Differences in Differentiation: Rising Variety and Markups in Retail Food Stores

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Microsoft

Disclaimer

Researcher(s) own analyses calculated (or derived) based in part on data from The Nielsen Company (US), LLC and marketing databases provided through 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 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.

Motivation

Retail supply chains have become much more vertically integrated in recent decades

- Investment in IT, RFID (Shin and Eksioglu, 2014)
- Chain-owned distribution centers (Fernie, Sparks, and McKinnon, 2010)

This has contributed to the rise of variety in retail stores: grocery stores grew from selling $\sim 9,000$ products in 1975 to $\sim 47,000$ by 2008 (Consumer Reports, 2014)

However, household consumption has become more concentrated (Neiman and Vavra, 2021)

- Newer products have new characteristics which are heterogeneously valued
- Consumers can find better matches for their needs
- $\rightarrow$ Less willing to substitute between products

Examples of new goods

Just say "sorry" to your butthole now. | Via
Instagram.com/mountaindew

FOOD & DRINK

No One Asked For It, But Mountain Dew Is Releasing a Flamin' Hot Cheetos Soda Anyway

Motivation

Recent work has shown that variable profit rates and concentration in the U.S. have been increasing since at least the 1980s

- The market share of the largest firms has been on the rise (Autor et al, 2020)
- Markups are rising in many industries (De Loecker, Eeckhout, and Unger, 2020)

Many candidate explanations, but many industry-specific factors

- Wholesale output has risen along with concentration (Ganapati, 2021)
- Grieco, Murry, and Yurukoglu (2021) highlight the role of rising costs and quality in auto industry markups

This paper: evaluating product differentiation as a source of "market power" in the retail sector

Simple model of portfolio choice

Let consumer i's utility from product j be

$$u_{ij} = -p_j + \epsilon_{ij}$$

Producers offer many goods, which are one of two types

$$\text{Staple}: \epsilon_{ij} = 1.5 \text{ for all } i$$
$$\text{Niche}: \epsilon_{ij} = 1 \text{ or } 2, \text{ each with probability } 0.5$$

Loose representations of new and existing products

- Staple: Pepsi, Coke
- Niche: Orange Vanilla Coke Zero

Simple model of portfolio choice

For the first good offered, sell either

- Staple at \$1.5
- Niche at \$2

If able to offer a second good, options are

- Two Staples at \$1.5
- One Staple at \$1.5, one Niche at \$2
- Two Niches at \$2

All additional products will be niche, so as portfolio size increases

- Newer products are more horizontally differentiated, increasing differentiation on average

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Taking model intuition to the data

Has differentiation changed over the past decade?

- Are consumers less willing to substitute between products?

Has firm pricing been consistent with a rise in markups in response to these changes?

What role has variety, and specifically the rise of niche products, played in these trends?

Nielsen data and selected categories

Weekly scanner data on price and units sold in stores classified as "Mass Merchandisers" and "Food Stores"

- 4,000-10,000 stores in both 2006 and 2017, first four months of the year

Module Description	# Stores
Fruit Drinks	10994
Soup	10991
Cookies	10995
Frozen Pizza	7528
Ice Cream	7393
Refrigerated Entrees	5613
Yogurt	5742
Fresh Fruit	4733
Light Beer	4138

Random coefficient discrete choice model

Consumers' indirect utility functions take the form

$$
\begin{aligned}
u_{ijsw} &= \alpha_i p_{jsw} + \xi_{jsw} + \epsilon_{ijsw} \\
u_{i0sw} &= \epsilon_{i0sw} \\
\xi_{jsw} &= \bar{\xi}_{js} + \bar{\xi}_{sw} + \Delta\xi_{jsw} \\
\alpha_i &\sim N(\bar{\alpha}, \sigma_\alpha^2) \\
\epsilon_{ij} &\sim T1EV(0, \sigma_\epsilon)
\end{aligned}
$$

Choices are made at the store-category-week level

Exogenous prices after absorbing store-week and product-store fixed effects

Ackerberg and Rysman

Nesting

Estimation: BLP and FRAC

Store-level BLP using pyblp (Conlon and Gortmaker, 2021)

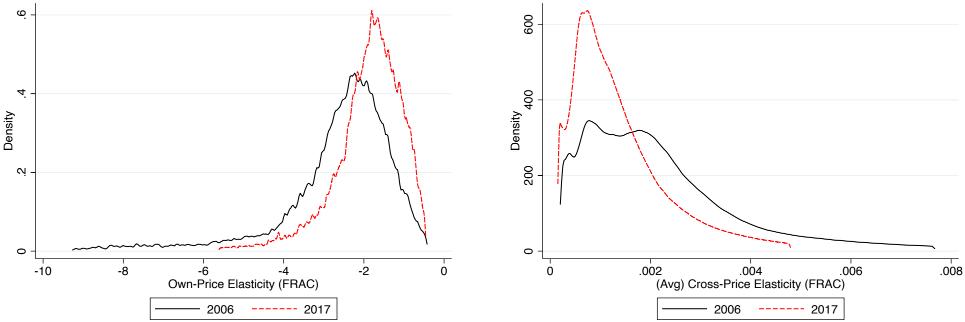
- Estimated for each category-year

Fast, "Robust," (or detail-free) and Approximately Correct (Salanie and Wolak, 2022)

- For small values of σ, the mixed logit model is approximately linear in parameters
- Estimated for each 3-digit ZIP-category-year

$$
\begin{aligned}
log\left(\frac{s_{jsw}}{s_{0sw}}\right) &= \bar{\alpha}_z p_{jsw} + \sigma^2_{\alpha,z} K_{jsw} + \xi_{jsw} + O(\sigma^4_{\alpha,z}) \\
K_{jsw} &= \left(\frac{p_{jsw}}{2} - e_t\right) p_{jsw} \\
e_{jsw} &= \sum_{k=1}^{J} s_{ksw} p_{ksw}
\end{aligned}
$$

Price elasticites have declined



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(b) 5% trimmed

Median own-price elasticity: (FRAC) $-2.33 \to -1.77$, (BLP) $-2.17 \to -1.65$

Median cross-price elasticity: (FRAC) $0.0019 \to 0.0011$, (BLP) $0.002 \to 0.0012$

BLP Estimates FRAC Correlation Yogurt Panel

Implied markups have risen in almost all modules

	BLP		FRAC	
Module	2006	2017	2006	2017
Fruit Drinks	1.79	2.26	1.82	2.20
Canned Soup	2.09	3.14	1.97	2.90
Cookies	2.16	3.06	2.01	2.55
Frozen Pizza	1.80	1.89	1.88	1.90
Bulk Ice Cream	2.22	2.20	2.01	2.28
Entrees	2.19	2.46	2.09	2.42
Yogurt	2.15	2.48	1.89	2.13
Remaining Fruit	1.75	2.47	1.73	2.18
Light Beer	1.49	1.62	1.49	1.67

Median implied markups, calculated assuming monopolistic portfolio pricing at the category-store-week level

Attributing differentiation to nicheness

Two key remaining questions from the toy model:

1. What role has rising preference heterogeneity played in rising differentiation?
    - Distinguishing between disutility of price and horizontal differentiation
2. Are newer products more niche than older products?
    - Advertising could make all products further differentiated

Decomposition: changes in α and σ_ϵ

Consider a model in which both the disutility of price and the variance of preferences change over time

$$u_{ijsw} = \begin{cases} \alpha_{2006} p_{jsw} + \bar{\xi}_{js} + \Delta\xi_{jsw} + \epsilon_{ijsw} & \text{in 2006} \\ \alpha_{2017} p_{jsw} + \bar{\xi}_{js} + \Delta\xi_{jsw} + \epsilon_{ijsw} & \text{in 2017} \end{cases}$$

$$\epsilon_{ijsw} \sim \begin{cases} T1EV(0, \sigma_{\epsilon,2006}) & \text{in 2006} \\ T1EV(0, \sigma_{\epsilon,2017}) & \text{in 2017} \end{cases}$$

Inferring heterogeneity from estimated fixed effects

The standard logit inversion yields

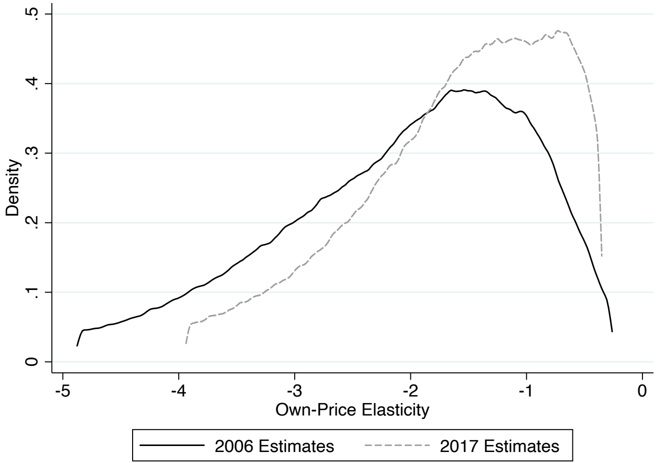
$$log\left(s_{jsw}/s_{0sw}\right) = \begin{cases} \frac{\alpha_{2006}}{\sigma_{\epsilon,2006}} p_{jsw} + \frac{\bar{\xi}_{js}}{\sigma_{\epsilon,2006}} + \Delta\xi_{jsw} & \text{in } 2006 \\ \frac{\alpha_{2017}}{\sigma_{\epsilon,2017}} p_{jsw} + \frac{\bar{\xi}_{js}}{\sigma_{\epsilon,2017}} + \Delta\xi_{jsw} & \text{in } 2017 \end{cases}$$

Comparing $\bar{\xi}_{js}$ in 2006, 2017 gives an estimate of $\frac{\sigma_{\epsilon,2006}}{\sigma_{\epsilon,2017}}$

- **Counterfactual**: Re-calculate price elasticities in 2017 under 2006 levels of σ_ϵ

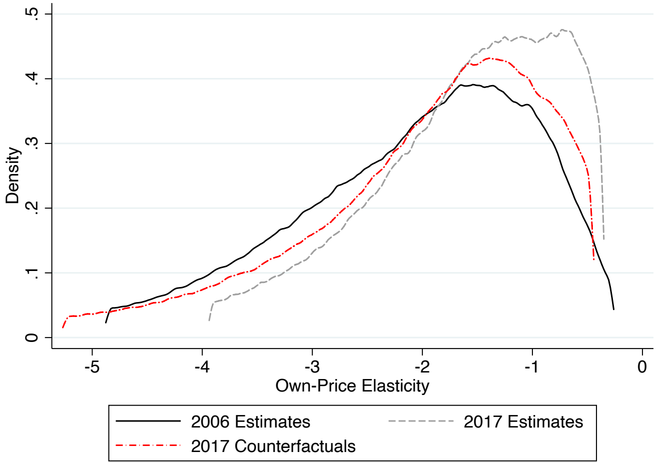
Outside Option Estimates of Ratio

Estimated own-price elasticities



By Module Table Average Elasticities

Counterfactual elasticities with $\sigma_{\epsilon,2006} = \sigma_{\epsilon,2017}$



By Module | Table | Average Elasticities | Full Decomposition

Allowing for nicheness in the empirical model

Simple model: let the variance of ϵ differ for newer and older products

$$u_{ijsw} = \alpha_i p_{jsw} + \xi_{jsw} + \epsilon_{ijsw}$$

$$\epsilon_{ijsw} \sim \begin{cases} T1EV(0, \sigma_{\epsilon,old}) \text{ for "old" products} \\ T1EV(0, \sigma_{\epsilon,new}) \text{ for "new" products} \end{cases}$$

Empirical Model:

$$u_{ijsw} = \begin{cases} \alpha_i p_{jsw} + \xi_{jsw} + \epsilon_{ijsw} \text{ for "old" products} \\ \rho(\alpha_i p_{jsw} + \xi_{jsw}) + \epsilon_{ijsw} \text{ for "new" products} \end{cases}$$

If all markets contained only "old" or "new" products, then $\rho = \frac{\sigma_{\epsilon,old}}{\sigma_{\epsilon,new}}$

Allowing for nicheness in the empirical model

	$\rho \approx \frac{\sigma_{old}}{\sigma_{new}}$
Fruit Drinks	0.92
	(0.02)
Soup	0.92
	(0.01)
Cookies	0.98
	(0.01)
Pizza	0.93
	(0.03)
Ice Cream	0.67
	(0.02)
Entrees	0.82
	(0.02)
Yogurt	0.79
	(0.02)
Remaining Fruit	1.08
	(0.04)
Light Beer	0.34
	(0.01)

Log Normal Higher Quality?

Summarizing findings

I find that price elasticities have decreased significantly in nine large retail product categories between 2006 and 2017

- Relative to 2006 levels, median price elasticities have declined by 25% across modules
- These findings are supported by Döpper, MacKay, Miller, and Stiebale (2022) in a much larger set of categories at a higher level of aggregation

Implied markups are of similar magnitude to retail markups in De Loecker, Eeckhout, and Unger (2020)

Summarizing findings

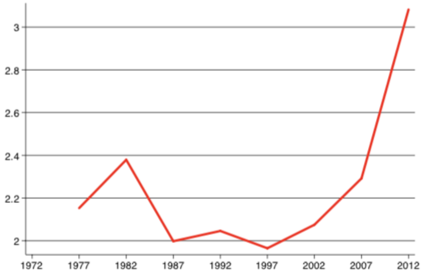
Average horizontal preference heterogeneity has increased in most categories, and newer products are often more heterogeneously valued

- Fundamentally store-level story: cost reduction changes optimal portfolio

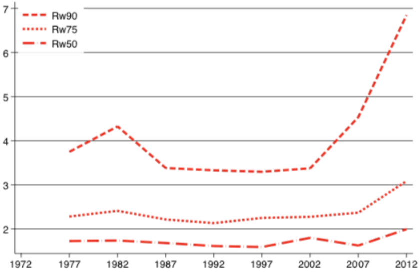
More work to do: scale up and evaluate other mechanisms

- Estimation of consideration set models with large choice sets (Brand and Demirer, 2022)
- Computational speed: iterating on FRAC.jl and ASCDemand.jl
- Vertical contracting difficult to assess but important alternative

Retail Markups in the Census (DLEU 2020)



(c) Retail: average



(d) Retail: percentiles

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Removing Modules with Storage

In the absence of storage, time since last purchase and the characteristics of lagged purchase should be independent conditional on price

With this in mind, I use the consumer panel data to estimate the following regression

$$Time\ Since_{it} = f(p_{it}) + \beta q_{it-1} + \theta_h + \delta_j + \eta_{it}$$

- Low prices predict shorter time since last purchase
- Household FEs - household size
- Product FEs - multi-unit packaging

I then test the hypothesis $H_0 : \beta = 0$ for each of 40 large modules

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Why Not Nest Inside Options?

Product(-store) fixed effects do a lot of what nesting aims to do (allowing asymmetries)

Nesting, unfortunately, ties together two features which are at odds in large choice sets:

- How close products are (in characteristic space) within a nest
- How close they are across nests

I have estimated nested logit models, and they are much more likely not to converge. When they do, my conclusions don't change at all

Light Beer Back

New Products Higher Quality?

So far, little discussion of vertical differentiation

- Higher quality often more expensive

Store-level logit models also return estimates of store-product fixed effects in 2017

- Are products which have been added to a store since 2006 higher "quality"?
- Captures both new product quality and dispersion

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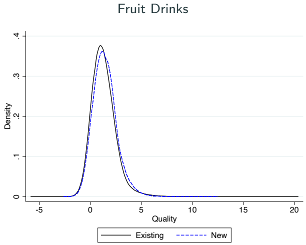
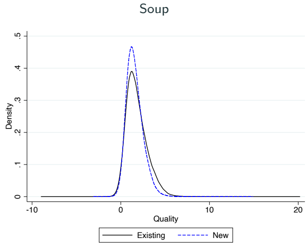
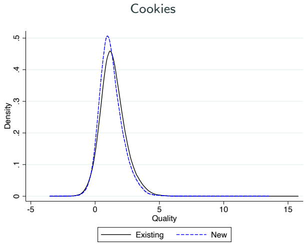
New Products Higher Quality?







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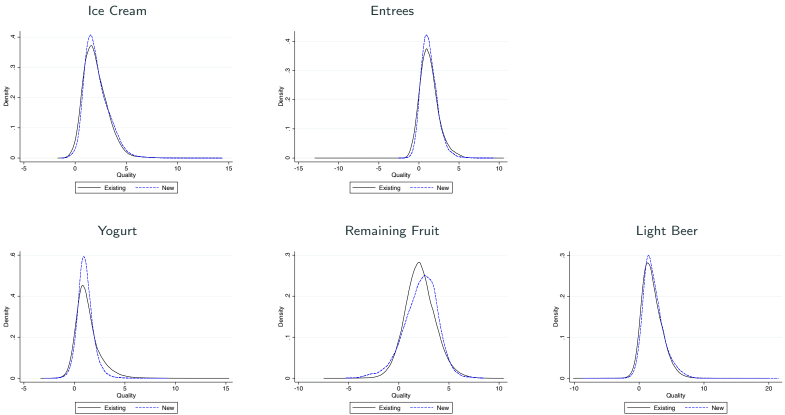
New Products Higher Quality?



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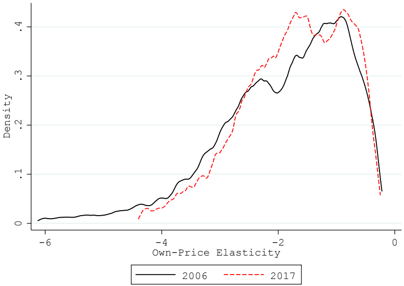
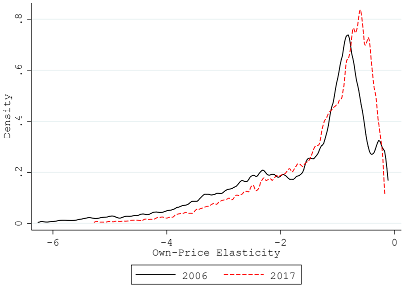
Additional Modules

(a) Fresh Eggs



(b) Soda



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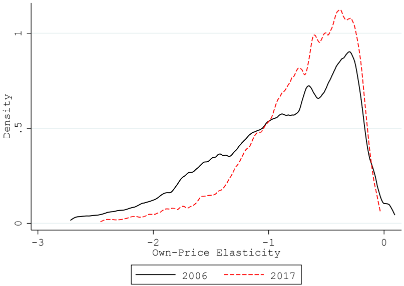
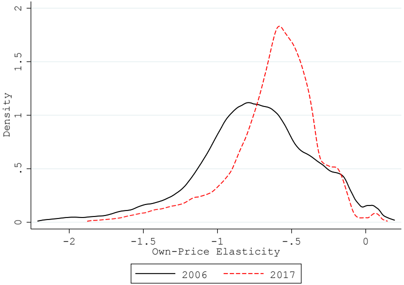
Additional Modules: Baby Milk

(a) Full Distribution



(b) Store-Week Average



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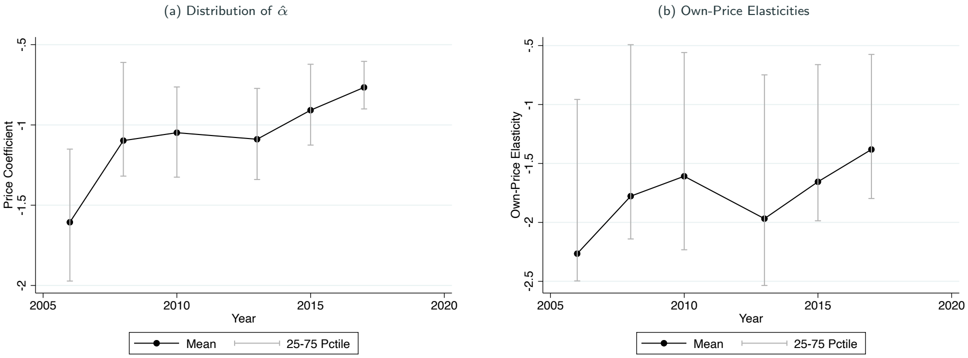
Yogurt Panel



- Results of store-year logit demand models for 2006, 2008, 2010, 2013, 2015, and 2017

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Calculating the Outside Option

Always assumptions involved in constructing the outside option

- Frequent approaches rely on population in a nearby area

Want to incorporate information about heterogeneity both

1. Across stores
2. Across categories

Suppose 100 households buy yogurt in 2006, but only 50 purchase yogurt in the average week.

- For each module-store, Market size $= \max(\text{units sold in store}) \times \frac{100}{50}$

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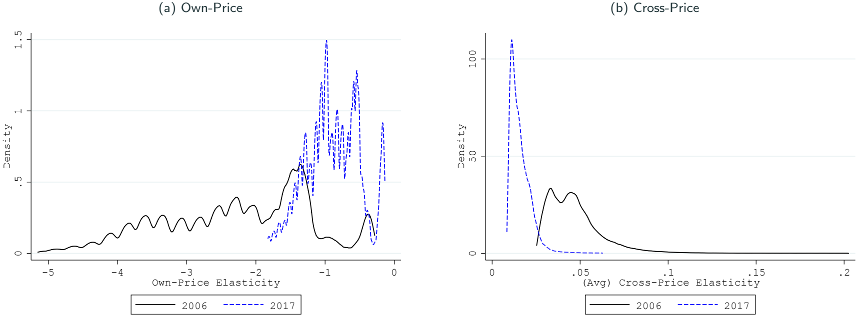
Nested Logit: Light Beer



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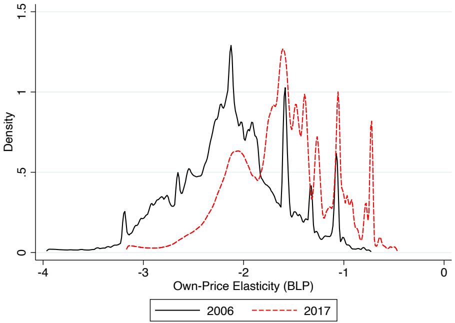
BLP Elasticities



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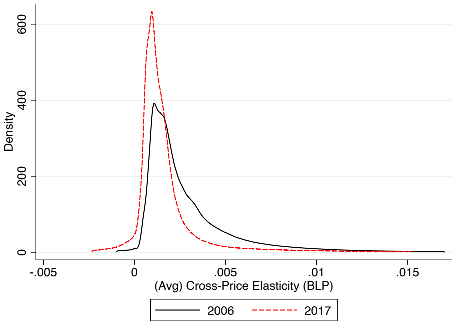

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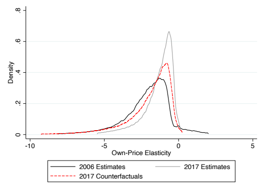
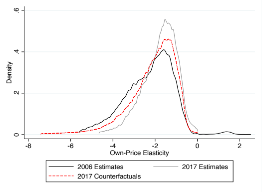
Preference Heterogeneity

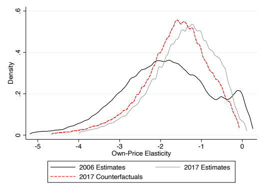
Fruit Drinks



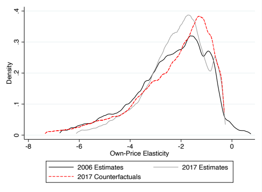
Canned Soup



Cookies



Frozen Pizza



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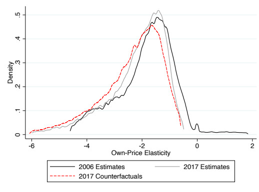
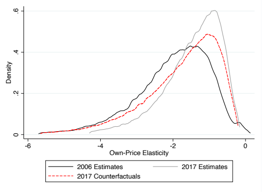
Preference Heterogeneity

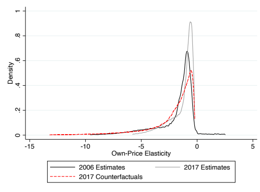
Ice Cream



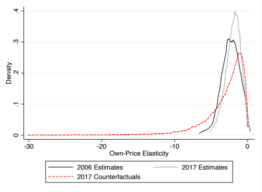
Entrees



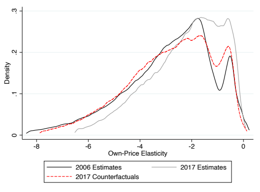
Yogurt



Remaining Fruit



Light Beer



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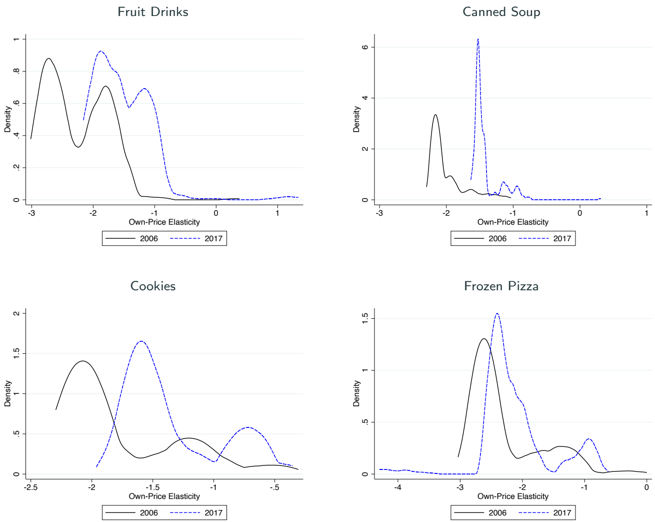
Average Price Elasticities (BLP)



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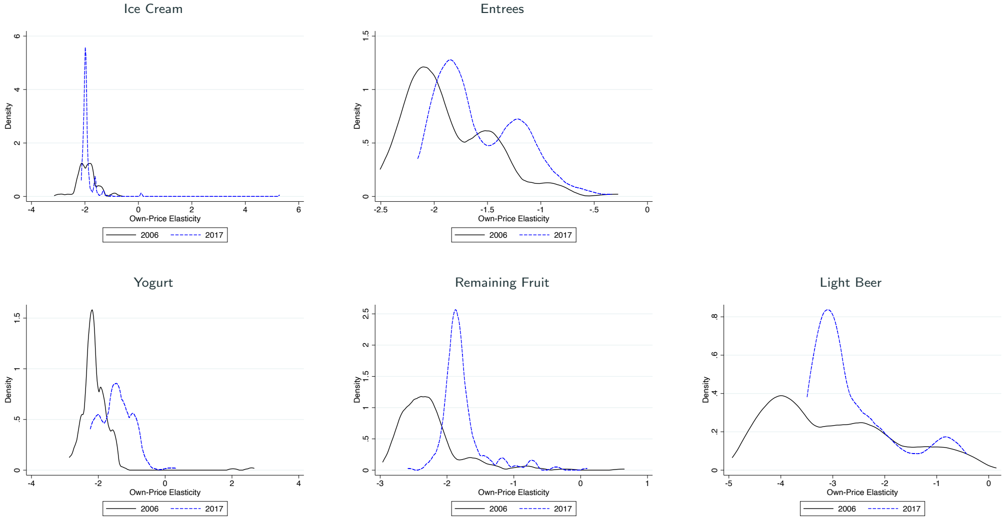
Average Price Elasticities (BLP)



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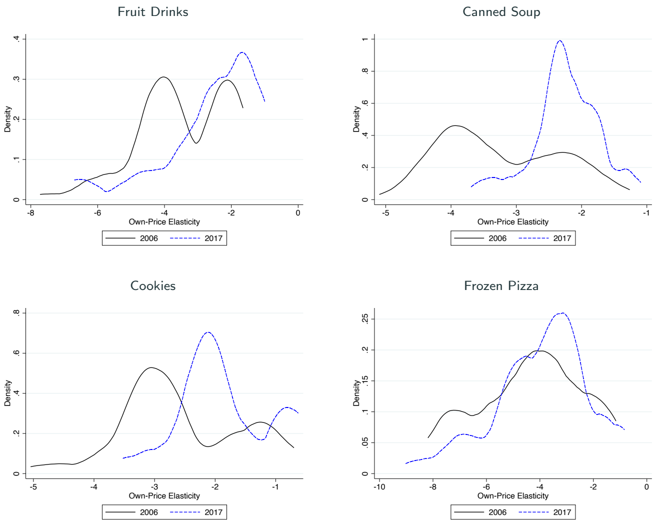
Average Price Elasticities (FRAC)



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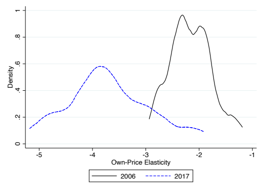
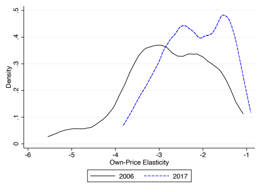
Average Price Elasticities (FRAC)

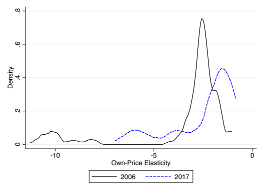
Ice Cream



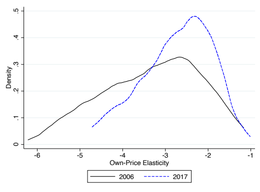
Entrees



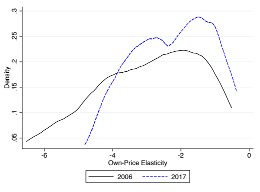
Yogurt



Remaining Fruit



Light Beer



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Ackerberg and Rysman

Ackerberg and Rysman (2003) note that SUPD in logit models imply strong assumptions about substitution patterns arising from changing choice sets.

Their additive fix:

$$u_{ijt} = x_{jt}\beta + \gamma ln(N_t) + \epsilon_{ijt}$$

To make this correction nonparametric, could include dummies for each level of N_t.

- Store-week fixed effects absorb these indicators

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FRAC Correlation Matrix, 2006

	Drinks	Soup	Cookies	Pizza	I.C.	Ent.	Yog.	Fruit	Beer
Fruit Drinks									
Soup	0.26								
Cookies	0.55	0.14							
Pizza	0.53	0.19	0.49						
Ice Cream	0.35	0.33	0.34	0.45					
Entrees	0.38	0.49	0.42	0.5	0.5				
Yogurt	0.29	0.41	0.32	0.35	0.41	0.41			
Fruit	0.28	0.39	0.49	0.48	0.11	0.51	0.27		
Light Beer	0.34	0.46	0.35	0.36	0.08	0.28	0.18	0.53	

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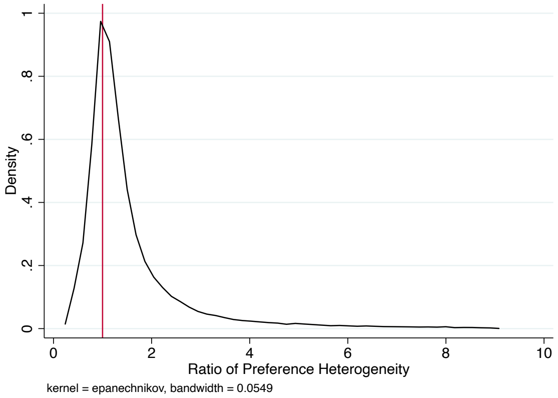
Estimates of $\frac{\sigma_{2017}}{\sigma_{2006}}$



- 70% greater than 1

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Size of Outside Option

	2006	2017
Fruit Drinks	0.942	0.941
Soup	0.931	0.942
Cookies	0.910	0.914
Pizza	0.941	0.942
Ice Cream	0.939	0.946
Entrees	0.960	0.958
Yogurt	0.902	0.877
Remaining Fruit	0.973	0.913
Light Beer	0.942	0.945

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Comparing Counterfactuals to 2006

	2006 Estimates	2017 Counterfactuals	2017 Estimates
Mean	-2.13	-2.33	-1.7
10%	-4.00	-4.08	-3.21
25%	-2.89	-2.73	-2.25
Median	-1.89	-1.76	-1.47
75%	-1.16	-1.10	-.87
90%	-.63	-.64	-.50

- Counterfactuals set preference heterogeneity to 2006 levels in each store

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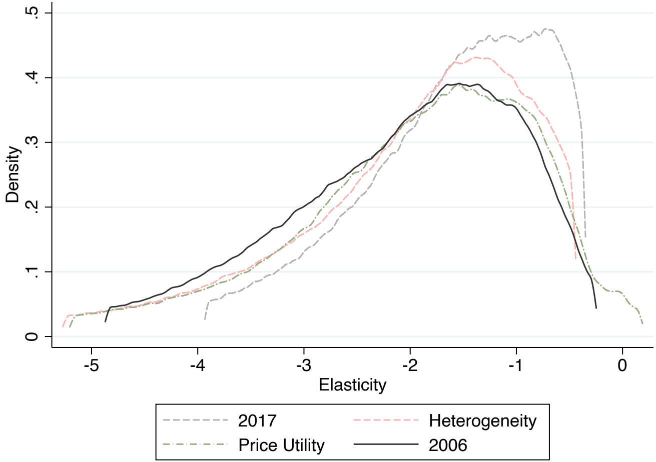
Full Decomposition



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Average Elasticities

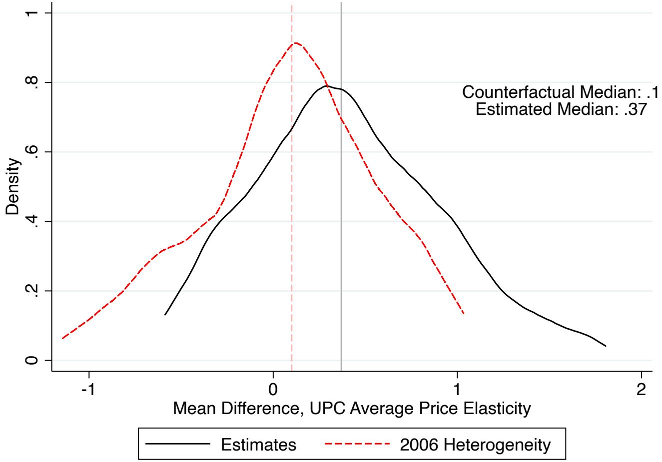
These distributions could be masking heterogeneity

- Might be matching moments well but making individual price elasticities *more* different

Alternative: compare product-level average elasticities among products sold in a store in both years

- Average price elasticities should move less after setting preference heterogeneity to 2006 levels

Average Elasticities



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New Products More Niche?

	$\frac{\sigma_{old}}{\sigma_{new}}$
Fruit Drinks	
Soup	0.88
	(0.04)
Cookies*	0.93
	(0.14)
Pizza*	0.77
	(0.04)
Ice Cream	0.90
	(0.10)
Entrees*	0.75
	(0.06)
Yogurt	
Remaining Fruit	1.07
	(0.04)
Light Beer	0.61
	(0.02)

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