How Do Entrants Build Market Share? The Role of Demand Frictions

By David Argente, Doireann Fitzgerald, Sara Moreira and Anthony Priolo*

We construct a new data set to show that successful entrants in the consumer food sector build market share by adding new customers. Entrants reach new customers by entering more geographical markets, placing their product in more stores in these markets, and for a positively selected subset of firms, by advertising direct to customers. These activities are costly and are associated with persistent increases in quantities, but there are no differences in markups between new and mature markets. This confirms a central role for marketing and advertising in overcoming demand-side frictions that slow firm growth.
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Firms are born small. Those that survive typically grow, initially fast, then more slowly as they age.[1] This is traditionally assumed to reflect the evolution of productivity, and frictions, financial or otherwise, that slow down accumulation of physical capital. More recently an empirical literature shows that demand-side dynamics also play a role in the firm life cycle.[2] Specifically, entrants are small because demand for their products is low, and successful entrants grow by building demand.

It matters for measurement of productivity and markups *how* firms build demand. Do firms exploit dependence of current demand on past sales (due to word-of-mouth effects or customer lock-in) by charging low markups on entry,

* Argente: Yale University, Evans Hall, 165 Whitney Ave, New Haven, CT 06511, USA, david.argente@yale.edu. Fitzgerald: Federal Reserve Bank of Minneapolis, 90 Hennepin Ave, Minneapolis, MN 55401, USA, doireann.fitzgerald@gmail.com. Moreira: Northwestern University, 2211 Campus Drive, Evanston, IL 60208, USA, sara.moreira@kellogg.northwestern.edu. Priolo: Lancaster University, Bailrigg, Lancaster, LA1 4YX, United Kingdom, a.priolo@lancaster.ac.uk. We are grateful to Nick Bloom, Gideon Bornstein, Andrea Chiavari, Pete Klenow, Chad Syverson and participants at seminars and conferences for their feedback. We would like to thank Guoxuan Ma and Ziqing Wang for excellent research assistance. 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. Researcher(s) own analyses calculated (or derived) based in part on (i) retail measurement/consumer data from Nielsen Consumer LLC ("NielsenIQ"); (ii) media data from The Nielsen Company (US), LLC ("Nielsen"); and (iii) marketing databases provided through the respective NielsenIQ and the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ and Nielsen data are those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

[1]See e.g. Dunne, Roberts and Samuelson (1989) and Hsieh and Klenow (2014).

[2]See e.g. Foster, Haltiwanger and Syverson (2008) and Eslava, Haltiwanger and Urdaneta (2023).

and higher markups as demand shifts out to its steady state as in the "customer markets" literature?[3] Or do they engage in costly marketing and advertising activities to attract customers, with gradual growth being due to investment adjustment costs or other frictions in this process?[4] In the absence of evidence, there is disagreement in the literature on this point.

We fill this gap by creating a micro-level dataset for the consumer food sector, accounting for 6 percent of GDP, which allows us to confirm the importance of gradual accumulation of customers for the firm life cycle, and provide evidence on the actions firms take to attract customers. Specifically, we combine data on retail store presence and sales, consumer purchases, advertising occurrences and expenditures, wholesale prices, and plant location, from the Nielsen Retail Scanner data, the Nielsen Household Panel, Nielsen Ad Intel data, Nielsen Promo data, and the National Establishment Time series.

Our headline finding is that firms do not use market-specific pricing strategies to reach customers in new markets. Instead, they do so by placing their products in more retail outlets within these markets, an activity that is costly.[5] The most successful entrants also advertise direct to customers. For entrants, both store placement and advertising are associated with persistently higher sales, but no change in prices. This is consistent with store placement and advertising shifting demand, but not affecting the price elasticity of demand.

We first use the retail scanner data to document the margins of growth of new and young firms, focusing on a fixed set of products. Entrants grow through a combination of expanding gradually across geographic markets, and selling more within each market. Since markets for consumer food are segmented by geography, expanding geographically necessarily implies acquiring new customers.

Of course, growth may be gradual due to supply-side as well as demand-side factors. We exploit firms' sequential expansion to isolate the role of demand-side factors in *within-market* growth. We do this by comparing outcomes in markets where a firm is a seasoned participant with outcomes in markets where it has just entered. Using the household panel data we show that following a firm's entry to a new market, sales growth is initially fast relative to growth in mature markets, but this gap shrinks over time. Assuming that supply-side factors are the same for all markets the firm serves, this confirms a role for demand-side frictions in shaping growth. The household panel data allow us to decompose this into the extensive margin of customers and the intensive margin of sales per customer. Two-thirds of sales growth after entry into a market is due to the extensive margin of customers.

We next use the retail scanner data to investigate the hypothesis that entrants initially depress markups to attract customers, later raising them as demand

[3] See e.g. Phelps and Winter (1970), Bils (1989), Ravn, Schmitt-Grohé and Uribe (2006), Nakamura and Steinsson (2011), Gourio and Rudanko (2014*b*), Gilchrist et al. (2017), Paciello, Pozzi and Trachter (2019) and Bornstein (2021).

[4] See, e.g. Arkolakis (2010), Drozd and Nosal (2012) and Gourio and Rudanko (2014*b*)

[5] See e.g. Federal Trade Commission (2003) and Elberg and Noton (2019).

converges to its steady state. We find that within a firm, quantities grow faster in new relative to mature markets, but prices are insensitive to firm age in a market. Assuming that marginal cost evolves in the same way in all markets served by a given firm, the behavior of prices implies that markups do not vary with firm age in a market. This remains true controlling for distance to the location of production, and whether we use retail or wholesale prices. In sum, we find that there is systematic within-firm cross-market variation in quantities with respect to firm-market age that is not associated with corresponding variation in markups.

What other actions might firms take that could explain cross-market differences in quantities? We provide evidence on store placement and advertising. From the retail scanner data we see that within-market sales growth is due to growth in number of stores as well as in sales per store. Impulse-responses show that expansion in store presence is associated with persistent increases in sales. This occurs through higher quantities sold; there is no relationship between store placement and prices. Moreover, the extensive margin of customers in the household panel data is accounted for by purchases from more stores, consistent with store presence being key to reaching new customers.

To document facts about advertising, we perform a global match of advertising at the firm-brand-product level from the Nielsen Ad Intel data to the Nielsen Retail Scanner and Household Panel data on consumer food. While these datasets have been matched before for a small subset of established brands, we are the first to do so for the universe of brands in a broad sector. We find that only a minority of firms advertise, and those that do are positively selected. For entrants who advertise, advertising is frequently initiated only some years after entry, and is intermittent.

For a subset of media types, we observe advertising at the level of the geographic market. Local TV is the medium with best coverage on this dimension, and it is used relatively intensively by entrants. We use Local TV advertising to estimate impulse-responses of quantities and prices to the extensive margin of advertising within a market. We find that quantities comove positively with advertising, both contemporaneously, and with a lag, but there is no comovement between prices and advertising. The response of sales to advertising is larger for entrants than for incumbents. New store acquisition and advertising are positively correlated, consistent with complementarity between these two actions.

Overall, we provide evidence that store placement and advertising play a crucial role in building customer base for entrants.

I. Relation to the Literature

Empirical literature

Our findings on the importance of demand for firm heterogeneity are related to Hottman, Redding and Weinstein (2016) and Eslava, Haltiwanger and Urdaneta (2023). Our results on the importance of customers and markets for demand are related to Eaton, Kortum and Kramarz (2011) who document market participation for French exporters, Einav et al. (2021) who show the importance of customers for retail stores, and Bernard et al. (2022) who show the importance of customers in firm-to-firm trade in Belgium. Relative to these papers, we focus on the dynamics of early-stage entrants in a particular consumer-facing sector.

Our results on the dynamics of within-market quantities and markups are similar to those of Fitzgerald, Haller and Yedid-Levi (2023) based on customs data on exports. The novelty of our paper lies in documenting not just what firms do not do (change markups differentially across markets) but also what actions they take to expand sales within a market, i.e. store placement and advertising. Meanwhile our findings contrast with Foster, Haltiwanger and Syverson (2008), who report a positive association between prices and firm age. We believe this positive association may be due to selection on quality rather than price dynamics, since their empirical specification does not control for survival. Consistent with this hypothesis, they find that firms with higher prices are less likely to exit, which is also a feature of the Nielsen data, as demonstrated by Argente, Lee and Moreira (2023).

Our findings on pricing are consistent with DellaVigna and Gentzkow (2019), who find uniform pricing within retail chains in the United States, though substantial price differences across chains. However our results do not automatically follow from uniform pricing within chains, since manufacturers place their products in multiple chains within a given market, and could choose to systematically vary the mix of low- and high-price chains over the life cycle within a market.

Although we do not attempt to establish causality, our results on advertising relate to a marketing literature estimating the causal effect of advertising on sales. This literature typically finds a positive but small effect. Most recently, Shapiro, Hitsch and Tuchman (2021) use similar data for established brands, finding that the elasticity of sales to advertising is small, heterogeneous and often statistically insignificant. Older work by Lodish et al. (1995) finds larger responses for entrants than for incumbents, but in a small sample. Relative to this literature, we examine the universe of entrants in the consumer food sector.

Our findings on the complementarity of market participation, store placement and advertising echo those of Shibuya (2022), who uses Japanese barcode data to show that heterogeneity in firm size is magnified by the complementarity of the extensive margins of number of products and number of geographical markets.

Implications for macroeconomics and trade

Our finding that increases in market share do not translate into increases in markups is inconsistent with workhorse models of demand and market structure with variable markups (e.g. Kimball (1995), Atkeson and Burstein (2008)) frequently used to infer the distribution of markups and marginal cost from the distribution of market shares and prices in the data (see, e.g. Edmond, Midrigan and Xu (2015) for an application to the welfare gains from trade). Afrouzi, Drenik and Kim (2023) show that when a Kimball model is augmented to allow for the type of endogenous customer base we document, the implied welfare losses due to misallocation are magnified relative to a model without this feature calibrated to the same data. This suggests caution in using models without a customer margin for welfare analysis.

Our results on the importance of marketing and advertising for reaching customers also have implications for the literature which builds on the cost-based approach of Hall (1988) to infer markups. If costs of accumulating customer base through marketing and advertising are not separated from production costs, productivity and markups may be systematically mismeasured for the most productive firms with the greatest incentive to acquire customers. This contrasts with the measurement issue when firms use dynamic pricing to attract customers. In that case, as pointed out by Foster, Haltiwanger and Syverson (2008), revenue-based productivity is systematically underestimated for growing firms, but quantity-based productivity is unaffected.

Finally, the customer markets literature assumes that firms use dynamic pricing to acquire customers at a business cycle frequency. This idea is appealing because it generates countercyclical markups, and therefore a countercyclical labor wedge, without recourse to sticky prices, see e.g. Ravn, Schmitt-Grohé and Uribe (2006). While our results do not rule out that firms use dynamic pricing at a business cycle frequency, they shift attention towards marketing and advertising. This may not matter for explaining business cycles: Gourio and Rudanko (2014*a*) show that a flexible-price model where firms accumulate customer base through marketing and advertising can also generate a countercyclical labor wedge.

II. Data

A. *Retail Sales*

Our primary source is scanner data from Nielsen Retail Measurement Services (RMS), provided by the Kilts-Nielsen Data Center. This dataset is collected from point-of-sale systems in grocery, drug, and general-merchandise stores. Each store reports weekly sales and quantities for barcodes with positive sales during that week. Nielsen links barcodes to brands. We link barcodes (and therefore also brands) to firms using information from GS1 US. For our baseline analysis we aggregate these data to the annual level.

We use data covering the food sector from 2006 to 2017. We focus on this sector because the market for consumer food is more likely to be geographically segmented than that for non-food consumer goods, and because Nielsen coverage is broad and likely to be representative. The RMS covers about half of all U.S. food sales, and nearly the universe of firms and products in the sector. Our data comprises food departments – dry grocery, dairy, deli, packaged meat, frozen foods, and fresh produce – covering about 600 product "modules," i.e. disaggregated product categories. Within products, barcodes are measured using a common unit of quantity, which means unit values are comparable. In our empirical analysis, for each firm we focus on the set of products it sells in the first year it appears in the sample. In this way, we focus on within-product sales growth.

Throughout the paper, we refer to the combination of firm-brand-product as "firms." This strikes a balance: it allows us to aggregate quantities consistently, while ensuring that we do not have to deal with entry and exit of barcodes. Meanwhile, advertising takes place at the brand rather than barcode or firm level, and it is likely firms' internal organization aligns closely with their portfolio of brands: see Bronnenberg, Dhar and Dubé (2011). This approach is also consistent with our focus on within-product sales growth, rather than growth through expansion in the number of products.

Our baseline definition of a geographical market is the Nielsen Designated Market Area (DMA). While sales can be tracked at the store level, the most disaggregated advertising data are at the DMA level. Besides allowing us to match sales with advertising data, DMAs are a convenient market definition since (unlike stores) they are large enough to be segmented from consumers' perspective and they align well with Metropolitan Statistical Areas across the country.

Appendix A provides additional details about our baseline retail data set. We also work with two related data sets: the Nielsen Household Panel (HMS), and the IRI-Symphony data, also described in Appendix A. Appendix A additionally provides a general overview of the institutional environment in the consumer food sector.

B. Advertising

Our advertising data come from the Ad Intel database (ADI) provided by the Kilts-Nielsen Data Center. This database has occurrence-level advertising information, including time, duration, format, and imputed dollar spending for an estimated \$150 billion worth of advertising, and nearly 400 million observations per year for the period 2010-2017.[6] For each occurrence there is detailed information on the brand, firm, and product type, using the ADI's own classification system. The ADI has data on ads featured on television, newspapers, coupons, and digital, among other media. For a limited subset of these media types, advertising is reported at the DMA level.

Some of our analysis focuses on Local TV advertising. For this medium, ADI provides uniquely comprehensive data covering all DMAs. In Appendix B.1, we show that Local TV is an important advertising medium for the consumer food sector. Figure B1 shows that while firms advertising using any medium account for 55% of sales, firms using Local TV account for more than 40%.

[6]More details can be found in Appendix A.7.

C. Matching Retail Sales and Advertising Data

Our main challenge in making use of the advertising data is to merge them with the retail scanner data. Each data source (RMS and ADI) uses its own brand and product designations, and a simple fuzzy match of the two produces unsatisfactory results. We develop a matching algorithm using methods from the natural language processing literature to create systematic links between ADI and RMS observations. Appendix B describes how we combine information on product descriptions, firm name, and brand name to derive a criterion for a many-to-many positive match, and how we ensure that our matching algorithm produces reliable variation. While there are other papers that combine retail and advertising data (for example, Shapiro, Hitsch and Tuchman (2021) match 288 of the top 500 brands in the RMS data), to date there is no work that performs this match for the universe of firms/brands across a wide range of products.

III. Margins of Entrants' Growth: Markets and Customers

We quantify the life cycle of firms in our data by regressing the log of sales on firm-product (i.e. firm-brand-product) and product-year fixed effects, and on a vector of indicator variables for firm age interacted with a vector of indicator variables for the number of years the firm survives. This specification separates firm growth from selection (i.e. the fact that firms that exit early may be systematically different from those that survive):

$$\ln \mathrm{sales}_t^{ip} = \gamma^{ip} + \psi_t^p + \beta' \left(\mathrm{age}_t^{ip} \otimes \mathrm{survival}^{ip}\right) + \mathrm{cens}^{ip} + \varepsilon_t^{ip} \tag{1}$$

Here, i indexes firms, p indexes products, and t indexes years. The variables γ^{ip} and ψ_t^p are firm-product and product-year fixed effects, while $\mathrm{age}_t^{ip}$and $\mathrm{survival}^{ip}$ are vectors of indicators for age and survival. The symbol $\otimes$ denotes the Kronecker product. Market age cannot exceed completed survival so redundant interactions are dropped. We topcode age and survival at 5 years, allowing us to include entrants who survive 5+ years and are still selling in the last year of our sample. cens^{ip} is a vector of indicators for left- and right-censored survival, i.e. firms that sell in the first year of the sample, and firms that have age less than 5 in the last year of the sample.

With outcome variables expressed in logs, by taking exponents of appropriate linear combinations of the coefficient estimates, we can present "trajectories" which map out the log-averaged evolution of sales (normalized to 1 at age 1 year because of the fixed effects), for firms which survive different lengths of time.

Panel (a) of Figure 1 shows the estimated trajectories for total sales by survival. Entrants who survive 5+ years grow to 6 times their initial size during the first 3-4 years of activity. Growth is fast in the initial years, and slows with age. Entrants who survive less than 5 years initially grow, and then shrink before they exit the market.[7] We next examine the margins contributing to this pattern.

Markets and sales per market

A key feature of the data is that most firms sell to few markets (DMAs) in their entry year, but conditional on survival, the number of markets grows as the firm ages.[8] To illustrate these patterns, we estimate equation (1) with log number of markets and log average sales per market in turn as the dependent variable. Panels (b)-(c) of Figure 1 show the resulting trajectories. Since total sales equals the number of markets times average sales per market, multiplying the latter two trajectories returns the total sales trajectory from Panel (a). Focusing on behavior for entrants who survive 5+ years, these figures show that the extensive margin of markets plays an important role in growth, especially after the first year.

Since geographical markets are segmented for consumer food, this implies that firms grow at least partially by reaching new customers. However gradual expansion across markets could be due to supply-side frictions which limit a firm's capacity to serve more customers, rather than demand-side frictions which make it costly to attract many customers at once. To cleanly identify a role for demand-side frictions, we next examine within-market growth, where the structure of the data allows us to control for the supply side.

Within markets: Sales, customers, and sales per customer

Because entry is staggered across markets, we can examine how market-level variables such as sales evolve with the number of years since a firm entered a given market, conditional on the average evolution across all markets the firm sells to. Under the assumption that supply-side factors evolve similarly in all markets served by the firm, we can thus isolate the contribution of market-specific demand to growth.[9]

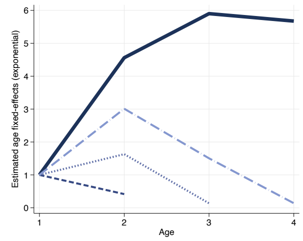
More precisely, we regress the log of the variable of interest at the firm-product-market-year level on firm-product-year and product-market-year fixed effects, and on a vector of indicators for firm-product age in the relevant market interacted with a vector of indicators for the number of years the firm-product survives in that market, topcoding at 5 years in each case. Our estimating equation is:

$$\ln \mathrm{Y}_t^{ipm} = \gamma_t^{ip} + \psi_t^{pm} + \beta' \left(\mathrm{age}_t^{ipm} \otimes \mathrm{survival}^{ipm} \right) + \mathrm{cens}^{ipm} + \varepsilon_t^{ipm} \tag{2}$$

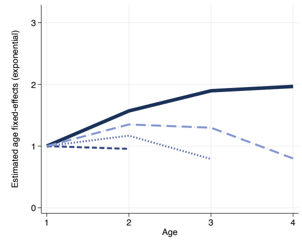
[7] These patterns, and all of our results, are robust to varying the level at which we topcode.

[8] Appendix Table A4 shows the distribution of number of markets for entrants and 5-year incumbents. Appendix Figure D1 illustrates these patterns for one successful firm. It enters in 2007, selling in just one market. By 2013, it sells in all markets in the U.S.

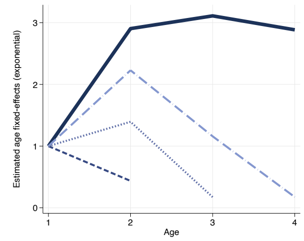
[9] Demand-side factors that evolve similarly in all markets are also conditioned out.



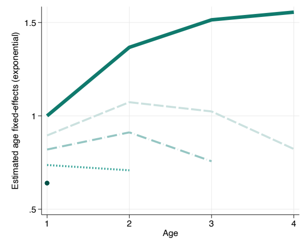
(a) Sales (RMS, National)



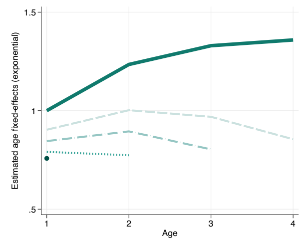
(b) # Markets



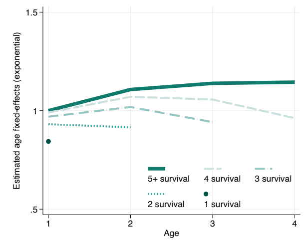
(c) Sales per Market



(d) Sales (HMS, Market)



(e) # Customers



(f) Sales per Customer

Figure 1. Life Cycle of Sales, Markets, and Customers

Note: Panels (a)-(c) use RMS data. They plot the exponents of the vector of coefficients β estimated in equation (1) against firm age, with log sales, log number of markets, and log sales per market in turn as dependent variables, for firms surviving 1, 2, 3, 4 and 5+ years. We drop re-entrants from the sample. Panels (c)-(e) use HMS data. They plot the exponents of the vector of coefficients β estimated in equation (2) against firm-market age, with log firm-market sales, log number of customers, and log sales per customer in turn as dependent variables, for firm-markets surviving 1, 2, 3, 4 and 5+ years.

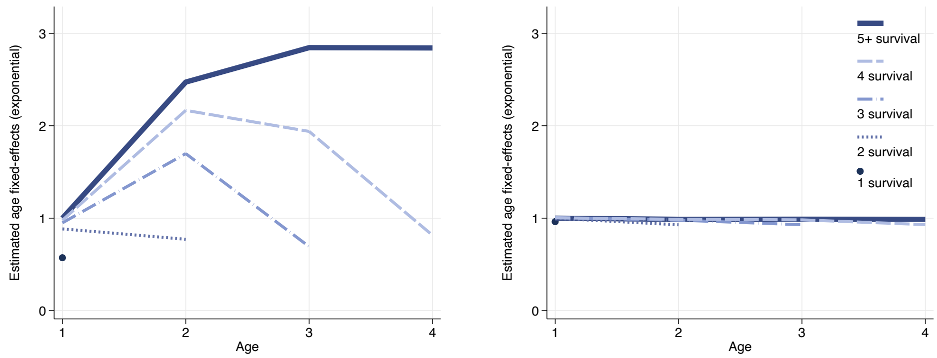
where i, p and t are as in equation (1), and m indexes markets. In contrast to the firm-level regressions, growth trajectories are identified by a combination of variation over time within a firm-product-market, and cross-sectional variation within a firm-product across markets with different age and survival. This allows us to make comparisons across markets with different survival in their entry year. We normalize to the initial year of spells that survive 5+ years.[10]

Panel (d) of Figure 1 shows the log-averaged trajectories for market-level sales, using data from the Nielsen Household Panel (HMS).[11] Focusing on spells that survive 5+ years (the top line), the key take-away is that even controlling for supply-side factors, there is gradual growth in within-market sales.[12] This confirms a role for demand in firm growth. Panels (e) and (f) show the trajectories for number of customers and average sales per customer. Focusing on spells that survive 5+ years, the extensive margin of customers accounts for two thirds of sales growth. Since we condition on supply-side factors through the fixed effects,

[10] In this analysis, firm-products already selling in a subset of markets at the start of the sample, but which enter new markets during the sample period, are considered entrants in the new markets.

[11] We provide a detailed description of these data in Appendix A.3.

[12] Panel (a) of Appendix Figure D3 shows that the pattern looks very similar using the retail scanner data.



(a) Quantity (b) Price

Figure 2. Life Cycle of Quantities and Prices Within Markets

Note: Panels (a) and (b) plot the exponents of the vector of coefficients β estimated in equation (2) against firm-market age, for firm-markets surviving 1, 2, 3, 4 and 5+ years, with log quantity and log price in turn as the dependent variables. Columns 2 and 3 of Appendix Table D1 report the relevant estimates of β.

this confirms the importance of the customer margin for demand growth.

IV. Price Actions

How do firms attract customers? As noted in the Introduction, the literature has identified two possibilities, which are not necessarily mutually exclusive: dynamic pricing, and non-price actions such as marketing and advertising. We first investigate evidence for dynamic pricing. We do so by examining within-market dynamics of quantities and prices conditional on firm-level averages, estimating equation (2) with log quantity and log price in turn as the dependent variable, using our baseline RMS sample.[13] Figure 2 illustrates the results in the usual format.

Quantities

Panel (a) of Figure 2 shows that quantities relative to firm average quantities grow by a factor of nearly 3 between years 1 and 4 in spells that survive 5+ years. Meanwhile, we see hump-shaped dynamics of quantities in sales spells where exit is observed. Because we control throughout for product-market-year effects, these are dynamics of market share. More importantly, since we also control for firm-product-year fixed effects, to the extent that a firm's marginal costs are similar across markets, these dynamics cannot be driven by costs. Instead, they must be

[13]Appendix Table A5 provides a variance decomposition of sales, quantities, and prices at different levels of aggregation.

due to movements *along* the demand curve through changing markups, or *shifts* in the demand curve in individual markets relative to the firm average.

Prices and Markups

Panel (b) of Figure 2 shows that in spells that survive 5+ years, relative to a firm's average price, prices paid by consumers in a new market are almost invariant to age in that market: they are just 1% lower in subsequent years than they are in the year of entry. The only substantial dynamics of relative prices are observed in spells lasting less than 5 years, with declines in the year prior to exit.[14]

Interpretation

Because prices in spells that survive 5+ years do not vary relative to firm average prices over the within-market life cycle, the dynamics in relative market share in Panel (a) of Figure 2 must be due to *shifts* in relative demand rather than movements *along* the relative demand curve. Moreover, because we condition on firm-product-year fixed effects, if a firm's marginal cost of production is the same in all markets, the behavior of relative prices in Panel (b) implies that gross markups do not vary across markets with market age either. This is suggestive, but we cannot automatically conclude that there is no cross-market variation in *manufacturer* markups, since the consumer price is given by:

$$P_t^{ipm} = \underbrace{C_t^{ip}}_{\text{marginal cost}} \quad \underbrace{\mu_t^{ipm}}_{\text{manufacturer markup}} \quad \underbrace{\tau_t^{ipm}}_{\text{transport cost}} \quad \underbrace{m_t^{ipm}}_{\text{retail margin}} \tag{3}$$

However, we can infer the behavior of retail margins and transportation costs by making use of additional data sets. To address the issue of retail margins we use Nielsen PromoData, which has barcode-level wholesale prices (i.e. prices net of the retail margin). Figure D5 in the Appendix shows that wholesale price behavior is similar to retail price behavior. To address the issue of transportation costs, we match the RMS data with production locations obtained from National Establishment Time series (NETS) using a name-matching algorithm and plant-level zip codes. This allows us to estimate equation (2) controlling for distance to closest plant (see Figure D6 in the Appendix). The behavior of prices does not change.

Together, these checks suggest that manufacturer markups μ_t^{ipm} do not vary systematically across markets with respect to firm-market age, while market share

[14] Argente and Yeh (2022) report that the duration of prices (including sales) in the Nielsen RMS is approximately 3.5 weeks. This is shorter than the 2-3 months reported by Nakamura and Steinsson (2008) based on the CPI Research Data for unprocessed and processed food, possibly because the CPI data are available at a weekly rather than monthly frequency.

does vary with respect to firm-market age. This does not necessarily imply that average markups across all markets are invariant to firm age. But since market-specific relative quantity dynamics cannot be accounted for by market-specific relative markup dynamics, it points to a role for alternative ways through which firms can attract customers, as we now explore.

Appendix D shows that our results are additionally robust to aggregating the data differently along firm, market, and time dimensions, to restricting the sample in several ways, to varying the specification, and to using the Nielsen Household Panel and IRI-Symphony data. In addition, we find similar patterns in non-food categories in the RMS data, both durables and non-durables.

V. Non-price Actions

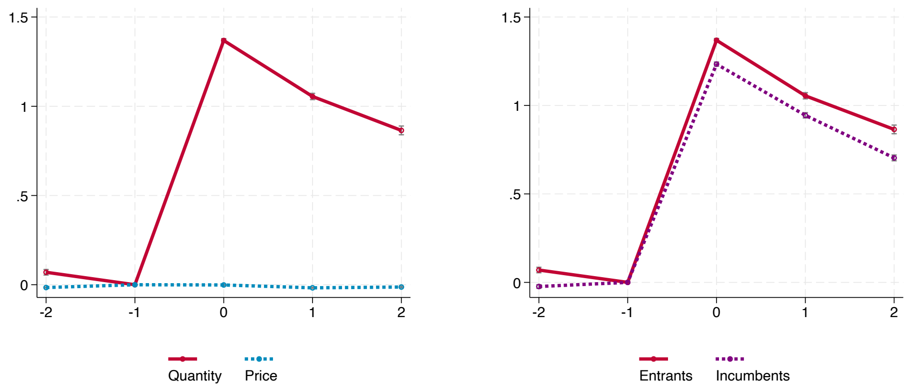
A. *Store Placement*

In the consumer food sector, retail store placement is a prerequisite for large-scale sales: Hortaçsu and Syverson (2015) report that e-commerce accounts for less than 0.9% of retail sales in the food and beverage sector in 2013. Moreover, there is evidence that costs of store placement for manufacturers are substantial. Using data for Chile, Elberg and Noton (2019) find that slotting allowances (payments to enter new stores and maintain access to shelf space in continuing stores) account for 13% of gross manufacturer revenues on average. This accords with evidence for the US, see e.g. Federal Trade Commission (2003).

We do not observe manufacturer expenditures on store placement, but we do observe how many stores in the RMS carry products of a given firm. Since Nielsen-monitored stores account for roughly half of retail sales of consumer food, this is a good proxy for store placement overall. In Appendix Figure D3, we report results from using RMS data to estimate equation (2) with log number of stores per market and log sales per store in turn as the dependent variable. The extensive margin of stores plays an important role in within-market growth. In Appendix Figure D4, we also show that the extensive margin of customers in Panel (f) of Figure 1 is accounted for by purchases from more distinct stores in the relevant firm-product-market-year cell. Additionally, we find that store placement is persistent: if a store carries a firm-product in one year, with probability 0.85 it carries it in the next year. These facts are consistent with store placement being crucial to reaching customers, and acting like a type of capital for firms.

Sales and store placement

We explore the relationship between quantities, prices, sales and store placement more directly by estimating impulse-responses using local projections as in Jordà (2005). This econometric approach cannot identify a causal relationship between store placement and quantity, or price, but it characterizes key facts about the joint distribution of these variables. Our estimating equation is:



(a) Quantity & Price (b) Entrants vs Incumbents

FIGURE 3. NON-PRICE ACTIONS: STORE PLACEMENT

Note: Panel (a) shows impulse-responses of quantity and price to number of stores, estimated using equation (4), restricting the sample to entrants. Panel (b) shows impulse-responses of quantity to number of stores for entrants and incumbents (the equation is estimated separately for each group).

$$\Delta w^{ipm}_{t+s,t-1} = \beta_s \cdot \Delta x^{ipm}_{t,t-1} + \gamma^{ipm}_s + \psi^{pm}_{s,t} + \varepsilon^{ipm}_{t,s}, \qquad s = -2, ...2 \tag{4}$$

where $\Delta w^{im}_{t+s,t-1}$ is the change in log quantity (or log price) of firm i selling product p in market m, in period $t+s$ relative to period $t-1$. $\Delta x^{ipm}_{t,t-1}$ is the change in the log number of stores carrying product p by firm i in market m between t and $t-1$. γ^{ipm}_s is a firm-product-market fixed effect, and $\psi^{pm}_{s,t}$ is a product-market-time fixed effect.

Panel (a) of Figure 3 reports the results from estimating equation (4) with changes in log quantity and log price in turn as the dependent variable, focusing on entrants, i.e. firms which start selling in the RMS data after 2006. Quantities and contemporaneous store placement are positively associated, with an elasticity above 1. This association is persistent, in the sense that more stores are associated with higher quantities sold, not just contemporaneously, but also one and two years after an innovation in the number of stores. Meanwhile we find no association between prices and number of stores. Panel (b) of Figure 3 reports the estimates of (4) with changes in log quantity as the dependent variable, estimating separately for entrants and incumbents. The elasticity of quantity to stores is slightly higher for entrants than for incumbents, possibly because entrants start from a lower base number of stores.

B. Advertising

We now turn to advertising, where we have direct data on firm actions. The top panel of Table 1 reports summary statistics on the extensive margin of advertising, aggregating across all media types. The first takeaway is that relatively few firms advertise, and those that do are positively selected. Over the period 2010-2017, 12% of firm-brand-products in the RMS data accounting for 57% of sales engage in some form of advertising. Entrants (10%) are less likely to advertise than incumbents (13%), and within entrants, the share of firms advertising is increasing in survival. In addition, advertisers sell in more markets than non-advertisers.

The second takeaway is that firms that advertise do not always advertise. Entrants frequently start advertising some years after they start selling, and advertising is often intermittent: in each category, the percentage of observations advertising both at t and $t-1$ is consistently half the percentage ever advertising. These stylized facts suggest that advertising is not necessary for sales, and given positive selection, it is likely that there are fixed costs of advertising.

Possibly because of the ability to target local markets, Local TV is a medium used relatively intensively by entrants: roughly half of entrants who advertise use Local TV. The bottom panel of Table 1 reports summary statistics on the extensive margin of Local TV advertising. These statistics echo those for all advertising. Appendix Figure D28 shows additionally that firms advertising on Local TV do not necessarily advertise in all the markets where they sell.

Sales and advertising

We provide information on the joint distribution of advertising, quantities, and prices using Local TV advertising, and the same econometric specification we use for store placement, equation (4). Since so few firms advertise, we focus on the extensive margin of advertising. In this case, $\Delta x^{ipm}_{t,t-1}$ is the change in an indicator variable for advertising by firm-brand i selling product p in market m.

Panel (a) of Figure 4 reports the results from estimating equation (4) with changes in log quantity and log price in turn as the dependent variable, focusing on entrants, i.e. firm-products which started selling in the RMS data after 2010. We find a positive association between quantities and advertising. This association is persistent, in the sense that starting to advertise is associated with higher quantities sold, not just contemporaneously, but also one and two years afterwards.[15] There is no evidence of pre-trends. Meanwhile we find no association between prices and advertising, consistent with advertising shifting demand, but not affecting the price elasticity of demand.

Panel (b) of Figure 4 reports the estimates of equation (4) with the change

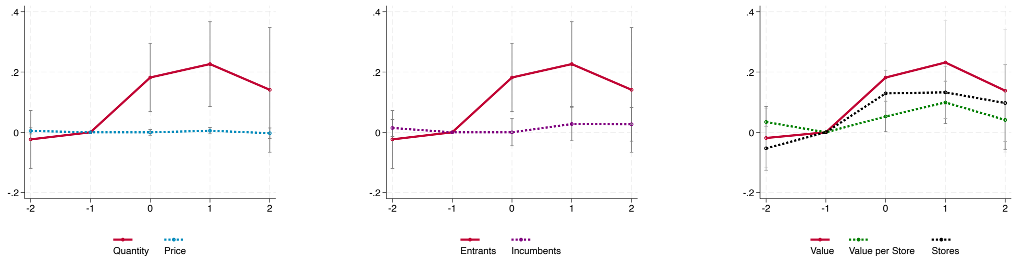
[15] This may be at least partially due to persistence in advertising. In Appendix Figure D30 we show the results from estimating equation (4) with the s-period difference in an indicator variable for advertising as the dependent variable. Advertising is persistent, but mean-reverts more quickly than sales in response to an innovation in advertising.

Table 1—Advertising by Entrants and Incumbents

				Entrants by survival				
	All	**Incumbents**	**Entrants**	**1**	**2**	**3**	**4**	**≥5**
Any Advertising: All Years								
Some advertising (% Firms)	0.12	0.13	0.10	0.07	0.07	0.06	0.10	0.12
Some advertising (% Sales)	0.57	0.59	0.48	0.51	0.45	0.58	0.37	0.48
Years with some advertising (#)	4.2	4.4	3.3	1.0	1.7	2.2	2.5	3.8
First year with some advertising	-	-	1.6	1.0	1.2	1.3	1.4	1.8
Some advertising t and t-1 (%)	0.06	0.07	0.05	-	0.04	0.03	0.04	0.06
Markets w/ sales (#), All	29	30	25	9	15	16	19	32
Markets w/ sales (#), Advertisers	69	70	65	27	37	47	46	78
Any Advertising: Entry Year								
Some advertising (% Firms)	-	-	0.07	0.05	0.05	0.04	0.07	0.08
Some advertising (% Sales)	-	-	0.37	0.49	0.26	0.22	0.23	0.38
Markets w/ sales (#), All	-	-	22	9	16	18	22	27
Markets w/ sales (#), Advertisers	-	-	72	33	43	60	67	82
Local TV Advertising: All Years								
Some advertising (% Firms)	0.06	0.07	0.05	0.03	0.04	0.03	0.05	0.06
Some advertising (% Sales)	0.45	0.46	0.36	0.25	0.39	0.55	0.31	0.36
Years with some advertising (#)	3.7	3.9	3.1	1.0	1.7	2.1	2.5	3.6
First year with some advertising	-	-	1.8	1.0	1.2	1.4	1.4	1.9
Some advertising t and t-1 (%)	0.03	0.03	0.02	-	0.02	0.01	0.02	0.02
Markets w/ sales (#), All	29	30	25	9	15	16	19	32
Markets w/ sales (#), Advertisers	80	80	79	36	51	63	57	92
Local TV Advertising: Entry Year								
Some advertising (% Firms)	-	-	0.03	0.02	0.02	0.02	0.03	0.04
Some advertising (% Sales)	-	-	0.24	0.23	0.17	0.13	0.17	0.25
Markets w/ sales (#), All	-	-	22	9	16	18	22	27
Markets w/ sales (#), Advertisers	-	-	88	43	52	75	83	99

Note: This table shows descriptive statistics for firm × brand × product averaged across years. It uses data from 2010 to 2017. An entrant is a firm × brand × product that enters between 2010-2013 at the national level. It is followed for at least 4 years, conditional on surviving. Some Advertising refers to the share of firms or sales that are matched to ADI (in percent). For each category (entrants, incumbents, etc.), we compute the average number of markets with positive sales, and the average number of markets with positive sales conditional on advertising. Appendix B provides details on the matching of retail sales data and advertising data. Appendix A.7.1 describes Local TV advertising and Appendix B.1 shows the coverage of Local TV advertising across different product categories.

in log quantities as the dependent variable, estimating separately for entrants and incumbents. Notably, the elasticity of quantities to advertising is higher for entrants than it is for incumbents. We cannot give a causal interpretation to this result, but it is consistent with a stronger informative role for advertising by entrants than incumbents. In robustness analysis reported in Appendix Figure D31, we repeat this exercise using instead the number of ad occurrences and total impressions to measure the intensive margin of advertising and find qualitatively similar results. More robustness on the relationship between advertising, quantities, and prices is in Appendix D.8.



(a) Quantity & Price (b) Entrants vs Incumbents (c) Stores, Sales per Store

Figure 4. Non-price Actions: Advertising

Note: Panels (a)-(c) show impulse responses to an indicator for advertising estimated using equation (4). The dependent variables in Panel (a) are quantity and price, and the sample is restricted to entrants. The dependent variable in Panel (b) is quantity and the equation is estimated separately for entrants and incumbents. The dependent variables in Panel (c) are sales, number of stores, and sales per store, and the sample is restricted to entrants.

Store placement and advertising

In panel (c) of Figure 4, we provide suggestive evidence that store placement and advertising are complementary investments. This panel shows the results from estimating equation (4) with the change in log sales, log number of stores and log sales per store in turn as the dependent variable, and the change in an indicator for advertising as the independent variable. The sample is restricted to entrants. We find a positive and persistent association between advertising and store placement. Consistent with this, in Appendix Figure D29, we show that firms engaging in advertising have steeper life cycle profiles of sales than those that never advertise.

VI. Conclusion

We show that the extensive margin of markets and customers plays an important role in firm growth in the consumer food sector. We show that firms in this sector expand sales in new relative to mature markets without varying markups differentially across these markets. We provide evidence that entrants expand sales through costly store placement, and for a subset of the most successful firms, through advertising. These activities appear to be complementary, and to be associated with persistent increases in quantities sold, but no changes in prices. Although our analysis is restricted to consumer food, many of the facts we document are consistent with evidence for broader sectors, e.g in Bronnenberg, Dubé and Syverson (2022) and Fitzgerald, Haller and Yedid-Levi (2023). Our findings highlight the importance of demand for firm dynamics. They also have implications for two separate strands of the macroeconomics and trade literatures which rely on the measurement of productivity and markups: those which exploit parameterized demand systems, and those which exploit cost minimization by producers.

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