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

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Abstract

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.

JEL Classifications: D25, E22, L11, L25
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1 Introduction

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, 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 4 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 Company, 2019), the Nielsen Household Panel (The Nielsen Company, 2019), Nielsen Ad Intel data (The Nielsen Company, 2020), Nielsen Promo data (The Nielsen Company, 2021), and the National Establishment Time series (Walls & Associates, 2019).

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

[1] See e.g. Dunne et al. (1989) and Hsieh and Klenow (2014).
[2] See e.g. Foster et al. (2008) and Eslava et al. (2023).
[3] See e.g. Phelps and Winter (1970), Bils (1989), Ravn et al. (2006), Nakamura and Steinsson (2011), Gourio and Rudanko (2014b), Gilchrist et al. (2017), Paciello et al. (2019) and Bornstein (2021).
[4] See, e.g. Arkolakis (2010), Drozd and Nosal (2012) and Gourio and Rudanko (2014b)
[5] See e.g. Federal Trade Commission (2003) and Elberg and Noton (2019).

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 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.

2 Relation to the Literature

Empirical literature Our findings on the importance of demand for firm heterogeneity are related to Hottman et al. (2016) and Eslava et al. (2023). Our results on the importance of customers and markets for demand are related to Eaton et al. (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 et al. (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 et al. (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 et al. (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 et al. (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 et al. (2015) for an application to the welfare gains from trade). Afrouzi et al. (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 et al. (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 et al. (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 (2014a) show that a flexible-price model where firms accumulate customer base through marketing and advertising can also generate a countercyclical labor wedge.

3 Data

3.1 Retail Sales

Our primary source is scanner data from Nielsen Retail Measurement Services (RMS), provided by the Kilts-Nielsen Data Center, (The Nielsen Company, 2019). 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 (GS1 US, 2017). 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 over one third of U.S. consumer 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 et al. (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) (The Nielsen Company, 2019), and the IRI-Symphony data (Information Resources Inc., 2019; Bronnenberg et al., 2008), also described in Appendix A. Appendix A additionally provides a general overview of the institutional environment in the consumer food sector.

3.2 Advertising

Our advertising data come from the Ad Intel database (ADI) provided by the Kilts-Nielsen Data Center (The Nielsen Company, 2020). 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%.

3.3 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 et al. (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.

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

4 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):

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

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 $\text{age}_t^{ip}$and 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.

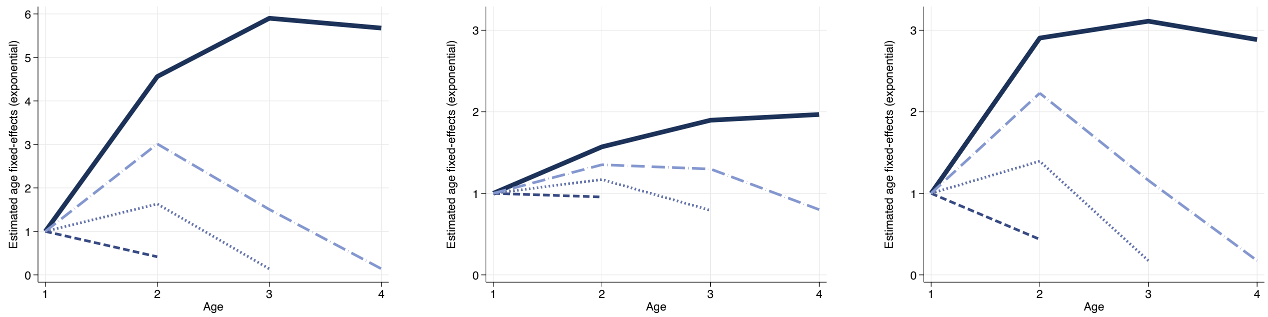
Panel (a) of Figure 1 shows the estimated trajectories for total sales by survival. Entrants who survive 5+ years grow to 6 times their initial size during the first 3-4 years of activity. Growth is fast in the initial years, and slows with age. Entrants who survive less than 5 years initially grow, 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

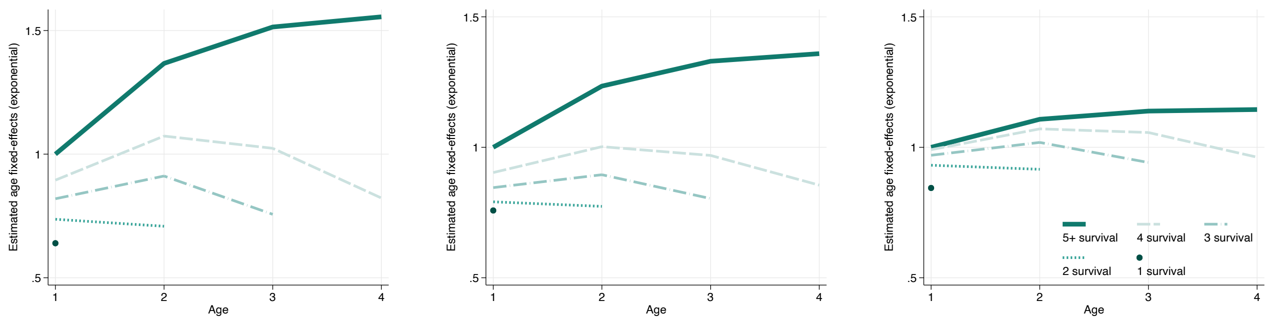
[7]These patterns, and all of our results, are robust to varying the level at which we topcode.

[8]Table A4 shows the distribution of number of markets for entrants and 5-year incumbents. 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.

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



(a) Sales (RMS, National) (b) # Markets (c) Sales per Market



(d) Sales (HMS, Market) (e) # Customers (f) Sales per Customer

Notes: 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.

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:

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

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

5 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

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

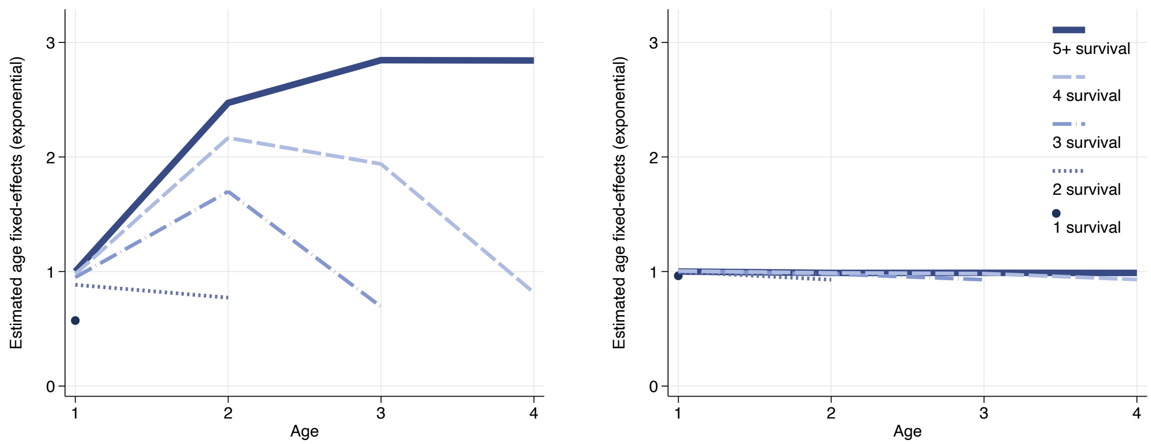
[10] In this analysis, firm-products already selling in a subset of markets at the start of the sample, but which enter new markets during the sample period, are considered entrants in the new markets.

[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.

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

Figure 2: Life Cycle of Quantities and Prices Within Markets



(a) Quantity (b) Price

Notes: 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 Table D1 report the relevant estimates of β.

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 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]

[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.

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 (The Nielsen Company, 2021), 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) (Walls & Associates, 2019) using a name-matching algorithm and plant-level zip codes. This allows us to estimate equation (2) controlling for distance to closest plant (National Bureau of Economic Research, 2021) (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 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 (The Nielsen Company, 2019) and IRI-Symphony data (Information Resources Inc., 2019). In addition, we find similar patterns in non-food categories in the RMS data, both durables and non-durables.

6 Non-price Actions

6.1 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.

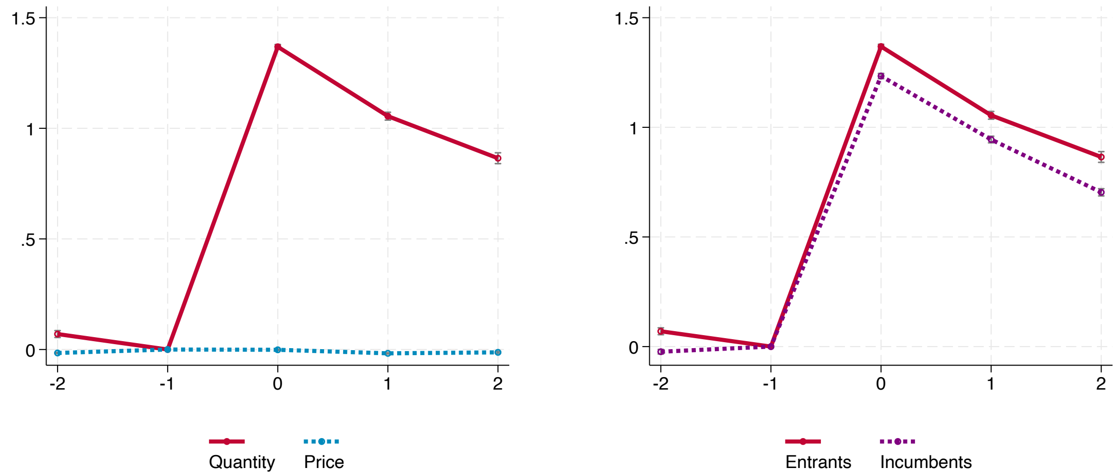
Sales and store placement We explore the relationship between quantities, prices, sales and store placement more directly by estimating impulse-responses using local projections as in Jordà (2005). This econometric approach cannot identify a causal relationship between store placement and quantity, or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

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

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

Figure 3: Non-price Actions: Store Placement



(a) Quantity & Price

(b) Entrants vs Incumbents

Notes: 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).

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.

6.2 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 fre-

Table 1: Advertising by Entrants and Incumbents

	All	Incumbents	Entrants	Entrants by survival 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

Notes: 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 and Appendix B.1 shows the coverage of local TV across different product categories.

quently 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, $\Delta x_{t,t-1}^{ipm}$ is the change in an indicator variable for advertising by firm-brand i selling product p in market m.

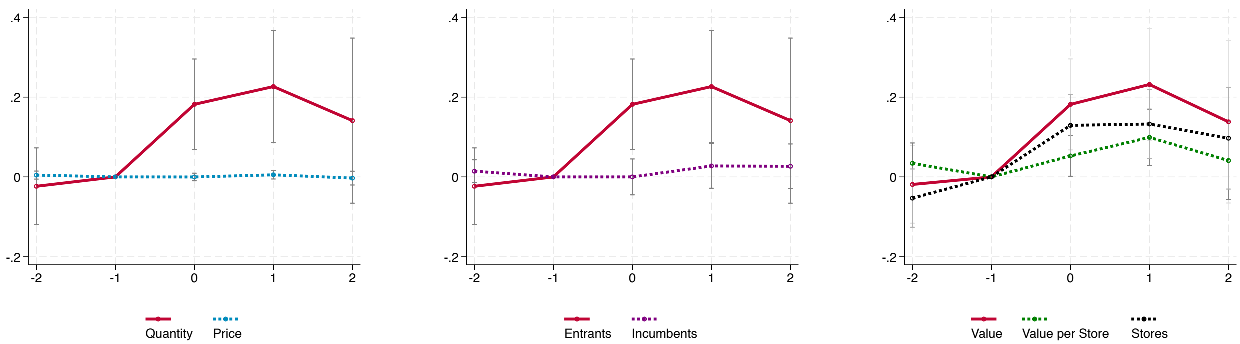
Panel (a) of Figure 4 reports the results from estimating equation (4) with changes in log quantity and log price in turn as the dependent variable, focusing on entrants, i.e. firm-products which started selling in the RMS data after 2010. We find a positive association between quantities and advertising. 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 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 Figure D31 in the Appendix, 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.

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 Figure D29 in the Appendix, we show that firms engaging in advertising have steeper life cycle profiles of sales than those that never advertise.

[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.

Figure 4: Non-price Actions: Advertising



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

Notes: 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.

7 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 et al. (2022) and Fitzgerald et al. (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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APPENDIX

A Data Sources

A.1 Institutional Environment

There are three (sometimes four) types of agent in the consumer food industry: manufacturers, retail chains, consumers, and in some cases, wholesalers.

Consumers take as given the set of stores they have access to, the product assortment in each store, and the price of each product-store pair. They choose which store(s) to purchase from, and what products and in what quantities to purchase at each store, in order to maximize welfare, subject to a budget constraint and time costs of visiting each store. Product awareness or tastes may be affected by advertising, observing the consumption patterns of others, or past consumption.

Retail chains choose what product assortment to carry in each store, and what prices to charge consumers for each product. They take as given consumer tastes and the set of manufacturers. Depending on their size, they may have market power vis-a-vis manufacturers. In some cases, wholesalers may intermediate between manufacturers and smaller retail chains.

Manufacturers take as given production costs, and the set of retail chains, and consumer tastes. Depending on their size, they may have market power vis-a-vis retail chains. They may be able to affect consumer product awareness or tastes directly through advertising.

The contractual arrangements between manufacturers and retail chains are the subject of a large literature. Given the strategic nature of these relationships, publicly available data on the terms of these arrangements is limited. See Ailawadi et al. (2010) for a description of what is known about these terms.

A.2 Nielsen RMS

Our primary data source is the Nielsen Retail Measurement Services (RMS) provided by the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business (The Nielsen Company, 2019). The data are generated by point-of-sale systems in retail stores. The collection points include more than 40,000 distinct stores from around 90 retail chains and 2,500 counties. Each individual store reports weekly sales (dollar amount) and quantities for every barcode (UPC) with positive sales during the week. We use data for the period 2006-2017. The RMS consists of more than 100 billion unique observations at the barcode $\times$ store $\times$ week level that cover approximately \$2 trillion in sales. This represents about 53% of all sales in grocery stores, 55% in drug stores, 32% in mass merchandisers, 2% in convenience stores, and 1% in liquor stores.

Products and brands There are ten Nielsen-defined departments. We focus on the six food departments: dry grocery, dairy, deli, packaged meat, frozen foods and fresh produce. We exclude Alcoholic Beverages, Health & Beauty Care, Non-Food Grocery and General Merchandise. Within each department, there are Nielsen-defined product groups, and within each product group, there are Nielsen-defined product modules. For example, in the Dairy department "YOGURT" is a product group, while "YOGURT-REFRIGERATED-SHAKES & DRINKS" is a product module within "YOGURT." There are roughly 600 product modules in food departments. Our baseline definition of a product is a Nielsen-defined product module, and from now on, we refer to product modules simply as "products."

Within products, all barcodes use the same unit of quantity, e.g. "oz" , "quart", etc., and the number of units in a package. This allows us to compare quantities and therefore also unit values across barcodes or aggregations of barcodes within products. For example, if Dannon yogurt is sold in 42 oz. tubs, while Chobani yogurt is sold in 4 oz. 6-packs, we can use ounces as the common unit of quantity, with Dannon being coded as 42 units and Chobani as 24 units.

Nielsen also classifies barcodes into brands. Brands (e.g. Yoplait, Chobani) often cross products. Firms (e.g. General Mills) may have multiple brands. The brand-product is a convenient unit of analysis for us, because the brand (rather than the barcode) is the level at which advertising takes place, and quantities are consistent within products.

Firms We link barcodes (and therefore also brands and products) to firms using information obtained from GS1 US (GS1 US, 2017). GS1 US is the single official source of barcodes in the US. It gives us a company prefix (firm) for each barcode generated in the US. We assign these company prefixes to barcodes in the RMS by merging the two data sets. This allows us to characterize the portfolio of barcodes, brands, and products of every firm in our sample.

Markets For each participating retail store, we know the parent chain, the 3-digit zip code, and the Nielsen Designated Market Area (DMA) where it operates. There are 210 Nielsen-defined DMAs (approximately 14 counties per DMA). Nielsen uses DMAs as the definition of a media market for their advertising data and defines them by OTA (over the air) TV signal strength. For example, the Philadelphia DMA includes eight surrounding counties in Pennsylvania, eight counties in New Jersey, and two in Delaware. Any cable provider serving a customer in one of these 18 counties is required to include local Philadelphia broadcast stations in the customer's cable package. We use the DMA as our baseline definition of a market because i) they are large enough to be segmented from consumers' perspective, ii) they align well with MSAs across the country, and iii) this definition allows us to match the RMS with the advertising data.

A potential concern with defining markets as DMAs is that entry may occur at the retail chain level instead of the DMA level (e.g. national retailers synchronizing entry across all their locations). Table A1 shows this is not the case. The top panel shows that the average new brand-product is introduced in 78% (median 86%) of DMAs covered by retailers that operate in less than 5 DMAs. On the other hand, the average new brand-product is introduced only in 15% (median 7%) of markets covered by national retailers (i.e. those present in more than 150 markets in the US). These numbers are very similar for brand-products that have been in the market for at least 40 quarters. These brand-products are sold in 75% of markets covered by local retailers and only in 18% of markets covered by national retailers. Overall, we do not find strong evidence that retailers synchronize entry of brands across all markets in which they operate, or carry an identical assortment of brand-products in all markets, justifying our definition of the market at the geographical level.

Baseline aggregation We select data covering the food sector over the period 2006-2017. We aggregate the data to the level of the firm-brand-product-market-year, summing over values and quantities within these cells. Unit values are then constructed as the ratio of value to quantity. We aggregate from weekly data to the annual level to avoid spurious entry and exit for seasonal items. We also present robustness analysis using aggregation at the level of

Table A1: Share of DMAs Covered by the Chain Where a Brand-product is Present

Age of Brand-prod quarters)	Number of DMAs Covered by Chain	Mean	p25	p50	p75
1	<5	0.78	0.60	0.86	0.97
1	5-50	0.38	0.15	0.30	0.60
1	50-150	0.19	0.06	0.12	0.29
1	>150	0.15	0.02	0.07	0.23
40	<5	0.75	0.64	0.77	0.85
40	5-50	0.44	0.28	0.42	0.59
40	50-150	0.25	0.15	0.22	0.34
40	>150	0.18	0.11	0.16	0.24

Note: The table documents patterns of the geographic roll-out of brand-products. We consider brand-products in the quarter of entry and brand-products that have been sold for at least 10 years (40 quarters). We divide retailers into bins according to the number of markets (DMAs) in which they operate in order to distinguish between local, regional, and national retailers. The table reports the average, median, 25th percentile and 75th percentile of the share of markets where the brand-product is sold.

the quarter. We deflate all dollar values by the US CPI for all urban consumers, so all values are expressed in terms of 2006 dollars. To minimize measurement error, we restrict attention to firm-brand-product-markets with an average revenue greater than 100 dollars per year over the sample period.

Entry, age, survival We say that a firm-brand-product enters in year t if it has zero sales in year $t-1$, and positive sales in year t. We define entry at the level of a firm-brand-product-market in a similar way. Entry is censored in 2006, and exit is censored in 2017. Note that firm-brand-products can (and do) enter multiple times during the sample. We define firm-brand-product *age* as the cumulative number of periods of continuous participation. Firm-brand-product-market age is defined analogously. Completed spell *survival* is the maximum age achieved in a firm-brand-product sales spell, i.e. the age on exit for that spell. Survival is defined analogously at the firm-brand-product-market level as age on exit for the firm-brand-product-market spell. Table A2 illustrates these definitions for a hypothetical firm-brand-product pair in a series of markets. In this table, as in our implementation, age and survival are top-coded at 5 years. This allows us to assign a survival to (some) sales spells where entry is observed, but exit is censored by the end of the sample.

Summary statistics Table A3 provides more details on the hierarchical structure of the data. It reports the number of distinct products, firms, firm-products, firm-brands, firm-brand-products, and firm-brand-products-markets in the full data set, as well as the average number of each level of aggregation present in a given year. Table A4 reports summary statistics on entry and survival for firms, firm-brand-products, and firm-brand-product-markets. In addition, it provides statistics on numbers of markets for the full sample and for entrants, and on sales for the full sample and for entrants. Table A5 reports the variance of log sales, log quantity, and log price at the firm-brand-product-market-year level, conditional on various controls.

Table A4: Summary Statistics

	Firms		Firm-Brand-Products		Firm-Brand-Prod-Market	
	All	Entrants	All	Entrants	All	Entrants
Total # unique	21,265	9,688	116,107	61,694	4,478,616	2,688,641
Survival (%)						
1 year	-	0.08	-	0.09	-	0.12
2 years	-	0.13	-	0.15	-	0.21
3 years	-	0.11	-	0.12	-	0.14
4 years	-	0.08	-	0.09	-	0.09
+5 years	-	0.59	-	0.53	-	0.42
Markets (#)						
mean	36	23	38	33	-	-
25th percentile	2	2	2	2	-	-
median	8	5	9	7	-	-
75th percentile	38	20	42	32	-	-
Sales ($1,000)						
mean	15,637	5,877	16,100	6,291	30,821	9,445
25th percentile	930	386	581	328	453	235
median	3,054	1,246	1,875	1,061	1,650	765
75th percentile	11,134	4,054	7,360	3,697	7,899	3,259

Notes: The table presents the summary statistics for the observations included in the baseline pooled sample for the period 2006-2017. For each of these categories, we report the total number of observations, statistics on survival, sales and market expansion. The statistics for sales are computed by determining the average annual sales (in thousands of dollars), deflated by the Consumer Price Index for All Urban Consumers.The table presents the average and distribution statistics of this variable.

Table A2: Illustrative Example of Definitions

Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Market	a. Participation										
A	X	X	X					X	X	X	X
B		X	X	X	X		X	X	X		
C	X	X			X	X	X	X	X	X	X
D		X	X			X	X	X	X	X	
E	X	X	X	X	X	X	X	X	X	X	X
Market	b. Market age, topcoded at 5										
A	cens	cens	cens					cens	cens	cens	cens
B		1	2	3	4		1	2	3		
C	cens	cens			1	2	3	4	5	5	5
D		1	2			1	2	3	4	5	
E	cens	cens	cens	cens	cens	cens	cens	cens	cens	cens	cens
Market	c. Completed spell survival, topcoded at 5										
A	cens	cens	cens					cens	cens	cens	cens
B		4	4	4	4		3	3	3		
C	cens	cens			5	5	5	5	5	5	5
D		2	2			5	5	5	5	5	
E	cens	cens	cens	cens	cens 5	cens	cens	cens	cens	cens	cens

Table A5: Variance Decomposition: Sales, Quantity, and Price

	All	Entrants		Incumb.
		1st year	All	All
Sales (log)				
Year	11.9	7.6	9.1	11.5
Product-market-year	5.6	3.1	4.4	5.2
Firm-brand-product-year	3.1	2.1	2.6	3.0
Firm-brand-product-year, product-market-year	1.7	1.1	1.6	1.4
Quantity (log)				
Year	12.5	7.5	9.2	12.1
Product-market-year	6.3	3.6	4.8	5.8
Firm-brand-product-year	3.1	2.1	2.6	3.0
Firm-brand-product-year, product-market-year	1.7	1.1	1.6	1.5
Price (log)				
Year	0.4	0.5	0.5	0.4
Product-market-year	0.4	0.4	0.4	0.3
Firm-brand-product-year	0.04	0.03	0.04	0.03
Firm-brand-product-year, product-market-year	0.03	0.02	0.03	0.03

Note: This table reports the variance of the residual after regressing log sales, log quantity, and log price at the firm-brand-product-market-year level on various controls: year fixed effects, product-market-year fixed effects, firm-brand-product-year fixed effects, or firm-brand-product-year and product-market-year fixed effects.

A.3 Nielsen Household Panel

We make use of the Nielsen Household Panel (HMS) data set from 2004 to 2017 (The Nielsen Company, 2019). This data set tracks the shopping behavior of 40,000–60,000 households every year covering 49 states and 2,967 counties in the United States. Each panelist uses in-home scanners to record their purchases. A twelve-digit universal product code (barcode) identifies the items the panelists purchase. The data contain around 3.27 million distinct barcodes grouped using the same hierarchical structure as the RMS. For each barcode, we have information on the brand and size. If the panelist purchases a good at a store covered by Nielsen, the price is automatically set to the average price of the good at that store during the week when the purchase was made. If not, the panelist directly enters the price. Nielsen reports detailed transaction information for each product purchased (e.g. barcode, quantity, price, deals, and coupons). We combine this information with the weight and volume of the product to compute unit values. The data also contain information about each purchasing trip the panelist makes, such as the date of the transaction, and the store, if it is covered by

Nielsen, and the retail chain and county where the store is located, if it is a non-Nielsen store.

A.4 IRI-Symphony Data

We also use the IRI Symphony data (Information Resources Inc., 2019), a data set very similar to the Nielsen RMS. It includes prices and quantities for barcodes across the US. It also provides a sales flag which indicates when a product is on sale in a certain store. The data contain approximately 2.4 billion transactions from January 2001 to December 2011 which represent roughly 15 percent of household spending in the Consumer Expenditure Survey (CEX). Our sample contains approximately 170,000 products and 3,000 distinct stores across 43 metropolitan areas (MSA). The data covers 31 product categories which include: Beer, Carbonated Beverages, Coffee, Cold Cereal, Deodorant, Diapers, Facial Tissue, Photography Supplies, Frankfurters, Frozen Dinners, Frozen Pizza, Household Cleaners, Cigarettes, Mustard & Ketchup, Mayonnaise, Laundry Detergent, Margarine & Butter, Milk, Paper Towels, Peanut Butter, Razors, Blades, Salty Snacks, Shampoo, Soup, Spaghetti Sauce, Sugar Substitutes, Toilet Tissue, Toothbrushes, Toothpaste, and Yogurt. The dataset is discussed in more detail in Bronnenberg et al. (2008).

A.5 Nielsen Promo Data

PromoData, provided by the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business (The Nielsen Company, 2021), is a dataset on manufacturer prices for packaged foods from grocery wholesalers (the largest wholesaler in each location). PromoData provides the price per case charged by the manufacturer to the wholesaler for a barcode in a particular day, for 48 markets, over the period 2006-2012. The data set contains information on both base prices and "trade deals" (discounts offered to the grocery wholesalers to encourage promotions). In other words, PromoData contain wholesale costs instead of retail prices. The data include information on almost 900 product categories and more than 500,000 distinct barcode-market combinations.

A.6 NETS Data

We make use of data obtained from the National Establishment Time Series (NETS) (Walls & Associates, 2019) on firms and establishments covering all sectors from 1990 to 2016. NETS consists of longitudinally linked Dun & Bradstreet establishment-level data. NETS provides yearly employment and sales information for "lines of business" in a specific location (similar to the definition of an establishment). Each establishment is assigned an identifier that makes it possible to track its sales and employment over time. For each establishment, we know the location, industry classification, and parent company. We use parent company information as our definition of a firm.

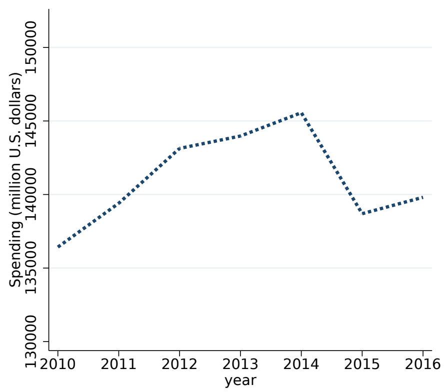
To match the RMS data with production locations from NETS, our initial step is to apply a name-standardization routine to all firm names in both datasets, thereby generating unique company identifiers. Our matching algorithm builds on the method developed by Hall et al. (2001). Once the firm names are successfully matched across the datasets, we use the store locations associated with each firm-product in RMS (identified by the first three digits of the ZIP Code and/or county information) to link them with the corresponding county of the closest plant for each year. To accomplish this, we rely on the County Distance Database provided by the NBER. These data contain great-circle distances between counties, calculated using the Haversine formula based on internal geographic points within the area. We then create a weighted average measure of distance to the closest plant at the firm-product-market-year level, where the weights are sales of the firm-product at the store level for all stores within the market with positive sales, and the distance is distance from the relevant store to the closest plant for that firm. Note that in contrast to our baseline exercise, this exercise aggregates across brands within a firm-product.

A.7 Nielsen Ad Intel

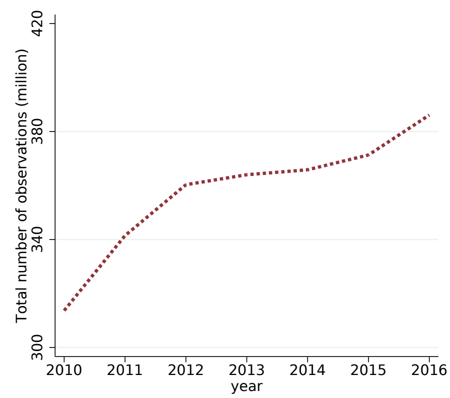
Our advertising data come from the Nielsen's Ad Intel (ADI) database provided by the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business (The Nielsen Company, 2020). This database provides information on advertising starting in 2010, covering nearly $150 billion per year of spending in the U.S., and nearly 400 million observations per year (Figure A1). It provides occurrence-level advertising information such as time, duration, format, product type, and estimated cost of running each advertisement. The data are available for ads featured on television, newspaper and magazines, radio, cinema, coupons, outdoor, digital, among other media (see Figure A1 and Table A6).

In our analysis we use data for the period 2010-2017, with some exercises restricted to 2010-2016. While the ADI covers all sectors, we use the product classification system to select ads for food goods sold in grocery and drug stores. Figure A1 (d) shows that food products are advertised across all media types and account for an especially high share of advertising in Coupons and Local TV. For both Coupons and Local TV, ads are reported at the DMA level. The regional coverage is best for Local TV, where we have data for all 210 DMAs. In addition, spending on Local TV is much greater than that on Coupons. Because of this, we make intensive use of the Local TV data.

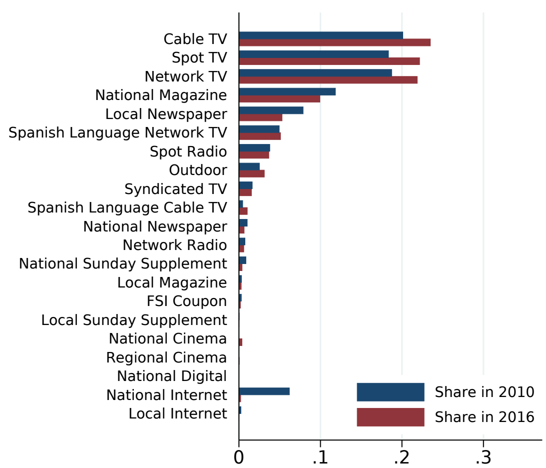
Figure A1: Overview Ad Intel



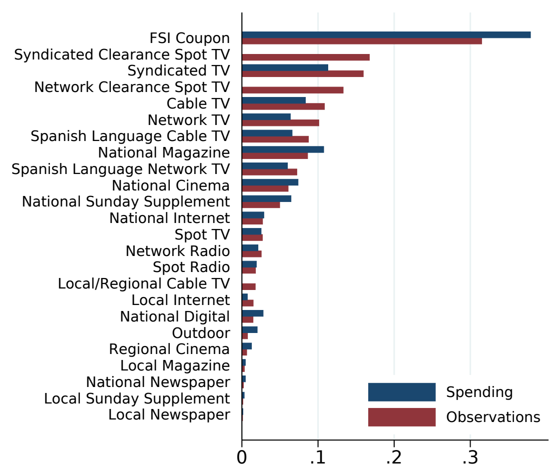
(a) Total Spending



(b) Total Number of Observations



(c) Share of Spending by Medium



(d) Share of Food for Each Medium

Note: Panels (a)-(b) present total spending and the total number of observations in the Ad Intel data 2010-2016. Panel (c) presents the share of spending by media type in 2010 and 2016. Panel (d) presents for these media types the share of spending and advertising observations that are in food related categories over the period 2010-2016. Local TV includes Spot TV, Network Clearance Spot TV, Syndicated Clearance Spot TV, Local/Regional Cable TV.

Table A6: List of Media Types Covered by Ad Intel

Detailed Description	Our Description	Markets National/Local	Markets Number DMAs	Time period
Network TV	National TV	National	-	2010-2017
Spanish Language Network TV	National TV	National	-	2010-2017
Cable TV	National TV	National	-	2010-2017
Spanish Language Cable TV	National TV	National	-	2010-2017
Syndicated TV	National TV	National	-	2010-2017
Spot TV	LocalTV	Local	210	2010-2017
Network Clearance Spot TV	LocalTV	Local	210	2010-2017
Syndicated Clearance Spot TV	LocalTV	Local	210	2010-2017
Local/Regional Cable TV	LocalTV	Local	51	2010-2017
National Magazine	National Magazine	National	-	2010-2017
Local Magazine	Local Magazine	Local	31	2010-2017
FSI Coupon	Coupon	Local	78	2010-2017
National Newspaper	National Newspaper	National	-	2010-2017
National Sunday Supplement	National Newspaper	National	-	2010-2017
Local Newspaper	Local Newspaper	Local	76	2010-2017
Local Sunday Supplement	Local Newspaper	Local	5	2010-2017
Network Radio	National Radio	National	-	2010-2017
Spot Radio	Local Radio	Local	43	2010-2017
Outdoor	Outdoor	Local	164	2010-2017
National Internet	National Internet	National	-	2010-2017
Local Internet	Local Internet	Local	82	2010-2017
National Cinema	National Cinema	National	-	2013-2017
Regional Cinema	Local Cinema	Local	1	2013-2017
National Digital	Digital	National	-	2017-

Notes: National Internet and Local Internet has information until August 2017, and is then replaced by new Digital media type data. There is no spending for media types "Syndicated Clearance Spot TV". "Network Clearance Spot TV", and "Local/Regional Cable TV".

A.7.1 Local TV

What is Local TV? We observe the following types of TV advertising: (1) *Cable ads*, which are aired nationally, with viewership data available only at the national level; (ii) *Spot ads* are bought locally, and viewership measures are recorded locally, separately for each DMA; (iii) *Network and Syndicated Spot TV ads* are recorded in national occurrence files that can be matched with local measures of viewership in each DMA. The Network TV and Syndicated TV occurrence files record the ads at the national level (i.e. the date and time the ad is supposed to be broadcast at every local station). The Network Clearance Spot TV and Syndicated Clearance Spot TV occurrence files record them at local level (i.e. the date and time each ad is actually broadcast at every local station). The local channels have some authority to replace or move nationally scheduled ads. For each network program, ads from the local market are compared to commercials in the national database, thus identifying the local TV stations that did or did not air the "national" ad.

Local TV advertising combines Spot TV, Network Clearance Spot TV and Syndicated Clearance Spot TV.

Variation in a brand's aggregate ad viewership across markets is due to both variation in occurrences across markets (more Spot ads were aired in market A than in market B) and variation in impressions (eyeballs) across markets (a Network or Syndicated ad aired in both markets A and B, but more people saw the ad in market A than in market B).

Variables We are interested in the following measures of advertising: (i) indicator variable on whether there was some ad occurrence; (ii) number of ad occurrences; (iii) number of impressions. We also compute measures of total duration, spending, and Gross Rating Points (GRPs).

GRP is a measure of how many people within an intended audience might have seen the ad. It can take a value above 100. Say that an ad is seen by 40% of the population and it is aired 3 times, then we have a GRP of 120. Rating is the percentage (0 to 100) of the Media Market that will likely be exposed to your advertisement (in this case 40%). In other words, it is used as a cumulative measure of the impressions an ad campaign can achieve.

The advertising information is recorded at the *occurrence* level, where an occurrence is the placement of an ad for a specific brand on a given channel, in a specific market, at a given day and time. Occurrences can then be linked to viewership/impressions using the natural keys described by Nielsen. Viewership data estimate the number of *impressions*, or eyeballs, that viewed each ad. We use estimates of *universe* of TV audience in each market.

After merging merging the occurrences, impressions and universe files, we obtain a dataset organized in a per-occurrence manner, so the next step is to collapse occurrences into a unique time $\times$ dma $\times$ brand code (varies by product type, an advertiser parent/subsidiary, and a brand description). We create datasets collapsing at the quarterly and annual levels.[16]

B Matching Retail Sales and Advertising Data

The RMS and the ADI do not use the same product and brand identifiers. As a result it is challenging to merge the two datasets. We develop a procedure that uses text similarity techniques for three distinct inputs that characterize identifiers across observations: product type descriptions, name of the firm, and name of the brand. Below we describe the algorithm, from the selection of these inputs and how we combine them to derive a criteria for a positive match, followed by alternative algorithms that we use for robustness analysis, and an extensive set of validation exercises.

Representative inputs – The retail sales data include three pieces of information that are key to distinguishing between observations: a product module description (Nielsen RMS), a firm name text (GS1), and a brand description (Nielsen RMS). The advertising data includes a product category, an advertiser parent/subsidiary, and a brand description.[17] Thus, we develop a crosswalk between datasets at the level of product module $\times$ firm $\times$ brand level (r) on the RMS, and at the level of product category $\times$ parent/subsidiary $\times$ brand (a) on the ADI.[18] None of these three dimensions – product type, firm, brand – is fully overlapping across the two data sets. For example, the brand identifiers in the ADI do not match the brand descriptions in the RMS data. The advertised brand description is either more or less specific than the brand associated with each barcode. We also studied the possibility of using only brand descriptions in our match (as in Shapiro, Hitsch and Tuchman, 2021) and decided against it because there are several brand descriptions that are same or very similar and represent barcodes from distinct firms and product categories. By using information on the nature of the product advertised and the firm advertising we can reduce these sources of measurement error.

Measures of similarity for each input– We start by studying the product description on the ADI dataset to select the set of observations that are related to consumer food products. After studying the classification system of ADI, we select 271 distinct product categories,

[16]Because we have high time frequency data but not all markets are observed all the time, we follow Shapiro et al. (2021) imputation procedure for the missing observations.

[17]ADI provides two distinct sources of firm information: advertiser parent and advertiser subsidiary.

[18]There are 147,665 unique RMS combinations, and 13,039 unique ADI combinations corresponding to 20,124 unique codes.

covering more than 5,000 distinct firms and almost 13,000 distinct brand descriptions. Using this sample, we compute measures of similarity across each of input.

We match the RMS **product modules** (in r) to the ADI product categories (in a) manually as a many-to-many crosswalk, with a few non-matched product types. We do this manually because there are a small number of doubtful matches that are better resolved by reading the barcode descriptions in the RMS data and the product descriptions in ADI. In the baseline algorithm we attribute a similarity score $s^P_{ra} = 1$ if a product category in a matches to a product module in r, and $s^P_{ra} = \frac{1}{2}$ if a product category in a matches to other product modules of group of product module r but not to the product module in r. We allow for this possibility because there are cases where the product category in ADI is too general and has too many close product modules that constitute a good alternative match.

We determine the level of association of **firms** across datasets by using string matching algorithms applied to company name from GS1 and information on the advertiser from ADI. For most cases the advertiser parent and subsidiary coincide. When they do not coincide, we use both variables in our algorithm. We start by running all names through a name-standardization routine adapted from Argente et al. (2020).[19]

Using the standardized firm name we compute two measures of text similarity: a similarity score between the firm from GS1 in r and the parent from ADI in a (s^{FP}_{ra}) and another similarity score between firm GS1 in r and subsidiary ADI in a (s^{FS}_{ra}). We define the similarity scores of firm names as $s^F_{ra} = \max\{s^{FP}_{ra}, s^{FS}_{ra}\}$. The similarity scores are obtained using a token-based vectorial decomposition algorithm using log-weight to reduce false positive matches coming from words that are frequently found. The similarity is guaranteed to lie in the range $[0, 1]$, with zero corresponding to zero word overlap and one corresponding to the case in which the names are identical (or are multiples of one another). Almost 35% of parent/subsidiaries in ADI have a similarity score of 1 which implies an exact match, and more than 60% of parent/subsidiaries have a similarity score above 0.5.

We determine the level of association of **brands** across datasets by using string matching algorithms applied to brand descriptions from RMS and ADI. Merging brands is a challenge because brand variables in the RMS and ADI are not always specified at the same level. RMS assignes UPCs to brands, which are more aggregated than UPCs but are still typically disaggregated, with some exceptions. ADI assigns ads to brands and the ad itself may be specific to a reduced set of products or to the aggregated brand. For example, both datasets include brands like "Chobani" and specific sub-brands like "Chobani Simply 100", "Chobani Simply 100 Crush", or "Chobani Flip". After running all brand text through a name-standardization routine, we create two distinct brand definitions for each original brand b^0: a specific b^1 and

[19]The routine handles capitalization, spaces, frequent abbreviations, common misspellings, among other.

a general brand b^2.[20] We compute measures of text similarity for each level of aggregation: a similarity score between original RMS brand r and original ADI brand a (s^{B0}_{ra}), similarity score between b^1 of RMS brand r and b^1 of ADI brand a (s^{B1}_{ra}), and similarity score between b^2 of RMS brand r and b^2 of ADI brand a (s^{B2}_{ra}). In our baseline analysis, we use the similarity score $s^B_{ra} = s^{B1}_{ra}$. We use the other levels of aggregation for robustness exercises. As with the firm match, the similarity scores are obtained using a token-based vectorial decomposition algorithm using log-weight to reduce false positive matches coming from words that are frequently found. Almost 60% of distinct ADI brands have a similarity score of 1 which implies an exact match, and only 10% have a similarity score below 0.5.

Criteria for match – The final step of the matching algorithm consists of using the similarity scores and determining the mapping between observations in the RMS and ADI. Every combination of the RMS product module × firm × brand level (r) with the ADI Intel product category × parent/subsidiary × brand (a) on the ADI is characterized by $\{s^F_{ra}, s^B_{ra}, s^P_{ra}\}$. After an extensive manual review of the datasets, we decided to treat every dimension equally and defined a systematic criterion that requires that at least one of the inputs needs to have a very high association (similarity score above 0.9), while still requiring that the other two dimensions have a sufficiently high degree of similarity (similarity above 0.7 and 0.5). More, specifically we define as a positive match when the following conditions are satisfied:

$$\text{Baseline} = \{ra \in \Omega \mid \max\{s^F_{ra}, s^B_{ra}, s^P_{ra}\} \geq 0.9 \ \wedge \ \text{median}\{s^F_{ra}, s^B_{ra}, s^P_{ra}\} \geq 0.7 \ \wedge \ \min\{s^F_{ra}, s^B_{ra}, s^P_{ra}\} \geq 0.5\} \tag{B5}$$

There are clear trade-offs when setting these thresholds. Increasing these thresholds can potentially decrease the false positive matches but comes at the expense of largely increasing the false non-matches. Therefore, we consider decreasing the thresholds and evaluate its impact on the results:

$$\text{Match 2} = \{ra \in \Omega \mid \max\{s^F_{ra}, s^B_{ra}, s^P_{ra}\} \geq 0.8 \ \wedge \ \text{median}\{s^F_{ra}, s^B_{ra}, s^P_{ra}\} \geq 0.5 \ \wedge \ \min\{s^F_{ra}, s^B_{ra}, s^P_{ra}\} \geq 0.5\} \tag{B6}$$

[20] For example, for the original brand "Chobani Simply 100 Crush", b^1 becomes "Chobani Simply 100" and b^2_i is "Chobani"; for the original brand "Chobani Simply 100", b^1 is the same and b^2 is "Chobani"; for the original "Chobani", both b^2 and b^1 are the same.

We also define algorithms weighting differently the scores (s^P_{ra}, s^F_{ra}, and s^B_{ra}). More specifically, we define an alternative algorithm that satisfis the following conditions

$$\begin{aligned}\text{Match 3} = \{ra \in \Omega \mid\ & ra \in B^2 \vee \\ & (s^F_{ra} \geq 0.9 \wedge s^{B2}_{ra} \geq 0.7 \wedge X_r = 1) \vee \\ & (s^F_{ra} \geq 0.9 \wedge s^{B2}_{ra} \geq 0.7 \wedge s^P_{ra} \geq 0.5 \wedge 2 \leq X_r \leq 5) \vee \\ & (s^F_{ra} \geq 0.9 \wedge s^{B2}_{ra} \geq 0.7 \wedge s^P_{ra} = 1 \wedge X_r \geq 6)\}\end{aligned}$$

where X_a is the number of product modules in RMS of each firm-brand pair.

Level of aggregation – Using the matching algorithm, we produce a dataset at the level of product module × firm × brand (referred to as *agg1*) after merging advertising into the RMS. When an observation from RMS is matched with multiple ADI observations, we aggregate the advertising variables from all sources. In the case a single ADI merges into multiple RMS observations, we attribute to all RMS observations the same advertising variables. As discussed above, brand variables in the RMS and ADI are not always defined at the same level. Therefore, we also explore using two other distinct levels of aggregation that ensure a smaller number of many-to-many. First, after applying the baseline matching, we created the dataset with retail and advertising at the product *group* × firm × brand level (referred to as *agg2*). Second, we created a dataset using a iterative procedure that aggregates the units of observation such that ensures a one-to-one matching. We use these two alternative aggregations of the baseline dataset in several robustness exercises (referred to as *agg3*).

Statistics of match – Table B1 provides statistics on the baseline matched dataset. Our baseline algorithm produces a many-to-many match that has 94,364 total pairs, with 15,742 distinct RMS observations and 11,471 distinct ADI observations. This indicates that there are on average six ADI observations per RMS observation matched, and eight RMS observations per ADI observation. To a large extent the many-to-many is a desirable feature because of the differences of aggregation across the two datasets, and the fact that often the ads do not target a specific brand or specific product module. However, a large number of many-to-many matches can also result in a dataset that does not produce a close link between retail and advertising information. Both alternative matching algorithms *match 2* and *match 3* produce many more matches and with relatively smaller increase in the total unique observations matched on the ADI.

We perform validation exercises to evaluate the robustness and quality of our match. We use three types of validation exercise: i) we evaluate manually the impact of each step of the algorithm (described above); ii) an external validation using a sample dataset matching RMS and ADI; iii) use statistics on cohorts and exit time for sales and advertising.

External Validation – For a random sample of 0.5% RMS observations, we manually find the best matched ADI observation. To ensure an independent selection of the best match, we assigned this task to independent readers who did not know any details of our algorithm. The external manual match found a match for less than 1/3 of the observations and the remaining were considered not matched. This manually checked data sample serves as our benchmark reference.

We start by comparing the comparing the many-to-many feature of our algorithm. Table B2 lists the matching pair distribution for the three criteria and compares it to the manually checked data. Among them, the *baseline match*, *match 2*, and *match 3* represent different selection rules (from most strict to least strict) with respect to firm name, brand description and the product category. The manual procedure generates more than half unique matches, while our baseline algorithm produces about 40% of unique matches, comparing with about 35% by *match 2* and 30% by *match 3*. As expected, allowing for lower thresholds of similarity scores of our inputs may increase the cases of many-to-many and may reduce the precision of the match.

Next, assuming that the manual matching produces the true match, we evaluate the per-

Table B1: Match Statistics

	All	Baseline Match	Alternative Match 2	Match 3
RMS				
Unique codes	147,665	15,742	17,998	29,418
Observations r	147,665	15,742	17,998	29,418
Product Modules	603	580	583	596
Firm name	23,784	1,935	5,530	8,849
Brand Description	62,820	7,409	2,486	3,868
ADI				
Unique codes	20,124	11,471	12,203	13,793
Observations a	13,039	6,436	6,948	8,091
Product Categories	271	259	261	264
Parent Advertiser	5,070	1,722	1,842	2,186
Subsidiary Advertiser	5,562	2,009	2,139	2,518
Brand Description	10,138	4,631	5,022	5,921
Pairs Matched		94,364	138,101	560,312
average obs/unique RMS		6	8	19
average obs/unique ADI		8	11	41

Note: The table reports the number of distinct observations for each dataset and input of our algorithm in column "All". Column "Baseline Match" shows the statistics of the baseline match algorithm, and columns "Alternative" shows the statistics for the alternative algorithms.

formance of our algorithm by categorizing each matched pair by the algorithms relative to the manual into five mutually exclusive cases. Starting with RMS observations that the algorithms matched, we can have the following cases:

- *True-positive* – The RMS-ADI matching pair in the algorithm is identical to the manual pairs;

- *False-positive absolute* – The RMS-ADI matching pair from the algorithm is different from the manually checked data sample. The absolute means that the RMS should have been matched (it was matched in the manual) but the matched ADI observations are different;

- *False-positive redundant*: The RMS-ADI matching pair from the algorithm is different from the manually checked data sample. The redundant means that because of many-to-many matching issues, we have multiple matching pairs for the same RMS, and some are correct and some do not coincide with manually matching.

A natural outcome of our algorithm is that many firms that have sales do not advertise. In the cases our algorithm did not produce any match, we can have the following cases:

- *True-negative* – The RMS observation has not matched to any ADI observation, coinciding with the manual sample also does not have any matching observations.

- *False-negative* – The RMS observation has not matched to any ADI but the manual sample assigns ADI observations.

The main validation test results are summarized in Table B3. Regarding the three different selection criteria, the baseline match has the lowest true-positive matches while *match 3* has the highest true-positive matches. This is not surprising because the number of unique RMS

Table B2: Distribution of Number of ADI Observations per RMS Observations

Number	Baseline Match	Alternative Match 2	Alternative Match 3	Manual
1	6,225	6,601	9,013	108
2	2,173	2,297	2,849	25
3-5	3,016	3,389	5,014	35
6-10	1,860	2,150	3,714	18
11-20	1,489	1,897	2,783	1
21-50	811	1,298	2,827	2
+50	168	366	3,218	-
Total	15,742	17,998	29,418	189

Notes: The table reports the distribution of the number of ADI observations per RMS observation. For example, there are 2,173 unique RMS observations that match to two ADI observations, generating 4,346 matched pairs.

Table B3: Validation Results for Different Matching Criterion

	Matched						Not matched			
	True		False-absolute		False-redundant		true		False	
	pairs	*unique*	*pairs*	*unique*	*pairs*	*unique*	*pairs*	*unique*	*pairs*	*unique*
Baseline	288	99	45	10	43	2	383	383	77	77
Match 2	317	105	42	11	61	4	379	379	70	70
Match 3	398	142	276	6	97	2	362	362	38	38

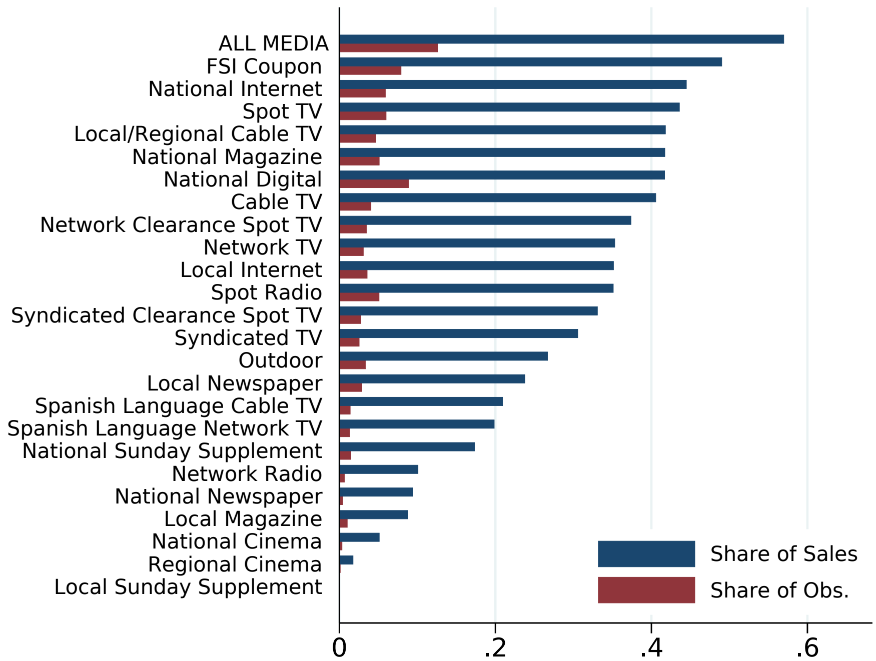
Notes: The table reports the distribution of matches of the baseline and alternative matches when comparing the with the manual match. Each pair is classified according to 5 possible cases. The *pairs* represent the number of (r,a) combinations that are included for each case. The *unique* represent the number of RMS observations underlying the pairs.

observations matched in *match 3* is double that in the baseline match (see Table B1). But more true-positive matches comes with the cost of more false positive observations: 45 absolute false-positive matches in the baseline match versus 276 in *match 3*, and 43 redundant false-positive matches in the baseline versus 97 in *match 3*. Moreover, when evaluating with the negative matching outcomes, the baseline match outperforms *match 3* with 383 versus 362 true-negative matching results.

Our conclusion from this exercise is that the baseline match performs best. While, each selection criterion has its own advantages, our goal is to minimize false positives. A doubtful match with many-to-many will reduce the precision of our results.

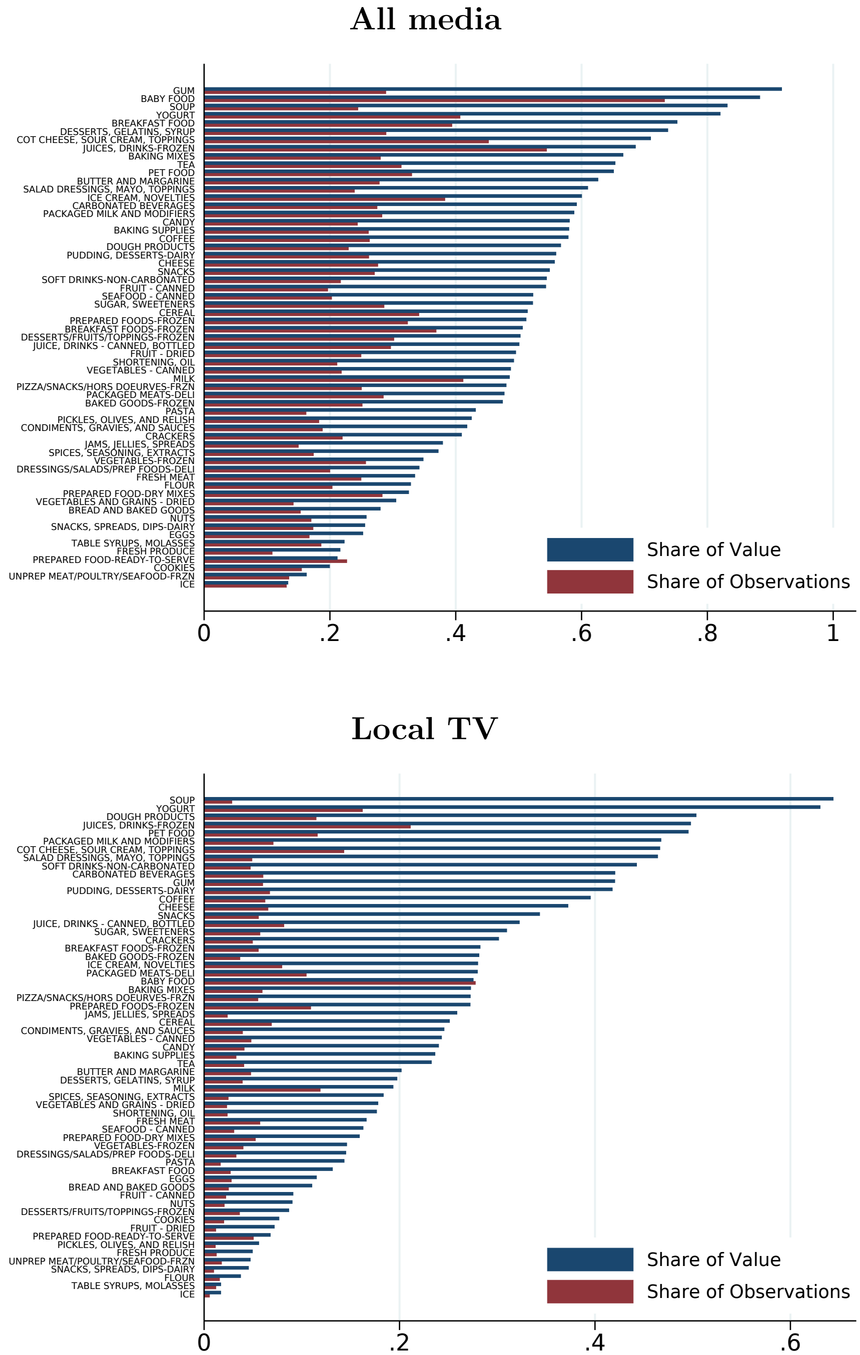
B.1 Summary statistics on Matched Retail and Advertising Dataset

Figure B1: Share with Some Advertising by Media



Note: The figure presents the share of RMS observations/sales that used advertising in any year between 2010–2017 by media type. "ALL MEDIA" refers to share at any medium across the distinct media types. Local TV includes Spot TV, Network Clearance Spot TV, Syndicated Clearance Spot TV, Local/Regional Cable TV. Sales are measured as total sales in period 2010-2017.

Figure B2: Share with Some Advertising by Product Group - All Media



Note: The figure presents the share of RMS observations/sales that used advertising in any year between 2010–2017 by media type. “ALL MEDIA” refers to share at any medium across the distinct media types. Local TV includes Spot TV, Network Clearance Spot TV, Syndicated Clearance Spot TV, Local/Regional Cable TV. Sales are measured as total sales in period 2010-2017.

C Conceptual Framework

Firm i produces a differentiated variety of product module p which it may sell in J segmented monopolistically competitive markets indexed by m. Let $J_t^{ip} \subseteq J$ be the set of markets where the firm sells at date t. Marginal cost is given by:

$$C_t^{ip} = c\left(\omega_t^{ip}, Q_t^{ip}\right) \tag{C7}$$

where ω_t^{ip} is firm i's productivity, while Q_t^{ip} is the sum of quantity sold in all markets:

$$Q_t^{ip} = \sum_{m \in J_t^{ip}} Q_t^{ipm} \tag{C8}$$

The firm faces demand in market m at time t given by:

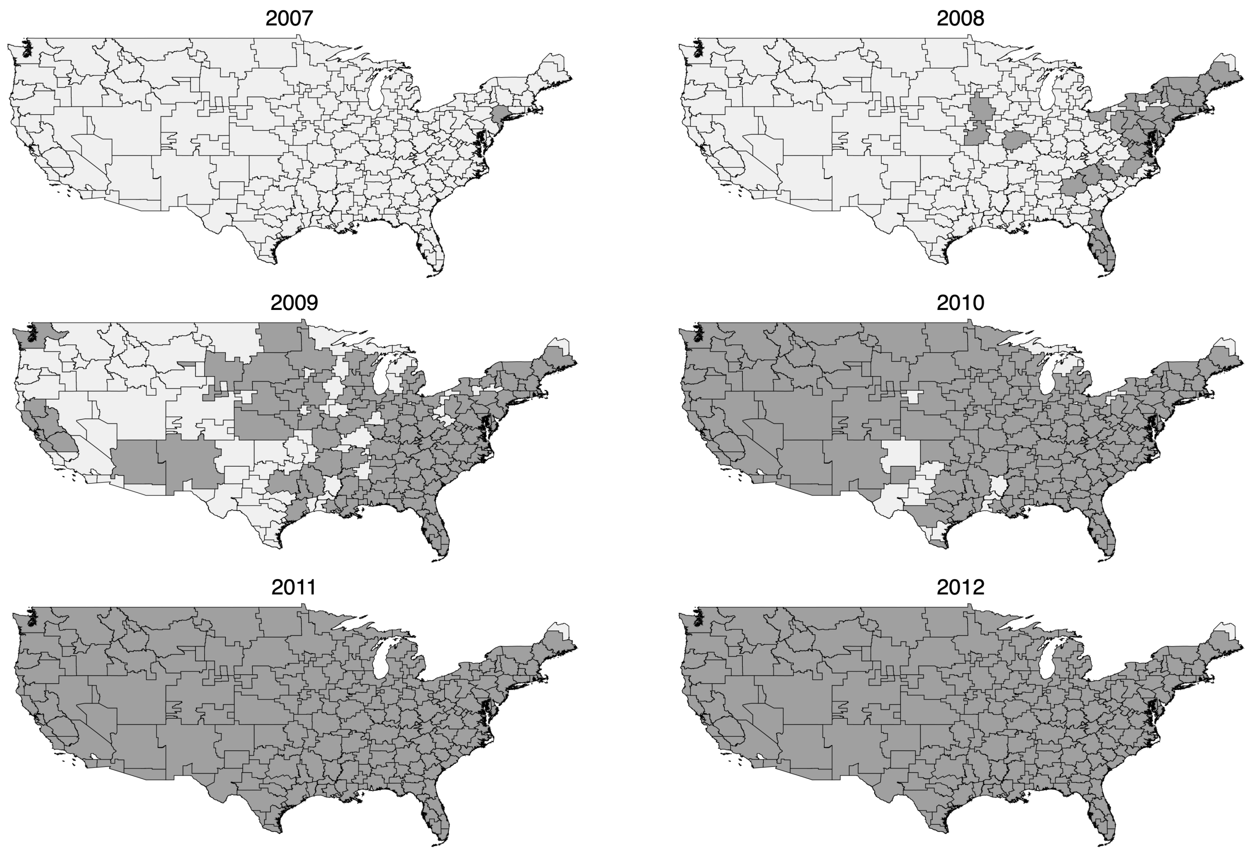
$$Q_t^{ipm} = \left(P_t^{ipm}\right)^{\theta} Y_t^{pm} \chi_t^{ip} \times \Phi\left(D_t^{ipm}\right) \times \varepsilon_t^{ipm} \tag{C9}$$

P_t^{ipm} is the price the firm charges in market m. By definition, price is a markup over marginal cost, $P_t^{ipm} = \mu_t^{ipm} C_t^{ip}$. Because markets are segmented, price discrimination is possible. Y_t^{pm} captures the size of market m for product p, and the impact of competitors' prices, identical for all participants under monopolistic competition. χ_t^{ip} captures factors such as product quality and consumer tastes which are idiosyncratic to firm i, and shift demand equally in all markets. D_t^{ipm} is market-specific customer capital, which shifts demand conditional on prices in market m only. It may be accumulated (i.e. need not depreciate fully from one period to the next), and may be subject to decreasing returns ($\Phi'(\cdot) > 0$,$\Phi''(\cdot) < 0$). ε_t^{ipm} is idiosyncratic demand.

D Additional Results

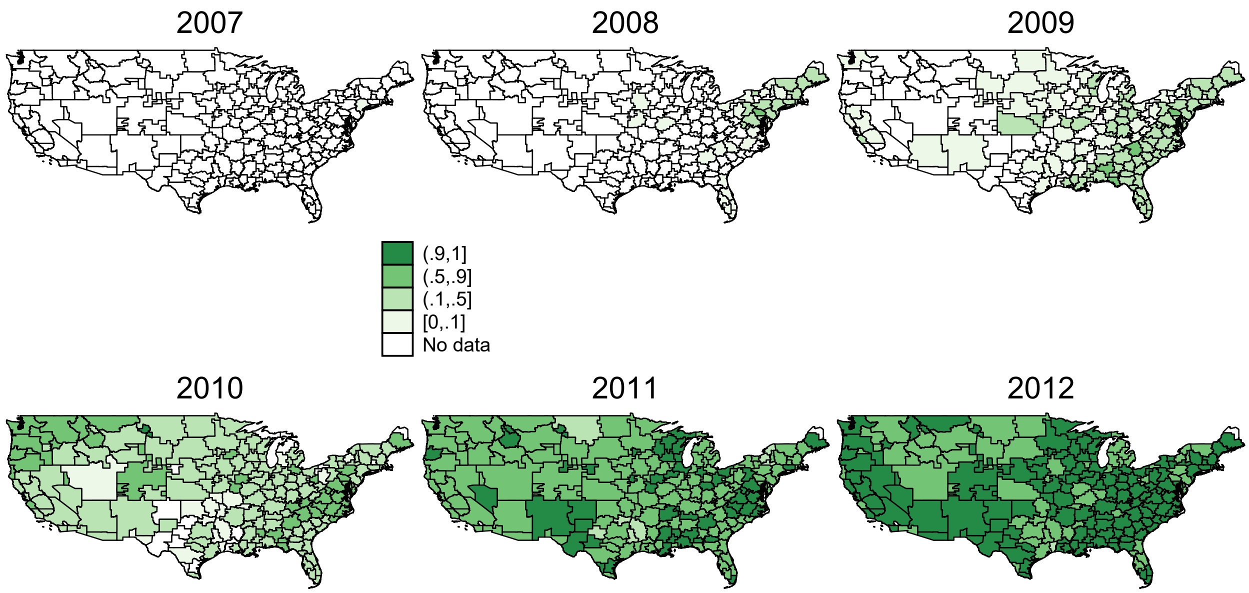
D.1 Geographical Expansion

Figure D1: Example Geographic Expansion - Large Yogurt Brand



Notes: The figure shows the entry across markets of one of the largest yogurt firms in the US. The darker regions depict the DMAs where the firm had positive sales in the relevant year.

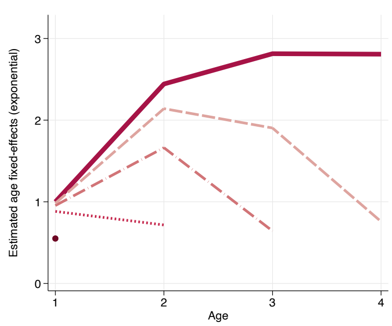
Figure D2: Example Store Expansion - Large Yogurt Brand



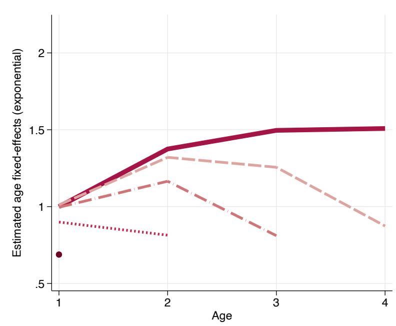
Notes: The figure shows the total number of stores that sell the products of one of the largest yogurt firms in the US as a fraction of the total number of stores that sell yogurt in each DMA-year. The darker regions depict the DMAs that have a higher store-level penetration ratio.

D.2 Stores and Sales per Store

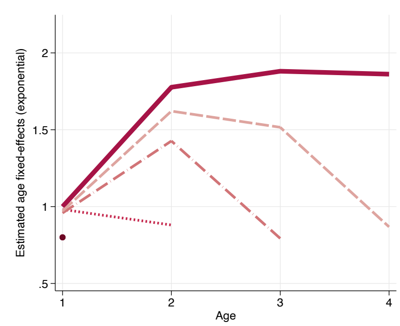
Figure D3: Life Cycle of Stores



(a) Sales (RMS, Market)



(b) # Stores

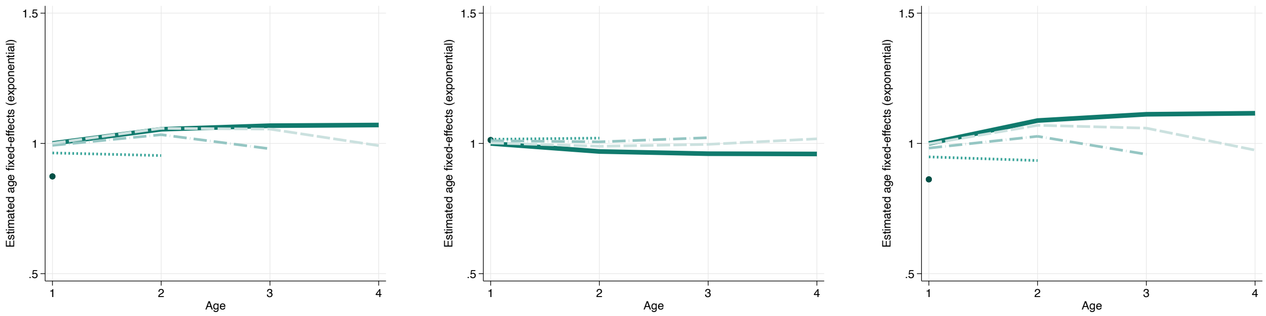


(c) Sales per Store

Notes: Panels (a)-(c) use RMS 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 stores, and log sales per store in turn as dependent variables, and for firm-markets surviving 1, 2, 3, 4 and 5+ years.

D.3 Consumers: Controlling for The Number of Stores

Figure D4: Life Cycle of Sales and Customers: Number of Stores Control



(a) Sales (HMS) (b) Customers (c) Sales per Customer

Notes: Panel (a)-(c) 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 of firm-market sales, log number of customers, and log sales per customer as the dependent variables using the Nielsen Consumer Panel. Each specification controls in addition for for the log number of stores within the DMA where any customer purchased from the relevant firm in the relevant year.

D.4 Price Actions

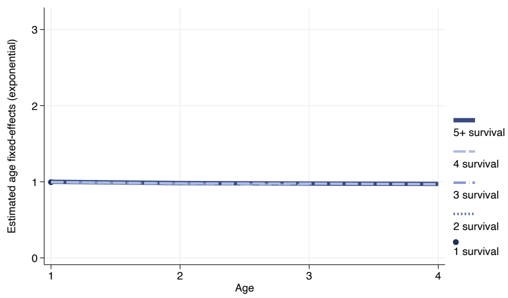
Table D1: Dynamics of Revenue, Price, and Quantity

Dependent Variable (Logs)	Revenue	Price	Quantity
Spell Length		Spell Intercept	
2 years	0.631***	0.0464***	0.585***
	(0.00456)	(0.000758)	(0.00458)
3 years	0.741***	0.0537***	0.687***
	(0.00510)	(0.000823)	(0.00513)
4 years	0.780***	0.0536***	0.727***
	(0.00575)	(0.000903)	(0.00579)
5+ years	0.798***	0.0492***	0.749***
	(0.00502)	(0.000813)	(0.00504)
Right cens.	1.060***	0.0379***	1.022***
	(0.00462)	(0.000761)	(0.00463)
Left cens.	2.539***	0.0313***	2.508***
	(0.00441)	(0.000743)	(0.00441)
Market Age		2-year Spells	
2 years	-0.187***	-0.0697***	-0.118***
	(0.00442)	(0.000719)	(0.00445)
Market Age		3-year Spells	
2 years	0.568***	-0.0247***	0.593***
	(0.00445)	(0.000676)	(0.00450)
3 years	-0.342***	-0.0757***	-0.266***
	(0.00544)	(0.000840)	(0.00546)
Market Age		4-year Spells	
2 years	0.783***	-0.0153***	0.798***
	(0.00541)	(0.000793)	(0.00547)
3 years	0.694***	-0.0200***	0.714***
	(0.00573)	(0.000843)	(0.00579)
4 years	-0.198***	-0.0734***	-0.124***
	(0.00681)	(0.00104)	(0.00683)
Market Age		5-year Spells	
2 years	0.901***	-0.0113***	0.913***
	(0.00356)	(0.000508)	(0.00360)
3 years	1.062***	-0.00984***	1.072***
	(0.00372)	(0.000534)	(0.00377)
4 years	1.084***	-0.0103***	1.094***
	(0.00381)	(0.000549)	(0.00385)
5 years	1.066***	-0.0167***	1.082***
	(0.00350)	(0.000502)	(0.00354)
Prod-brand-year	Yes	Yes	Yes
Prod-mkt-year	Yes	Yes	Yes
Observations	23,951,656	23,951,656	23,951,656
R-squared	0.762	0.967	0.803

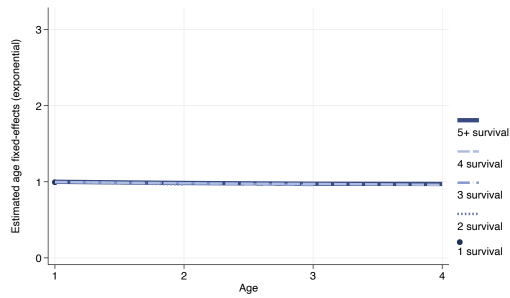
Notes: The omitted category is market age equal to one year. *** significant at 1%.

D.5 Quantity and Price Dynamics Within Markets

Figure D5: Wholesale Price Dynamics - PromoData



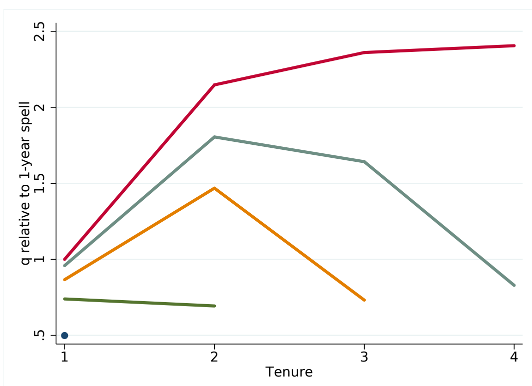
(a) Price



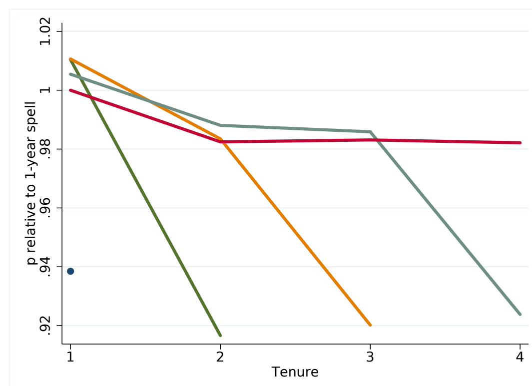
(b) Price (Including Deals)

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation (2) for wholesale prices using the PromoData.

Figure D6: Quantity and Price Dynamics - Controlling for Distance to Closest Plant



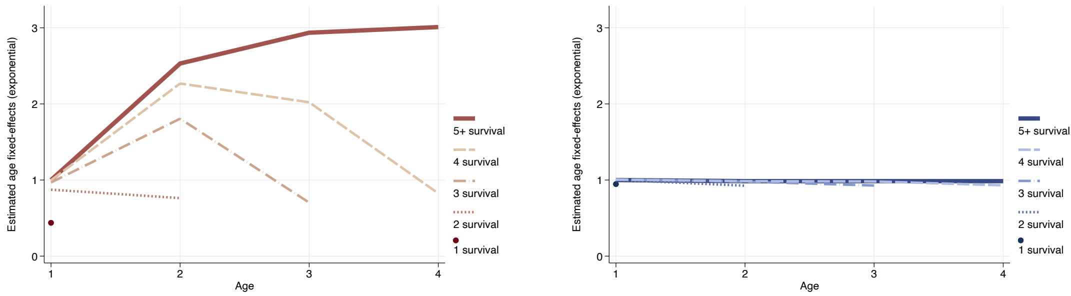
(a) Quantity



(b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation (2) on data aggregated at the firm-product level. The estimation controls for the distance from the relevant store to the closest plant for that firm.

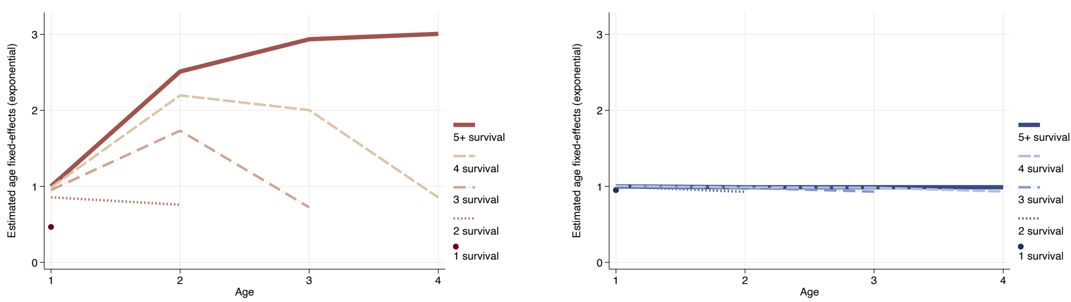
Figure D7: Quantity and Price Dynamics Within Markets - Firms



(a) Quantity (b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2 on data aggregated at the firm level.

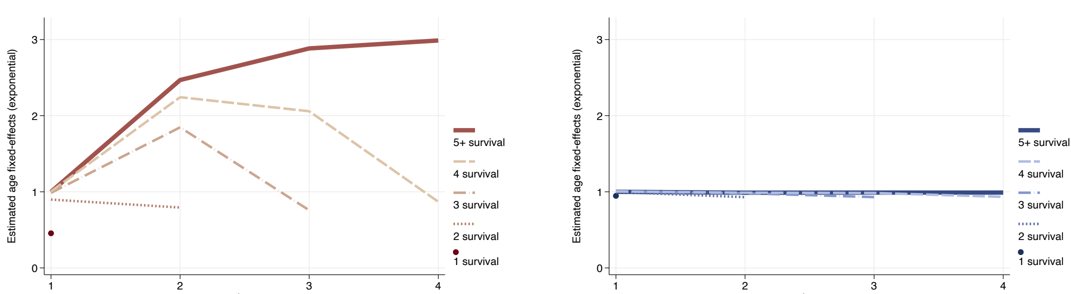
Figure D8: Quantity and Price Dynamics Within Markets - Broad Brands



(a) Quantity (b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2 on data aggregated using a definition of brands where we combine brands with similar names.

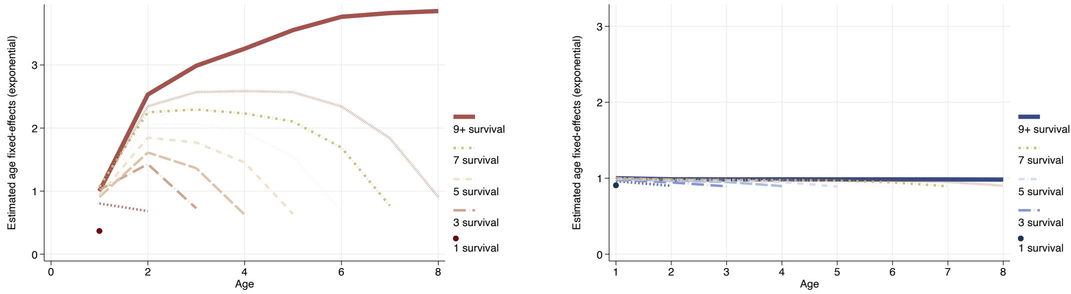
Figure D9: Quantity and Price Dynamics Within Markets - Only Original Brands



(a) Quantity (b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2 on data using only the brands each firm had at entry.

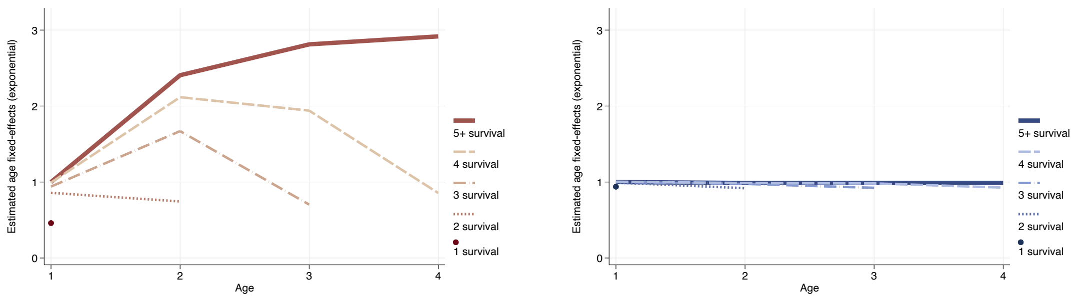
Figure D10: Quantity and Price Dynamics Within Markets - Quarterly



(a) Quantity (b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2 on data aggregated at the quarterly level.

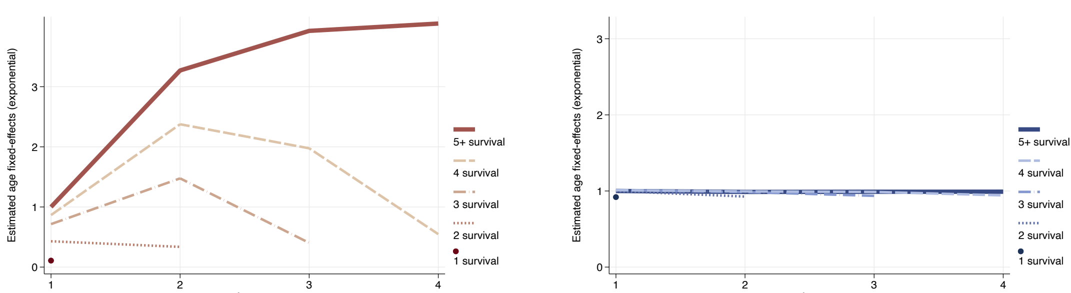
Figure D11: Quantity and Price Dynamics Within Markets - Balanced Stores



(a) Quantity (b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2 on data balanced at the store level.

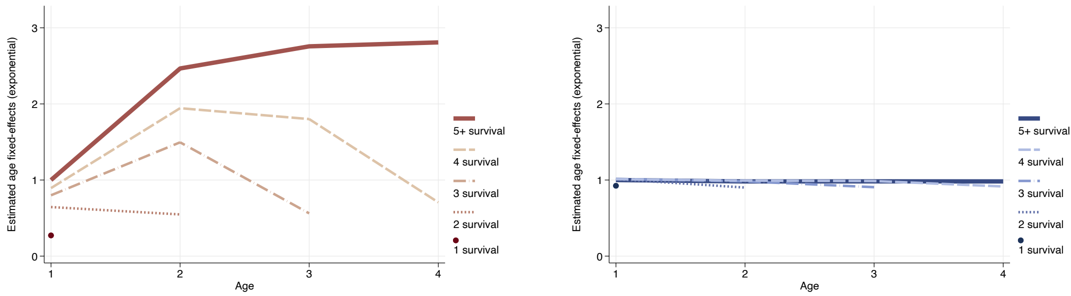
Figure D12: Quantity and Price Dynamics Within Markets - Chains



(a) Quantity (b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2 defining chains instead of DMAs as markets.

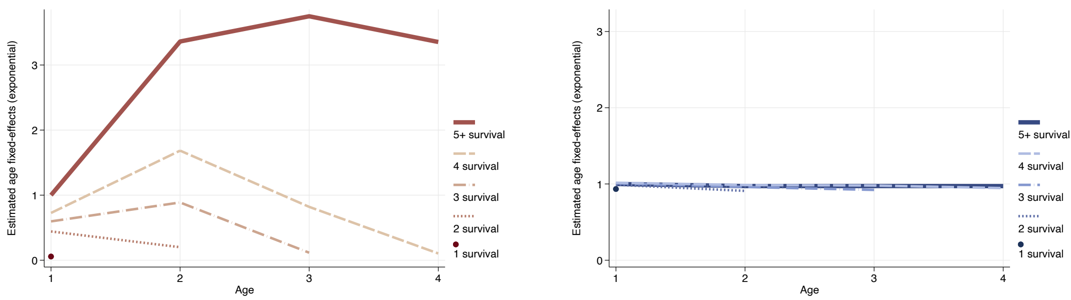
Figure D13: Quantity and Price Dynamics Within Markets - Chain × DMA



(a) Quantity (b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2 defining chain-DMA instead of DMAs as markets.

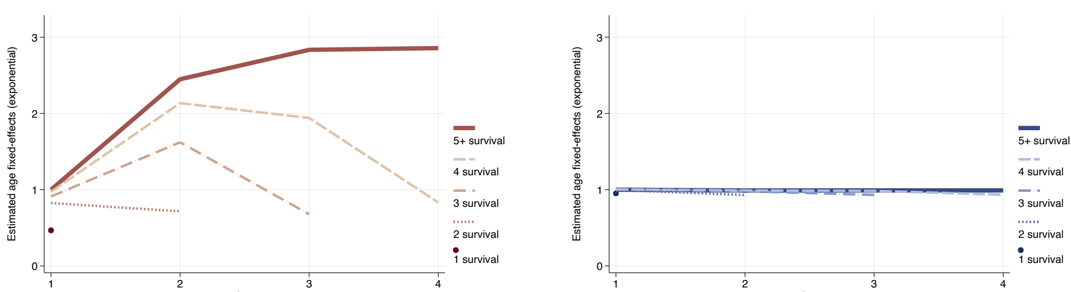
Figure D14: Quantity and Price Dynamics Within Markets - National



(a) Quantity (b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2 defining market at the national level, but with firm-brand-product and product-market instead of firm-brand-product-year and product-market-year fixed effects.

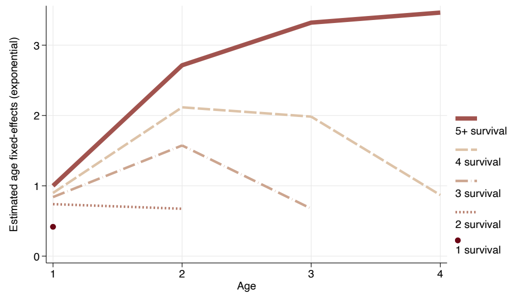
Figure D15: Quantity and Price Dynamics Within Markets - Cohort Control



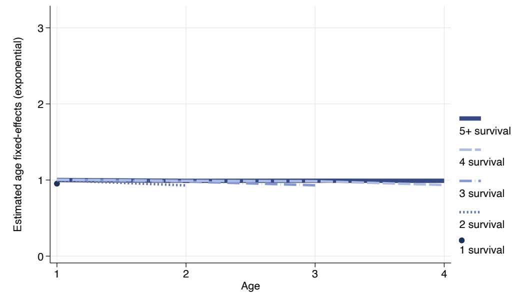
(a) Quantity (b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2 controlling for cohort effects.

Figure D16: Quantity and Price Dynamics Within Markets - Only New Firms



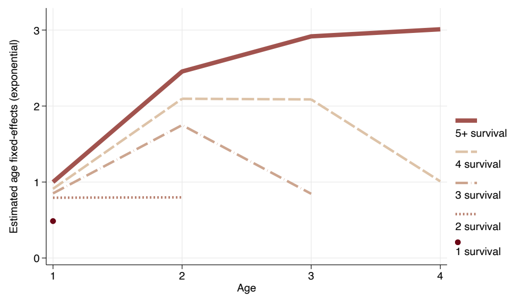
(a) Quantity



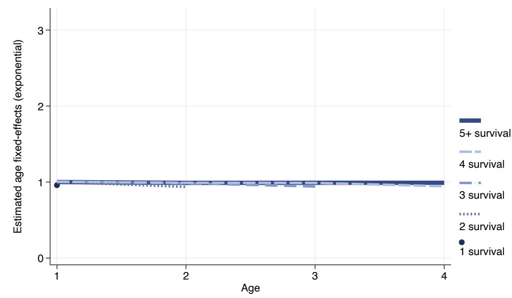
(b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2, where we include only firms that entered the sector during our sample period.

Figure D17: Quantity and Price Dynamics Within Markets - Before 2015



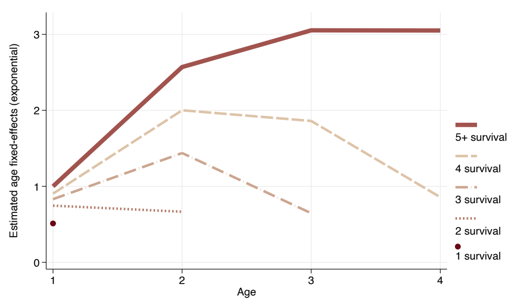
(a) Quantity



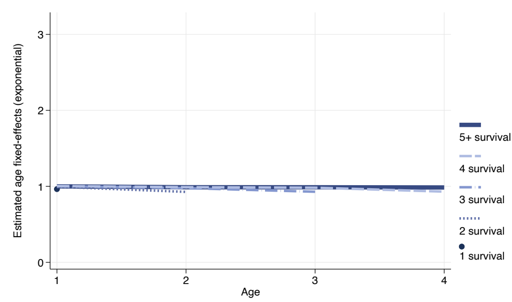
(b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2, where we consider only periods before 2015.

Figure D18: Quantity and Price Dynamics Within Markets - Only New Brands



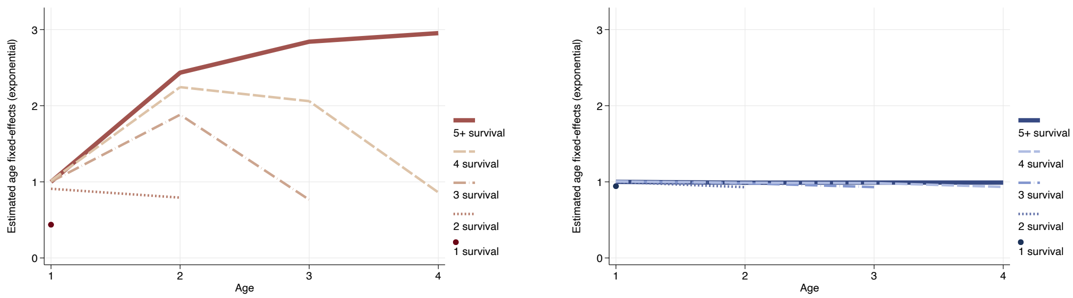
(a) Quantity



(b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2, where we include only firm-brands that entered the sector during our sample period.

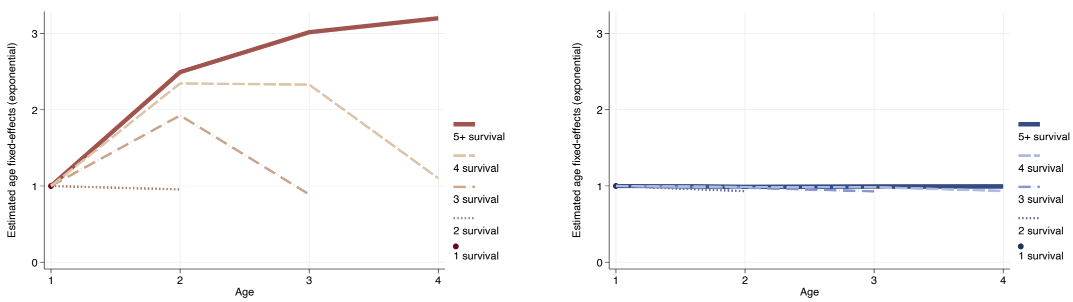
Figure D19: Quantity and Price Dynamics Within Markets - Only Incumbent Brands



(a) Quantity (b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2, where we include only incumbent firm-brands, those in the data at the beginning of our sample period.

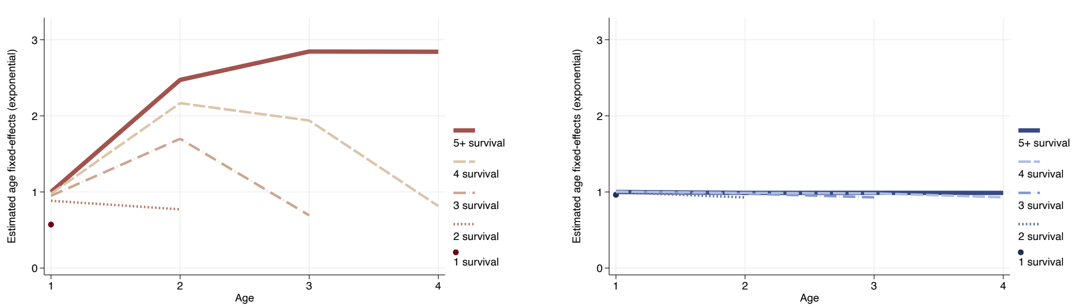
Figure D20: Quantity and Price Dynamics Within Markets - Spell Control



(a) Quantity (b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2, controlling for firm-brand-product-market-spell effects in addition to the benchmark controls.

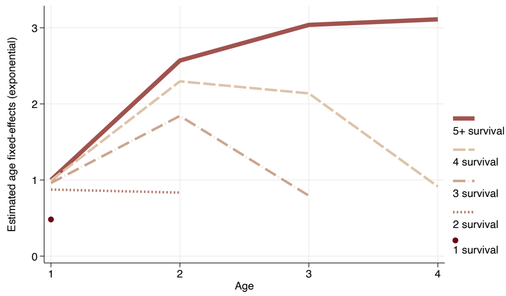
Figure D21: Quantity and Price Dynamics Within Markets - First Spell



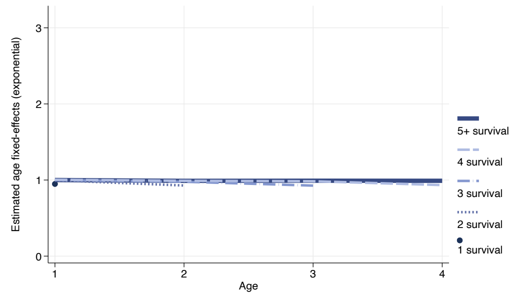
(a) Quantity (b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2, where we include only the first spell of each firm-brand-product-market.

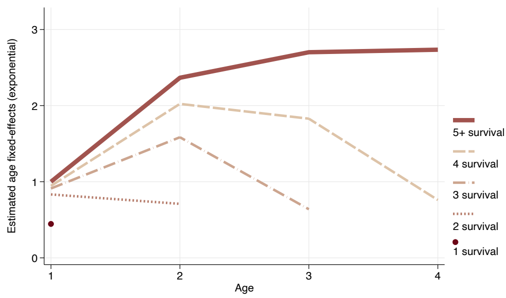
Figure D22: Quantity and Price Dynamics Within Markets - Consumer Inertia



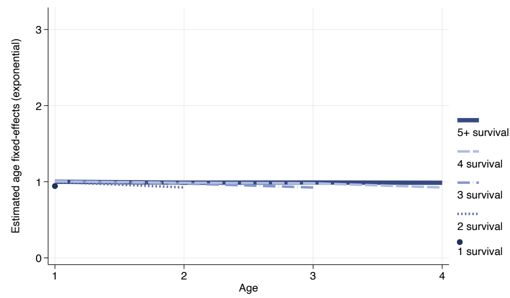
(a) Quantity - High-inertia



(b) Price - High-inertia



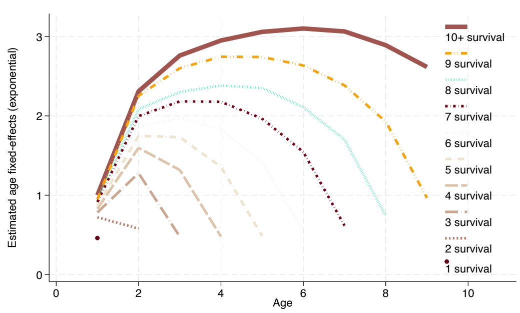
(a) Quantity - Low-inertia



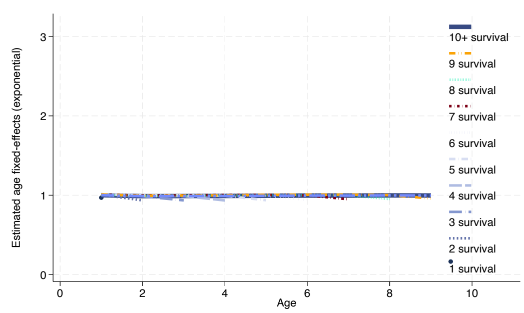
(b) Price - Low-inertia

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2, dividing consumer food products according to their degree of consumer inertia. We approximate the consumer inertia of each module in consumer food by using the Nielsen Household Consumer Panel Data, and dividing them by those more likely to be consumed by younger households (i.e. between 20-34 years of age) following Bornstein (2021). We classify products as "High-inertia" if their consumer inertia is in the top tercile of the distribution. "Low-inertia" refers to products with consumer inertia below the top tercile.

Figure D23: Quantity and Price Dynamics Within Markets - Long Horizon



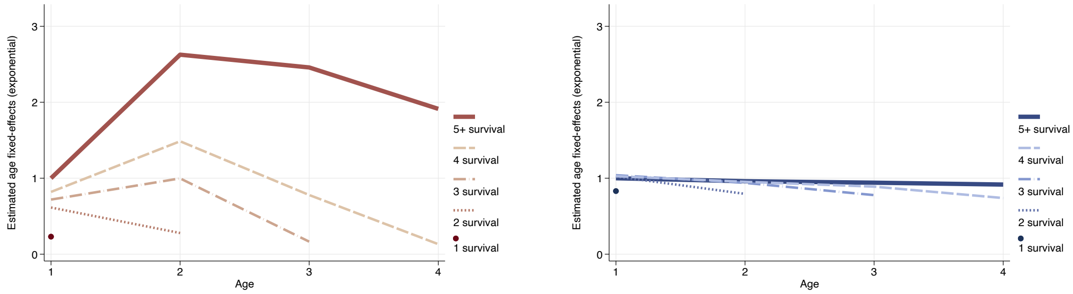
(a) Quantity



(b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2 for products lasting 10 years or more.

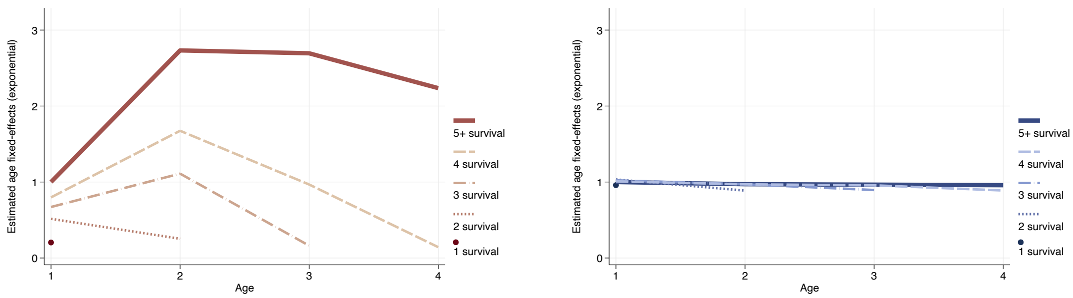
Figure D24: Quantity and Price Dynamics Within Markets - All Categories



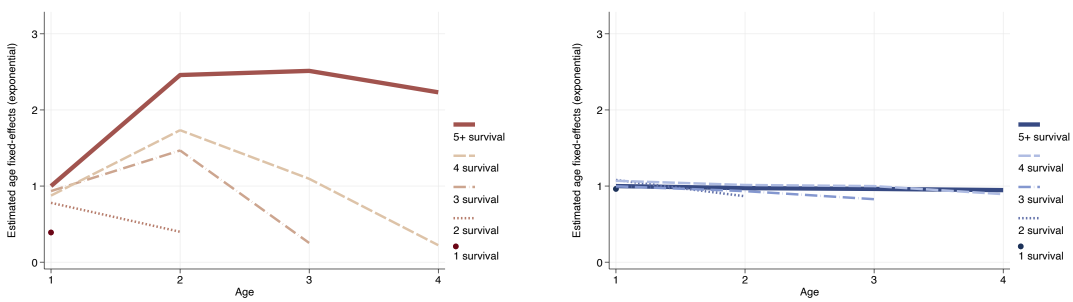
(a) Quantity (b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2 including all categories available in the Nielsen RMS.

Figure D25: Quantity and Price Dynamics Within Markets - Durability



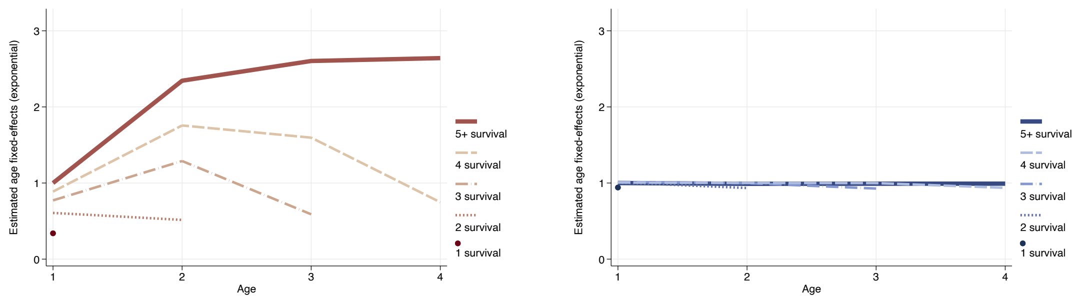
(a) Quantity - Non-durable (b) Price - Non-durable



(a) Quantity - Durable (b) Price - Durable

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2, dividing products according to their durability. This uses all categories available in the Nielsen RMS. We approximate the durability of each module by using the Nielsen Household Consumer Panel Data to count the average number of shopping trips made by households. We classify products as "Non-durable" if their durability is in the top tercile of the distribution of number of shopping trips. "Durable" refers to products with durability below the top tercile.

Figure D26: Quantity and Price Dynamics Within Markets - IRI Data



(a) Quantity (b) Price

Notes: Based on exponentiating appropriate sums of coefficients after estimating equation 2 using the IRI Symphony Data.

D.6 Clearance Sales

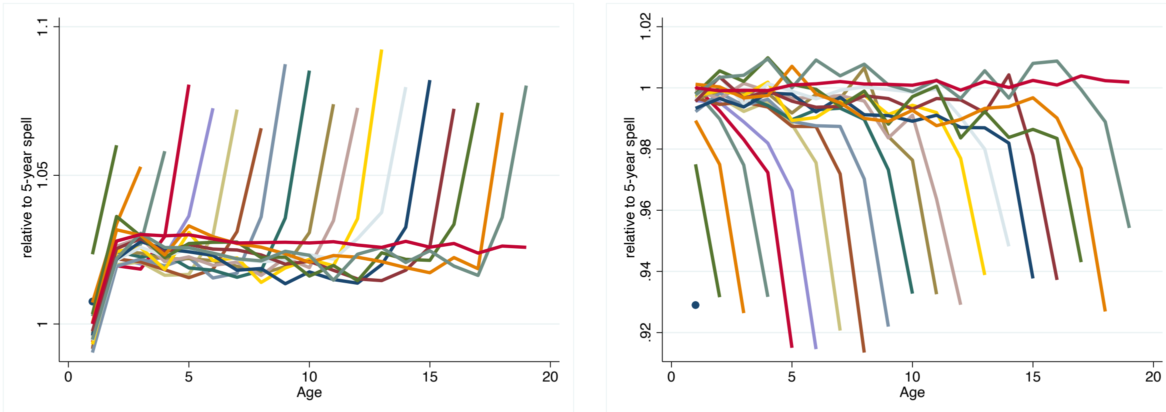
In this subsection we explore whether the decrease in price at the end of the life cycle of brands is due to clearance sales. This type of sales occur when retailers offer extra discounts on items about to permanently disappear from the shelves. The IRI-Symphony data include sales flags to detect temporary discounts.

Previous studies have use this flag to determine the prevalence of clearance sales. For instance, Gagnon et al. (2015) report that, on average, the price of an exiting item is over 8 percent lower than the price that prevailed a quarter before the item's exit (that is, 14 to 26 weeks earlier), with a majority of product categories having a price drop of over 10 percent. In fact, the probability that an item is on sale in its final week in the sample is higher, at 30.5 percent, than for the typical item in the sample, at 23.4 percent, contributing to lower average prices at exit.[21]

These patterns can also be seen in Figure D27, where we implement the specification in equation (2) using as dependent variables both the frequency of sales and the size of sales. Frequency of sales is measured as the fraction of barcode-stores where the item was marked as being on sale within a brand-market in a quarter. Size of sales is measured as, conditional on being on sale, the percent deviation from the previous price. Panel (a) shows that the frequency of sales increases drastically the last quarter the brand is sold. Panel (b) shows that the size of sales also increases indicating that the reductions in prices at exit are larger than sales that take place at other stages of the life cycle. Both panels indicate the prevalence of clearance sales in the consumer goods sector.

[21] Argente and Yeh (2022) document that there is an increase in the frequency of sales and size of sales during the last weeks of the life cycle of a barcode.

Figure D27: Clearance Sales

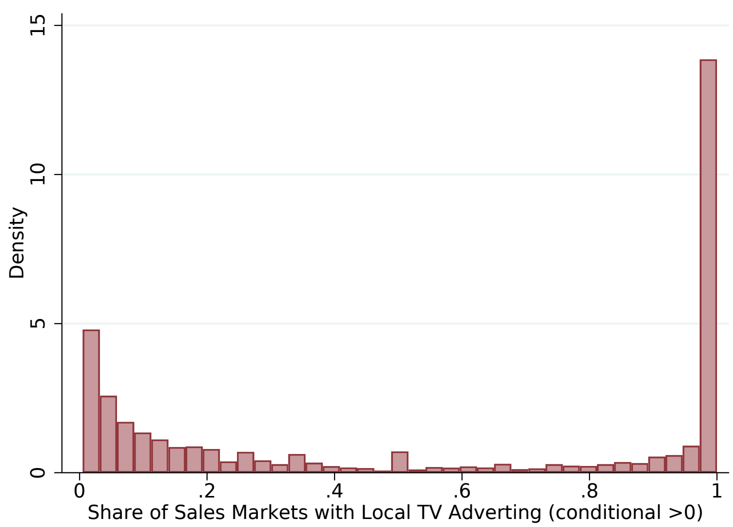


(a) Frequency of Sales (b) Size of Sales

Note: Panel (a) shows the life cycle patterns of the frequency of sales estimated using equation 2. Frequency of sales is based on an indicator at the barcode-store level, which equals to one if the item is on sale, aggregated at the brand-market level. Panel (b) shows the life cycle patterns of the size of sales calculated as the average percent deviation from the price before the sale takes place. The data source is the IRI Symphony data.

D.7 Additional Summary Statistics on Matched RMS-ADI Data

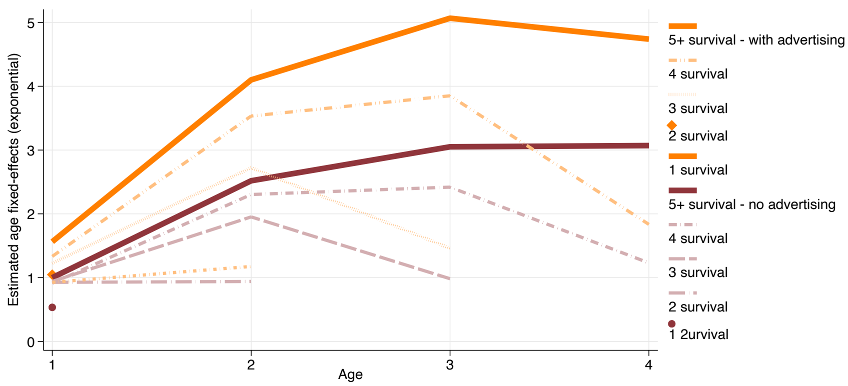
Figure D28: Histogram of Share of Markets - Local TV



Notes: The figure shows the share of sales in markets with local TV, conditional on positive sales.

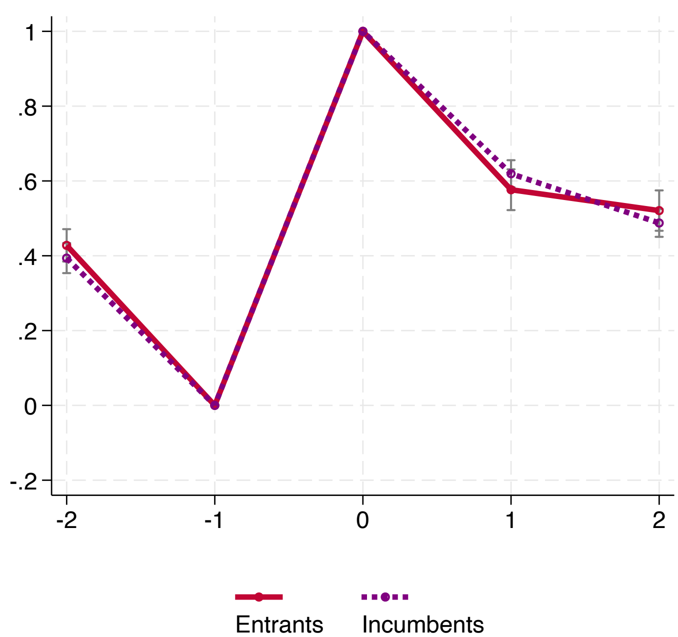
D.8 Relationship Between Advertising and Sales

Figure D29: Life Cycle of Sales: Advertising vs No Advertising



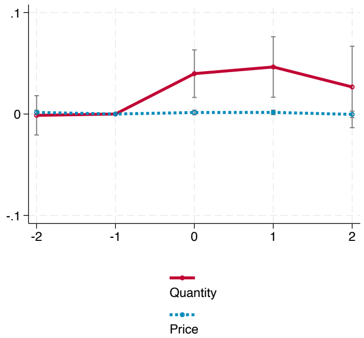
Notes: The figure plots the exponents of the vector of coefficients β estimated in an equation similar to 2 against firm-market age, for firm-markets surviving 1, 2, 3, 4 and 5+ years , with log sales as the dependent variable. In the underlying regression, the trajectories are allowed to differ for firms that advertise in the ADI data set and those that do not record an observation with advertising. This is implemented by interacting the trajectories with an indicator for ever advertising. The omitted category is the first year of a 5+-year spell for firms that never advertise, so sales are normalized to 1 for these observations.

Figure D30: Persistence of Advertising

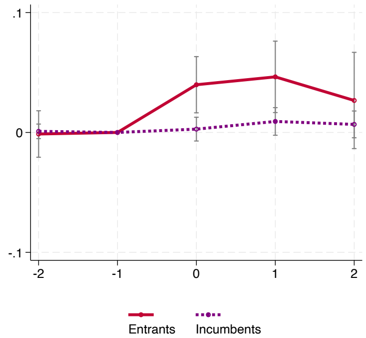


Notes: The figure shows the persistence of advertising by plotting the impulse-response to an indicator for advertising, estimated using equation (4), and using as dependent variable an indicator for advertising. The equation is estimated separately for entrants and incumbents.

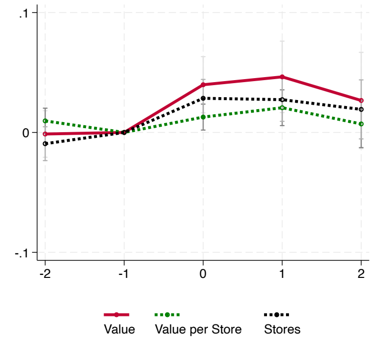
Figure D31: Non-price Actions: Advertising - Number of Ads and Impressions



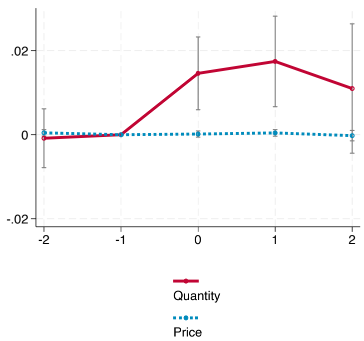
(a) Ads: Quantity & Price



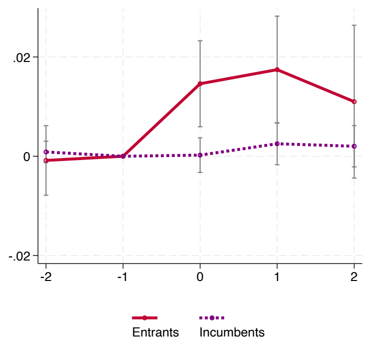
(b) Ads: Entrants



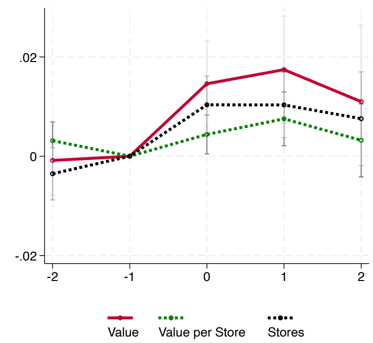
(c) Ads: Stores



(d) Imp: Quantity & Price



(e) Imp: Entrants



(f) Imp: Stores

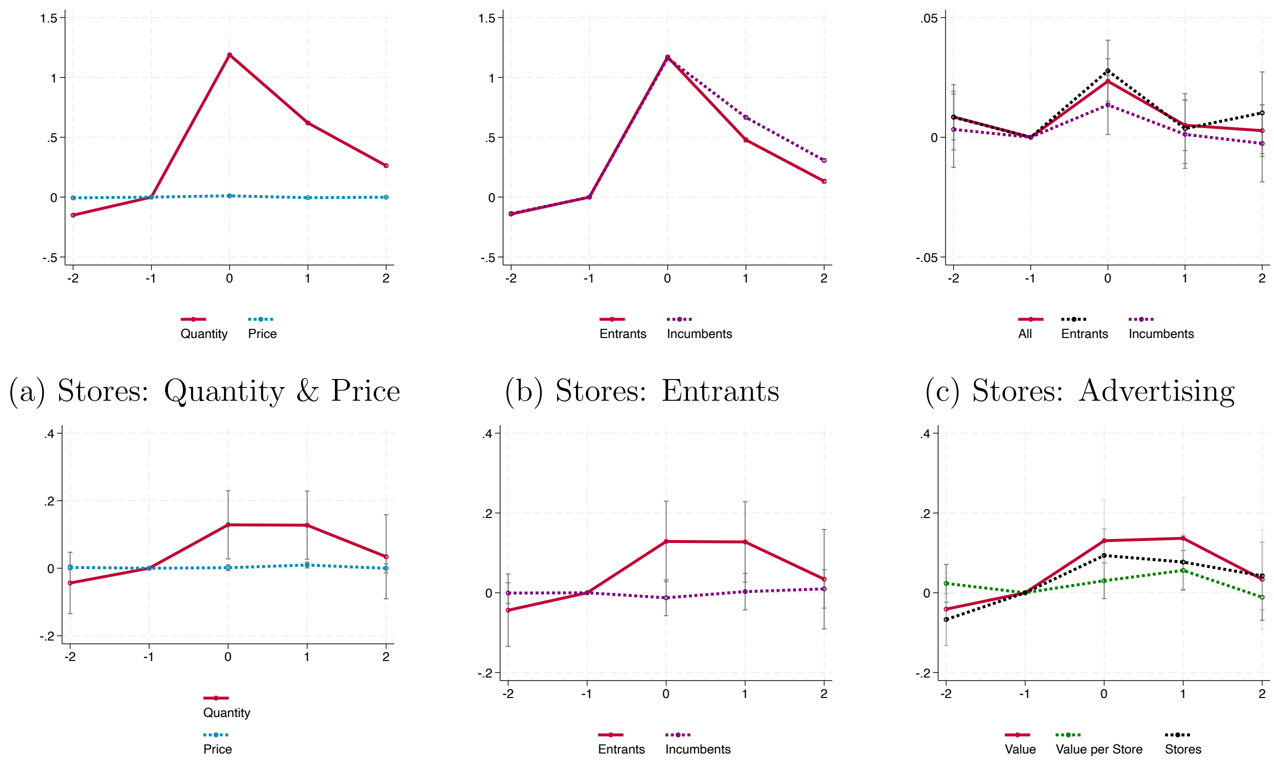
Notes: Panels (a)-(c) show impulse responses to number of advertisement occurrences estimated using equation (4). Panels (d)-(e) show impulse responses to the total viewership/impressions. The dependent variables in Panel (a) and (d) are quantity and price, and the sample is restricted to entrants. The dependent variable in Panels (b) and (e) is quantity and the equation is estimated separately for entrants and incumbents. The dependent variables in Panels (c) and (f) are sales, number of stores, and sales per store, and the sample is restricted to entrants. All specifications use the inverse hyperbolic sine transformation in the independent variable.

We conduct some robustness exercises of the relationship between quantities, prices, sales, store placement and advertising. As in the paper, we do so by estimating impulse-responses using local projections as in Jordà (2005). Our alternative estimating equation is:

$$\Delta w^{ipm}_{t+s,t-1} = \beta_s \cdot \Delta x^{ipm}_{t,t-1} + \gamma^{ipm}_s + \psi^{pm}_{s,t} + w^{ipm}_{t-1} + \varepsilon^{ipm}_{t,s}, \qquad s = -2, ...2 \tag{D10}$$

where as before $\Delta w^{im}_{t+s,t-1}$ is the change in log quantity (or log price or log sales) 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 $t-1$ or the change in an indicator variable for advertising by firm-brand i selling product p in market m. γ^{ipm}_s is a firm-product-market fixed effect, and $\psi^{pm}_{s,t}$ is a product-market-time fixed effect. Importantly, we include w^{ipm}_{t-1} as a control which is the lag of the dependent variable, consistent

Figure D32: Non-price Actions: Store Placement and Advertising - Lag Augmented



(a) Stores: Quantity & Price

(b) Stores: Entrants

(c) Stores: Advertising

(d) Adv: Quantity & Price

(e) Adv: Entrants

(f) Adv: Stores

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

with the lag-augmented approach proposed by Montiel Olea and Plagborg-Møller (2021).