RESET Project

Re-Engineering Statistics using Economic Transactions

Presentation for CNSTAT panel

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December 9, 2021

Acknowledgements and Disclaimers

This research is supported by the Alfred P. Sloan Foundation with additional support from the Michigan Institute for Data Science and the Michigan Institute for Teaching and Research in Economics.

This presentation uses the researchers' 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 researchers 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.

This presentation also uses data from NPD housed at the U.S. Census Bureau. All results using the NPD data have been reviewed to ensure that no confidential information has been disclosed (CBDRB-FY19-122, CBDRB-FY21-074). Opinions and conclusions expressed are those of the authors and do not necessarily represent the view of the U.S. Census Bureau.

We thank Jamie Fogel, Tian Gao, Diyue Guo, Seula Kim, Michael Navarrete, Edward Olivares, Luke Pardue, Dyanne Vaught, Dawn Zinsser, and Laura Zhao for their collaboration. They are co-authors on papers resulting from this project. See last slide for list of papers available for distribution (others in process).

We also thank staff at the U.S. Census Bureau working on related projects for their collaboration and assistance. We particularly thank Nick Orsini, Catherine Buffington and Rebecca Hutchinson.

Statistical Agencies Moving into 21st Century

- End-state objective: Re-engineer key economic indicators such as real output and inflation to release **consistent, timely, and granular** statistics
- Census, BLS, and BEA exploring integrated data collection from naturally occurring data
- Quality-adjusted measures of real output and inflation for all goods
- Reduced survey burden on firms
- Data harvested from item-level transactions data that firms and information aggregators are already actively using
- **The RESET project:**
  - ***Address conceptual, practical, and contractual issues for implementation at scale***
  - ***Blueprints for new architecture for collecting data and creating official statistics.***

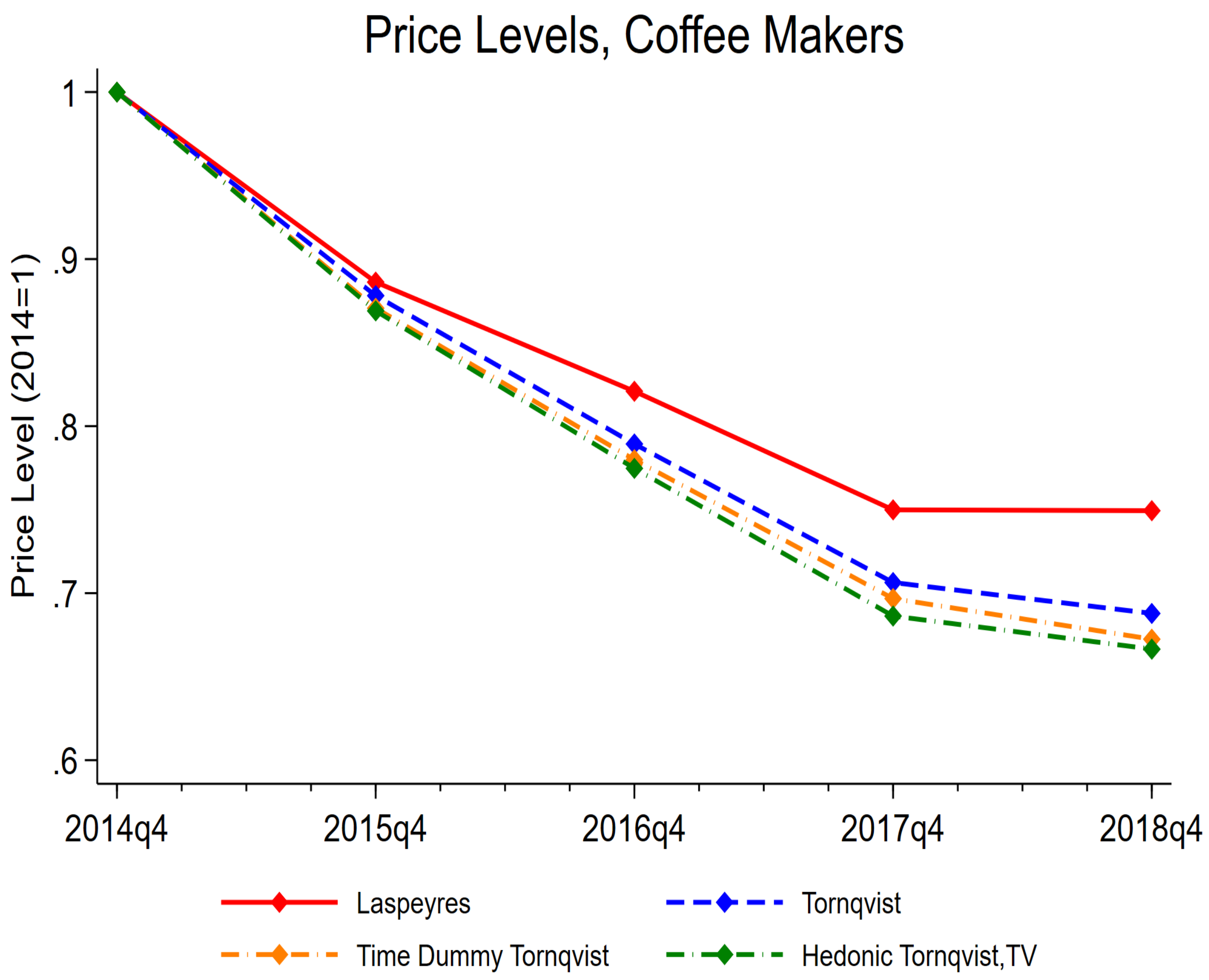
Transactions data used to date

- NPD (general merchandise stores, including online)
    - Monthly prices and quantities at store-item level
    - High-quality attributes at item level from value-added by NPD
    - Started with 5 product groups. Now have scaled to 500 groups covering Apparel and Consumer Electronics
    - Collaborative Project with Census (building on project using NPD data to improve Retail Statistics)
    - Working behind Census firewall with Census DRB approving output
- Nielsen (Kilts Center: grocery, discount, convenience, drug and liquor store items for food and nonfood)
    - Weekly prices and quantities at store-item level
    - Using machine learning methods to extract information from limited product attribute data
    - Access through University of Maryland and Michigan contracts with Kilts
    - Kilts Center reviews papers/presentations
- Individual retailer (Company X: large range of goods)
    - Working behind their firewall
    - Item-level prices and quantities
    - Rich information on attributes that require machine learning to process
    - NDA and access agreements with University of Maryland and Michigan.
    - No results in today’s presentation, but lessons learned discussed

Lessons learned on re-engineering prices

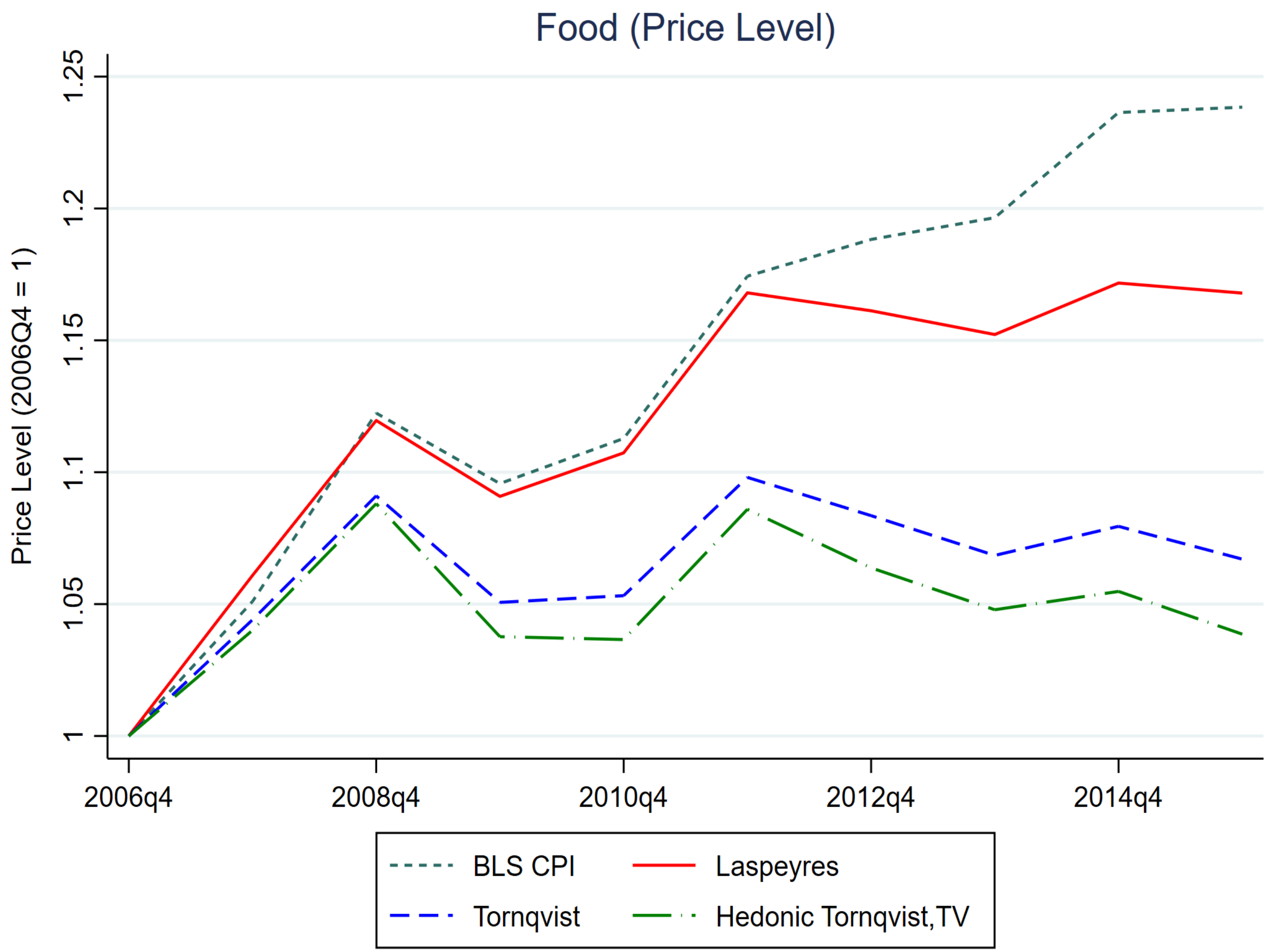
- Substantial gains from using superlative price indices (e.g., Tornqvist) rather than Laspeyres even without quality adjustment
- Quality change is pervasive
  - Need P, Q and Attribute Data
- Attribute data comes in many flavors
  - High value added from information aggregators like NPD
  - Abbreviated text fields from Kilts Nielsen
  - Text and image fields from individual retailers.
- Strikingly, similar patterns emerge from these distinct sources
  - Rely on methods from Erickson and Pakes (2011) (EP) that incorporate time varying unobservable characteristics
  - Machine learning enables using disparate attribute data with methods
- Scalable approaches under development:
  - Need to show that indices can be produced on a timely basis at scale.
  - API to be used behind company's firewall or with information aggregators data

High quality value-added attribute data from NPD



- High pace of product entry and exit
  - 5.7% entry, 4.5% exit per qtr
- Rapid quality change
  - Single-serve pod makers entered over our sample period
- Laspeyres shows more inflation than Tornqvist (one advantage of P &Q data is ideal indices easy to compute).
- Time dummy method yields additional adjustment.
- Hedonic Tornqvist, TV lower than Time Dummy.
- All price indices are chained, quarterly.

Price Indices – Food



Substantial improvements — even in food

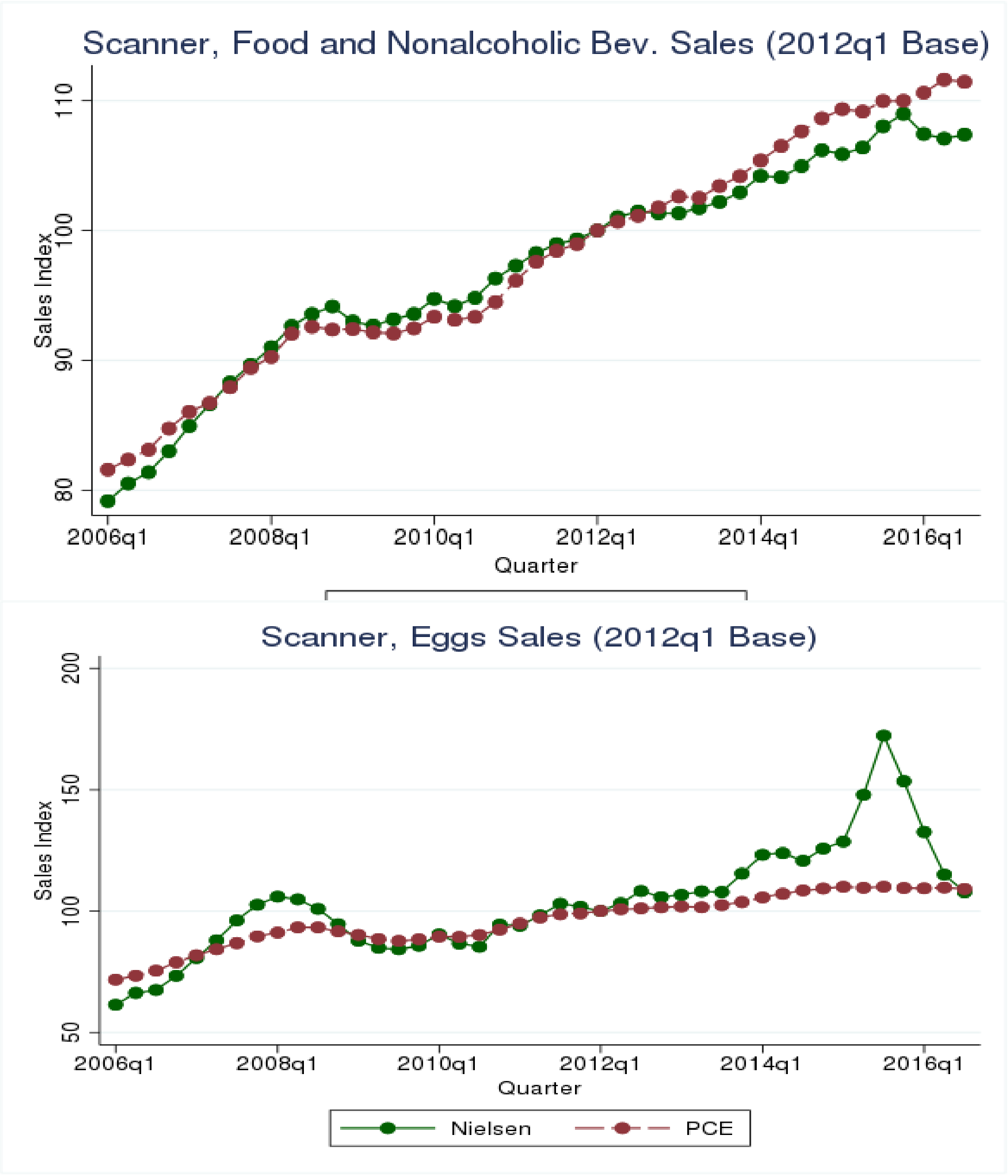
- CPI and Laspeyres (Nielsen) track each other (reasonably) well.
- Tornqvist substantially lower inflation correcting for inflation.
- Quality change in food substantial
- ML techniques effective!

Lessons learned about nominal revenues

This part of the project at earlier stage.

We find evidence that official statistics (e.g., PCE) and transactions data (e.g., from Nielsen):

- Track each other reasonably well at broad group level (e.g., food and non-alcoholic beverages)
- PCE too smooth at high frequency for detailed product categories, consistent with extrapolation/interpolation.
  - Less cyclicality
  - Misses item-specific events (surge in nominal expenditures for eggs during bird flu).
  - Interestingly CPI picked up but PCE nominal expenditures did not
- Coverage issues are a challenge for specific data providers:
  - Nielsen high quality on food items.
  - Nielsen also covers non-food items sold at Grocery Stores.
    - Poorer coverage and becoming less representative over time.
- Benchmarking to Economic Census likely still critical.



Lessons Learned + Next Steps

- Using item-level P and Q transactions data with attributes can be used to produce
  - Internally consistent nominal sales
  - Price deflators that adjust for quality
  - Quality adjustment at scale using machine learning
- Next Steps
  - Create new indicators at scale on timely basis.
    - Need to demonstrate to statistical agencies this is feasible and yields improvements.
    - Objective: Deliver RESET estimates for entire retail goods sector
  - Robustly and efficiently scale to new partners
    - Information aggregators such as Nielsen and NPD + Private Firms (aiming for 100 largest + sample of smaller)

Challenges

- Incentivize private sector firm participation
  - New more granular, real time statistics
  - Reduce survey burden
- Technology
  - APIs
  - Secure multi-party computing
  - Stability/consistency of data stream
  - Heterogeneity of company information systems
- Legal and Institutional
  - Implementing this approach will require changes in statistical agency interaction and structure
  - Data synchronization essential

For more information see:

"Re-engineering Key National Economic Indicators." by Gabriel Ehrlich, John Haltiwanger, Ron Jarmin, David Johnson, and Matthew D. Shapiro. Paper prepared for NBER/CRIW Conference *Big Data for 21st Century Economic Statistics* (Bethesda, March 2019). Revised July 2020 pdf

"Quality Adjustment at Scale: Hedonic versus Exact Demand-Based Price Indices" by Gabriel Ehrlich, John Haltiwanger, Ron Jarmin, David Johnson, Ed Olivares, Luke Pardue, Matthew D. Shapiro, and Laura Yi Zhao. August 2021.

"Minding Your Ps and Qs: Going from Micro to Macro in Measuring Prices and Quantities." by Gabriel Ehrlich, John Haltiwanger, Ron Jarmin, David Johnson, and Matthew D. Shapiro. *AEA Papers and Proceedings* 109 (2019) 438-443. DOI: 10.1257/pandp.20191004 pdf