is normalized to 0 for age equal to 1. Again, full results are reported in the Appendix (Tables 15, 16 and 17).[25] Conditional on our proxies for cost and market size, the probability of exit at both firm-product-market and firm-market levels is initially steeply decreasing in market tenure. This is consistent with selection on the permanent component of idiosyncratic demand. This both implies that it is important to control for this dimension of heterogeneity to correctly identify dynamics, and justifies our use of duration a proxy.

In Appendix Table 18, we report entry rates and 1-year exit rates conditional on t $\left\{\bar{m}^i, \bar{f}^k\right\}$. These are moments we match in the structural estimation.[26]

5.2 Interpretation

Figure 1 shows that when a firm simultaneously enters multiple equally-sized markets with the same product, initial quantity is on average more than two times bigger in the market where it ultimately survives at least seven years than in the market where it exits two years after entry (the impact of part-year effects is similar for these two markets). In addition, in the market where the firm ultimately survives at least seven years, quantity relative to the firm's average quantity across all markets grows on average 75% between the second and sixth years of participation (again, part-year effects do not play a role).

Meanwhile Figure 2 shows that when a firm simultaneously enters multiple equally-sized markets, the price it charges in the market where it ultimately survives for at least seven years is statistically indistinguishable from the price it charges in the market where it exits two years after entry. In fact this is true for all durations. In addition, in the market where the firm ultimately survives at least seven years, between years two and six, there is no statistically significant evolution of price relative to the average price across all markets the firm serves. Assuming that marginal cost is the same for all the markets the firm serves, this implies that markups on entry are statistically indistinguishable across markets, and that within the same firm, markups do not vary systematically with age in a market.

Because markups do not decline systematically with age in a market, quantity growth in long-duration markets cannot be accounted for by firms moving along the demand curve. This suggests that there is an important role for shifts in demand, and in particular, customer base accumulation, in explaining the dynamics of quantities. But again, since there are no

[25] At the firm-product-market level, the exit hazard is less steeply decreasing for high m^i firms than for low m^i firms. At the firm-market level, the exit hazard is less steeply decreasing for high m^i firms and high f^k markets than for low m^i firms and low f^k markets.

[26] At both levels, entry is increasing in m^i and f^k, while exit is decreasing in m^i and f^k.

statistically significant dynamics of markups, Figures 1 and 2 are consistent with firms relying primarily on non-price actions such as marketing and advertising to accumulate customer base, and therefore shift demand.

In the next section of the paper, we provide a more formal test of this hypothesis by structurally estimating the model from Section 2. But first, we explain the role of the different components of our baseline estimating strategy, and examine the the robustness of our results.

5.3 Building up our specification

As a benchmark, we regress log quantities and prices on firm-product-year and product-market-year fixed effects, without any other controls. These fixed effects explain 78% of the variation in quantities, and 87% of price variation.

Next, we add our controls in steps. The results of this exercise for quantities are reported in Table 6, while results for prices are reported in Table 7. Column (1) of each table reports results from regressing log quantities and prices on the two sets of fixed effects, and a set of indicator variables for duration. Column (2) regresses log quantities and prices on the fixed effects, a set of indicator variables for age, and a dummy for next period exit. The exit dummy allows for nonlinear dynamics just prior to exit. In column (3), we include indicator variables for duration, age, and the exit dummy simultaneously. In column (4), we include the full set of interactions between duration and age and report the resulting coefficients on duration when age is equal to 1, and the coefficients on age for spells of duration 7+ years. Full results for this specification are reported in Appendix Table 23.

Finally, in column (5), we reproduce the corresponding coefficients from estimating our baseline specification, which interacts each age-duration indicator with m^i and f^k, evaluating at $\bar{m}^i$ and $\bar{f}^k$.

From Table 6 we learn that for quantities, inference about the nature of dynamics and selection on unobserved heterogeneity is sensitive to the specification used. Both selection and dynamics appear to be present, so failure to control for one leads to misleading inference about the other. Based on specification (1), we might infer a bigger role for selection than is actually present, because dynamics are ignored. Based on specification (2), we might infer more dramatic dynamics in quantities than are actually present, because we fail to take account of the fact that initial quantities are systematically lower in short spells than in long spells. Comparing specification (3) with specifications (4) and (5) shows that controlling simultaneously for duration and age is not sufficient. If we do not allow dynamics to vary with duration, we might not do too badly in capturing the dynamics in long spells, but we would draw very misleading inference about selection. Finally, allowing dynamics to vary with costs and market size, as well as duration, as we do in our baseline specification (5), affects our understanding of selection, but does not much affect our understanding of dynamics.

In the case of prices, none of the controls add much in terms of R^2. Irrespective of specification, we find no evidence of markup dynamics or of a systematic impact of selection on idiosyncratic demand on markups.

5.4 Robustness

5.4.1 Specification

We estimate a specification which includes firm-product-market-spell fixed effects to control for the first order effect of idiosyncratic demand. If anything, the dynamics in quantities identified using this approach are a little steeper than those based on our baseline specification, while the behavior of markups is very similar to the baseline. The relevant tables are reported in Appendix F and the relevant figures are reported in Appendix G, as are the results of all robustness checks in this subsection.

Results are very similar when we use logs instead of levels of m^i and f^k as proxies for marginal cost and market size. Results are also very similar when we use the number of markets per firm-product and the number of firms per product-market (m^{ij} and f^{jk}) instead of m^i and f^k.

We estimate a specification where we drop unit value outliers. Our criterion for an outlier is an observation where the absolute value of the the log change in the unit value between the current and previous period exceeds 2. Results are very similar to the baseline. We also estimate a specification where we use only observations which have a measure of quantity which is not tonnes (the default measure of quantity). This reduces the sample size by a factor of 8, and results are very noisy as a result.

We estimate a specification where we topcode age and duration at 10 years rather than at 7 years. To do so, we make use of the longer sample of customs data (1996-2014) which is not matched to CIP firms. The behavior of relative quantities and markups is qualitatively similar to the baseline using this specification and data.

5.4.2 Firm, product, and market characteristics

Foreign multinationals have a substantial presence in Ireland in the manufacturing sector. They are export-intensive (mainly platform FDI) and due to this, account for 55% of the firms in our baseline analysis of quantities and prices. We confirm that our results are very similar for domestic-owned and foreign-owned firms by splitting the sample, and re-estimating on the two subsamples.

The importance of marketing and advertising relative to markup distortions in accumulating customer base could differ across sectors. We split the sample into four broad sectors, two consumer-facing (consumer food, consumer non-food non-durables), and two business-facing (intermediate goods, capital goods), and estimate our baseline equation separately for each sector. Splitting the sample in this way greatly reduces sample size, and results are correspondingly noisy. However they are qualitatively consistent with the baseline in all sectors.

We also check whether results are similar for markets which are close, and for which trade barriers are low,[27] and for markets which are distant, and barriers are greater. We do this by splitting the sample into EU markets and non-EU markets. Results are very similar for the two different samples.

5.4.3 Are our results driven by special features of the Irish data?

To alleviate concerns that our results may be due to some special features of the Irish data, we note that we can replicate the findings of a large body of literature working with firm and customs micro data for other countries. As mentioned above, summary statistics on the cross-sectional dimension of exporting in our data are in line with those for other small open European economies. Our findings on the post-entry dynamics of revenues and exit are consistent with those in the previous literature, (e.g., Eaton et al. (2021), Ruhl and Willis (2017)). Using our data, we can also replicate a number of facts about the behavior of unit values in customs data for other countries. In the cross-section, export prices vary with destination market characteristics just as in the literature surveyed in Harrigan et al. (2015). Meanwhile, in Fitzgerald et al. (2019), we show that the degree of pricing-to-market in our data is very similar to that for other countries (e.g. France, as shown by Berman et al. (2012)). The consistency of these findings with those based on other data sets suggests that our results cannot be attributed to special features of the Irish data.

[27] As long as trade barriers are the same for all firms selling a given product to a given market, they are captured by the product-market-year fixed effects.

5.4.4 Relation to the empirical literature on price dynamics

Foster et al. (2008) use the quinquennial U.S. manufacturing census data on plants in a narrow set of commodity-like sectors, and find that older plants have *higher* prices. Their specification does not control for firm- or firm-product-level unobserved heterogeneity, or condition on duration, and may therefore confound selection on firm-product-level heterogeneity with dynamics. We estimate a specification which resembles that of Foster et al. using our data and find an increasing (though not always statistically significant) relationship between prices and age. We hypothesize that this may be due to selection on quality, or to quality upgrading by successful firms. Both of these are controlled for in our baseline specification by the inclusion of firm-product-year fixed effects.

Using customs data for France, Berman et al. (2019) show a *decreasing* relationship between prices and age in an export market. In contrast to us, they do not control for product-market-year effects or duration in their empirical specification. When we implement their specification, we also obtain negative point estimates, but the magnitudes are quantitatively small, and we do not find statistical significance. We hypothesize that they may find statistical significance because they work with a much larger data set.

Piveteau (2021) uses the same French customs data as Berman et al. (2019), and concludes that prices are *increasing* with tenure in a market. He regresses log price on age, including firm-product-year as well as product-market-year fixed effects. With this specification, he finds that prices in observations with age of 7 years are 4% higher than prices in observations which have just entered. We cannot replicate this finding in our data.

Finally, Argente et al (2021) use Nielsen data on consumer food sales in 206 distinct geographical markets in the U.S. to estimate a restricted version of our baseline specification (they do not interact the vector of duration-age indicators with proxies for firm- and market-level heterogeneity). They find that markups are invariant to tenure, with the exception of markup declines immediately before exit from a market which are associated with fire-sales at the store level.

6 Structural estimation

We now turn to structural estimation of the model from Section 2 by simulated method of moments. The key moments we target are the results we have just described from Figures 1, 2 and 3. Because we are careful to evaluate post-entry dynamics at fixed values of our proxies for marginal cost and market size, we can estimate thestructural model conditional on fixed firm and market types. As a result some of our parameter estimates (we note which) are tied to these firm and market types.

6.1 Assumptions about distributions and functional forms

Since we abstract from variation in marginal cost and market size, we normalize both costs (C_t^i) and market size ($Y_t^k = Q_t^k \left(P_t^k\right)^\theta$) to 1.

Idiosyncratic demand follows the process: $\nu_t^{ik} = \bar{\nu}^{ik} + \tilde{\nu}_t^{ik}$, where $\bar{\nu}^{ik} \sim N\left(0, \sigma_\nu^2\right)$ and $\tilde{\nu}_t^{ik} = \rho\tilde{\nu}_{t-1}^{ik} + \eta_t^{ik}$, with $\eta_t^{ik} \sim N\left(0, \sigma_\eta^2\right)$.

Sunk cost is given by:

$$S_t^{ik} = \begin{cases} 0 & \text{with probability } \lambda \\ \infty & \text{with probability } 1-\lambda \end{cases}$$

With probability $\lambda \in [0, 1]$, entry is possible. In the absence of cost and market size heterogeneity, this assumption is without loss of generality, though the value of λ is tied to the mean values of the cost and market size proxies at which our target moments are evaluated. Note that just because entry is possible, it does not mean that a firm will choose to enter. The decision to enter depends also on the realizations of fixed cost, F_t^{ik} and idiosyncratic demand $\left\{\bar{\nu}^{ik}, \tilde{\nu}_t^{ik}\right\}$.

Fixed cost is given by:

$$F_t^{ik} = \begin{cases} 0 & \text{with probability } (1-\omega)\,\gamma \\ F & \text{with probability } (1-\omega)\,(1-\gamma) \\ \infty & \text{with probability } \omega \end{cases}$$

where $\omega \in [0, 1]$ and $\gamma \in [0, 1]$. If $\gamma < 1$ and $0 < \omega < 1$, this process generates both exogenous and endogenous exit. If $0 < \gamma < 1$, it contributes to selection on idiosyncratic demand and a downward-sloping exit hazard. This is because a firm may participate in a market where idiosyncratic demand is weak as long as $F_t^{ik} = 0$, but as soon as it draws a realization of $F_t^{ik} = F$, exit is triggered. In contrast, in markets where idiosyncratic demand is strong, the firm will continue to participate as long as $F < \infty$. The parsimony of this specification is justified by the absence of cost and market size heterogeneity, but the estimated parameters are tied to the mean values of the cost and market size proxies.

The cost of marketing and advertising investment takes the form:

$$c\left(D_t^{ik}, A_t^{ik}\right) = \begin{cases} A_t^{ik} + \phi \frac{\left(A_t^{ik}\right)^2}{D_t^{ik}} & \text{if } A_t^{ik} > 0 \\ 0 & \text{otherwise} \end{cases}$$

This builds in quadratic adjustment costs, as is standard in the literature on investment in physical capital, and irreversibility, which makes sense in the context of investment in an intangible.

Because all firms and markets are identical, we estimate a single value $\underline{D}$ for the exogenous inital customer base. This is also tied to the mean values of the cost and market size proxies at which our target moments are evaluated.

6.2 Estimation procedure

Given values for the parameters, we discretize both exogenous and endogenous states and use value function iteration to solve for the optimal policies, i.e. participation X_t^{ik}, advertising and marketing effort A_t^{ik}, and prices P_t^{ik}. Using the model parameters, the value functions, and the corresponding optimal policies, we simulate post-entry trajectories for 10,000 "firm-markets" for 14 periods. To account for the fact that there are part-year effects in the data, the length of a period in our model is 6 months. We stagger entry across 6-month periods, and aggregate up to an annual frequency to construct the equivalents of the data moments from Section 5 out to 7 years post-entry. The goal of the estimation is to choose the vector of parameters that best matches these moments.

We match 59 moments: the ratios of initial relative quantities and markups across spells of different duration to relative quantities and markups in 1-year spells; the evolution of relative quantities and markups with age for export spells of different duration; the evolution of exit probabilities at the firm-market level with age, normalized by the exit probability in the first year; the rate of entry at the firm-market level, and the exit rate in the first year in a market, also at the firm-market level. See Tables 63 and 64 in the Appendix for the complete list of moments.[28]

We preset the rate at which firms discount the future. Since the period length is 6 months, we set $\beta = 1.05^{-0.5}$. We also preset the trade elasticity i.e. the long-run elasticity of exports with respect to e.g. tariffs, which in our model is given by $\theta/(1-\alpha)$. Based

[28]We match entry and exit moments at the firm-market level rather than at the firm-product-market level because we do not wish to address the role of the extensive margin of products in our analysis.

on the work of Fitzgerald and Haller (2018), we set it equal to 3. This value is within the range of estimates in the literature.[29] Since our assumption about the trade elasticity implies $\theta = 3(1-\alpha)$, this leaves us with 12 parameters to be chosen to match the moments just described: $\left\{\sigma_\nu^2, \sigma_\eta^2, \rho, \lambda, F, \omega, \gamma, \underline{D}, \alpha, \delta, \phi, \psi\right\}$.

Because of its key role, we treat ψ, which governs the relative effectiveness of marketing and advertising compared to current sales in adding to future customer base, differently from the other parameters. We first choose a vector of possible values for ψ on the interval $[0,1]$.[30] Then for each value of ψ in this vector, we search over the space of the remaining 11 parameters to minimize the criterion function $m(\psi)' \Omega m(\psi)$, where $m(\psi)$ is the difference between the data moments and the equivalent moments in the model given ψ, and Ω is a diagonal matrix with the inverse of the standard deviation of the estimates of the data moments on the diagonal. This gives us an understanding of how the fit of the model and the estimates of other parameters vary with ψ. In a robustness check, we minimize $m'\Omega m$ by searching over all 12 parameters, including ψ. We use a combination of a particle swarm algorithm and the simplex method to optimize in both cases. As we will see, both approaches point to the same conclusion on how the fit of the model varies with ψ.

6.3 Baseline results

Figure 4 plots the optimized value of the criterion function $m(\psi)' \Omega m(\psi)$ ("Fit") for the series of values of ψ in the range $[0,1]$ that we consider. When $\psi = 0$, expenditure on marketing and advertising does not contribute to future customer base. When $\psi = 1$, current sales have no impact on future customer base. Lower values of the criterion indicate smaller deviations between data and model moments, and therefore a better fit.

For values of ψ close to zero, we find that firms optimally choose $A = 0$ because the marginal benefit of marketing and advertising, which scales with ψ, is less than the marginal cost. In this range, model fit is invariant to ψ. For values of ψ close to 1, we find that firms optimally choose $A > 0$. The range of ψ where firms optimally choose $A > 0$ is indicated in Figure 4 by the shaded region. In this range, model fit improves as $\psi \to 1$. Within the set of values of ψ we consider, $\psi = 1$ is the value that minimizes the criterion function. When we search over the full vector of 12 parameters allowing ψ to take on any value on the interval $[0,1]$, the criterion $m'\Omega m$ is again minimized at $\psi = 1$.

[29] See Head and Mayer (2014) for a survey.

[30] As noted in Section 2, the assumption that the weights on marketing and advertising and lagged sales in the accumulation equation sum to 1 is without loss of generality.

To understand which moments of the data identify ψ, we calculate fit in terms of quantity moments, price moments, exit moments and entry moments separately. Fit for each of these four components is also plotted in Figure 4. Fit of quantity moments improves as $\psi \to 1$. Fit for prices is better when ψ is such that $A > 0$ (shaded region) than when $A = 0$ (non-shaded region), but does not vary much with ψ within the range where $A > 0$. Fit for exit and entry moments does not vary systematically with ψ. The joint behavior of export quantities and prices is therefore crucial to identifying ψ. In Appendix I, we provide a more extensive discussion of identification of ψ.

Table 8 reports the estimates of the remaining 11 parameters of the model conditional on $\psi = 1$, along with 95% confidence intervals calculated using a parametric bootstrap as described in Appendix H. Figures 5, 6 and 7 illustrate the fit to the target quantity, price and exit moments. Appendix Tables 63 and 64 report the exact target moments and model values. Although there are many more moments than parameters, the fit of the model is good. It can generate dispersion in initial quantities that is positively correlated with spell duration, and of the right order of magnitude. Quantities increase with tenure in successful spells as in the data. Since $\psi = 1$, markups are constant by constructioin. Initial markups are therefore uncorrelated with spell duration, and markups are flat with respect to age. The exit hazard closely matches the data, and the rate of entry matches that in the data.

Our structural estimates thus confirm what our reduced form analysis suggests: the post-entry behavior of export quantities and prices does not provide evidence that firms use dynamic markups to accumulate customer base. Through the lens of the model, investment in customer base through non-price activities such as marketing and advertising accounts for the post-entry behavior of export quantities and prices.

6.4 Robustness

We check that our results are robust to the choice of trade elasticity. To understand why this matters, note that when $\psi = 1$ (i.e. firms use only marketing and advertising to invest in customer base as in our baseline estimates), the fit of the model is invariant to the trade elasticity.[31] However when future customer base depends on current sales (i.e. $\psi < 1$), the trade elasticity matters, because given α, it governs the price elasticity of demand θ. When θ is low, big markup discounts today are required to generate a given increase in sales today. When θ is high, small markup discounts today can generate the same increase in sales, and it is therefore less costly to shift future demand.

[31] F and $\underline{D}$ must be scaled by a function of θ and α, but the remaining parameters are invariant to θ.

We re-estimate the full model, setting the trade elasticity equal to 5 and 8 (within the range of values found in the literature) and 100 (well outside the plausible range). In each case, the criterion is minimized at our baseline parameter estimates, with F and $\underline{D}$ appropriately scaled.

In addition, we estimate a version of the model where we set $\psi = 0$ (i.e. assume no role for marketing and advertising in accumulating customer base), but instead of using the trade elasticity to pin down θ, we estimate θ along with the other parameters. The fit of this model is worse than that of the baseline model with $\psi = 1$, and most strikingly, the trade elasticity implied by the resulting estimates of θ and α is just over 100, an implausibly large value. These results are reported in Table 65 in Appendix K, and Figures 107-109 in Appendix L.

We conclude that our baseline result that the data prefers a model where firms invest in customer base only through marketing and advertising does not depend on our choice of trade elasticity.

6.5 Selling expenses

Although we do not have data on selling expenses for our firms, we can still provide a sanity check for our model by comparing its predictions with what we know about these expenses from other data sources. We use our model estimates to calculate the ratio of selling expenses in a market to revenue in that market as follows:[32]

$$sell_t^{ik} = \frac{c\left(D_t^{ik}, A_t^{ik}\right)}{P_t^{ik} Q_t^{ik}}$$

In Figure 8, we show the evolution of this ratio for export spells of different duration. As a share of revenue, selling expenses are highest at the beginning of an export spell, and decline with age thereafter.[33] Initial selling expenses are also higher in spells that are ultimately successful than in spells that are ultimately unsuccessful, as firms invest more when idiosyncratic demand, and therefore the probability of survival, is higher. Our estimates suggest that selling expenses on average account for 18.5% of revenue in the 6th year of export spells that last 7+ years.

Arkolakis (2010) calculates that marketing and advertising expenditures may account for

[32]Fixed costs of export participation are not counted as part of selling expenses. In this sense, we report a lower bound.

[33]The steady state ratio of selling expenses to revenue depends on $\{\alpha, \delta, \phi, \theta\}$ and the probability of exit. We report the formula in Appendix D.

7-8% of U.S. GDP. The CMO Survey of chief marketing officers in the U.S. reports that over the period 2008-2018, firms in goods-producing sectors spend between 7% and 11% of revenue on marketing.[34] Gourio and Rudanko (2014) report that the share of Selling, General & Administrative expenses in total revenue for Compustat firms is even higher, on the order of 17-27%. Traina (2018) notes that this share has increased from 12% on average in 1950 to 22% today. Our estimates for the share of selling expenses in revenue are within this range.

7 Model-implied export responses to tariff changes

Although we use the steady state dynamics of entrants to estimate our model, our estimates have implications for the responses of incumbent exporters to shocks, and in particular, to changes in tariffs. Consider how gross ad valorem tariffs τ_t^k enter the firm's demand:

$$Q_t^{ik} = Q_t^k \left(\frac{\tau_t^k P_t^{ik}}{P_t^k} \right)^{-\theta} \left(D_t^{ik} \right)^{\alpha} \exp \left(\nu_t^{ik} \right)$$

Changes in ad valorem tariffs affect export demand directly, since they change the price that customers pay holding fixed the price that exporters charge. But they also affect exports through their impact on exporters' incentives to accumulate customer base. This can generate different responses over different time horizons, and to shocks with different stochastic properties.

We illustrate the implications of our model of customer base accumulation for these responses by calculating impulse-responses of incumbents to different types of tariff shock. We consider (a) a permanent unanticipated 10% decrease in ad valorem tariffs, (b) a one-standard-deviation innovation to tariffs, assuming that log tariffs follow an AR(1) process with high persistence, and (c) a one-standard-deviation innovation to tariffs assuming that log tariffs follow an AR(1) with low persistence, i.e.:

$$\ln \tau_t = \rho_x \ln \tau_{t-1} + \varepsilon_t$$

where $\rho_x \in \{0.5, 0.9\}$, and ε_t is distributed iid normal with mean 0 and standard deviation 0.05.

Figure 9 reports the impulse-responses to these three shocks in the form of elasticities

[34] See answers to the question "Marketing expenses account for what percent of your firm's revenues?" for goods-producing firms selling business-to-business and business-to-consumer.

of export revenue to the initial tariff innovation (solid lines). The elasticity of export prices with respect to tariffs is equal to zero at all horizons, and for all types of tariff shock. Dashed lines indicate revenue responses holding fixed customer base. Export revenue and tariffs are aggregated over the two periods in a model-year for comparability with empirical estimates of trade elasticities, which rely on annual trade data. There are two notable features of the impulse-responses.

First, the trade elasticity in response to the unanticipated permanent shock to tariffs is greater (in absolute value) in the long run than in the short run. The elasticity on impact is governed by the price elasticity of demand, θ, while the long run trade elasticity is governed by $\theta/(1-\alpha)$. Our estimate of α is such that this gap is significant. Adjustment from short run to long run is slow: full adjustment takes 5 years from the time of the shock. The speed of adjustment depends on the depreciation rate of customer base, δ and the adjustment cost parameter ϕ, in addition to α and θ.

Second, the elasticity of exports to the innovation in the low-persistence AR(1) process is lower (in absolute value) at all horizons than the elasticity of exports to the same innovation in the high-persistence AR(1) process, which in turn is lower at all horizons than the response to the permanent shock. There is very little endogenous persistence in exports in response to the innovation to the low-persistence process, but due to customer base accumulation there is considerable endogenous persistence (and an initial hump shape) in response to the innovation in the high-persistence process.

These features of dynamic export responses of incumbents - trade elasticities that rise over time in response to permanent shocks, trade elasticities that vary with the persistence of the tariff shock, and a zero elasticity of export prices with respect to tariffs (or unit elasticity with respect to tariff-inclusive prices) - are consistent with empirical evidence based on macro data reported and cited in Amiti, et al. (2020), Boehm et al. (2022) and Ruhl (2008), among others. The behavior of incumbent exporters in our model complements explanations for these features of trade elasticities which rely on the export participation margin.

In contrast, our best estimates of the customer markets model (i.e. the model estimated conditional on $\psi = 0$) imply only modest differences between short-and long-run resposes of exports to permanent shocks (a ratio of 5/6 compared to 2/3 under the baseline estimates), fast adjustment, and counterfactual dynamic responses of export prices to tariff changes. We provide further details in Appendix M.

8 Conclusion

We use customs data for Ireland to show that successful entry into an export market is associated with substantial growth in quantities conditional on costs, but no change in markups. This is compelling evidence that customer base and demand play an important role in post-entry export dynamics. These facts also suggest that firms invest in customer base primarily through marketing and advertising. We show this formally by structurally estimating a model which nests these two possibilities. We find that the data prefer a model where firms use only marketing and advertising to attract customers. We do not have data on marketing and advertising expenditures for our firms, but our parameter estimates allow us to back out an estimate of the selling expenses associated with building and maintaining customer base. We find that they are substantial, though in line with evidence from other sources. In an application of our estimated model, we show that it can generate responses to changes in tariffs that are consistent with empirical evidence that long-run responses to permanent tariff changes are bigger in absolute value than short-run responses, and that responses are increasing in the persistence of the shock.

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Table 1: Summary statistics: Firms and exports, averages 1996-2009

Mean number of firms per year	4748
Mean employees	50
Mean age (years)	17
Share of firms foreign owned	0.12
Share of multi-plant firms	0.03
Mean number of concorded products per firm	4
Share of firms exporting	0.44
Exporter size premium (employees, mean)	1.65
Exporter size premium (revenue, mean)	1.85
Mean export share conditional on exporting	0.32
Mean number of markets per exporter	6.6

Notes: Statistics are for our cleaned data set of CIP firms. Firms are defined as exporters if they are matched to positive concorded product exports from customs data. Export intensity is calculated as total concorded product exports from customs divided by sales reported in the CIP. Values greater than 1 are replaced by 1. Source: CSO and authors' calculations.

Table 2: Percentage of exporters by change in number of markets year to year

Change	<-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	>6
%	2	1	2	3	5	11	51	11	5	3	2	1	3

Notes: Statistics are for our cleaned data set of CIP firms. Firms are defined as exporters if they are matched to positive concorded product exports from customs data. Export revenue is concorded product export revenue from customs data. There are 140 export markets. Source: CSO and authors' calculations.

Table 3: Correlations of m^i and f^k with employment, GDP and distance

	m^i	Log emp.	Rev/worker	TFP	f^k	Sh. GDP	Log dist.
# markets per firm (m^i)	1						
Log employment	0.57	1					
Rev/worker	0.37	0.32	1				
TFP	0.17	0.04	0.56	1			
# firms per market (f^k)	-0.29	-0.10	-0.16	-0.12	1		
Sh. world GDP	-0.15	-0.05	-0.11	-0.06	0.67	1	
Log distance	0.18	0.05	0.02	0.06	-0.43	-0.05	1

Notes: For correlations between firm-level variables, an observation is a firm. For correlations between market-level variables, an observation is a market. For correlations between firm-level and market-level variables, an observation is an export spell at the firm-product-market level. Source: CSO and authors' calculations.

Table 4: Distribution of duration: Export spells and export observations

Obs. level	Firm-mkt		Firm-prod-mkt	
duration	Spells	Obs.	Spells	Obs.
1	0.34	0.09	0.51	0.26
2	0.10	0.06	0.10	0.10
3	0.05	0.04	0.04	0.06
4	0.03	0.03	0.02	0.04
5	0.02	0.03	0.01	0.03
6	0.01	0.02	0.01	0.02
7+	0.06	0.17	0.02	0.11
Left cens.	0.25	0.45	0.17	0.28
Right cens.	0.14	0.10	0.11	0.11
N	55,131	187,409	262,969	526,438

Notes: Table reports share of relevant unit of observation (export spells, or export observations) with given duration, for data at the firm-product-market level, and data aggregated to the firm-market level. Source: CSO and authors' calculations.

Table 5: Regression of duration on m^i and f^k

	coeff	s.e.
m^i	0.40	(0.01)**
f^k	0.62	(0.02)**
N	188,435	
R^2	0.006	

Notes: Dependent variable is duration. Observations are at the firm-product-market spell level. Duration is top-coded at 7. Left- and right-censored spells are excluded. Source: CSO and authors' calculations.

Table 6: Building our specification: Quantity

	(1)		(2)		(3)		(4)		(5)	
	duration		tenure, exit		dur, tenure, exit		dur × tenure		baseline	
	duration						duration at tenure = 1			
2 yrs	0.47	(0.03)**			-0.53	(0.03)**	0.50	(0.04)**	0.57	(0.04)**
3 yrs	0.83	(0.03)**			-0.60	(0.04)**	0.74	(0.05)**	0.86	(0.06)**
4 yrs	1.10	(0.04)**			-0.57	(0.05)**	0.82	(0.07)**	1.04	(0.07)**
5 yrs	1.31	(0.04)**			-0.54	(0.06)**	0.98	(0.09)**	1.17	(0.10)**
6 yrs	1.51	(0.05)**			-0.45	(0.06)**	0.92	(0.11)**	1.07	(0.12)**
7+ yrs	2.26	(0.03)**			0.06	(0.06)	1.18	(0.07)**	1.42	(0.07)**
	tenure						tenure at duration = 7+			
2 yrs			0.61	(0.02)**	0.85	(0.03)**	0.86	(0.08)**	0.80	(0.09)**
3 yrs			0.93	(0.03)**	1.10	(0.04)**	1.19	(0.08)**	1.13	(0.09)**
4 yrs			1.18	(0.04)**	1.25	(0.05)**	1.31	(0.08)**	1.24	(0.09)**
5 yrs			1.37	(0.04)**	1.32	(0.05)**	1.38	(0.08)**	1.35	(0.09)**
6 yrs			1.53	(0.05)**	1.34	(0.06)**	1.29	(0.09)**	1.27	(0.09)**
7+ yrs			1.79	(0.05)**	1.49	(0.06)**	1.32	(0.08)**	1.25	(0.08)**
l-cens	2.61	(0.03)**	1.85	(0.03)**	1.63	(0.04)**	2.62	(0.03)**	2.75	(0.03)**
r-cens	1.22	(0.04)**			-0.37	(0.05)**	1.32	(0.04)**	1.54	(0.04)**
Exit			-1.13	(0.02)**	-1.25	(0.03)**				
f.e.	fpy & pmy		fpy & pmy		fpy & pmy		fpy & pmy		fpy & pmy	
N	183,831		171,683		171,683		183,831		183,831	
R^2	0.80		0.81		0.81		0.81		0.81	

Notes: Dependent variable is log quantity at the firm-product-market level. All equations include firm-product-year and product-market-year fixed effects. Column (4) includes full set of duration-tenure interactions and reports only a subset of results. Column (5) reports a subset of the coefficients from our baseline specification as reported in Table 9 in Appendix F. Robust standard errors calculated. ** significant at 5%, * significant at 10%. Source: CSO and authors' calculations.

Table 7: Building our specification: Price

	(1)	(2)	(3)	(4)	(5)
	duration	tenure, exit	dur, tenure, exit	dur × tenure	baseline
	duration			duration at tenure = 1	
2 yrs	-0.02 (0.02)		-0.01 (0.02)	-0.02 (0.02)	-0.02 (0.02)
3 yrs	0.00 (0.02)		0.03 (0.02)	0.01 (0.03)	0.00 (0.03)
4 yrs	0.02 (0.02)		0.00 (0.03)	0.01 (0.04)	0.01 (0.04)
5 yrs	-0.02 (0.02)		0.00 (0.03)	-0.01 (0.05)	-0.02 (0.05)
6 yrs	-0.03 (0.02)		-0.00 (0.03)	0.01 (0.05)	0.00 (0.05)
7+ yrs	-0.07 (0.02)**		-0.04 (0.03)	-0.04 (0.03)	-0.05 (0.03)
	tenure			tenure at duration = 7+	
2 yrs		-0.01 (0.01)	-0.01 (0.02)	-0.02 (0.04)	0.00 (0.04)
3 yrs		-0.03 (0.02)**	-0.04 (0.02)*	-0.08 (0.04)**	-0.05 (0.04)
4 yrs		-0.02 (0.02)	-0.01 (0.02)	-0.03 (0.04)	-0.01 (0.04)
5 yrs		-0.02 (0.02)	0.00 (0.03)	-0.02 (0.04)	-0.01 (0.04)
6 yrs		-0.04 (0.03)	-0.01 (0.03)	-0.03 (0.04)	-0.03 (0.04)
7+ yrs		-0.07 (0.02)**	-0.02 (0.03)	-0.05 (0.04)	-0.04 (0.02)**
l-cens	-0.04 (0.02)**	-0.02 (0.01)**	-0.03 (0.02)	-0.04 (0.02)**	-0.05 (0.02)**
r-cens	0.01 (0.02)		0.03 (0.03)	0.01 (0.02)	0.01 (0.02)
Exit		0.02 (0.01)**	0.02 (0.01)		
f.e.	fpy & pmy	fpy & pmy	fpy & pmy	fpy & pmy	fpy & pmy
N	183,831	171,683	171,683	183,831	183,831
R^2	0.87	0.87	0.87	0.87	0.87

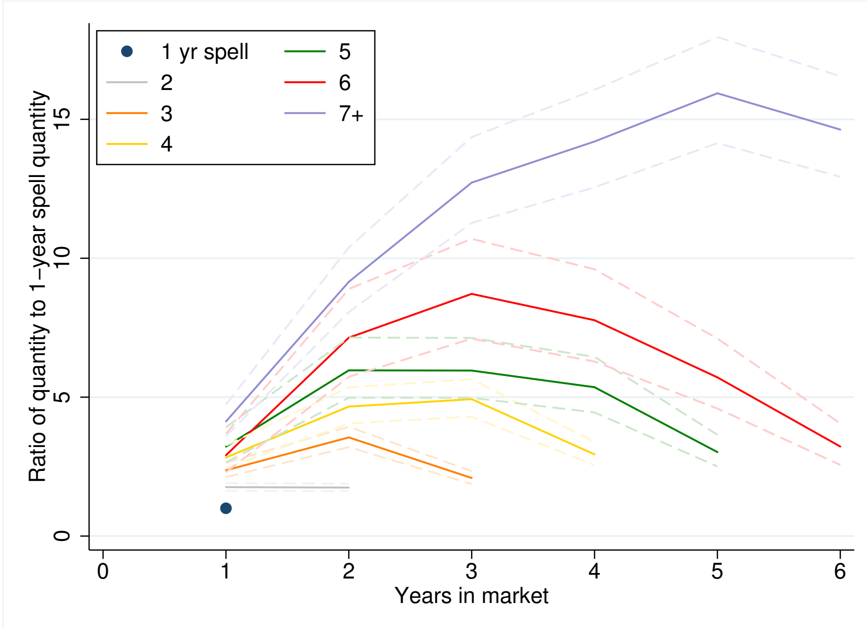
Notes: Dependent variable is log price at the firm-product-market level. All equations include firm-product-year and product-market-year fixed effects. Column (4) includes full set of duration-tenure interactions and reports only a subset of results. Column (5) reports a subset of the coefficients from our baseline specification as reported in Table 9 in Appendix F. Robust standard errors calculated. ** significant at 5%, * significant at 10%. Source: CSO and authors' calculations.

Table 8: Structural model: parameter estimates conditional on $\psi = 1$

	Parameter	95% CI
α	0.41	[0.25, 0.56]
δ	0.62	[0.41, 0.95]
ϕ	1.46	[0.45, 19.4]
σ_ν	0.63	[0.54, 0.69]
σ_η	0.09	[0.05, 0.42]
ρ	0.87	[0.00, 0.92]
λ	0.05	[0.05, 0.05]
$F^\dagger$	0.07	[0.04, 0.17]
ω	0.07	[0.04, 0.07]
γ	0.68	[0.64, 0.74]
$\underline{D}^\S$	0.08	[0.01, 0.17]

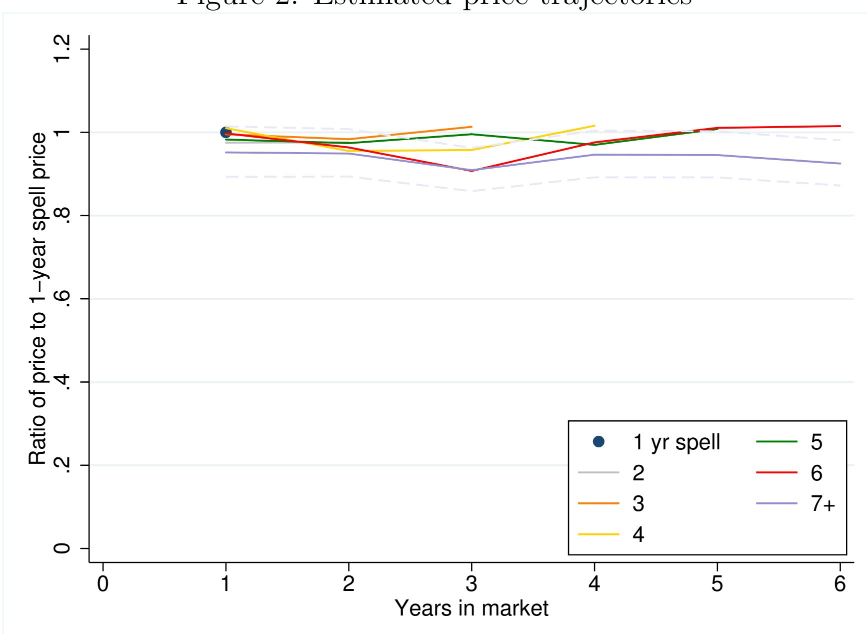
Notes: 95% confidence intervals are calculated using a parametric bootstrap as described in Appendix H. †The value reported for F is the average ratio of F_t^{ik} to revenue across all participants in their first period (6 months) of participation. This includes participants for whom $F_t^{ik} = 0$. §The value reported for $\underline{D}$ is the average of $\underline{D}/D_{13}$ across all participants who survive 13 (6-month) periods in the market, and have nonnegative investment in period 13, where D_{13} is customer base in period 13.

Figure 1: Estimated quantity trajectories



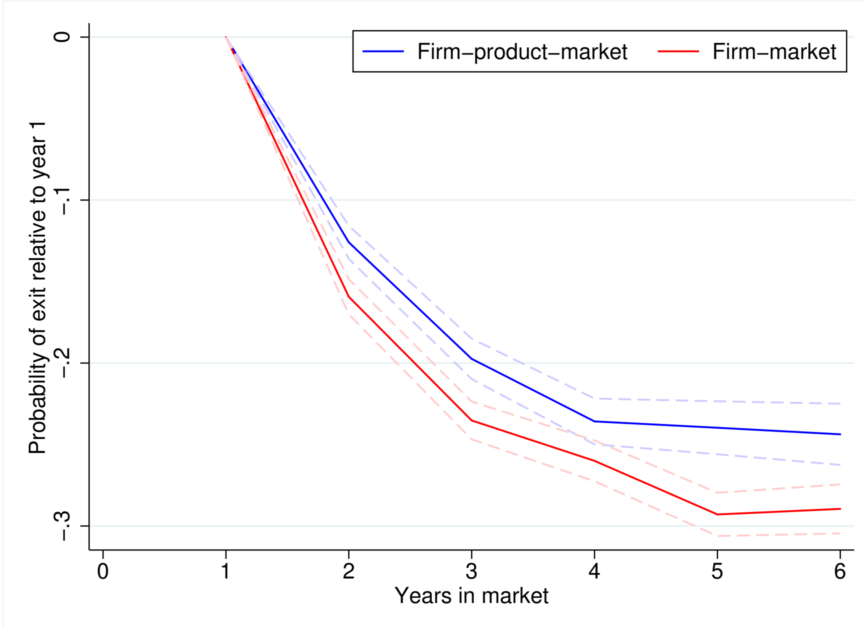
Notes: Figure shows evolution of quantities at the firm-product-market level with market tenure, allowing trajectories to differ by export spell duration. Trajectories are conditional on firm-product-year and market effects. 95% confidence intervals are plotted. Corresponding table is Table 9 in Appendix F. Source: CSO and authors' calculations.

Figure 2: Estimated price trajectories



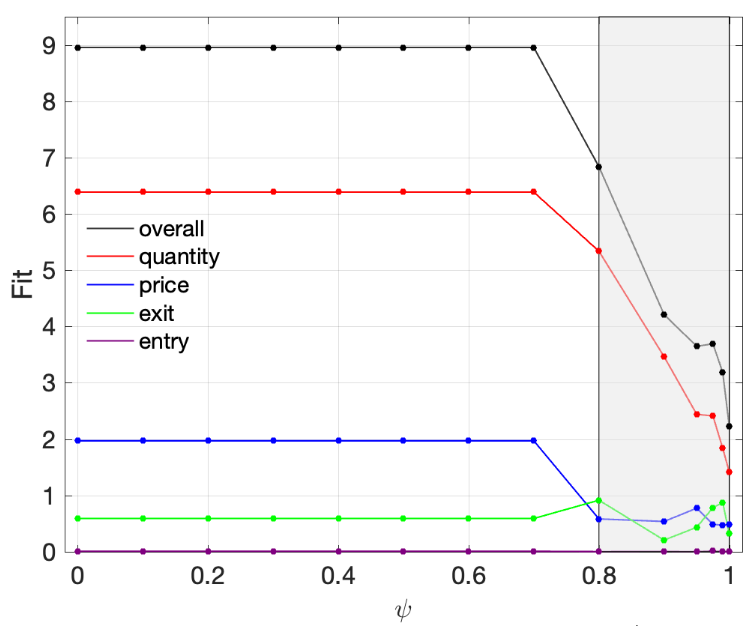
Notes: Figure shows evolution of prices at the firm-product-market level with market tenure, allowing trajectories to differ by export spell duration. Trajectories are conditional on firm-product-year and market effects. 95% confidence interval for spells of 7+ years is plotted. Corresponding table is Table 9 in Appendix F. Source: CSO and authors' calculations.

Figure 3: Estimated exit trajectories



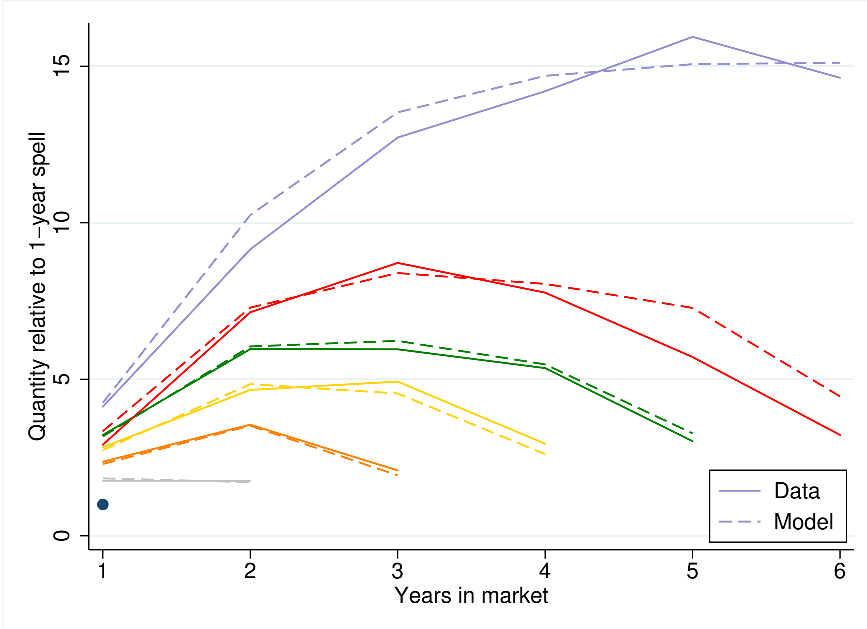
Notes: Figure shows reduction in probability of exit at the firm-market and firm-product-market levels with compared to probability of exit in the first year in a market. Trajectories are conditional on firm-year and market and firm-product-year and market effects, respectively. 95% confidence intervals are plotted. Corresponding Table is Table 17 in Appendix F. Source: CSO and authors' calculations.

Figure 4: Model fit for different values of ψ



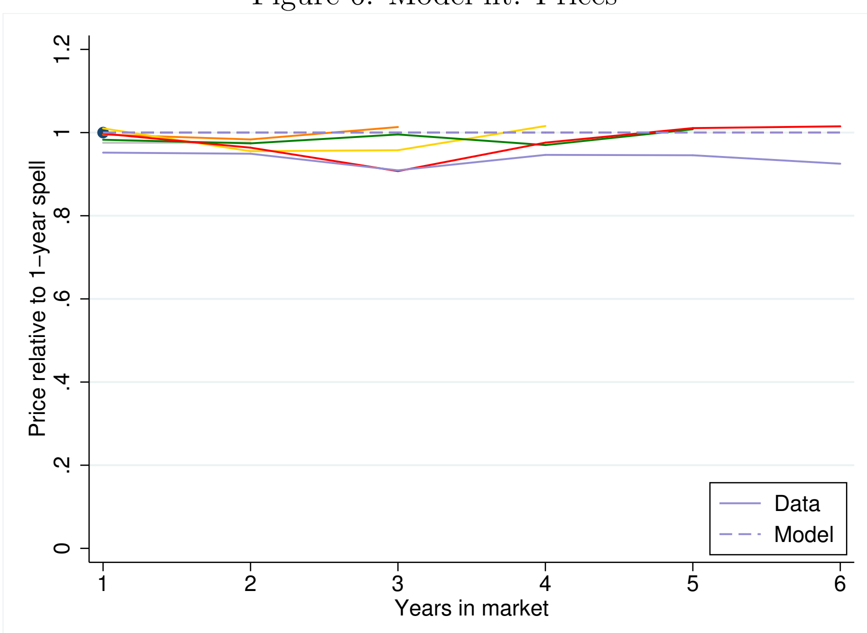
Notes: Figure shows how model fit (i.e. the optimized value of the criterion function $m(\psi)' \Omega m(\psi)$) varies with ψ, the parameter governing the relative effectiveness of marketing and advertising and current sales in adding to future customer base. Lower values of fit indicate smaller differences between data and model moments. This is based on estimates of the model holding ψ fixed at the values indicated by the circles. In the shaded region, firms optimally choose $A > 0$. Overall refers to fit summing over all moments. Quantity refers to fit for quantity moments only. Price refers to fit for price moments only. Exit refers to fit for exit moments only. Entry refers to fit for entry moments only. Source: Authors' calculations.

Figure 5: Model fit: Quantities



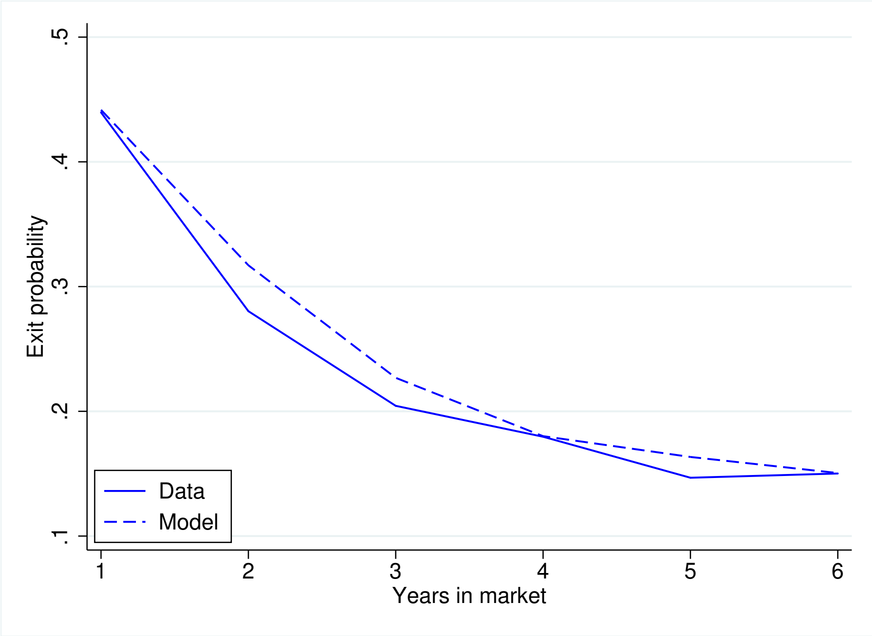
Notes: Figure shows evolution of quantities with age, for spells of different duration. Data is from Figure 1, while Model refers to the corresponding fitted values from our estimated model. All quantities are expressed relative to the quantity in a 1-year spell. Source: CSO and authors' calculations.

Figure 6: Model fit: Prices



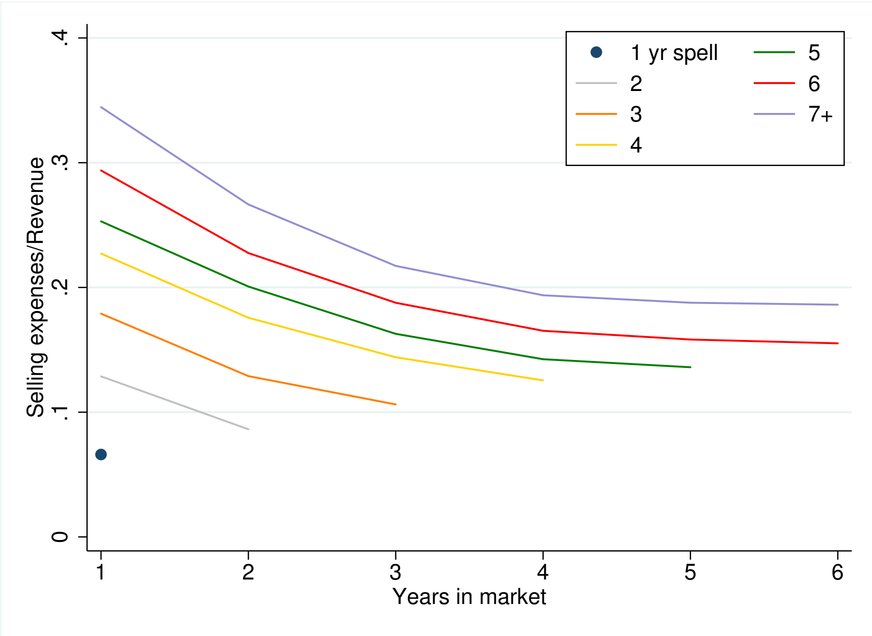
Notes: Figure shows evolution of prices with age, for spells of different duration. Data is from Figure 2, while Model refers to the corresponding fitted values from our estimated model. All prices are expressed relative to the price in a 1-year spell. Source: CSO and authors' calculations.

Figure 7: Model fit: Exit



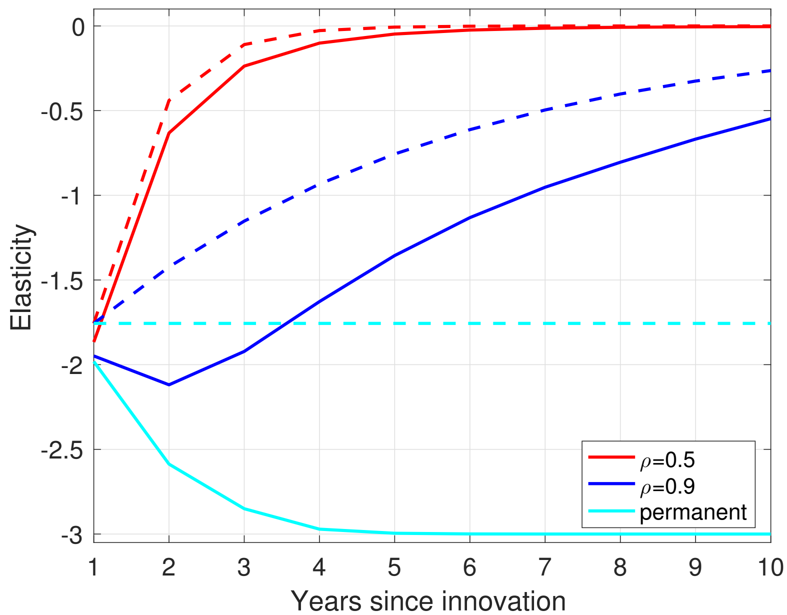
Notes: Figure shows evolution of probability of exit with tenure. Data (at the firm-market level) is from Figure 3 combined with the 1-year exit rate of 0.44, while Model refers to the corresponding fitted values from our estimated model. Source: CSO and authors' calculations.

Figure 8: Selling expenses as a share of revenue



Notes: Figure shows average ratio of selling expenses to revenue predicted by the model for export spells of different length. Source: Authors' calculations.

Figure 9: Impulse-responses of incumbent exports to tariff changes



Notes: Figure shows trade elasticity based on impulse-responses of incumbent exports to (a) an unanticipated permanent change in tariffs, (b) a one-standard-deviation innovation to an AR(1) process for log tariffs with persistence 0.9, and (c) a one-standard-deviation innovation to an AR(1) process for log tariffs with persistence 0.5. The dashed lines show the responses to shocks holding fixed customer base. Source: Authors' calculations.