# How do Entrants Build Market Share? The Role of Demand Frictions


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# Disclaimers

The views expressed here are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

Researcher(s) own analyses calculated (or derived) based in part on (i) retail measurement/consumer data from Nielsen Consumer LLC ("NielsenIQ"); (ii) media data from The Nielsen Company (US), LLC ("Nielsen"); and (iii) marketing databases provided through the respective NielsenIQ and the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ and Nielsen data are those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

# Introduction

- Firms are born small, grow, and die.
  Dunne, Roberts and Samuelson (1989); Hsieh and Klenow (2014)

- Differences in demand are important in explaining variation in firm sales.
  Hottman, Redding and Weinstein (2016); Eslava and Haltiwanger (2019); Argente, Lee and Moreira (2020)

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- Differences in demand can result from frictions in the accumulation of customers.
  - Firms can overcome frictions by making investments to build **intangible customer capital**. Two main theories:
    (i) Non-price actions - marketing and advertising.
    Arkolakis (2010); Drozd and Nosal (2012); Fitzgerald, Haller and Yedid-Levi (2019).
    (ii) Price actions - past sales affect future sales.
    Bils (1989); Nakamura and Steinsson (2011); Gourio and Rudanko (2014).

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3. ONGOING PROJECT: Develop a **dynamic structural** model with investments in customer capital using moments from micro data

# Conceptual framework

# Firm Problem

- **Demand**: Each firm $i$ produces a differentiated product facing a demand at $t$

$$Q_t^i = q\left(P_t^i, \chi_t^i, D_t^i\right)$$

$P_t^i$: price
$\chi_t^i$: appeal - exogenous and non-customer capital endogenous demand-side factors
$D_t^i$: endogenous **customer capital** (subject to adjustments costs $a(D_t^i, A_t^i)$ and depreciation)

$$D_t^i = d\left( D_{t-1}^i \quad , \quad A_t^i \quad , \quad P_{t-1}^i Q_{t-1}^i \right)$$

Two theories: (i) non-price actions (ii) price actions

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- **Technology**: Marginal production cost $C_t^i = c\left(Q_t^i, \zeta_t^i\right)$

$Q_t^i$: quantity
$\zeta_t^i$: productivity - exogenous and endogenous supply-side factors

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$Q_t^i$: quantity

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- Assume monopolistic competition and $\chi_t^i$ and $\zeta_t^i$ are exogenous

# Firm Problem

- Specifications for simplicity: demand and law of motion for customer capital

$$Q_t^i = \chi_t^i \left(P_t^i\right)^{-\theta} \left(D_t^i\right)^{\alpha}$$
$$D_t^i = (1-\delta)D_{t-1}^i + \lambda A_t^i + (1-\lambda)P_{t-1}^i Q_{t-1}^i$$

- The net flow profit function

$$\pi_t^i \left(D_t^i, A_t^i; \chi_t^i, \zeta_t^i\right) = \left(P_t^i - c\left(Q_t^i, \zeta_t^i\right)\right) \times q\left(P_t^i, D_t^i, \chi_t^i\right) - \lambda a(D_t^i, A_t^i) - F_t^i$$

- The Bellman equation is:

$$V\left(D_t^i; \chi_t^i, \zeta_t^i\right) = \max_{A_t^i, P_t^i} \left\{\pi\left(D_t^i, A_t^i; \chi_t^i\right) + \beta \mathbb{E}\left\{V\left(D_{t+1}^i; \chi_{t+1}^i, \zeta_{t+1}^i\right) | \chi_t^i, \zeta_t^i\right\}\right.$$

- Polar cases: (i) $\lambda = 1$ current non-price actions theories impact future customer capital
  (ii) $\lambda = 0$ current price actions impact future customer capital

# Testable implications: patterns over the life cycle

1. **Quantities**
    - Model (i) and (ii):
      growth after entry indicates the existence of frictions in accumulation of customer capital
2. **Markups**
    - Under model (i): constant markups
    - Under model (ii): markups grow as customer base grows
3. **Investment in marketing and advertising**
    - Under model (i): marketing and advertising affects sales
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$\hookrightarrow$ **Goal**: Find variation that allows us to control for other factors

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$\hookrightarrow$ **Goal**: Find variation that allows us to control for other factors

$\hookrightarrow$ **Goal** Provide direct measurement of marketing and advertising investments in customer acquisition

# Data

# Data sources

1. Nielsen **retail scanner data** (RMS) 2006-2017 ▸ sumstats
   - Price and quantity: **value** and **volume** (e.g. oz, gallons) by **store-barcode** at weekly level
   - Also know **product module**, **brand**, store **location** (county) and **chain**
   - Use GS1 to match barcodes to **firms**
2. Nielsen data on **advertising** (Ad Intel) 2010-2017 ▸ sumstats
   - Provides occurrence-level advertising (date, duration, format, spending, viewership) for ads featured on television, newspapers, coupons, digital, among other.
   - Also know advertising brand, firm, and product type.
   - Some media types are reported at the local level (e.g. Local TV, coupon)
3. **Merge quantity and prices data with advertising data at very detailed level**
   - Develop a matching algorithm using methods from the natural language processing literature to create systematic links between Ad Intel and RMS observations.
4. Additional: Nielsen household panel (# households, sales per household, prices paid), IRI (clearance sales), Promo (wholesale prices), NETS (plant location)

# Data

- **Firm** $i$ is hqfirm-brand-module combination
    - $> 20k$ distinct hqfirms (e.g. General Mills, Chobani)
    - $> 60k$ distinct brands (e.g. Yoplait, Chobani)
    - $\sim 600$ distinct product modules (Nielsen detailed product classification)
  - Why?
    - Can aggregate quantities consistently & unit of measurement of advertising
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- **Market** $k$ is Nielsen DMAs

  210 DMAs: 1 DMA = 14 counties on average

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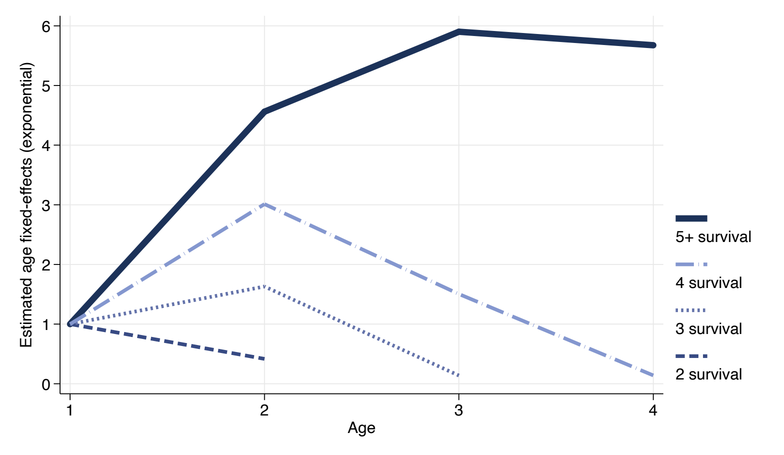
- Baseline: **Food** products
  - Why?
    - Markets are segmented from the consumer perspective (key for identification!)
    - Explore heterogeneity within modules, and robustness including other industries

# Identification Strategy

# Evolution of Entrants Size

- Entrant firms in this sector grow slowly toward their steady state size
  [Consistent with the findings and magnitudes of a large literature on firm dynamics.]




▸ Specifications

▸ Definitions i

▸ Price&Quant

$$\ln \text{sales}_t^i = \beta' \left(\text{age}_t^i \otimes \text{survival}^i\right) + \psi_t + \gamma^i + \text{cens}^i + \varepsilon_t^i, \qquad i = \text{firm} \times \text{brand} \times \text{prod},\ t = \text{prod} \times \text{year}$$

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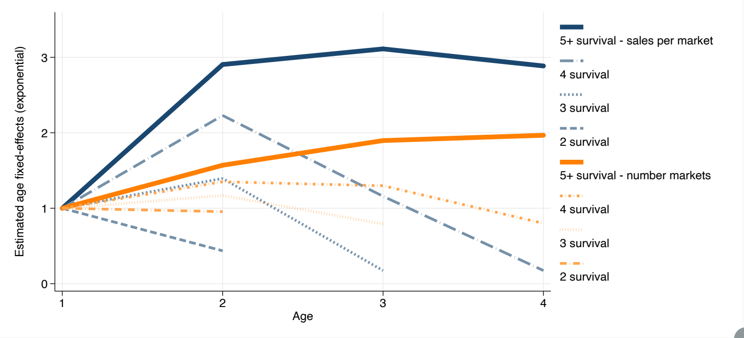
- Splitting sales into average sales per market and number of markets:

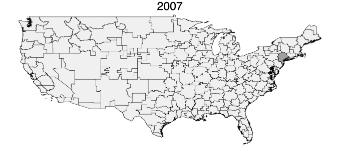



Dist. # markets
Var decomposition
Selection into markets

# Staggered entry across markets

- Variation from staggered entry across multiple segmented markets

  Example: Chobani enters the market in 2007



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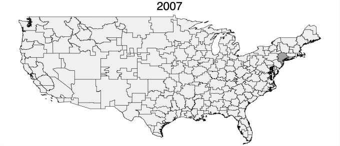


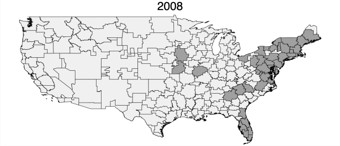

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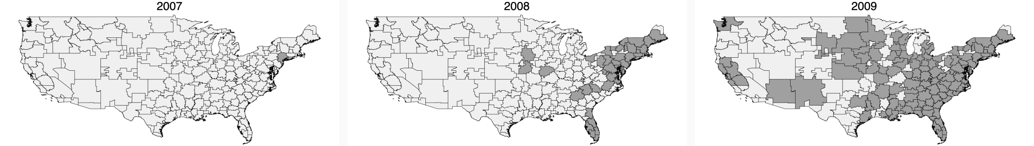

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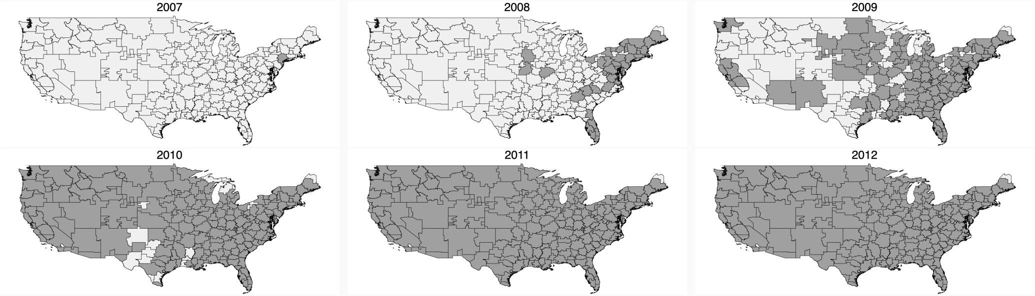

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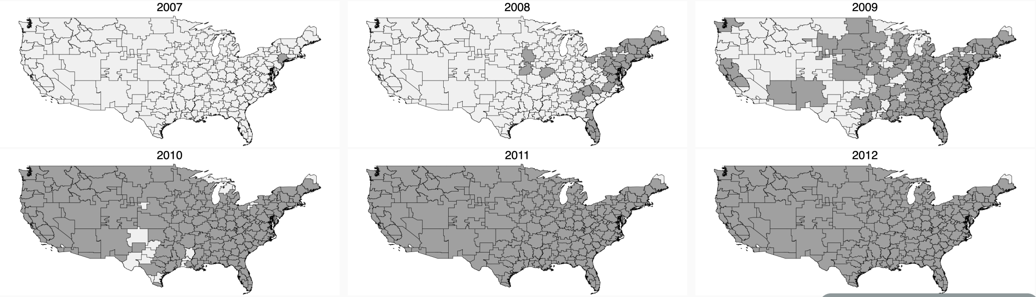



▸ Penetration Ratio (continuous)

- Expanding into new markets implies reaching new customers, and time in a market indicates more time to overcome frictions in reaching new customers within market.
- If supply-side and other demand-side dynamic factors are the same in all markets, then we isolate the role of presence of demand-side frictions

$$\ln W_t^{im} = \beta' \left( age_t^{im} \otimes survival^{im} \right) + market_t^m + firm_t^i + \varepsilon_t^{im}$$

# Testing Implications of Customer Capital Theories

# Testable predictions of customer capital theories

1. **Quantities**

   Quantity patterns consistent with customer acquisition

2. **Markups**

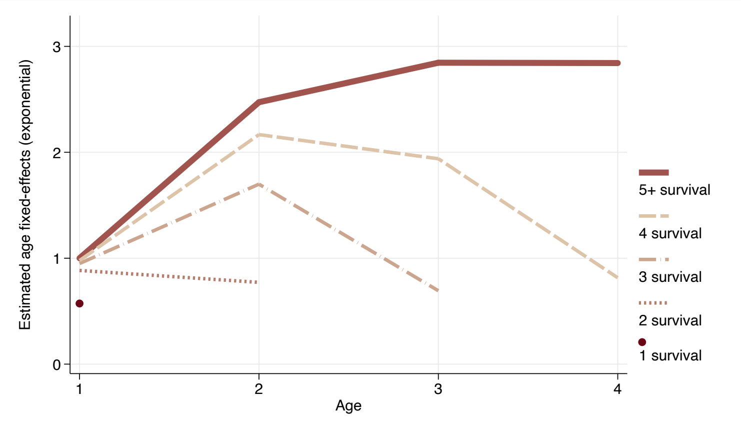
   Price patterns show lack of dynamics

   Evidence does not support the use of price-actions to build customer capital

3. **Marketing and advertising investments**

   Evidence consistent with firms using non-price actions to built customer capital

# Quantity patterns consistent with customer acquisition




Without firm FE

$$\ln \text{quantity}_t^{im} = \beta' \left( age_t^{im} \otimes survival^{im} \right) + market_t^m + firm_t^i + \varepsilon_t^{im}$$

- Using variation within firm-year (removes effect of firm appeal and productivity common across markets) and within market-year (differences in market size and taste)
- We allow for the effect to vary with survival to capture selection bias

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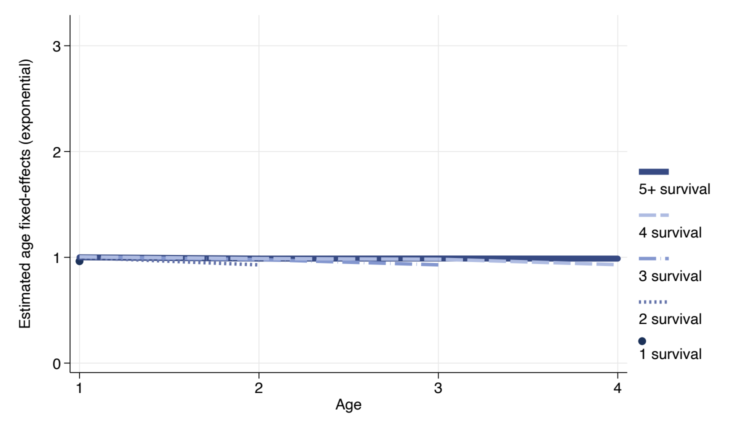
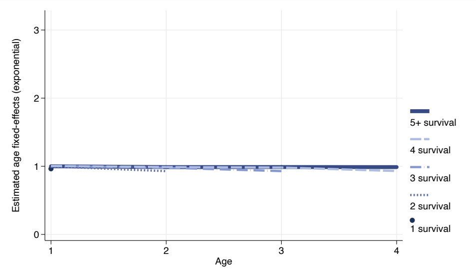
# Prices patterns show lack of life cycle dynamics




Without firm FE

$$\ln \text{price}_t^{im} = \beta' \left( age_t^{im} \otimes survival^{im} \right) + market_t^m + firm_t^i + \varepsilon_t^{im}$$

# From price dynamics to markup dynamics




**How about markups?**

- Using variation within firm-year (removes effect of firm appeal and productivity common across markets) and within market-year (differences in market size and taste)
- Assumption: **marginal cost same for all markets** & **no dynamics in transportation cost and retail margin**

$$\underbrace{\text{price}_t^{im}}_{\text{retail}} = \underbrace{\mu_t^{im}}_{\text{mfg markup}} \quad \underbrace{c_t^{i}}_{\text{marg cost}} \quad \underbrace{\tau_t^{im}}_{\text{transp cost}} \quad \underbrace{\tau_t^{im}}_{\text{retail margin}}$$

# Robustness: No markup life cycle dynamics

- Retail Margin - PromoData ▸ Wholesale
- NETS Plant location ▸ Distance
- Sample selection:
  - Incumbent brands ▸ Incumbents
  - New brands ▸ New
  - Only original brands ▸ Original
- Definition of markets:
  - National level ▸ National
  - Chains ▸ Chain ▸ Chain-DMA
  - Balanced stores ▸ Balanced
- Brand aggregation ▸ Firm
- Time aggregation ▸ Quarter
- Other data sets:
  - IRI-Symphony ▸ Price ▸ Sales
  - Nielsen Homescan Panel ▸ HMS
- Additional controls:
  - All categories ▸ All
  - Market size ▸ Size
  - Cohort effects ▸ Cohort
  - Spell controls ▸ Spell

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# Marketing and Advertising Investments in Customer Capital

**Data covers two types of non-price actions $A_t^{im} = \{A_{Mt}^{im}; A_{Dt}^{im}\}$**

- $A_{Mt}^{im}$ **Marketing and Distribution - relationships with retailers (indirect)**
  - Firms need to place their products in stores to reach consumers.
  - Expenses to establish relationships with retailers such as slotting fees (pay-to-enter/-to-stay) should be partially capitalized. Not directly observed in data!

    (a) Patterns of placement in stores and in new stores over life cycle

    (b) Relationship between placement in new stores and sales

- $A_{Dt}^{im}$ **Advertising - relationships with customers (direct)**
  - Spending in advertising communicate and build intangible brand equity among customers, and should be partially capitalized.

    (c) Prevalence of advertising among entrants and incumbent firms

    (d) Patterns of advertising over the life cycle

    (e) Relationship between advertising and sales

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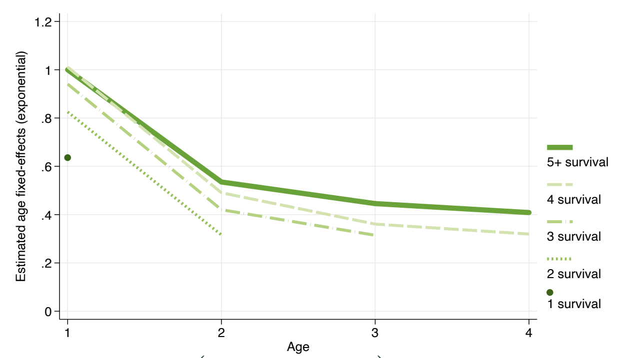
- $A_{Dt}^{im}$ **Advertising - relationships with customers (direct)**
  - Spending in advertising communicate and build intangible brand equity among customers, and should be partially capitalized.
  - *Focus on Local TV to use variation from staggered entry.*
    - (c) Prevalence of advertising among entrants and incumbent firms
    - (d) Patterns of advertising over the life cycle
    - (e) Relationship between advertising and sales

# Store dynamics

(a) Life cycle patterns of new stores consistent with **investment with convex adjustment costs**




$$\ln \textbf{newstores}_t^{im} = \beta' \left( age_t^{im} \otimes survival^{im} \right) + market_t^m + firm_t^i + \varepsilon_t^{im}$$

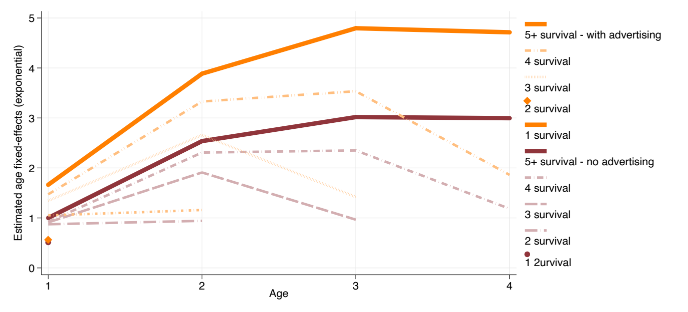
(b) Not surprisingly, entry into new stores associated with increase in quantity – diff-in-diff/Linear projection analysis ▸ LPnewstores

# Advertising Dynamics

(c) Only a small share of entrants uses advertising (all ADI media, with focus on local TV advertising) ▸ Extensive

(d) The life cycle patterns of advertising exhibit slow growth over life cycle (but decline as share of sales) ▸ LifeCyclelocalTV

(e) Advertising associated with increase in sales (also in diff-in-diff and linear projection analysis) ▸ LPDadv



# Conclusion

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CONTRIBUTION: **Measure nature and magnitude of investments to overcome frictions in the accumulation of customers.**

- Builds new micro data covering prices, quantities, and marketing and advertising investments for firms (including entrants) in the consumer food goods sector
- Results

1. **Quantities**

   Quantity patterns consistent with customer acquisition

2. **Markups**

   Price patterns show lack of dynamics

   Evidence does not support the use of price-actions to build customer capital

3. **Marketing and advertising investments**

   Evidence consistent with firms using non-price actions to built customer capital

# Retail scanner summary statistics

**Table 1:** Number of observations in different categories

| | Avg yearly | Total distinct |
|---|---|---|
| Markets | 205 | 206 |
| Products | 602 | 603 |
| Firms | 12,620 | 21,265 |
| Firm-products | 41,087 | 72,500 |
| Firm-brands | 32,354 | 63,230 |
| Firm-brand-products | 60,086 | 116,107 |
| Firm-brand-product-DMAs | 2,018,137 | 4,478,616 |

back

# What does placing a brand in a chain mean?

- Placing a brand in a chain does not mean placing it in all DMAs served by that chain

**Table 2: Share of chain DMAs where brand is sold**

| Age of brand (quarters) | Number of DMAs where chain has stores | Share of these DMAs where brand is sold: Mean | Share of these DMAs where brand is sold: Median |
|---|---|---|---|
| 1 | 1-5 | 0.78 | 0.86 |
| 1 | 5-50 | 0.38 | 0.30 |
| 1 | 50-150 | 0.19 | 0.12 |
| 1 | 150+ | 0.15 | 0.07 |
| 40 | 1-5 | 0.75 | 0.77 |
| 40 | 5-50 | 0.44 | 0.42 |
| 40 | 50-150 | 0.25 | 0.22 |
| 40 | 150+ | 0.18 | 0.16 |

back

# Ad Intel summary statistics

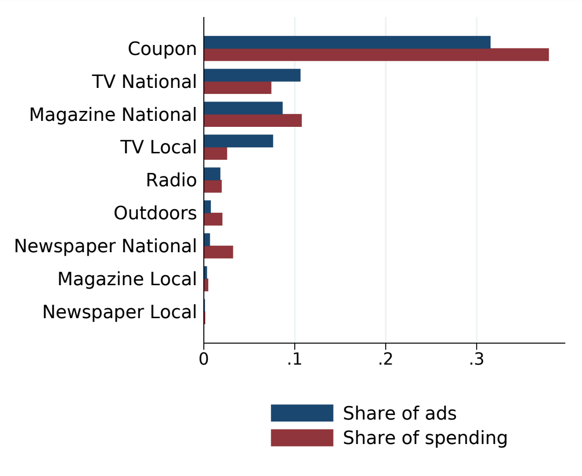
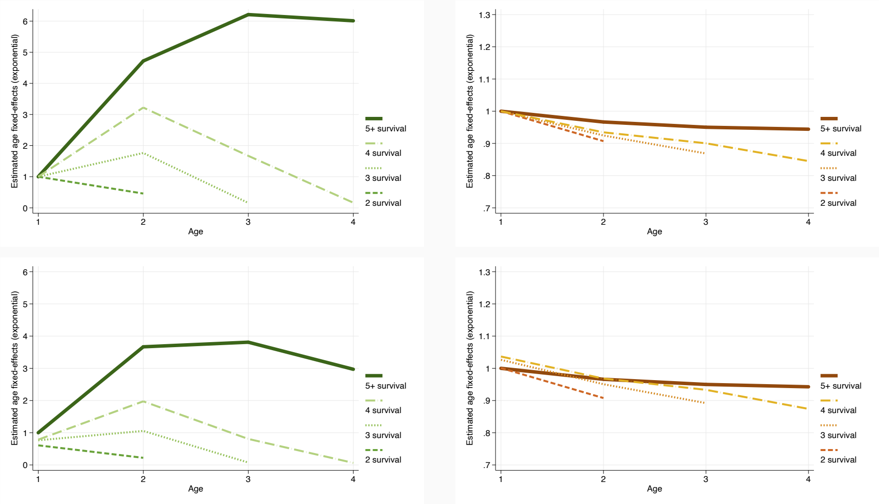



**Figure 1:** Food share in advertising by medium

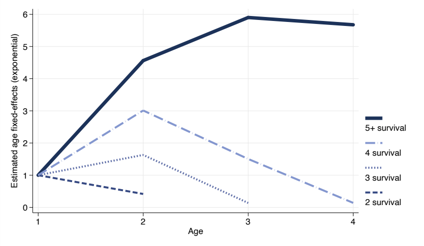
# Evolution of Entrants Size (national): Quantity and Price

Back

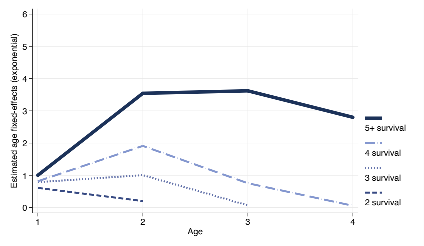


# Evolution of Entrants Size (national): alternative specifications

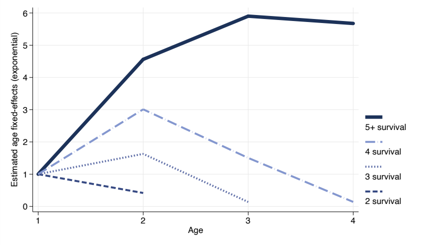
Back



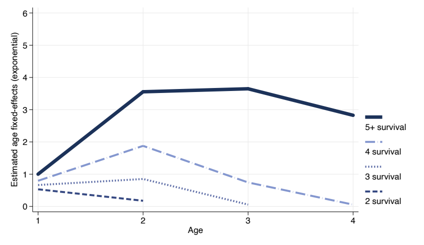

$$\ln \text{sales}_t^i = \beta' \left(\text{age}_t^i \otimes \text{surv}^i\right) + \text{year}_t + \text{firm}^i + \text{cens}^i + \varepsilon_t^i$$




$$\ln \text{sales}_t^i = \beta' \left(\text{age}_t^i \otimes \text{survl}^i\right) + \text{year}_t + \text{cens}^i + \varepsilon_t^i$$

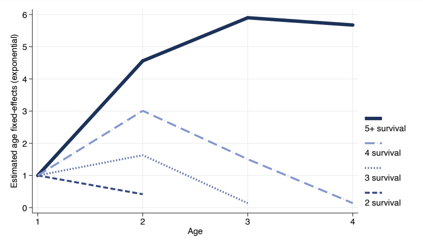



$$\ln \text{sales}_t^i = \beta' \left(\text{age}_t^i \otimes \text{surv}^i\right) + \text{year}_t + \text{firm}^i + \text{cens}^i + \text{cohort}_i + \varepsilon_t^i$$

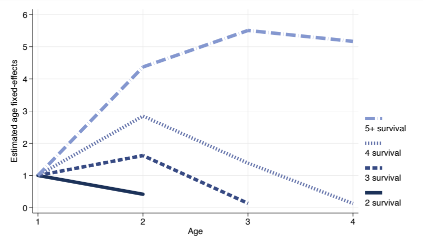



$$\ln \text{sales}_t^i = \beta' \left(\text{age}_t^i \otimes \text{surv}^i\right) + \text{year}_t + \text{cens}^i + \text{cohort}_i + \varepsilon_t^i$$

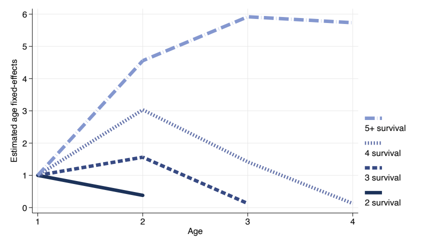
# Evolution of Entrants Size (national): alternative definition firm ▸ Back



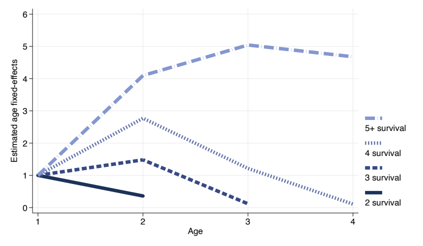

i= firm x brand x prod




i= firm x prod



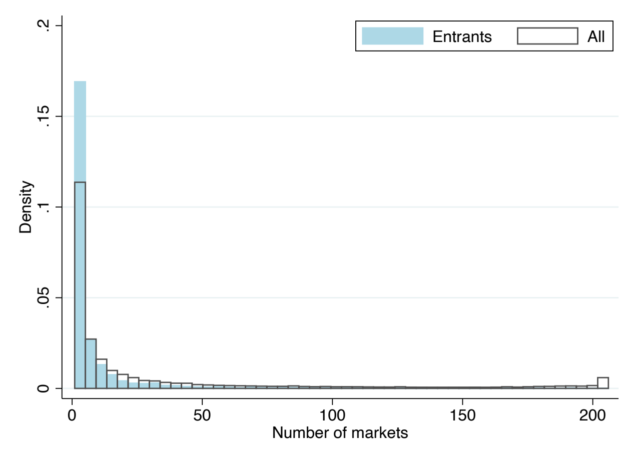

i= firm x brand




i= firm

# Most firms start in few markets and many never expand

Back



# Variance contribution of markets

Back

- Extensive margin of markets accounts for about 1/3 of variance in sales (about the same in sales growth)

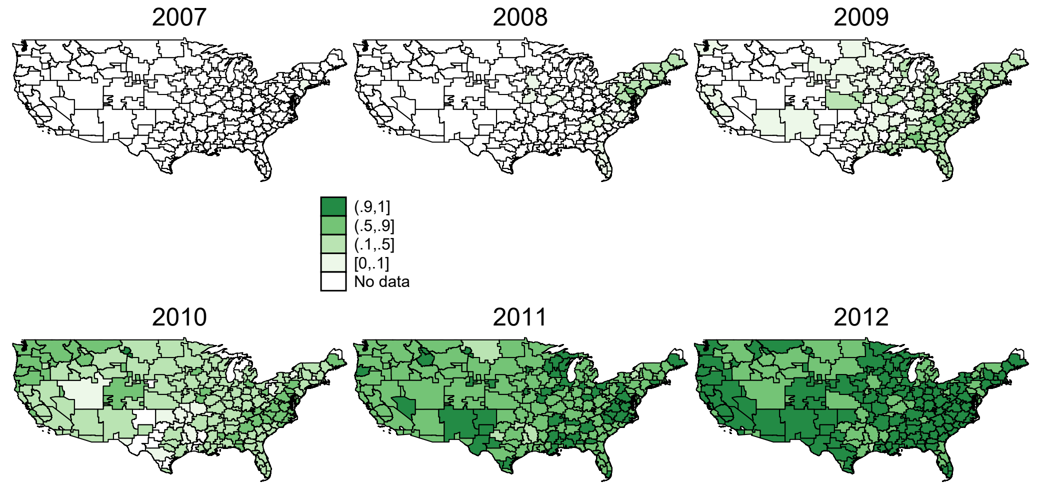
| Share | Int | 2Cov(Int,Ext) | Ext |
|---|---|---|---|
| | Markets | | |
| Entrants | 0.60 | **0.14** | **0.27** |
| All | 0.52 | 0.25 | 0.23 |
| | Comparison:# barcodes | | |
| Entrants | 0.96 | 0.03 | 0.03 |
| All | 0.80 | 0.15 | 0.06 |

# Selection into markets

Back

# Chobani: Growth through entering new store

Back

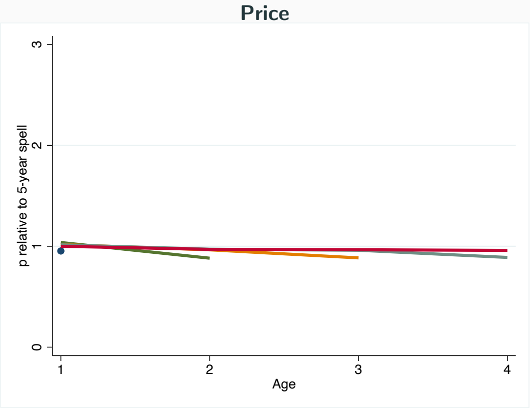



Note: Fraction of the total number of stores that sell yogurt in each market-year.

# price dynamics

- We estimate:

$$\ln Y_t^{ik} = b_t^k + \boldsymbol{\beta_P}' \left( duration^{ik} \otimes age_t^{ik} \right) + \varepsilon_t^{ik}$$



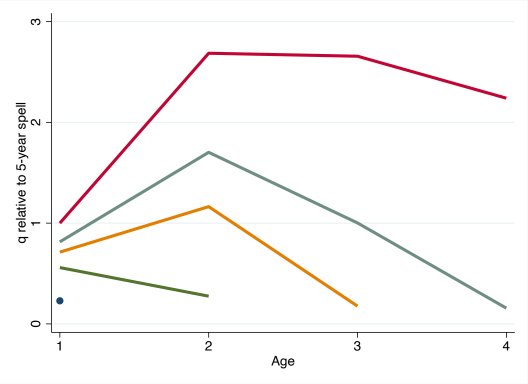

▸ Back

# quantity dynamics

- We estimate:

$$\ln Y_t^{ik} = b_t^k + \boldsymbol{\beta_Q}' \left( duration^{ik} \otimes age_t^{ik} \right) + \varepsilon_t^{ik}$$

**Quantity**

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# Quantity & price in household panel

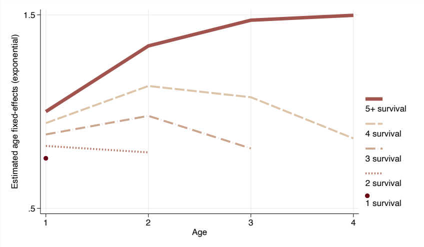


**Figure 2:** Quantity

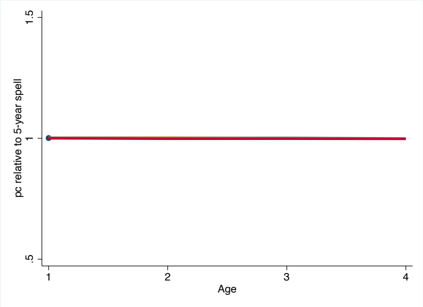


**Figure 3:** Price

- Quantity behaves similarly to scanner data
- Don't see clearance sales in prices viewed from consumer perspective

# Customers & sales per customer in household panel

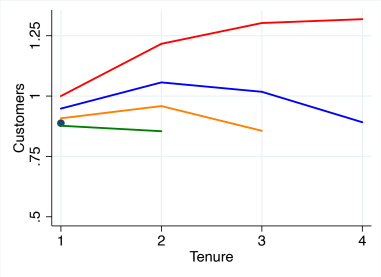


**Figure 4:** Number of consumers

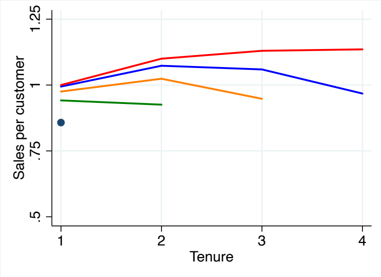


**Figure 5:** Value per consumer

- Extensive margin of customers contributes more than sales per customer

back

# Fact 1 : Clearance sales in IRI Symphony

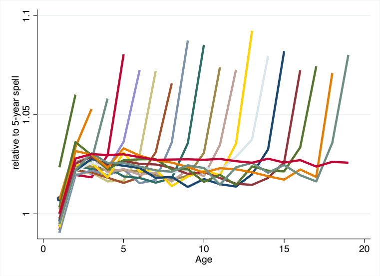


**Figure 6:** Frequency of sales

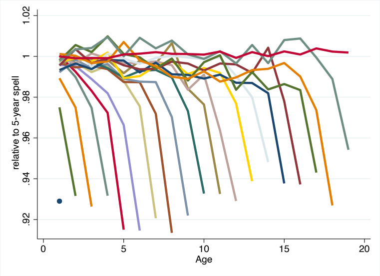


**Figure 7:** Size of sales

- Probability brand is on sale in its final quarter is 6-7% higher than penultimate quarter
- Price of exiting brand is 6-7% lower than in quarter before exit

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# Fact 1 : Number of stores & sales per store

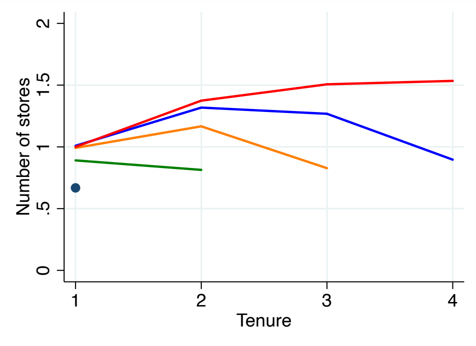


**Figure 8:** Number of stores

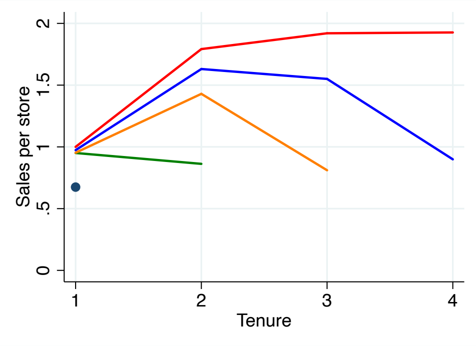


**Figure 9:** Sales per store

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# Fact 1 : Number of UPCs & sales per UPC

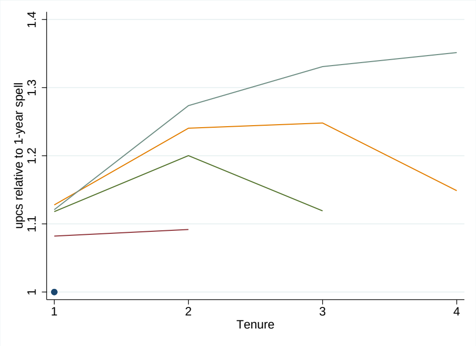


**Figure 10:** Number of UPCs

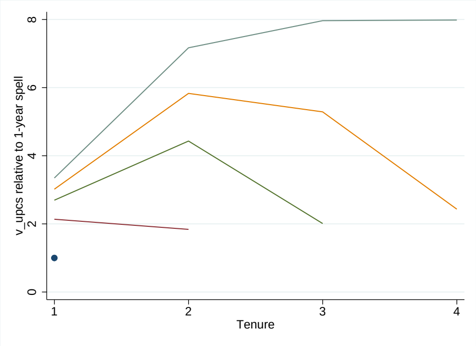


**Figure 11:** Sales per UPC

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# Fact 1 : Aggregating across brands within a firm

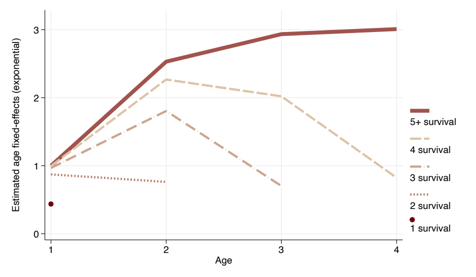


**Figure 12:** Quantity

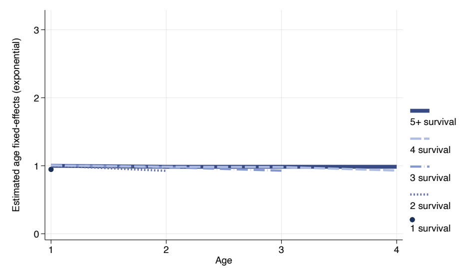


**Figure 13:** Price

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# Fact 1 : Quarterly data

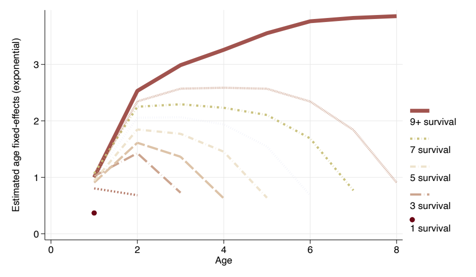


**Figure 14:** Quantity

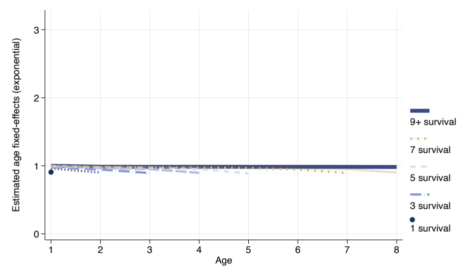


**Figure 15:** Price

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# Fact 1 : Chain instead of DMA

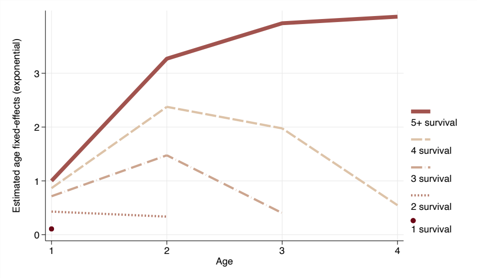


**Figure 16:** Quantity

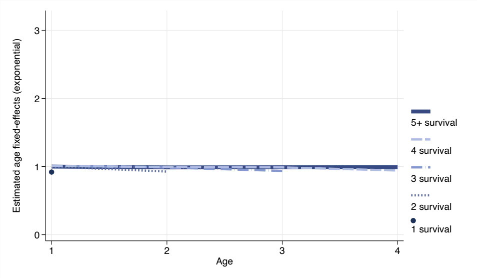


**Figure 17:** Price

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# Fact 1 : Chain-DMA instead of DMA

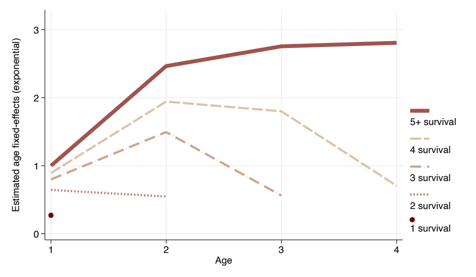


**Figure 18:** Quantity

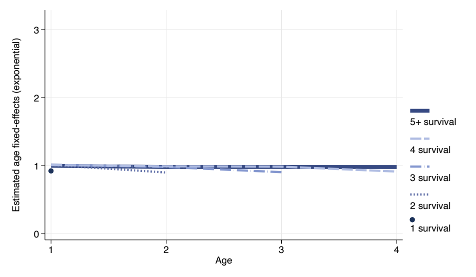


**Figure 19:** Price

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# Fact 1 : Balanced panel of stores

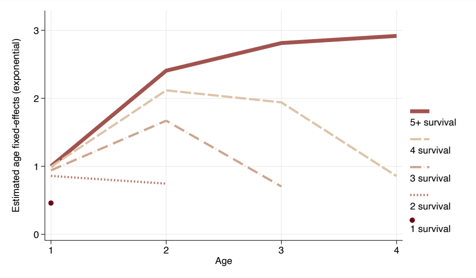


**Figure 20:** Quantity

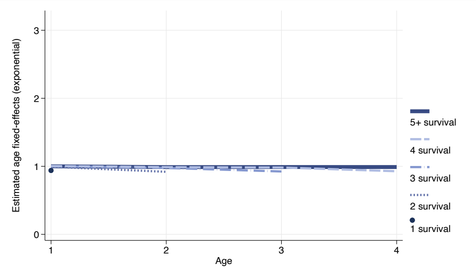


**Figure 21:** Price

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# Advertising and the firm life cycle

$$W_t^{fij} = d_t^j + \gamma^{cohort(fij)} + \boldsymbol{\beta}' \left( \mathrm{l}_t^{fij} \otimes \mathrm{a}_t^{fij} \right) + \mathrm{cens}^{fij} + \varepsilon_t^{fij}$$

- $f$: firm, $i$: brand, $j$: product
- $W_t^{fij}$: indicator for some advertising, number of markets (IHS), number of ads (IHS), impressions (IHS)
- $d_t^j$: product-year effect (market size)
- $\gamma^{cohort(fij)}$: entry year fixed effect
- $\mathrm{l}^{fij}$: vector of indicators for **duration**
- $\mathrm{a}_t^{fij}$: vector of indicators for **tenure**
    - Topcode duration, tenure at 5 years
    - Reference category: 1st year of 1-year spells
- $\mathrm{cens}^{fij}$: indicators for left- and right-censored duration
- Tenure / duration based on first and last appearance in RMS

# Advertising and the firm life cycle

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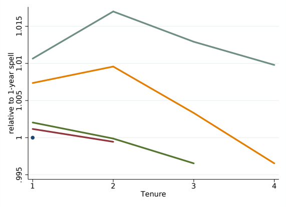



**Figure 22:** $1\{\text{advertising} > 0\}$

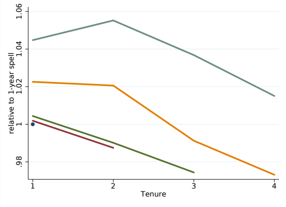



**Figure 23:** Markets

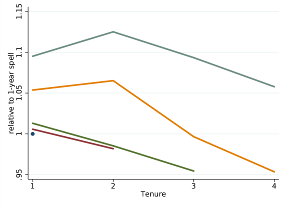



**Figure 24:** Ads

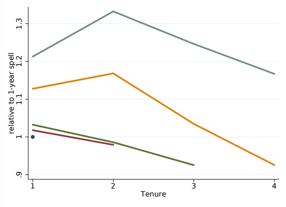
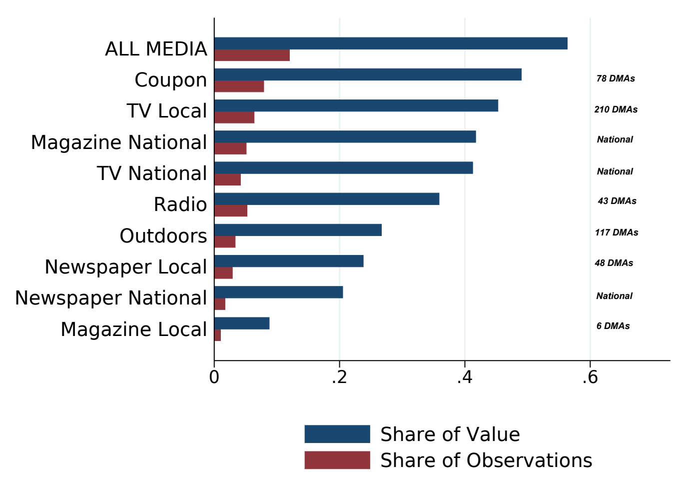



**Figure 25:** Impressions

# Advertising: Share with advertising

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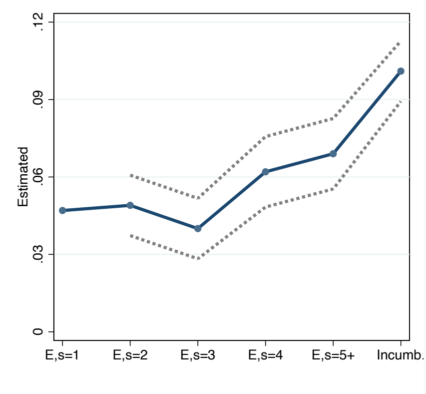
# Advertising: by Entrants

- We estimate:

$$\mathbb{I}[A_t^{ik} > 0] = \alpha + \sum_{s=2}^{5} \beta_{E,s}\mathbb{I}[\text{Entrant } s]_t^{ik} + \beta_I \mathbb{I}[\text{Incumbent}]_t^{ik} + \theta_t^k + \varepsilon_t^{ik}$$

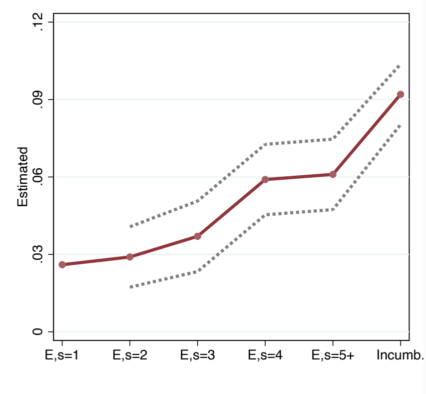
**Any Media**

National




**Local TV**

Markets

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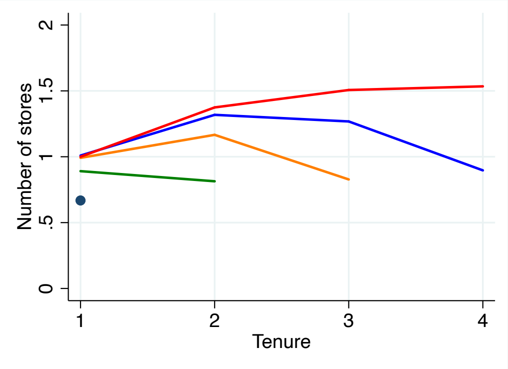
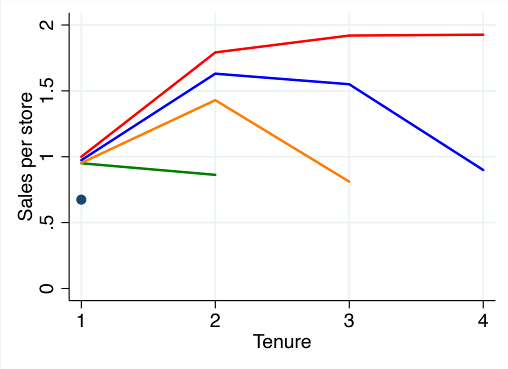
# Product Placement: Dynamics

- We estimate for number of stores and sales per store:

$$\ln A_t^{ik} = a_t^i + b_t^k + \boldsymbol{\beta_Q}' \left( duration^{ik} \otimes age_t^{ik} \right) + \varepsilon_t^{ik}$$




number of stores




sales per store

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# Entrants use non-price actions such as advertising

| | 1[local tv > 0] | | 1[local tv > 0] | | 1[any media > 0] | | IHS(local tv imp) | |
|---|---|---|---|---|---|---|---|---|
| | All | Entry | All | Entry | All | Entry | All | Entry |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Entrant $\beta_{E,2}$ | 0.003 | 0.003 | 0.007** | 0.008*** | 0.002 | 0.003 | 0.020 | 0.032 |
| | (0.006) | (0.004) | (0.003) | (0.003) | (0.006) | (0.006) | (0.087) | (0.060) |
| Entrant $\beta_{E,3}$ | 0.011* | 0.014*** | 0.011*** | 0.009*** | -0.007 | -0.005 | 0.141 | 0.181*** |
| | (0.007) | (0.005) | (0.003) | (0.003) | (0.006) | (0.007) | (0.097) | (0.070) |
| Entrant $\beta_{E,4}$ | 0.033*** | 0.023*** | 0.019*** | 0.015*** | 0.015** | 0.022*** | 0.481*** | 0.333*** |
| | (0.007) | (0.006) | (0.003) | (0.003) | (0.007) | (0.007) | (0.109) | (0.086) |
| Entrant $\beta_{E,5}$ | 0.035*** | 0.017*** | 0.016*** | 0.014*** | 0.022*** | 0.023*** | 0.523*** | 0.253*** |
| | (0.007) | (0.006) | (0.003) | (0.003) | (0.007) | (0.007) | (0.111) | (0.084) |
| Incumbent $\beta_I$ | 0.066*** | | 0.039*** | | 0.054*** | | 1.013*** | |
| | (0.006) | | (0.002) | | (0.006) | | (0.096) | |
| Observations | 5,801,851 | 924,856 | 200,900 | 21,796 | 218,997 | 25,881 | 5,801,851 | 924,856 |
| R-squared | 0.179 | 0.285 | 0.051 | 0.147 | 0.067 | 0.137 | 0.178 | 0.278 |
| Sample | market | market | national | national | national | national | market | market |
| Module-mkt-t | Y | Y | - | - | - | - | Y | Y |
| Module-t | - | - | Y | Y | Y | Y | - | - |
| Uncond. $\bar{Y}_{E,1}$ | 0.026 | 0.026 | 0.004 | 0.004 | 0.047 | 0.047 | 0.380 | 0.380 |

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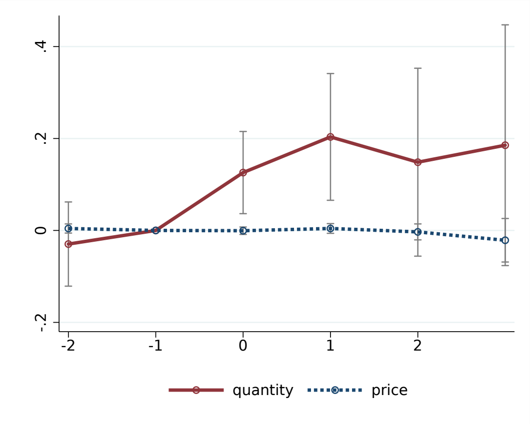
# Advertising

Back

We estimate impulse response (Jorda 2005) as follows:

$$\ln Y_{t+h}^{im} - \ln Y_t^{im} = \mathbf{b}_h^1(\ln A_t^{1,im} - \ln A_{t-1}^{1,im}) + \text{controls} + \omega^{im} + \theta_{t+h}^m + e_t^{im}$$

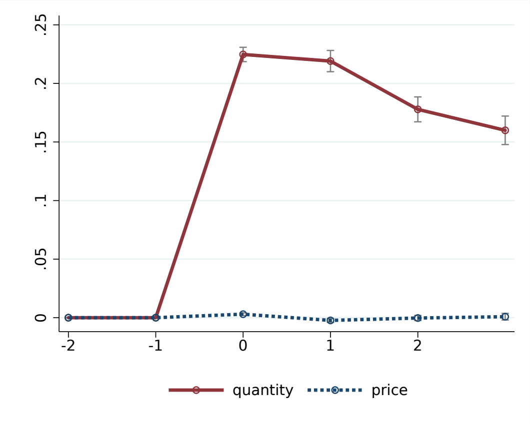


# Product placement in stores

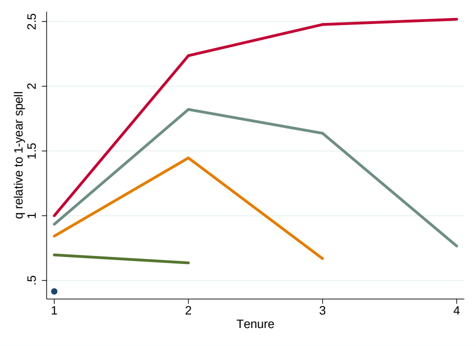
Back

We estimate impulse response (Jorda 2005) as follows:

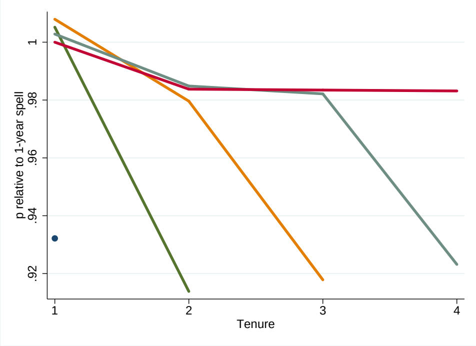
$$\ln Y^{im}_{t+h} - \ln Y^{im}_{t} = \mathbf{b}^2_h(\ln A^{2,im}_t - \ln A^{2,im}_{t-1}) + \text{controls} + \omega^{im} + \theta^m_{t+h} + e^{im}_t$$



# Controlling for distance between closet plant and store




(a) Quantity




(b) Price

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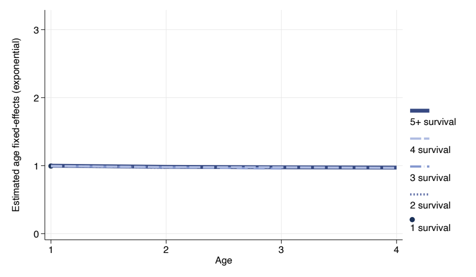
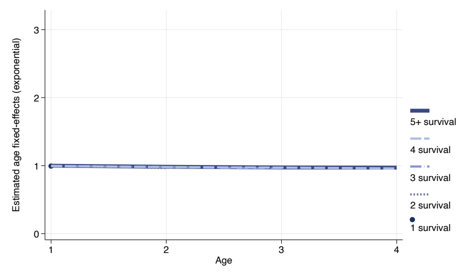
# Wholesale Price




(a) Price




(b) Price (Including Deals)

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# Advertising by entrants

**Table 3:** Local TV advertising by entering firms (type of advertising spending with local variation)

| | Entrants by survival (years) | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5+ |
| **All firms** | | | | | |
| Share advertising | 0.004 | 0.012 | 0.022 | 0.040 | 0.125 |
| Mean # markets w/ advertising | 0.7 | 1.2 | 2.6 | 4.4 | 15.7 |
| **Firms who advertise in at least one market** | | | | | |
| Avg # years advertising | 1.0 | 1.6 | 2.3 | 2.8 | 4.4 |

# Marketing & Advertising dynamics within market

- We estimate for spending with local TV ads:

$$\ln \mathrm{A}_t^{im} = market_t^m + firm_t^i + \boldsymbol{\beta_A}' \left( age_t^{im} \otimes survival^{im} \right) + \varepsilon_t^{im}$$

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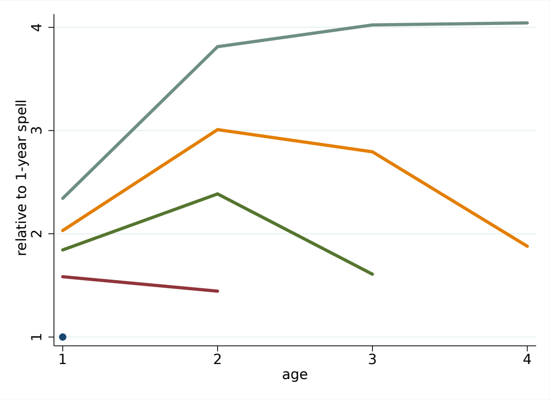
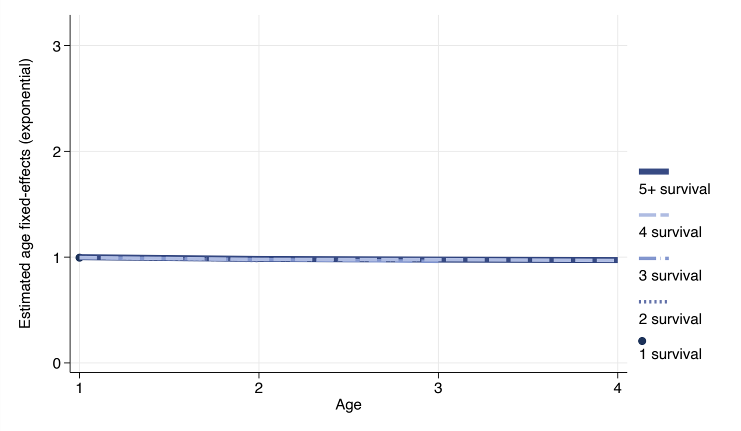


# Robustness: No markup dynamics

(1) We use data set contains UPC-level wholesale prices for each date in each market.

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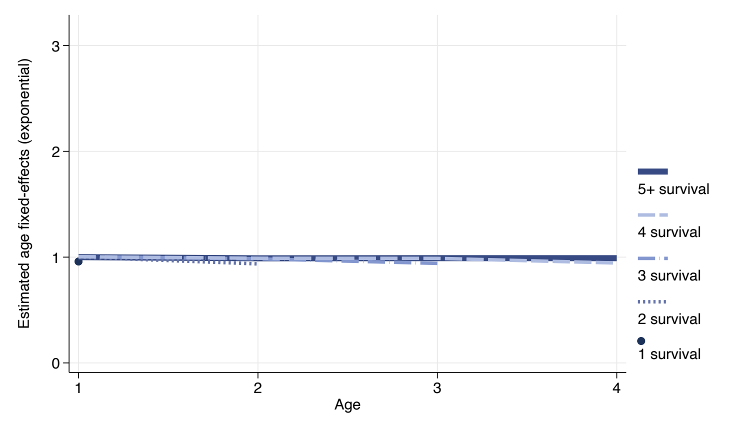
# Robustness: No markup dynamics

(2) Transportation Costs - merge NETS plant location. We control for distance.

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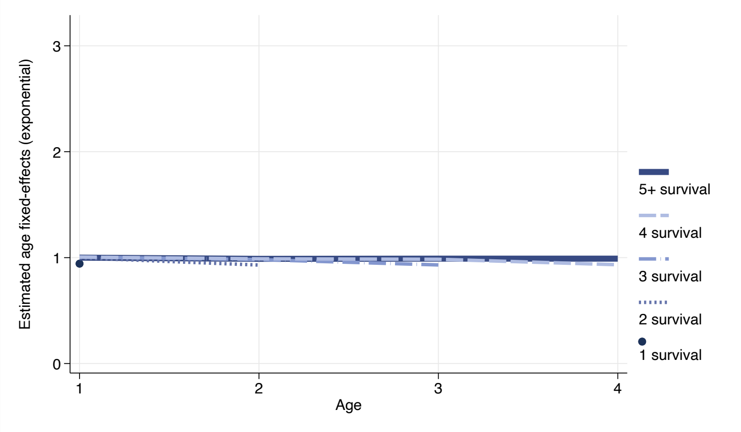
# Robustness: No markup dynamics

(3) Our results are not driven by sample selection. We find similar results when we use only incumbent brands.

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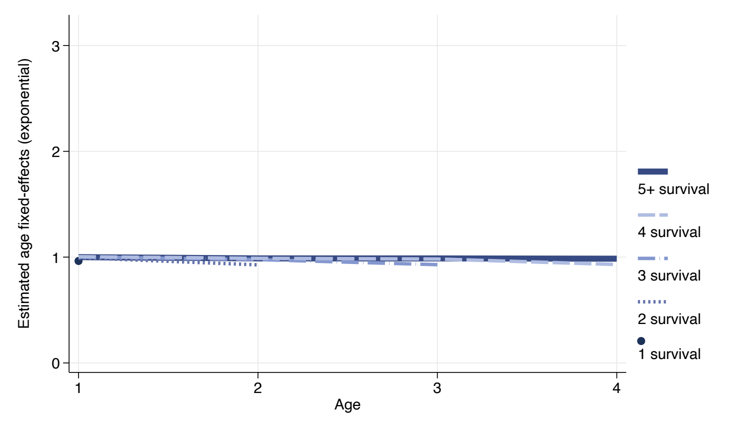
# Robustness: No markup dynamics

(4) Similar findings when we use only new brands.

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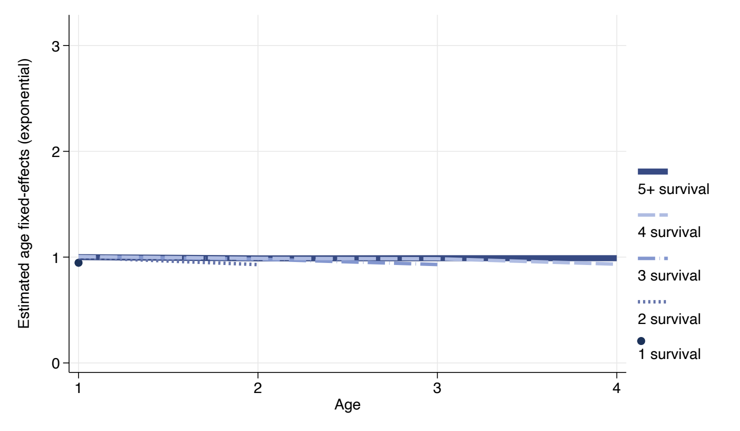
# Robustness: No markup dynamics

(5) Similar findings when we use only original brands, the set of brands firms have at entry.

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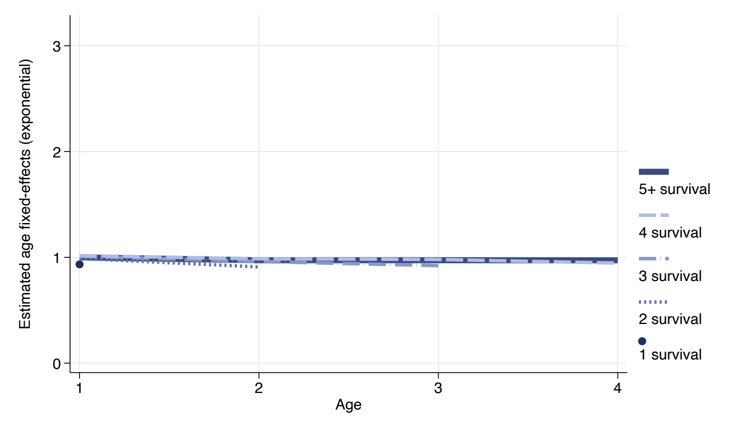
# Robustness: No markup dynamics

(6) Entrants at local level may be incumbents at national level. National level customer capital may impact the pace and nature of customer acquisition at local level. Restricting to national level entrants:

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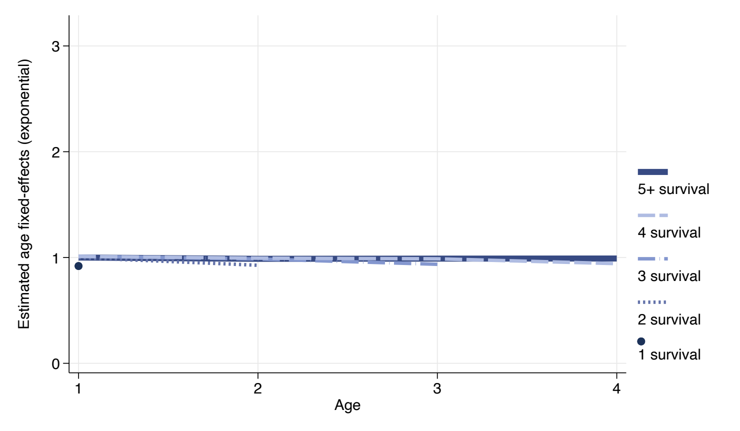
# Robustness: No markup dynamics

(7) Our findings are also not sensitive to how we define markets. They are robust to defining markets as retail chains. Most entrants into chains enter just a few stores segmented by markets.

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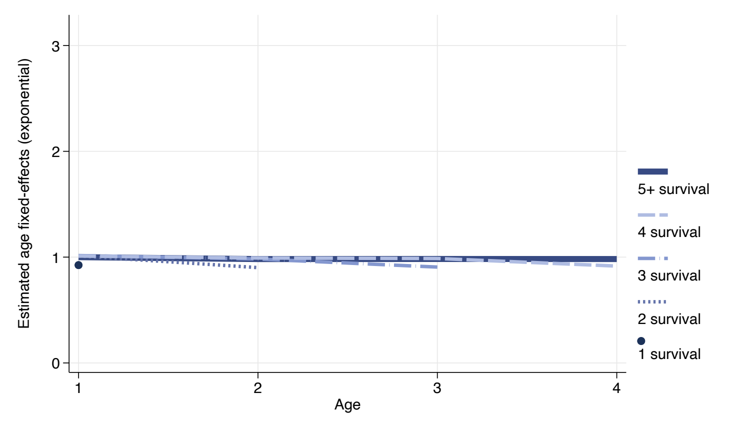
# Robustness: No markup dynamics

(8) Markets as retail chain-DMA.

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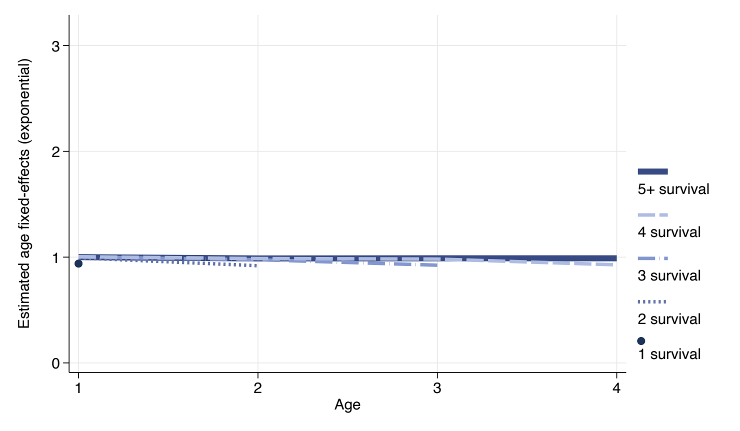
# Robustness: No markup dynamics

(9) We find similar patterns when we consider a balanced panel of stores.

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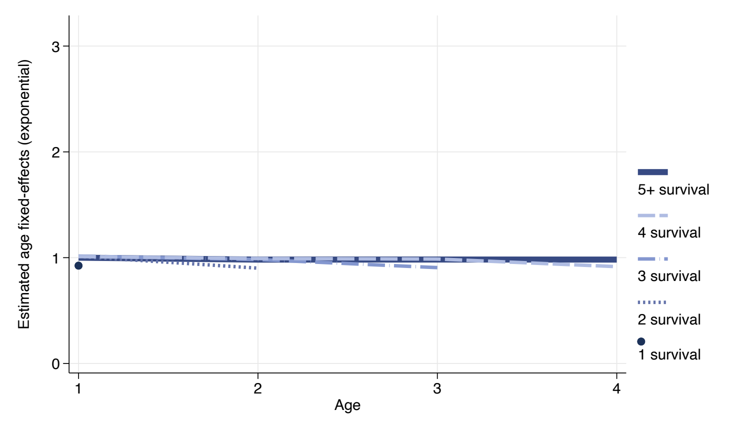
# Robustness: No markup dynamics

(10) Our results are similar when we use different brand aggregations. Here we aggregate across brands within firms.

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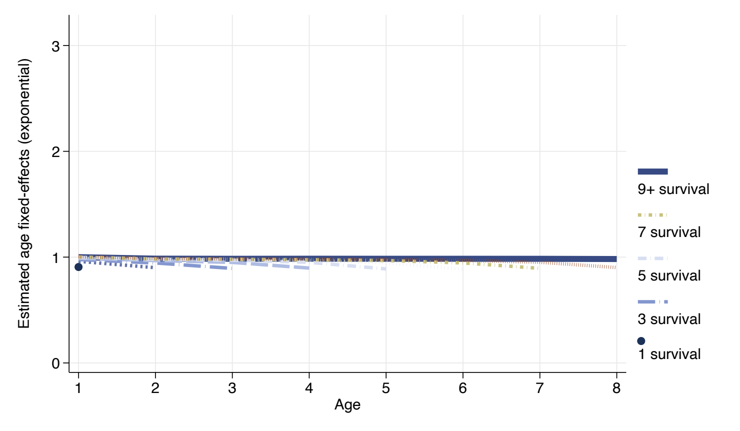
# Robustness: No markup dynamics

(11) Results not sensitive to time frequency. This uses quarterly data.

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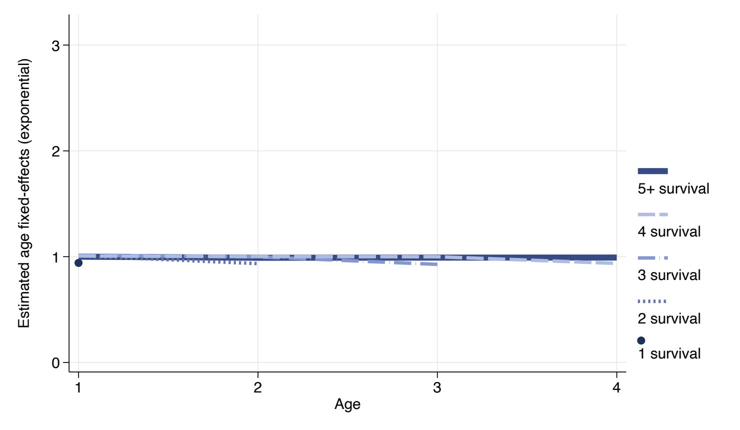
# Robustness: No markup dynamics

(12) We also use the IRI Symphony data. Use sales flag to document presence of clearance sales. ▸ IRI

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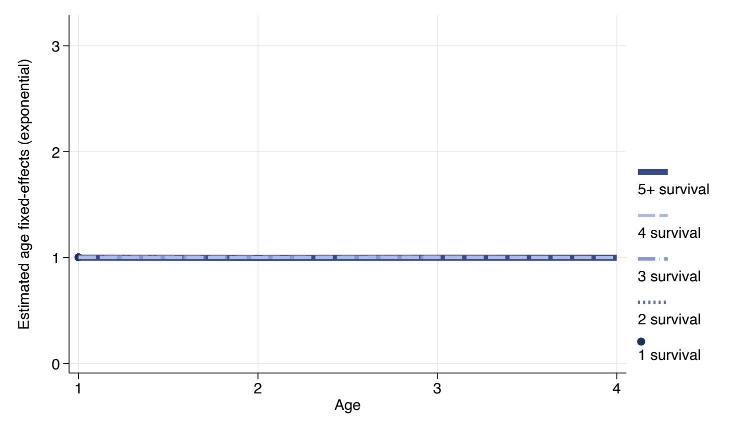
# Robustness: No markup dynamics

(13) The behavior of market share confirmed in consumer level data from the Nielsen Homescan Panel. Fall in markups prior to exit is not present in the consumer data.

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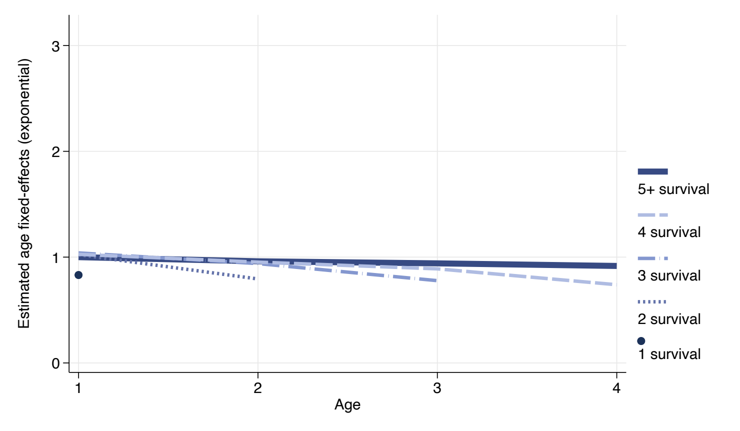
# Robustness: No markup dynamics

(14) Results are robust to using all categories in the data, including non-food.

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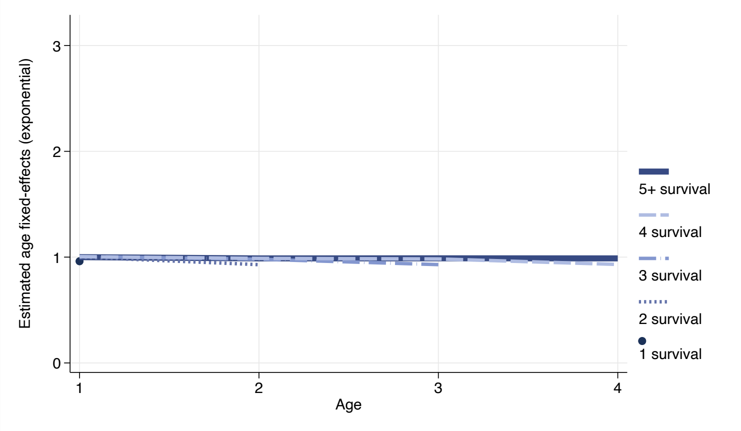
(15) We explore several specification including additional controls such as market size.

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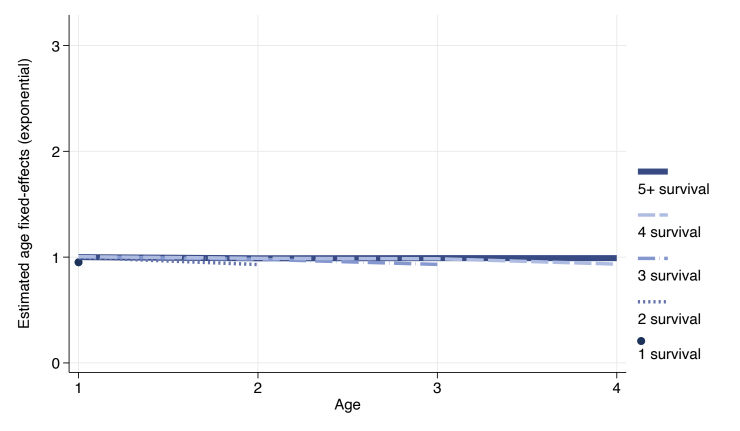
(16) Controlling for cohort effects.

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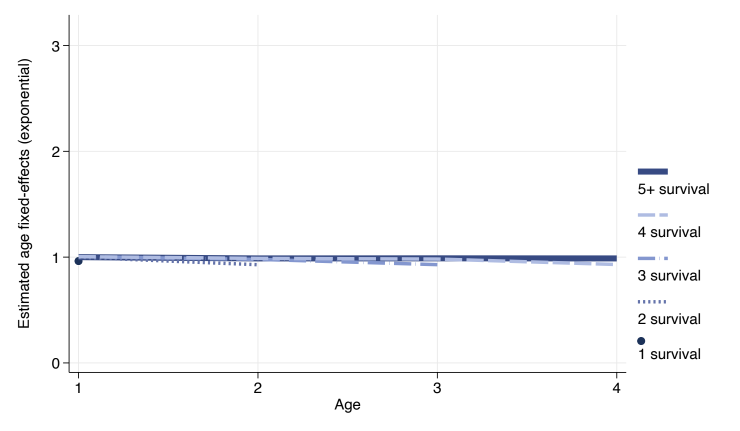
(17) Including spell controls.

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