Scalable Demand and Markups

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[1] Researchers' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researchers and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein. Research results and conclusions expressed are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia, the Federal Reserve System, or the Federal Reserve Board of Governors.

Introduction

- Recent literature has documented upward trends in markups across many industries.
- Methodological approaches have mostly been "macro":
  - e.g. use a cost minimization assumption to infer markups from firm-level data on revenues and input costs
  - Not many microeconomic studies (yet), even though measuring markups is a standard exercise in empirical IO
- Conventional micro approach involves estimating supply and demand models tailored to a particular industry or market. Difficult to scale.

What we do / what we find

Using the conventional microeconomic approach, we estimate markups in 75 different product markets for the years 2006-2018

To make the demand estimation tractable/scalable, we use nested logit demand and automate the assignment of products to nests

We find an overall upward trend in markups, but with considerable heterogeneity both within and across product markets

Changes in markups appear to reflect changes in household price sensitivity and firms' marginal costs more than changes in firm ownership

Related literature (non-exhaustive)

Macro studies:

- De Loecker, Eeckhout, and Unger (2020): estimate trends in markups using "production approach"
- Covarrubias, Gutiérrez, and Philippon (2020): ask why profits, concentration have increased since 1980— greater returns to scale or higher barriers to entry?

Micro studies:

- Döpper, MacKay, Miller, and Stiebale (2021), Brand (2020), Nieman and Vavra (2023): also attempt to measure trends in markups and market power using Nielsen data.
- Bhattacharya, Illanes, and Stillerman (2022): assess impacts of a large number of mergers on merging firms' and non-merging firms' prices and sales.
- De Loecker and Scott (2022): compare production and demand approaches for the U.S. brewing industry.

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Data

Nielsen Retail Scanner:

- 75 product "modules" (e.g. breakfast sausages, frozen pizza, refrigerated fruit drinks)
  - Within each module: focus on set of largest products that represent 85% of sales
  - 33K products in 22K different stores
  - Units sold and unit prices at the product-week-store level
  - At times, report results at brand (e.g., "Mountain Dew") vs. product (e.g., "8-pack of 12-oz. Mountain Dew bottles")
  - Hand collect manufacturer of each product (e.g., PepsiCo in the case of Mountain Dew) and how it varies over the sample.

Nielsen Consumer Panel:

- Grocery store purchase data for 183K households between 2004 and 2018

Scaling demand

Conventional microeconomic method for inferring markups (Berry, Levinsohn, Pakes, 1995; Nevo 2001)

1. Estimate a discrete choice model of demand
2. Assume Bertrand-Nash pricing, and invert first-order condition to get markups

Problem: Demand model is typically tailored to the specifics of the product market (e.g., need to hand classify the "mushiness" of cereals), and often computationally intensive.

Our solution: Use nested logit demand, which is computationally light.

In both approaches, high markups result if there are few "close substitutes"

- In the conventional approach, two products are close substitutes if they share demand-relevant characteristics.
- In our approach, two products in the same "nest" are likely to be close substitutes.

Question is: How to determine the nests?

Assigning products to nests

Idea: use co-consumption patterns from the Consumer Panel data

Specifically:

1. Compute v_j: vector $=1$ in i^{th}position if household i ever purchases good j
2. Calculate pairwise purchase correlations $\rho_{jj'}$ for all product pairs within a module
3. Construct a dissimilarity matrix $\mathbf{D}$ with $1 - \rho_{jj'}$ as its (j, j'^{th}) element
4. Apply an agglomerative clustering algorithm to $\mathbf{D}$ to divide products into nests

- Use a particular criterion function (Duda-Hart) to determine the number of nests.

Do this for each of the 75 product modules separately.

Are the nest assignments reasonable?

Wholesome	Berry/Healthy	Kids Fruity
Honey Bunches Of Oats 18 oz.	Special K Red Berry (12 oz)	Frosted Flakes
Honey Bunches Of Oats (w/ Almonds) 18 oz.	Special K	Froot Loops
Honey Bunches Of Oats 14.5 oz.	Special K Red Berry (16.7 oz)	Honey Nut Cheerios
Honey Bunches Of Oats (w/ Almonds) 14.5 oz.	Quaker Life	Apple Jacks
Frosted Flakes	Special K Fruit & Yogurt	Lucky Charms
Family Size	**Basic**	
Honey Nut Cheerios (25.25 oz)	Cheerios (18 oz)	
Frosted Flakes (17 oz)	Frosted Mini-Wheats (18 oz)	
Cinnamon Toast Crunch	Cheerios (14 oz)	
Frosted Flakes (14 oz)	Frosted Mini-Wheats (24 oz)	
Frosted Flakes (23 oz)	Rice Krispies	
Kashi	**Kids Cereal**	
Kashi Go Lean Crunch!	Honey Nut Cheerios (12 oz)	
Kashi Go Lean (14.1 oz)	Honey Nut Cheerios (17 oz)	
Kashi Heart To Heart	Honey Nut Cheerios (21.6 oz)	
Kashi Go Lean Crunch! (Honey Almond Flax)	Lucky Charms	
Kashi Go Lean (13.1 oz)	Frosted Flakes (15 oz)	

Demand estimation

We estimate a "nested logit" model of demand separately for each product module and year.

$$u_{ijt} = \underbrace{\underbrace{\alpha}_{\text{“price sensitivity”}} p_{jt} + \underbrace{\Delta\xi_{jt} + \xi_j + \xi_{b(j)d(t)q}}_{\text{“unobserved chars.”}}}_{=\delta_{jt}} + \underbrace{\zeta_{g(j),i,t}}_{\text{“taste for nest of prod. i”}} + (1-\sigma)\varepsilon_{ijt}$$

- t: a store-week, i: household, j: a product, $g(i)$ the nest of product i.
- $b(j)$: brand of product j, $d(r)$: direct marketing area of market t (somewhat larger than an MSA), q: quarter.

With this utility function:

$$s_{jt} = \frac{\exp\left(\delta_{jt}/(1-\sigma)\right)}{D_{gt}} \frac{D_{gt}^{1-\sigma}}{\sum_{g'} D_{g't}^{(1-\sigma)}},$$

where

$$D_{gt} = \sum_{j' \in \mathcal{J}_{gt}} \exp\left(\delta_{j't}/(1-\sigma)\right)$$

Demand estimation

From the last slide:

$$s_{jt} = \frac{\exp\left(\delta_{jt}/(1-\sigma)\right)}{D_{gt}} \frac{D_{gt}^{1-\sigma}}{\sum_{g'} D_{g't}^{(1-\sigma)}}$$

Taking logs and allowing preference parameters to vary by quarter $(y(q)$):

$$\log\left(\frac{s_{jt}}{s_{0t}}\right) = \alpha_{y(q)} p_{jt} + \sigma_{y(q)} \log\left(s_{jgt}\right) + \xi_t + \xi_{b(j)d(t)q} + \Delta\xi_{jt}$$

- s_{jgt}: the market share of product j within nest g in market t.
- s_{0t}: market share of "outside good" (share of the market not buying any product)

Both p_{jt} and $\log\left(s_{jgt}\right)$ may be correlated with demand shocks $(\Delta\xi_{jt})\Longrightarrow$ instrument using

- number of products within the market,
- the number of products within nest, and
- average price of j within the Census region of the U.S., excluding the designated market area of t.

Demand results

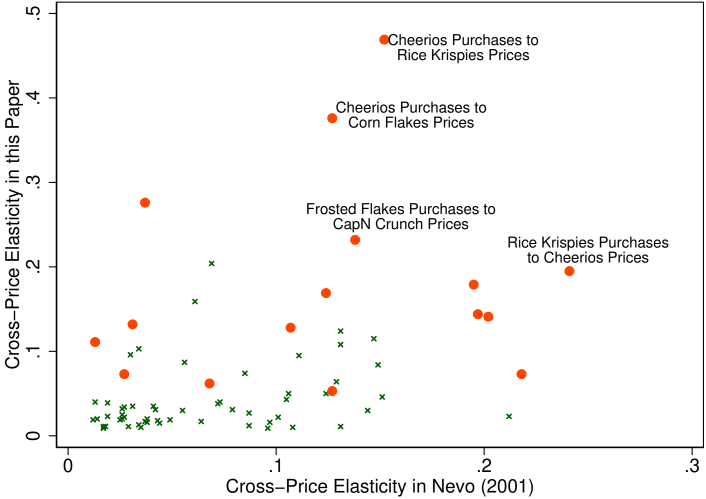
Price sensitivity parameters are appropriately negative in almost all cases (72 of 75 product modules)

Nest parameter is between 0 and 1 in 972 of 975 cases (13 years $\times$ 75 product modules)

Estimated own- and cross-price elasticities are similar to those from other previous studies (next slide).

If we estimate demand without clustering products into nests, the results are not credible — e.g. upward-sloping demands in at least one year for every product module

Demand results



From demand estimates to markups

Variable profits of firm f in market t are the sum of profits of individual profits in their portfolio ($\mathcal{J}_{ft}$):

$$\pi_{ft} = \sum_{j \in \mathcal{J}_{ft}} M_t s_{jt} \left(p_{jt} - c_{jt} \right)$$

- M_t: size of market t; c_{jt}: marginal cost of supplying j to market t.

Take first-order conditions for p_{jt}. In a Nash-Bertrand equilibrium:

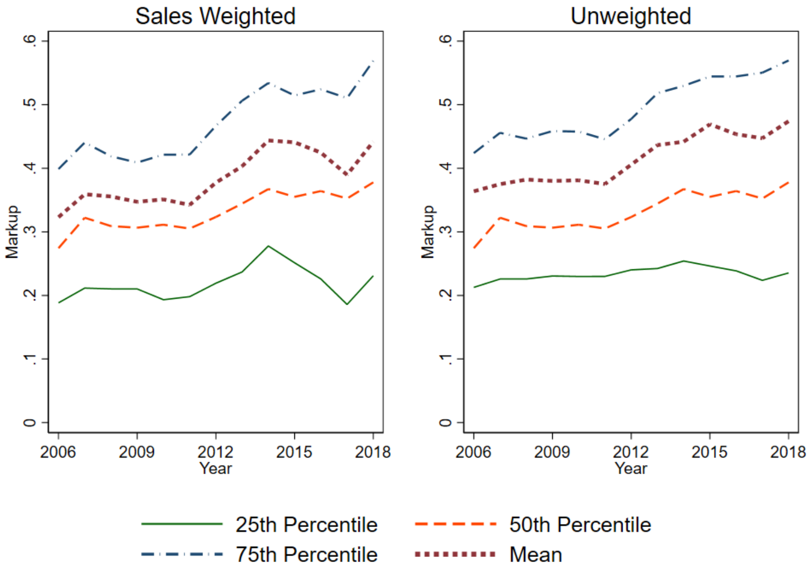
$$p_{jt} = c_{jt} - \left(\Omega_t \circ \frac{ds_t'}{dp_t} \right)^{-1} s_t$$

- Ω_t: ownership matrix $= 1$ in the j, j' entry if both products are produced by the same firm.

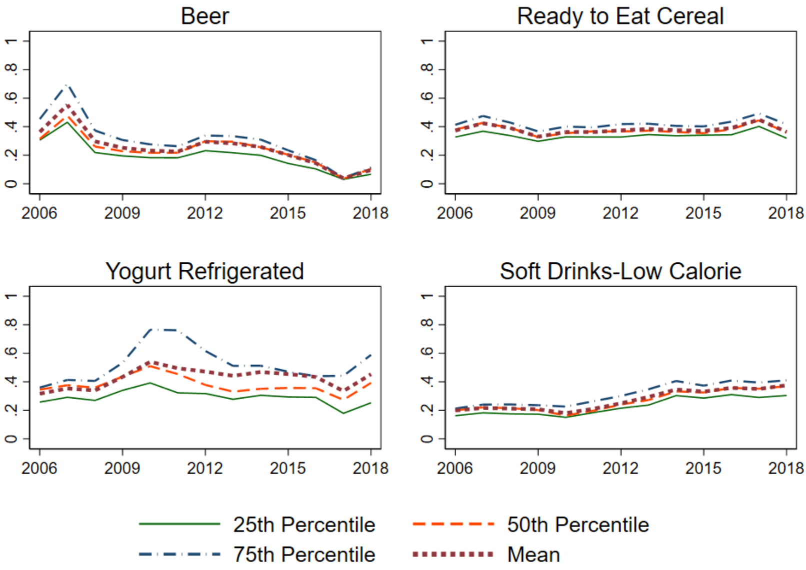
Define markups as

$$\mu_{jt} = \frac{p_{jt} - c_{jt}}{p_{jt}}$$

Markups, pooling across markets



Markups in individual markets



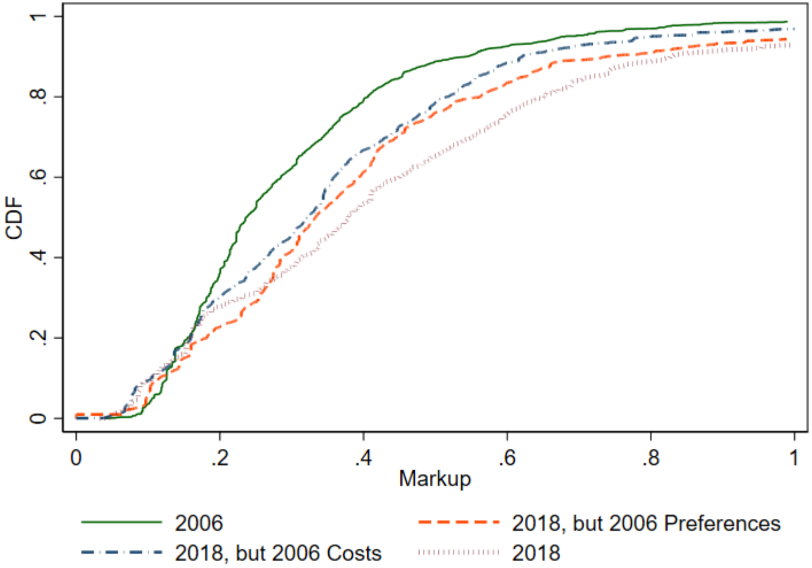
Counterfactual simulations

Primitives of the model: $\mathcal{J}$ (set of products), $c_{j,t}$ (marginal costs), Ω (ownership matrix), α (sensitivity to price), σ (correlation in taste shocks within nests).

1. What would markups have been in 2018 if preference parameters (α and σ) were held fixed at their 2006 values?
2. What would markups have been in 2018 if marginal costs (c) had remained unchanged from 2006?

We find that each explains a significant fraction of the shift in the markup distribution.

Counterfactual results



Conclusion

- Across 72 consumer packaged goods product markets, markups have broadly increased between 2006 and 2018
- But there is substantial heterogeneity in the markup changes, both within and across product markets
- Shifts appear to reflect changes in household preferences and marginal costs more than changes in firm ownership