Re-Engineering Key National Economic Indicators

Sloan Project

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Status quo: Decentralized data collections

Real output

- Census collects the "numerator": Revenue
- BLS collects the "denominator": Prices
- BEA does the division: $Q = P*Q/P$

Non-simultaneous collection of price and quantity

- Stratified surveys from small and deteriorating samples
- Mismatch of price and revenue data
- High cost and burden
- Difficulty of accounting for changes in products

Measuring Real and Nominal Consumer Spending—Current Architecture

Census (nominal spending)

Data collection:
Retail Trade surveys (monthly and annual)
Economic Census (quinquennial)
Consumer expenditure survey (conducted for BLS)

Published statistics:
Retail Trade (monthly and annual) by firm type
Retail Trade (quinquennial) by product class

BLS (prices)

Data collection:
Consumer Expenditure survey (used for spending weights), collected under contract by Census
Telephone Point of Purchase survey (purchase location)[a]
CPI price enumeration (Probability sampling of goods within outlets)

Published statistics:
Consumer Price Index (monthly) by product class

BEA (aggregation and deflation)

Data collection:
Census and BLS data; supplemented by multiple other sources

Published statistics:
Personal Consumption Expenditure: Nominal, real, and price (monthly)
GDP (quarterly)

Reengineered data for retail P and Q

Item-level transactions data

- Item-level data allows inferring price from sales and quantities
- Price, quantity, revenue (and potentially characteristics) measured
  - Simultaneously
  - At high frequency
  - Universe (or large sample) of transactions
  - With little lag
  - With reduced need for revisions
  - With granular information on location of sale (geography, store/online)
  - Immediate accounting for changes in goods
  - Need characteristics and/or detailed product classification

Roadmap of analysis presented today

Objective is to explore alternative methods for measuring revenue, real revenue and prices that are derived from the same (item-level transactions) source data.

Focus today on price indices using item-level transaction data for P and Q

- Nielsen covers grocery stores and mass merchandisers
  - More than 100 product groups and 1000 product modules (millions of products). Some of these match closely to BLS CPI and BEA PCE categories.
  - Classify into Food and NonFood items for broader perspective and comparisons with CPI and PCE measures.
- NPD covers general merchandise and online retailers
  - Product groups we have investigated include memory cards, headphones, coffeemakers, apparel bottoms (boy's jeans) and active footwear (work boots).
  - NPD data have rich product attributes
- We are also working with individual company level data.
- Explore hedonics vs. alternative methods (e.g., UPI) for quality adjustment

Price indices adjusted for quality at scale – Using same source data to measure revenue

Key challenge/opportunity: Enormous Product Turnover

- 650,000 products per quarter from 35,000 stores
- Product entry and exit rates (quarterly)
  - 9.62% (entry) and 9.57% (exit)
- Sales-weighted entry and exit rates
  - 1.5% (entry) and 0.3% (exit)
  - Rates vary substantially across product groups
  - Asymmetry in sales-weighted: “slow death” of exiting products
- Some of this entry/exit is substantive, other is marketing/packaging

Source: Nielsen scanner data (Food and NonFood)

CES Unified Price Index (CUPI) (Redding and Weinstein 2020)

$$\log(\text{CUPI}) = RPI + PV_{adj} + CV_{adj}$$

RPI is Jevons Index

$$RPI = \frac{1}{N_t^*} \sum_{k \in \Omega_t^*} \ln(\frac{p_{kt}}{p_{kt-1}}) \quad PV_{adj} = \frac{1}{\sigma - 1} \ln(\frac{\lambda_t}{\lambda_{t-1}}) \quad CV_{adj} = \frac{1}{\sigma - 1} \frac{1}{N_t^*} \sum_{k \in \Omega_t^*} \ln(\frac{s_{kt}^*}{s_{kt-1}^*})$$

Key Issues:

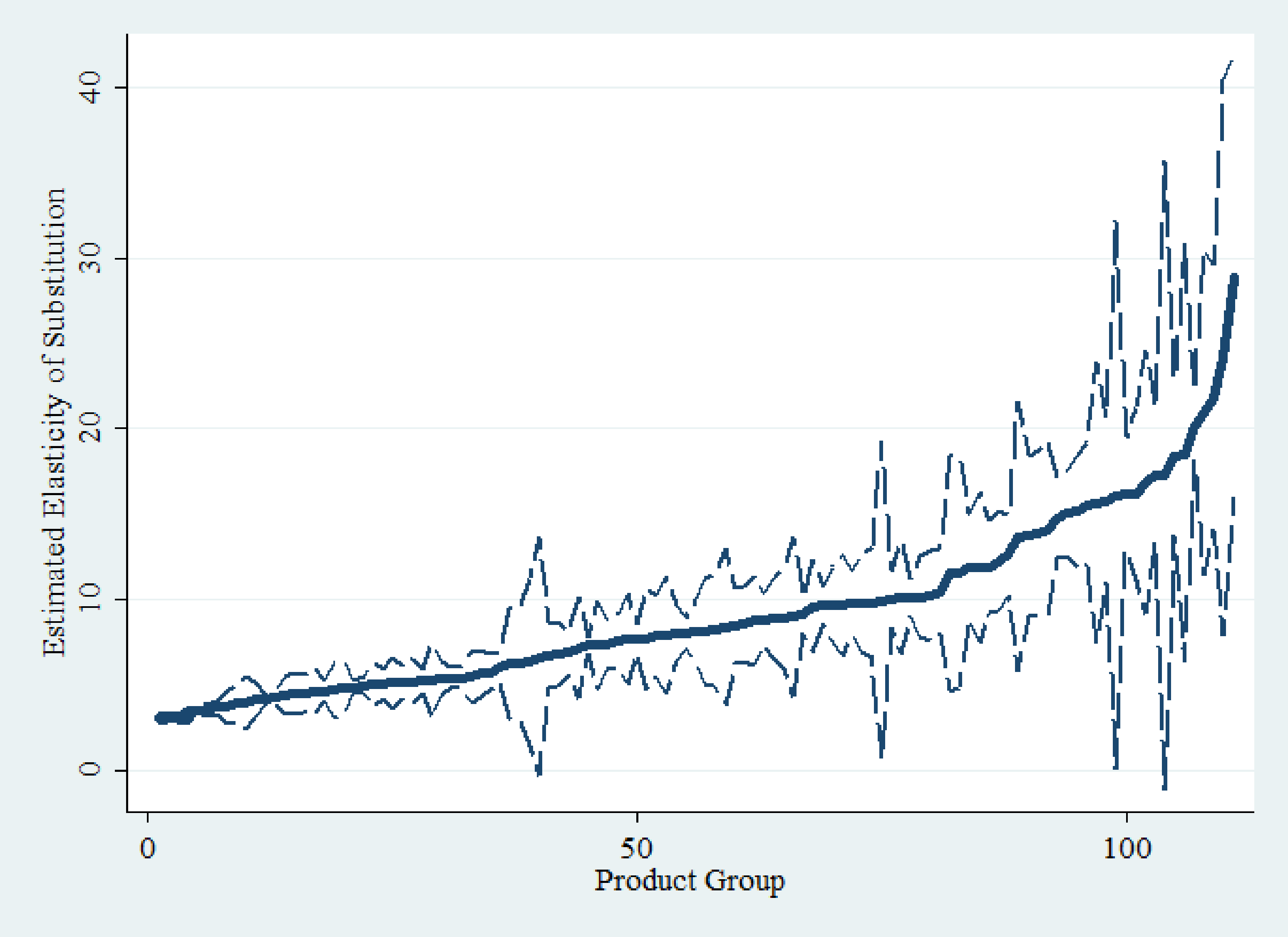
- Magnitude of adjustment factors depend on elasticity of substitution for narrow group.
- $\lambda_t \equiv \frac{\sum_{k \in \Omega_t^*} P_{kt} C_{kt}}{\sum_{k \in \Omega_t} P_{kt} C_{kt}}$ where Ω_t^* are common goods and Ω_t are all goods in t.
- s_{kt}^* is volatile for recently entered and goods about to exit as are prices. RPI and CV_{adj} very sensitive to definition of **COMMON GOODS**.
- Intermediate step: Only consider product turnover yields "Feenstra" index:
  $\log(Feenstra) = PV_{adj} + SV$, where SV is the Sato-Vartia index

Hedonics at scale with item-level transactions data

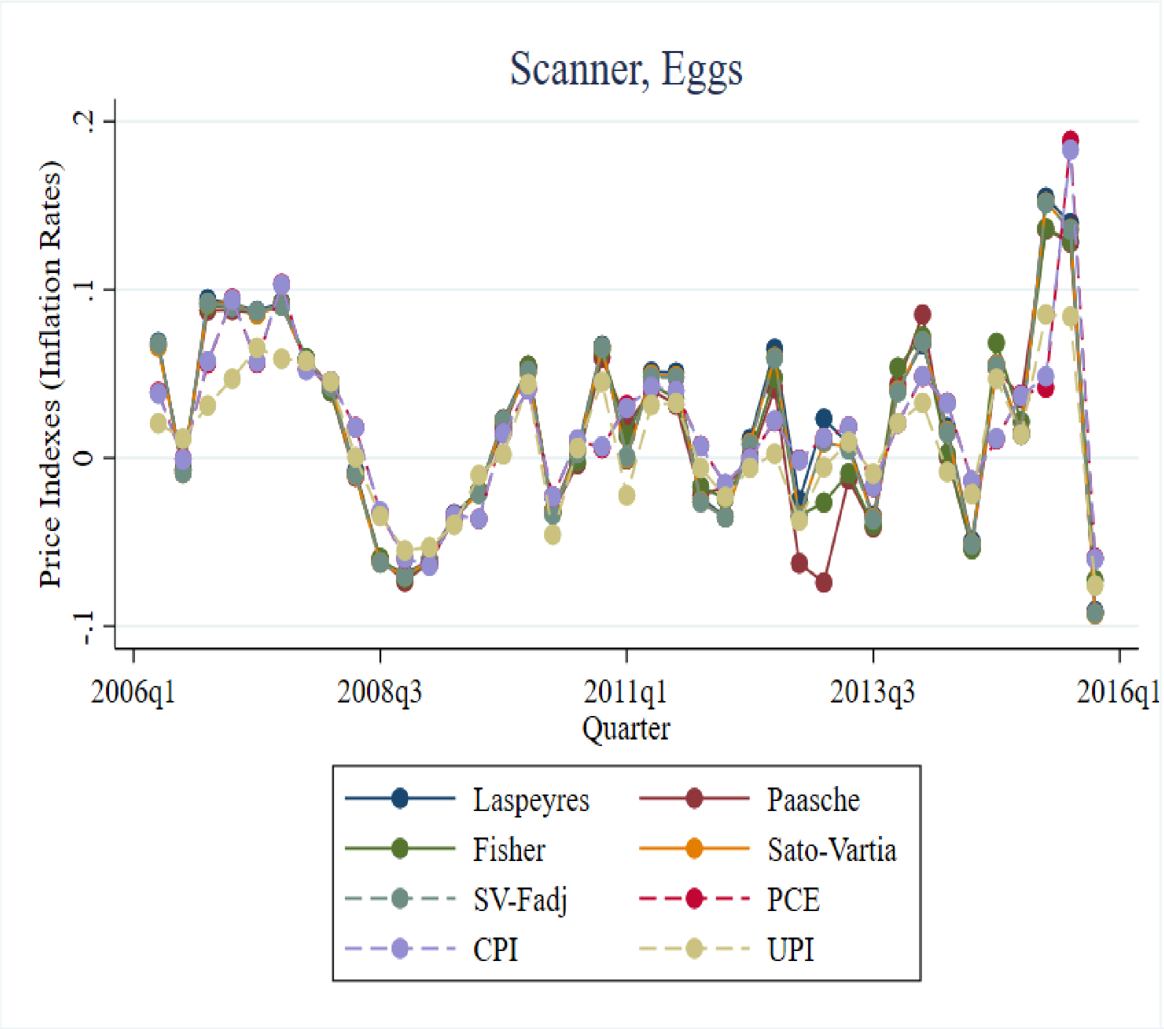
Following Bajari and Benkard (2005), Erickson and Pakes (2011), Byrne, Sichel and Aizcorbe (2019), Bajari et. al. (2019) we consider a variety of hedonic specifications using item-level data

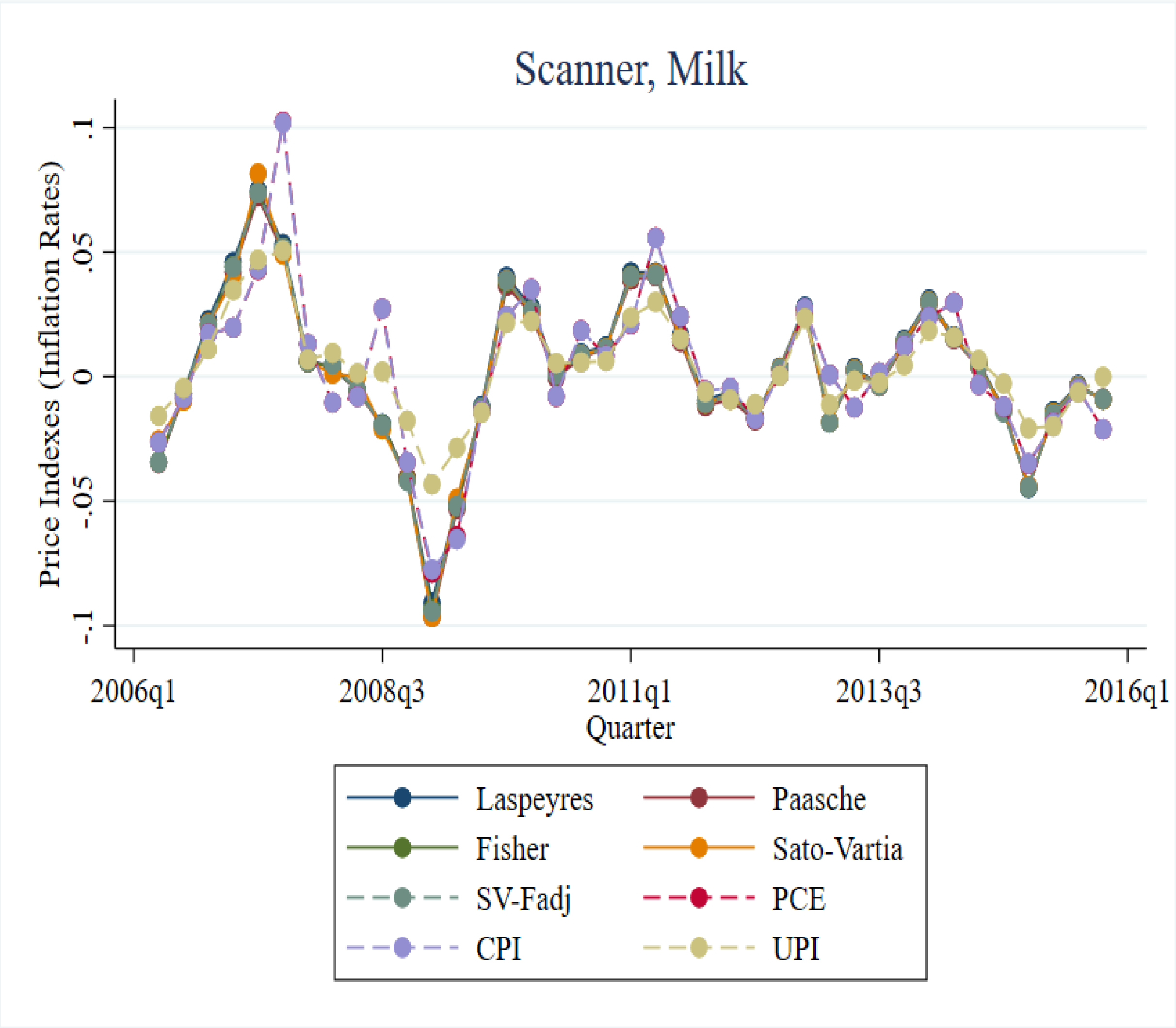
1. Log level and log first difference specifications.
    1. Erickson and Pakes (2011) control for unobservables (first difference and time varying unobservable specifications).
2. Time dummy method
3. Weighted and unweighted.
4. Also, exploring machine learning methods for measuring characteristics following Bajari et. al. (2019).
5. Much of this analysis is behind Census and company firewalls. Only have limited analysis for NPD released to date.

Estimated Elasticities of Substitution by Product Group for Retail Scanner



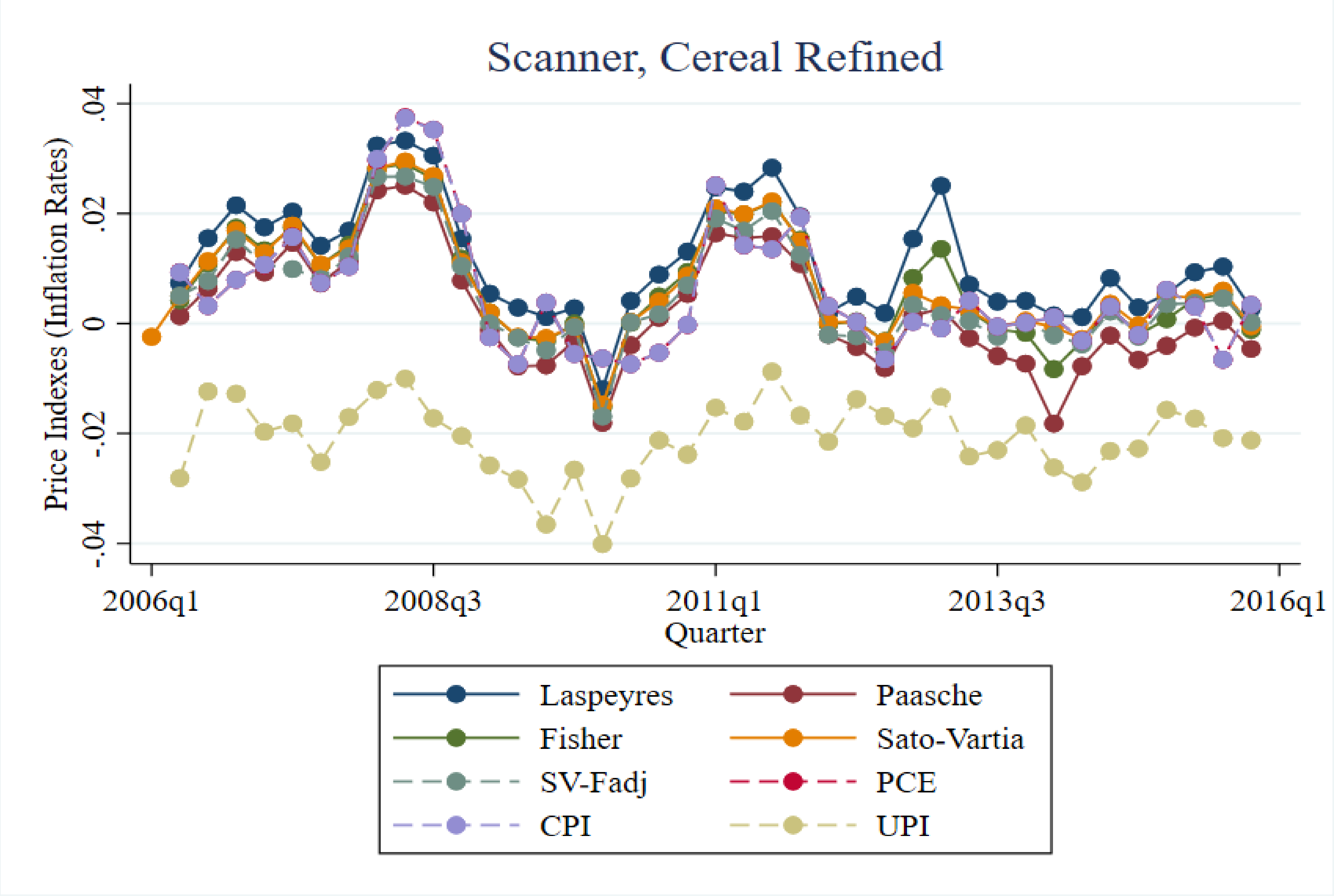
Scanner-based traditional price indices similar to CPI and PCE for basic food products. For these products, little difference with Feenstra (1994) adjusted SV for product turnover or UPI.





UPI uses 10% CGR (only goods with above 10% market share in t-1 and t in common goods, remainder in entry/exit)

More differences exist for less homogeneous products like cereal.

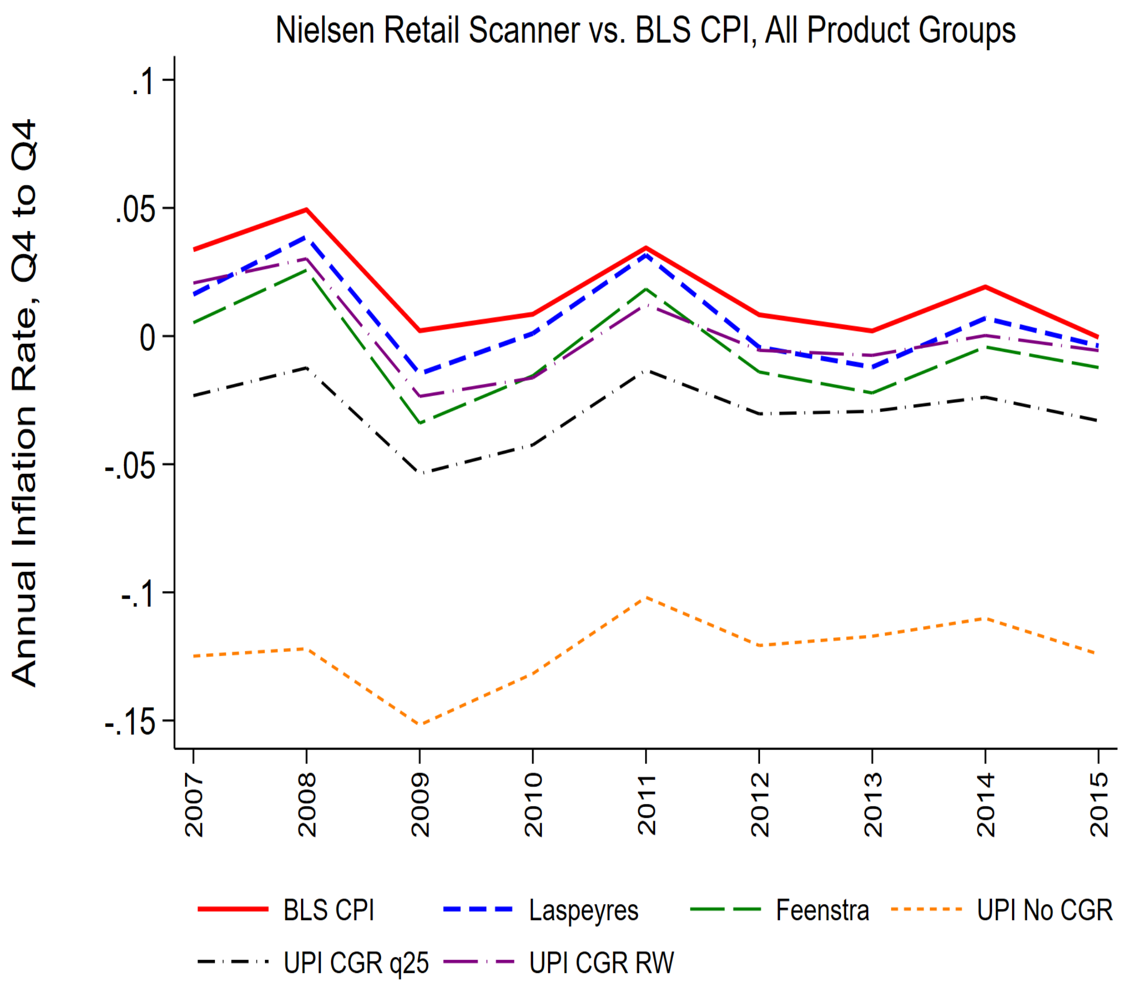


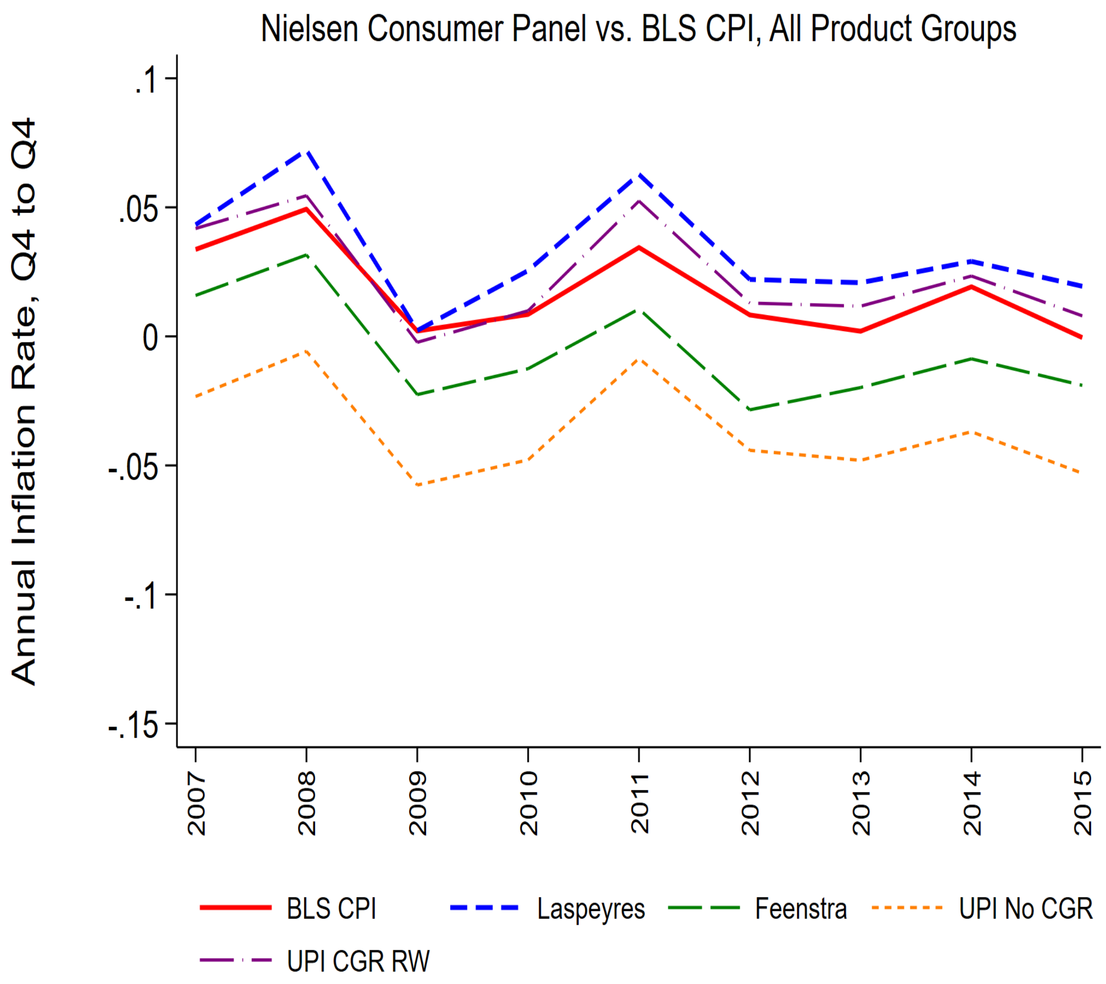
UPI yields much lower Price index, while Feenstra Yields little adjustment.

UPI uses a common goods Rule of 10%

More on CGR below.

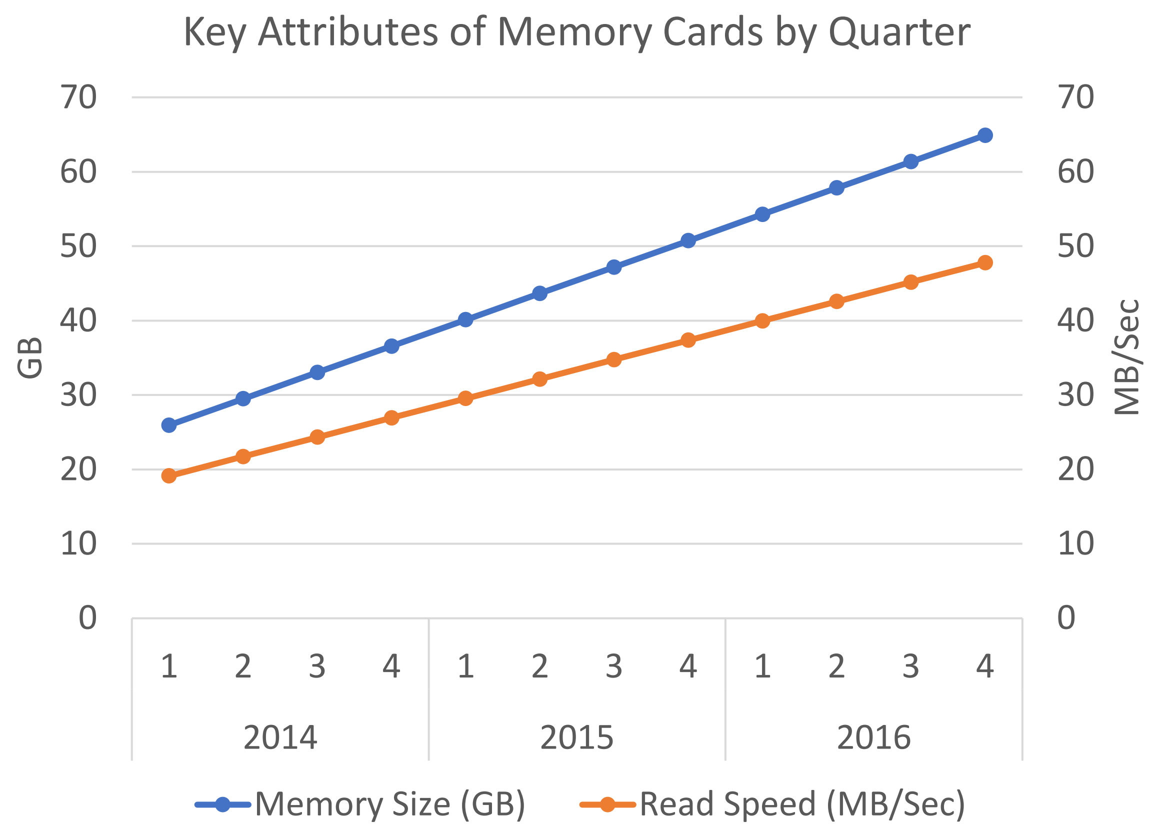
UPI implausibly low without Common Goods Rule (CGR).   Results sensitive to specific CGR.



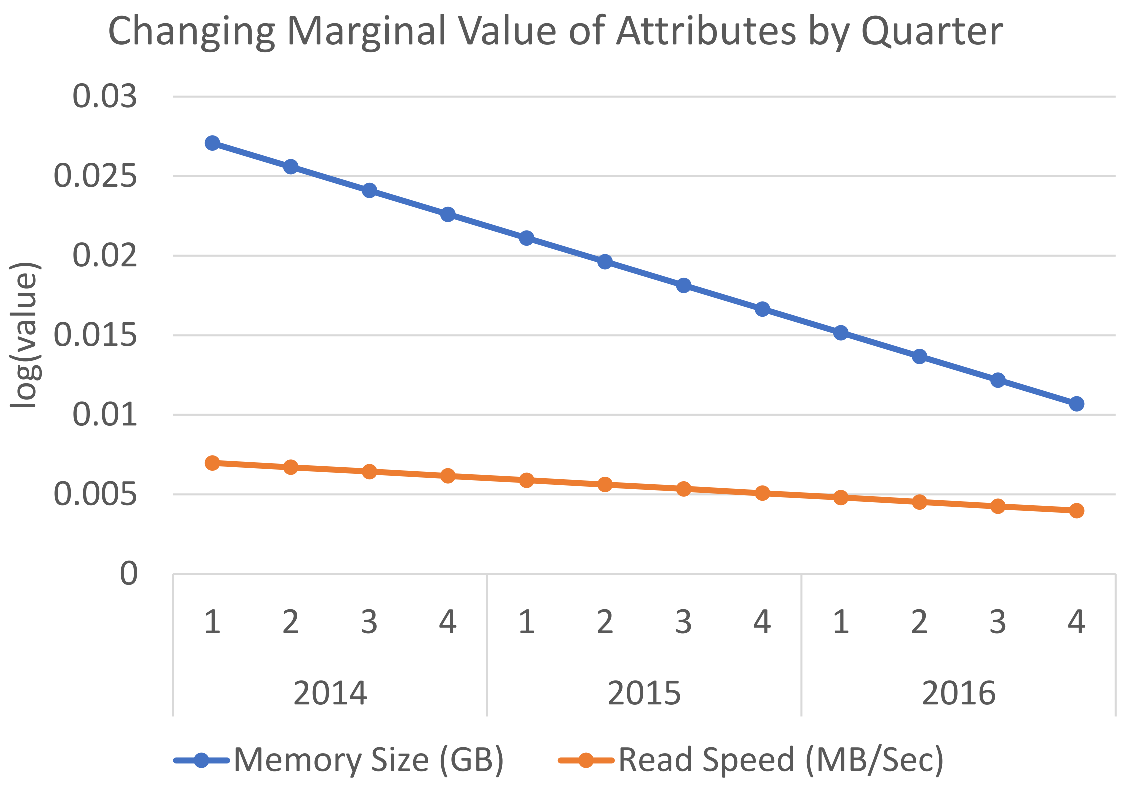


Notes: CGR= Common Goods Rule, CGR RW=CGR from Redding and Weinstein (2020) (approx. based on Consumer Panel).
BLS CPI is based on special tabulations by BLS to match 100 product groups (food and non-food) in Nielsen.

NPD item-level characteristics for Memory Cards
Quality improves over period; marginal value falls



Linear trend on sales-weighted Memory size and speed.



Trend of linear terms from hedonic regression

Table 4: Means, Standard Deviations, and Correlations of Alternative Price Indices: Memory Cards

	Laspeyres	Feenstra	Hedonic (Laspeyres)	Hedonic (Paasche)	UPI (No CGR)
Mean Price Change	-0.039	-0.059	-0.060	-0.049	-0.096
Standard Deviation (price change)	0.034	0.039	0.024	0.025	0.024
Laspeyres	1.00				
Feenstra	0.89	1.00			
Hedonic (Laspeyres)	0.72	0.72	1.00		
Hedonic (Paasche)	0.61	0.72	0.77	1.00	
UPI	0.15	0.07	0.32	0.48	1.00

Note: Source is NPD data at item-level quarterly from 2014 to 2016. Price indices constructed at a quarterly frequency. Reported statistics are correlations of quarterly indices (not seasonally adjusted).

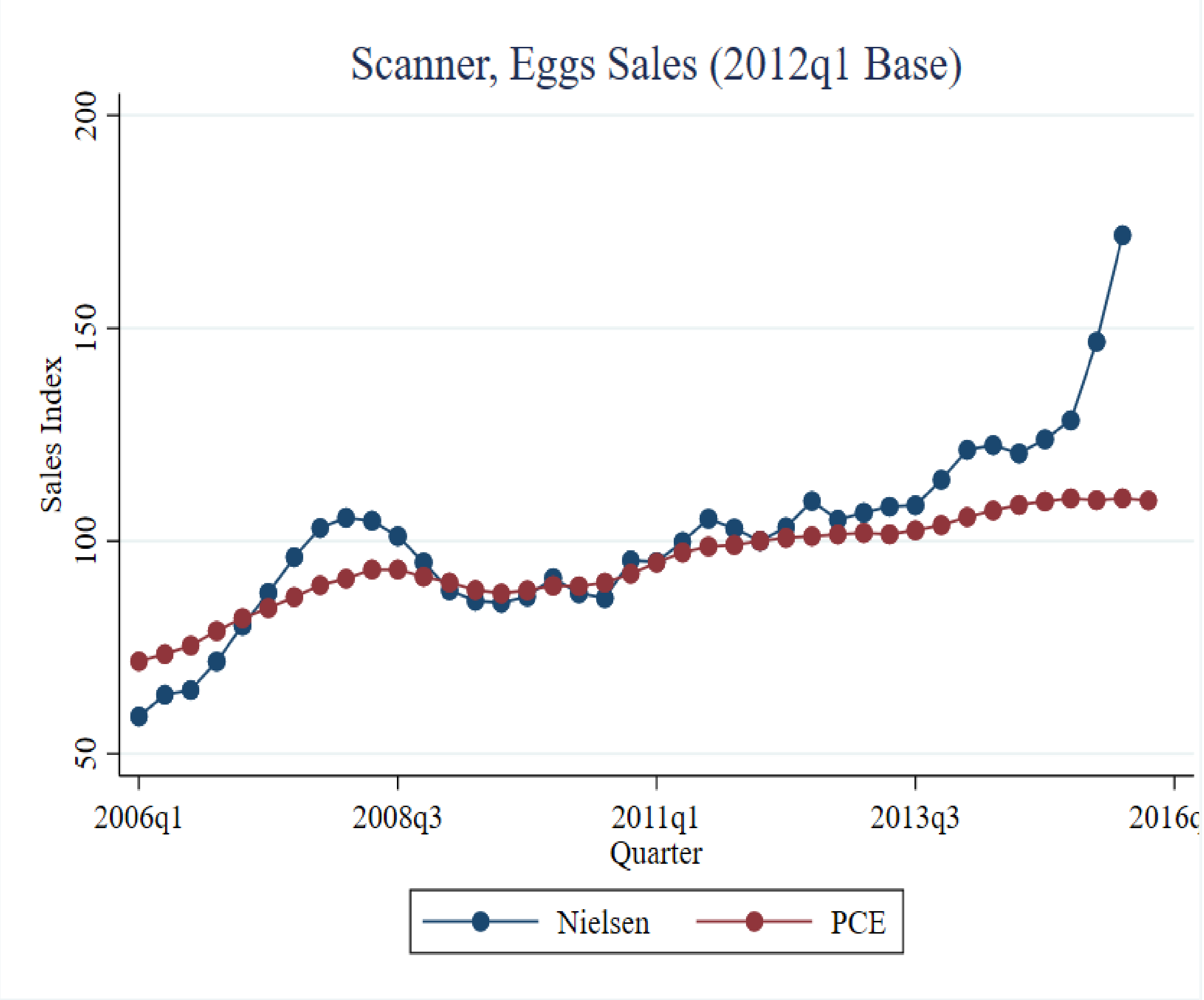
Feenstra and Hedonics Yield Substantial and Broadly Consistent Lower Rates of

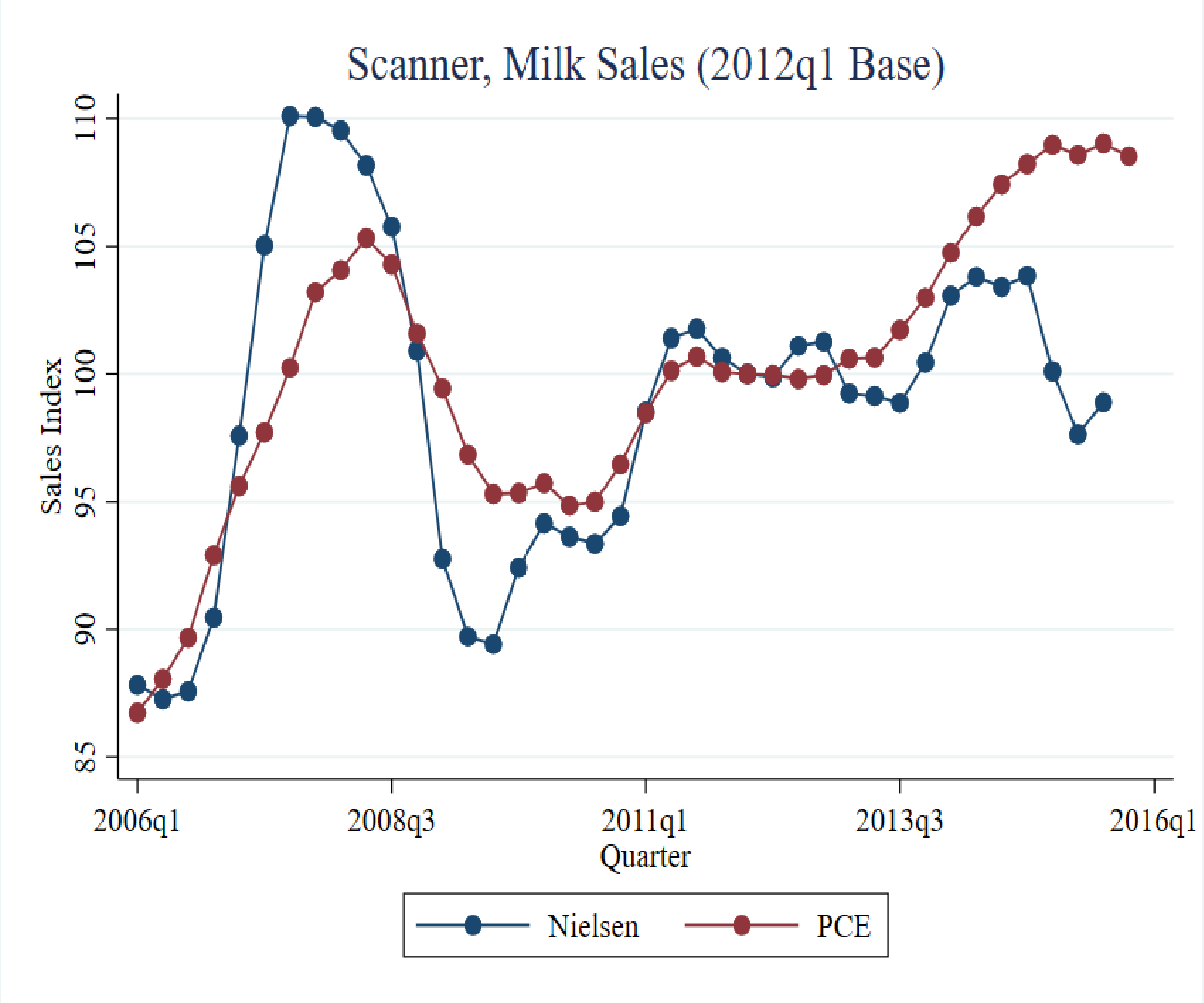
UPI (without CGR) remains an outlier.

In analysis in progress for all NPD product groups (memory cards, headphones, Coffeemakers, boy's jeans, And work boots) we find that using weighting and accounting for time varying unobservables yields robust patterns for quality adjusted prices.

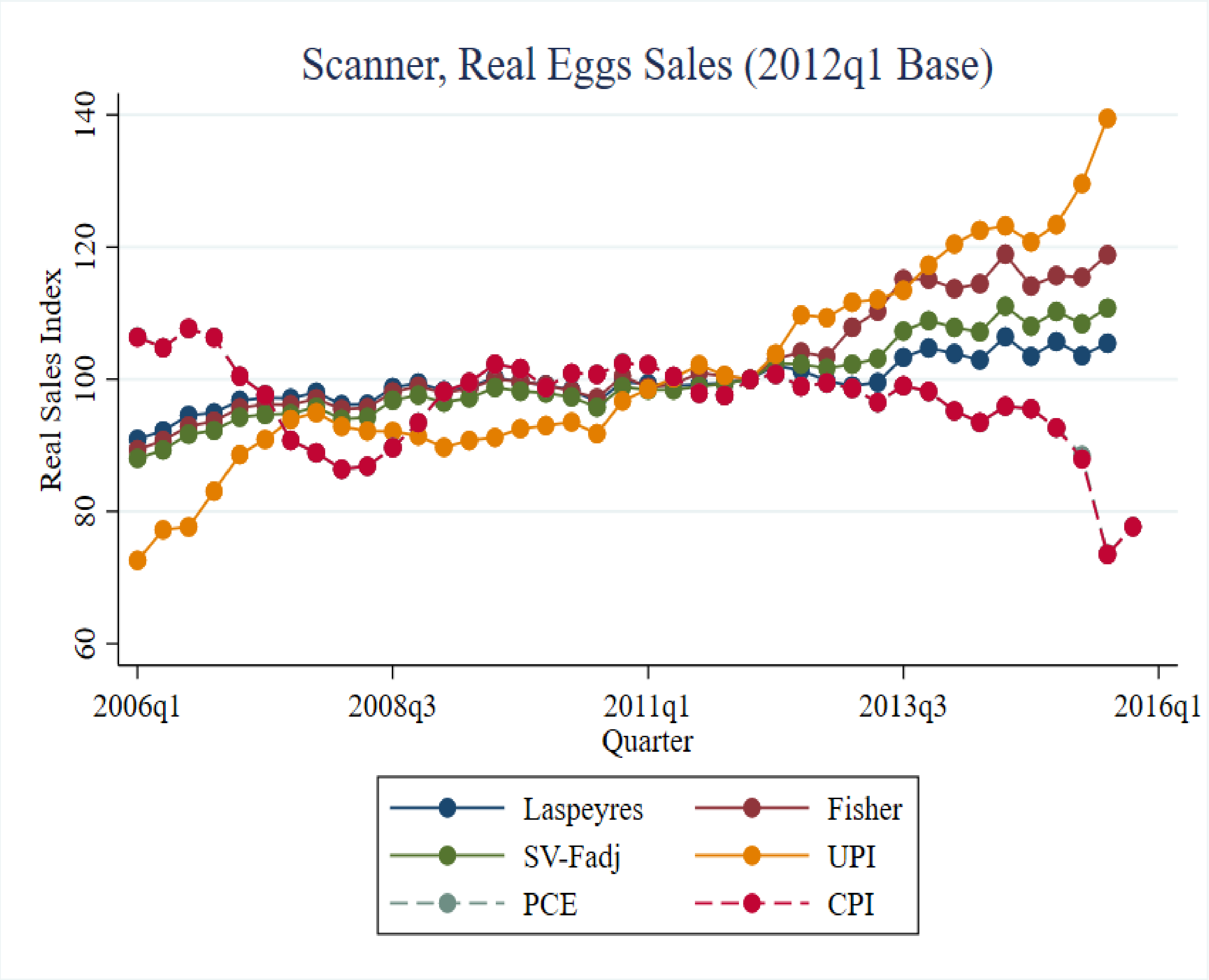
Limitations of UPI without CGR Hold for all products.

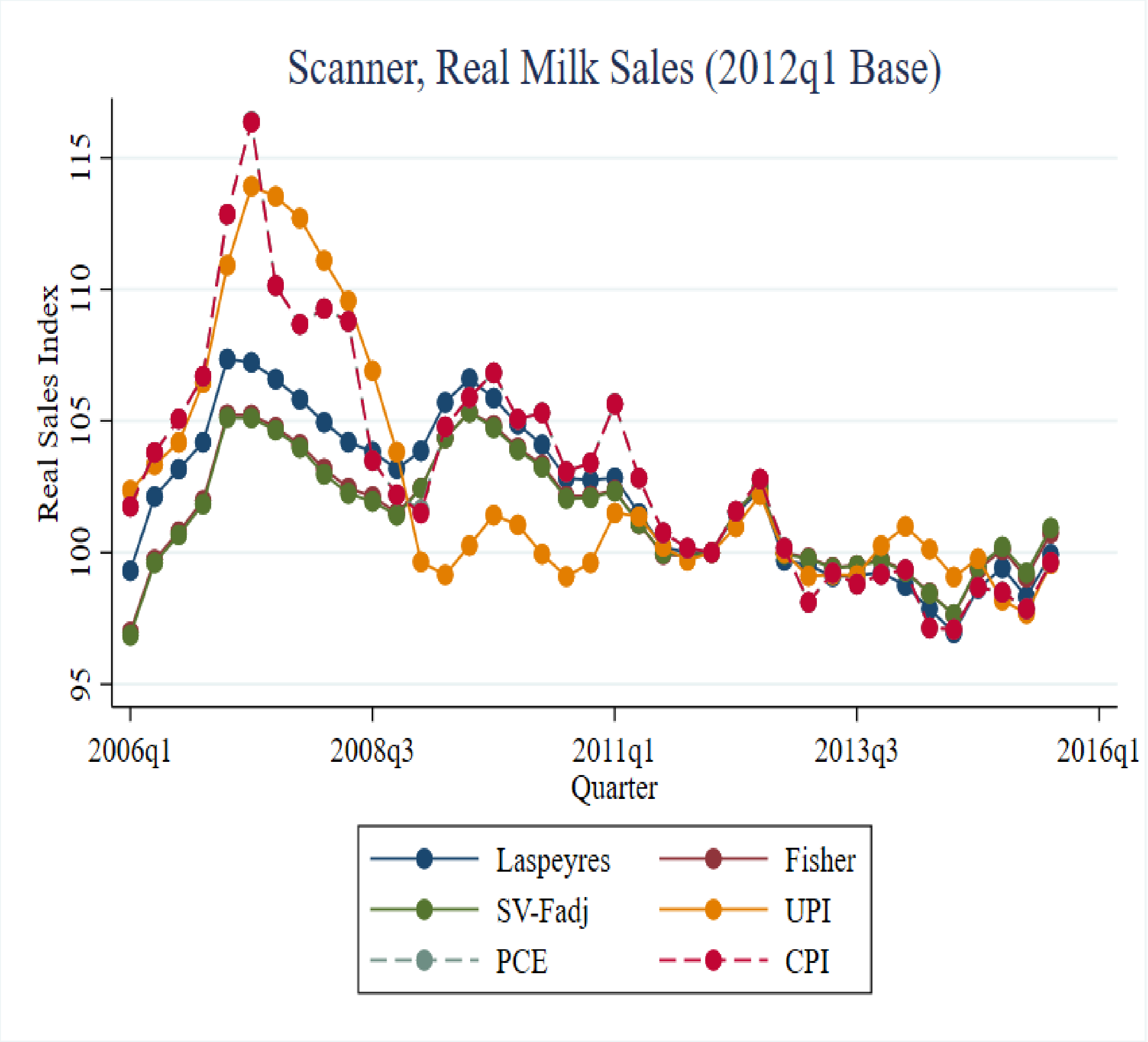
Item-level transaction data also has advantage that nominal sales can be computed from same data used to produce price indices. Potential to capture variation between Economic Censuses at more granular level.





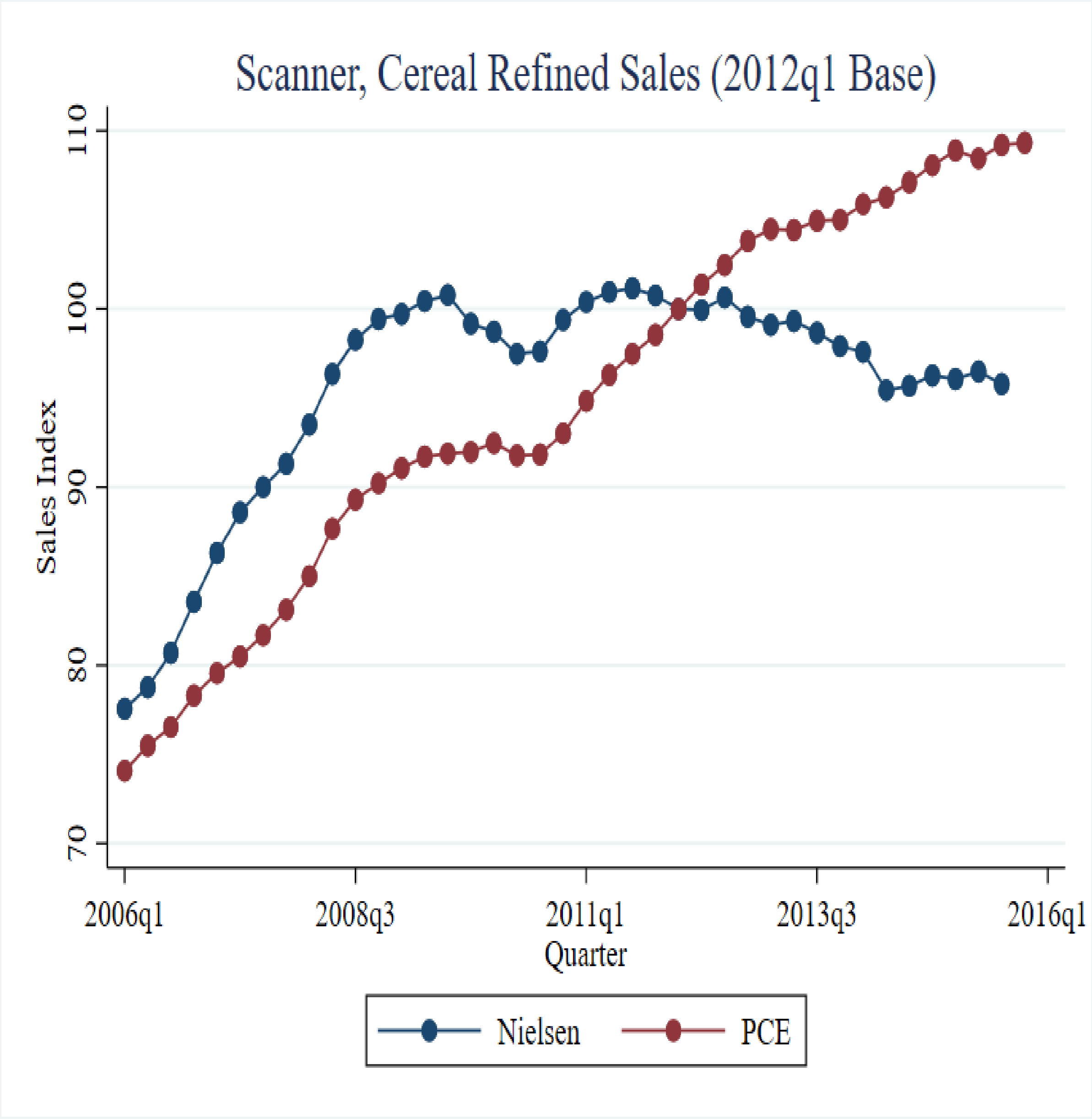
Using both P&Q yield differences in the trends and changes in real spending over the recessionary period, while the changes between 2007 and 2012 (i.e., Census years) are more similar.

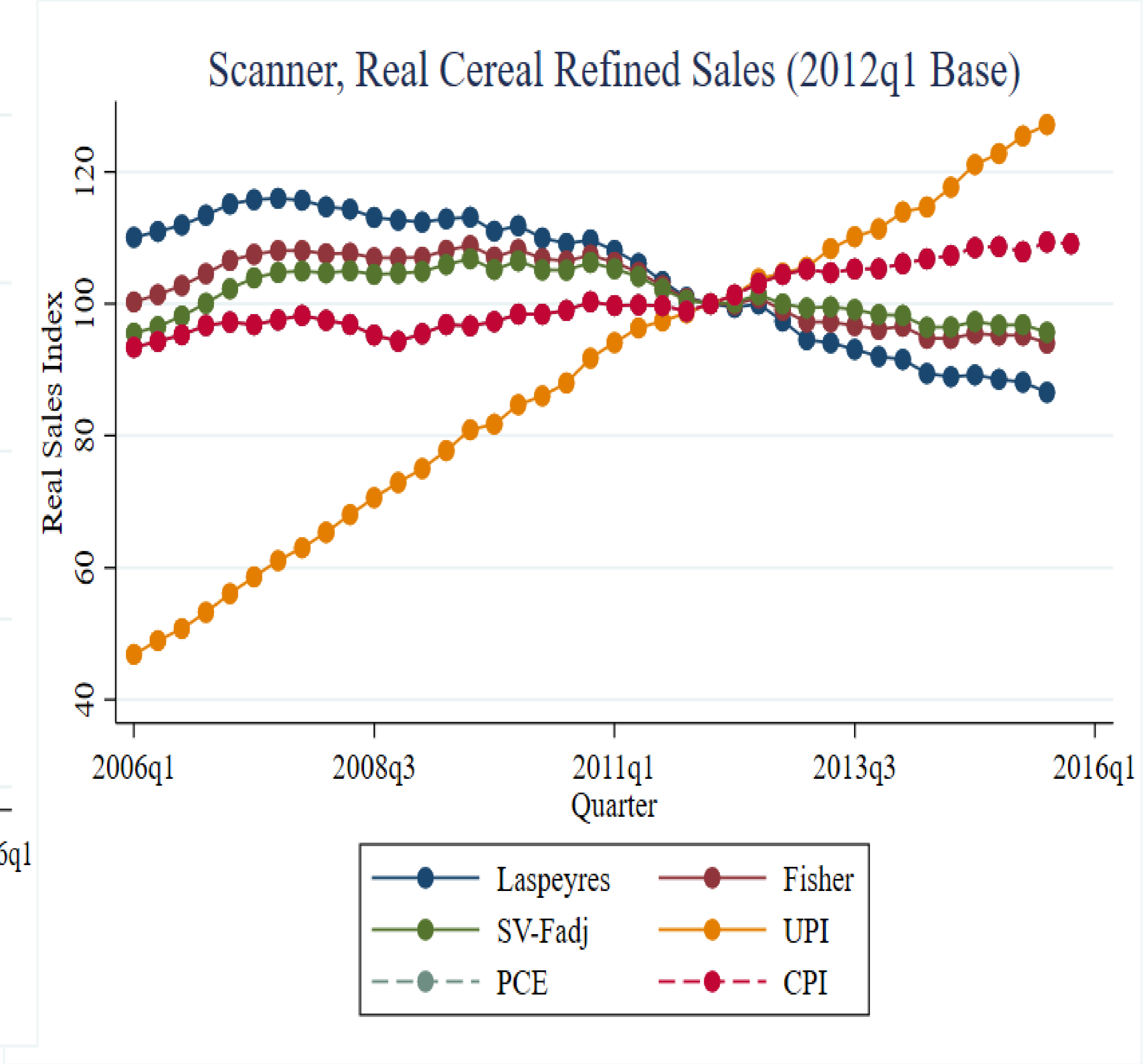




PCE and CPI use PCE nominal, all others use Nielsen nominal.

More dramatic differences for cereals.





Taking stock:

- Item-level P and Q data can be used to produce internally consistent nominal sales and price deflators that adjust for quality.
- Most robust results are using hedonics with econometric methods that account for time varying unobservables as well as observables.
- Machine learning on product descriptions in terms of text and images has potential to permit using these methods at scale.
- Integration of machine learning approach with econometrics is a needed next step (in process).
- Demand theory approach using nested CES approach is readily implementable at scale with these data. Should be in the toolkit. However, key limitations include (i) estimation of elasticities; (ii) defining nests; and (iii) defining common goods.