Secular Rise and Pro-cyclical Variation in Markups: Evidence from US Grocery Stores.

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Motivation

- **Evidence on Rising Markups**: across US sectors, especially in the retail sector (e.g. De Loecker et al. [2020, QJE] , Philippon [2019]).
- **Trend in markups affects important stylized facts** Eggertsson et al. [2021, JME] link markups to wealth-to-income ratio, Tobin's Q, real interest rate, and investment-to-output ratio (also see Syverson [2019, JEP])
- **Is there a connection between markups and the business cycle?** Stroebel and Vavra [2019, JPE] present evidence that retail prices react to household wealth, suggesting an effect on markups.
- **Little higher-frequency empirical evidence on pro-cyclical market power** Nekarda and Ramey [2020, JMCB] present macro-level time series evidence

Methodology

- **Estimate elasticity of demand faced by stores:** local elasticity is estimated based on observations resulting from market equilibrium outcomes.
- **Our Approach**: Use panel-IV to estimate local average *market-year-category* elasticity.
  1. Implement Hausman [1996] price IV by pairing geographically close markets.
  2. Use time fixed effects to control for common demand shocks.
  3. Estimate price elasticities at the less-noisy product-category level.
- **Use Lerner index of markups $\frac{e}{e-1}$:** corresponds to store's optimal price setting strategy in equilibrium [Lerner, 1934, DellaVigna and Gentzkow, 2019]

Preview of Results

- **New estimates of trend and business cycle variation in markups**: consistent with previous work on markup trend estimated from cost data.
  1. *Elasticity*: downward trend (0.04/year) + increase after recessions (0.16/year).
  2. *Implied Markups*: upward trend (4%/year) + decrease after recessions (14%/year).

- **New cross-sectional evidence on effects of income on markups**

- **Important implications for policy**: suggests transmission mechanism of monetary policy through effect on markups.

Previous Work on Sector-wide Rising Markups

- **Supply-side Evidence**: cost minimization; firm-level accounting data; many sectors; higher in retail sector De Loecker et al. [2020].
- **Demand-side Evidence**: profit maximization; scanner data of store-product sales; food retail sector.
  1. *Structural approach (BLP)*: analyze generally small sets of both food and nonfood products [De Loecker and Scott, 2016, Brand, 2021, Döpper et al., 2022].
  2. *Our Paper*: (i) panel-IV; (ii) all food products; (iii) sizable & significant markup variations around business cycles; and (iv) longer sample period.

Elasticity: Data

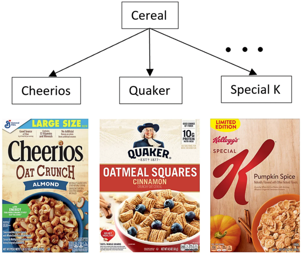
- **Retail Scanner Data**: 2001-2020.
  1. IRI, 2001-2012 (Bronnenberg et al., 2008).
  2. NielsenIQ, 2006-2020 (the Kilts Center for Marketing at UChicago).
  3. Weekly product quantities and revenues at the store level for each barcode (UPC).

- **Food Products, Food Stores**
  1. *IRI*: 16 categories.
  2. *Nielsen*: 60 categories.

Category-level statistics

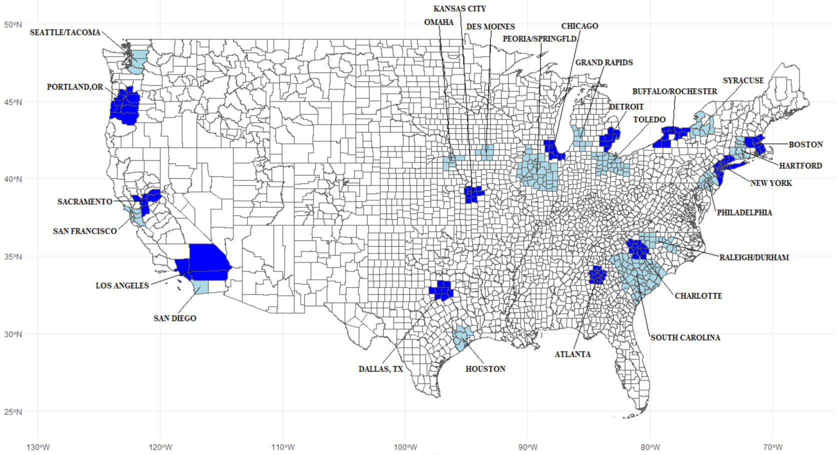
	IRI mean	Nielsen mean
#UPCs/year	2,097	4,412
#UPCs/year-market	541	1,052
#UPCs/year-market-store	214	339

- **Examples**: cereal.



Paired neighboring markets in major US regions

A market, defined by IRI, consists of one or several adjacent counties.
Among 50 IRI markets, select 26 relatively large ones as 12 close pairs.



Elasticity: panel-IV approach

- **Within each market(m)-category(c)-year(t) pair**:

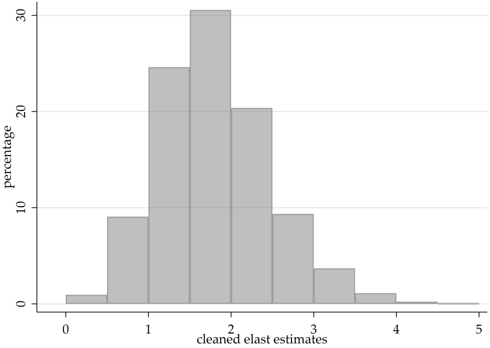
  $$log(q_{v,s,w}) = -\boldsymbol{e_{m,c,t}} log(p_{v,s,w}) + UPC_v + store_s + week_w + \varepsilon_{v,s,w},$$

  where $q_{v,s,w}$ and $p_{v,s,w}$ denote the quantity and (imputed) price of **product** v **sold by store** s **in week** w.

  1. *Price IV*: the quantity-weighted average of log weekly prices of the same product sold in the paired market(s).
  2. *Fixed effects*: various demand effects.
     (i) $week_w$: local demand shocks + prices of other categories;
     (ii) UPC_v: local preferences over products;
     (iii) $store_s$: local preferences over stores.
  3. *Clustered standard errors*: at store and week levels.

Elasticity: cleaned estimates

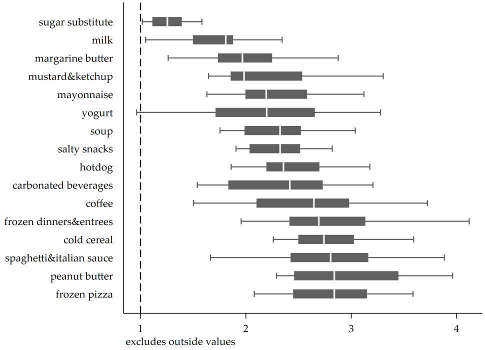
- Cleaned elasticity estimates: IRI & Nielsen, **25,100/27,500** (91%).
  1. *Drop*: weak IV + negative estimates.
  2. *Trim*: upper and lower 1% by year.



- *Distribution*: 5% significantly below 1 while 10% below 1.
- *Precision*: 95% standard errors below 0.4.

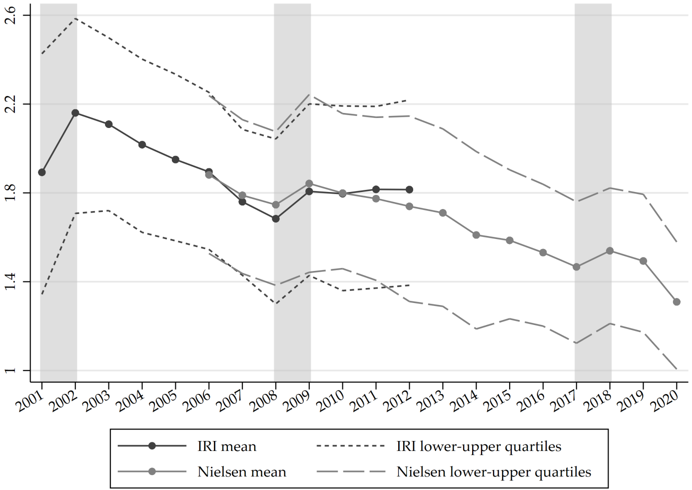
Elasticity: differences across categories and markets

- IRI elasticity estimates in 2010.



  - *Cereal*: mean of 2.5 for 2007-2010 in LA, close to mean of 2.2 estimated by Richards and Hamilton [2015, REStat].
  - *Yogurt*: [1.0, 4.2] for 2001-2010 in 26 markets; Hristakeva [2022, JPE] has a mean estimate of 4.0 for all markets during the same period.

Elasticity: Time Variation

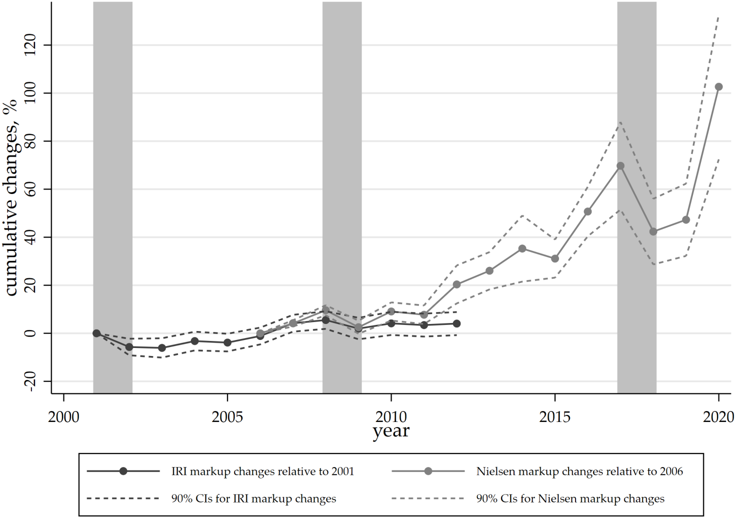


Levels of IRI estimates shifted to match mean Nielsen estimates in the overlap sample period. Quantiles reported: 25% and 75%

Impute Markup from Elasticity

- **Calculate average elasticity**: compute good-weighted elasticity at the market level.
- **Monopolistic Pricing**: set price to maximize profit (e.g., DellaVigna and Gentzkow [2019, QJE]).
  1. *Markup*: $\frac{p}{mc} = \frac{e}{e-1}$.
  2. *Cumulative percentage change*: $ln(\frac{e_t}{e_t-1}) - ln(\frac{e_{t_0}}{e_{t_0}-1})$.

Time Variation in Makrups

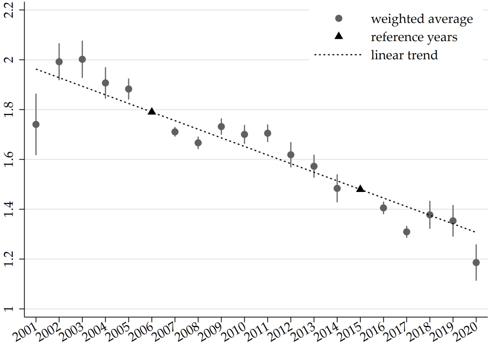


Elasticity: trend and cyclical decomposition

- **Panel regression**

$$\hat{e}_{m,c,t} = trend_t + year_t + data_d \times market_m \times category_c + u_{m,c,t},$$

with the inverse of elasticity s.e. as weights and $u_{m,c,t}$ clustered at the market level.



Elasticity and Implied Markup: trend and cyclical variation

Trend and Cyclical Variation in Elasticity and Implied Markup.

	elasticity	markup
Trend		
average annual change, 2001-2020	-0.035***	3.9%***
	(0.004)	(0.7%)
Cyclical changes		
from 2001 to 2002	0.286***	-15.1%***
	(0.052)	(2.8%)
from 2008 to 2009	0.100***	-8.0%***
	(0.013)	(1.0%)
from 2017 to 2018	0.103***	-17.8%***
	(0.025)	(4.3%)

Note: Standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Driving Factors of Elasticities: data & identification

- Market-year factors $X_{m,t}$: county-level raw data; take *ln* and then weight by population.

  real GDP per capita/unemployment rate/real housing price/population/ econ dependency ratio/No. of grocery establishments per 10k residents.

- Use fixed effects regression weighted by elasticity s.e.

Driving Factors of Elasticities: estimation results

	dependent variable: *elasticity*		
	(1)	(2)	(3)
explanatory variables	main	variety	balanced
real GDP per capita	-0.85***	-0.82***	-0.90***
	(0.16)	(0.15)	(0.14)
unemployment rate	1.49	1.51	1.46
	(1.25)	(1.20)	(0.98)
cum. change in real housing price	0.40***	0.38***	0.29***
	(0.13)	(0.11)	(0.09)
economic dependency ratio	0.35	0.31	-0.03
	(0.38)	(0.33)	(0.26)
population	-1.20**	-1.12**	-0.73***
	(0.56)	(0.42)	(0.26)
grocery establishments per capita	-0.02	-0.05	-0.13
	(0.17)	(0.14)	(0.11)
No. of UPCs per category		0.10	
		(0.12)	
market×category FE	YES	YES	YES
year FE	YES	YES	YES
$adj.R^2$	0.337	0.341	0.405
N	25,062	25,062	19,746

Note: (1)-(3) are OLS regressions with the reciprocals of elasticity variances as weights. Standard errors of coefficients, clustered at the market level, are listed in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Conclusion

- Implement a panel-IV approach to precisely estimate own-price elasticities of demand; aggregate at the year-market-category level.
- Trend and cyclical variation in own-price elasticities of demand imply rising and pro-cyclical markups in the food retail sector.
- Economic factors, such as real GDP per capita, drive these changes.

Elasticity: OLS versus IV

IRI sample: attenuation bias of OLS estimates relative to IV's.