

Best Prices: Price Discrimination and Consumer Substitution

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Motivation

- Pervasive Increase in IT-enabled price discrimination
 - Ellickson and Misra (2008)
 - Basker (2013)
 - Nakamura (1998,1999)
- How do we aggregate prices and measure inflation when a multi-product retailer is actively price-discriminating?
 - Relative prices of different brands of the same good can be quite volatile
 - Massive high-frequency substitution into discounted/promoted products
 - Must confront the heterogeneity that motivates the price discrimination

Outline

- ① Price Aggregation issues
- ② Introduce a model of price discrimination
 - Will highlight the role of the “best price”
- ③ Data
- ④ Results
 - Test store level predictions
 - Study implications for inflation
- ⑤ Implications/Discussion Points for FESAC

Price aggregation methodologies at

- Cost of living benchmark
 - Exact index tracks the cost of obtaining a given level of utility at different points in time.
 - Challenging to construct in modern retail environment.
 - Price discrimination strategies imply consumer heterogeneity.
 - Time horizons and stockpiling divorce purchases from consumption

Simple price aggregation methodologies varieties of the same good

- Fixed weight (Laspeyres)
 - Appropriate if elasticity of substitution is zero
- Geometric Mean
 - Appropriate if elasticity of substitution is one between varieties
- Constant Elasticity of substitution
 - Appropriate for constant elasticity of substitution between varieties
- Unit values
 - Appropriate if consumers view goods as perfect substitutes
- Tornquist

Empirical issues with standard methodologies

- If we are looking at different varieties of peanut butter or coffee, the elasticity of substitution is *much* greater than one
- Purchases are concentrated in the ordinaly lowest priced branded product in the category.
- Price discrimination renders the relative prices of the varieties very volatile.
- Must confront consumer heterogeneity; representative consumer is the microfoundation of aggregation methodologies
- Each consumer (typically) purchases no more than one variety; CES models not a microfoundation
- Tornquist/Unit Values require real time quantity data/ not possible with enumerator methodologies

Model overview

- Simple model of sales
 - Similar in spirit to Varian (1980), Salop and Stiglitz (1982), Sobel (1984) and Pesendorfer (2002).
 - Some consumers are active shoppers who chase discounts, use storage.
 - Other consumers are passive “Loyals”
 - Retailer controls pricing of multiple substitute products
 - Average “price paid” very different from average “price posted”.

Model Implications

- Derive implications from our model for price indices
 - Depending on the functional form of storage costs, unit values aggregated over time are (or approach) the exact index.
 - Introduce the notion of the “best price”
 - Aggregate can be approximated by the appropriately weighted average of the “best price” and a fixed weight price aggregate.

Model Assumptions

- Single retailer
- Two substitute differentiated products, A and B , with marginal cost of c .
- Measure 1 of consumers, each have unit demand per period
 - $\alpha/2$ of customers value A at V^H and B at V^L . “ A Loyals”
 - $\alpha/2$ of customers value B at V^H and A at V^L . “ B Loyals”
 - $1 - \alpha$ customers value both at $V^M = (V^L + V^H)/2$. “Bargain Hunters”
- Can shop for N periods
- Bargain Hunters may strategically engage in storage, incur storage disutility of $\delta(k)$, number of periods over which units are stored.
 $\delta'(k) > 0$ & $\delta''(k) \geq 0$.
- All consumers form rational expectations about future prices.

Storage decision

- Following Salop and Stiglitz (1982), consumers will only buy units for storage if their net utility of doing so is positive.
- Example: BH enters penultimate period $N - 1$ with no inventory and expects $P^A = P^B = V^H$ in the final period, then the Bargain Hunter will purchase two units in period $N - 1$ if $P^A < V^M - \delta(1)$ or $P^B < V^M - \delta(1)$ but only one unit if $P^A = V^M$ or $P^B = V^M$.
- Note that if the price posted is low enough to induce storing for k periods, then the net utility from buying k units is (at least weakly) higher than buying any fewer than k units.

Possible retailer pricing strategies

- i Always charge high prices and only service Loyals
 - ii Charge a low price for one good each period and serve both types of customers.
 - iii Iterate between high and low prices to capture demand from BH while exploiting the willingness to pay of Loyals.
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- We will focus on parameter values for which (iii) is optimal.

Equilibrium Definition

- An equilibrium consists of a sequence of prices for both goods A and B from period 1 onwards announced at date 1 by the retailer and demand functions for both type of consumers, such that:
 - 1 The consumers' demand functions maximize their expected utility taking the prices as given
 - 2 The retailer's profit is maximized at announced prices taking the consumers' demand functions as given
 - 3 The retailer doesn't want to deviate from the announced prices at any later date

Model Properties

- For $V^H - V^L$ large enough, it is never optimal for the retailer to charge less than V^H for both A and B in the same period.
- When will the retailer want to induce the bargain hunters to consume every period?
 - Roughly, when V^M is big enough relative to V^H , marginal cost is not too high, and α is not too big.
- When does the retailer want to do this by inducing the bargain hunters to store?
 - Basically, depends on the storage cost function
- Show that “surprises” are not optimal.

Retailer profits from holding periodic sales

$$N \frac{k-1}{k} \alpha (V^H - c) + \frac{N \alpha}{k} \frac{1}{2} (V^M - \delta(k) - c) + \\ + \frac{N \alpha}{k} \frac{1}{2} (V^H - c) + N(1 - \alpha) (V^M - \delta(k) - c)$$

Here, the prices are clearly always some combination of V^H and $V^M - \delta(k)$, but the seller will choose k to maximize profit.

In the paper, demonstrate optimal k for two functional forms of $\delta(k)$: linear storage costs and a discrete storage capacity. For linear storage costs, the optimal k is:

$$k = \frac{\sqrt{(V^H - V^L) \alpha}}{2\sqrt{(1 - \alpha) \delta}}$$

Observations

- “Price plan” is the full sequence of high and low prices that prevail over N periods.
- k is the key strategic choice variable
- For unchanging cost and demand parameters, prices iterate.
 - Contrast to Kehoe and Midrigan (2010), Eichenbaum et al (2011), Pesendorfer (2002) (where there is no price discrimination motive)
 - In those models, prices for close substitute products would tend to be *positively* correlated.
 - Contrast to Guimaraes and Sheedy (2011)
 - Consistent with Klenow and Willis (2007), Wong and Nevo (2014), Kryvtsov and Vincent (2014) findings that regular prices, sale prices, and the frequency of sales are responsive to shocks.
- Quantity purchased varies each period despite stable demand.

Implications for price measurement

- If storage costs are zero or small, measurement of changes in unit values over the k period cycle is the appropriate measures of changes in utility.
- Intuition: due to the strategic second degree pricing behavior of the retailer, the loyal customer never buys the “wrong” product.
 - Otherwise the storage costs create a wedge between price and utility gain

Weighted average prices paid when storage for k periods is free:

$$\alpha \left(\frac{1}{2k} V^M + \frac{2k-1}{2k} V^H \right) + (1 - \alpha) V^M$$

- Because BH store in response to discounts, the unit value must be calculated as an average over the k period sale cycle
- It is a weighted average of the fixed weight index and the “best price”, with the shares of the BH and Loyals as the weights.

Model summary:

- Two type model of “bargain hunters” and “loyals”
 - Bargain hunters willing to stockpile and value all brands equally
 - Loyals have a favorite brand.
- Creates retailer incentives to price discriminate.
- In equilibrium:
 - Bargain hunters stockpile and purchase cheapest item in category.
 - Loyals purchase the product to which they are loyal.
 - Retailers use occasional temporary discounts to price discriminate

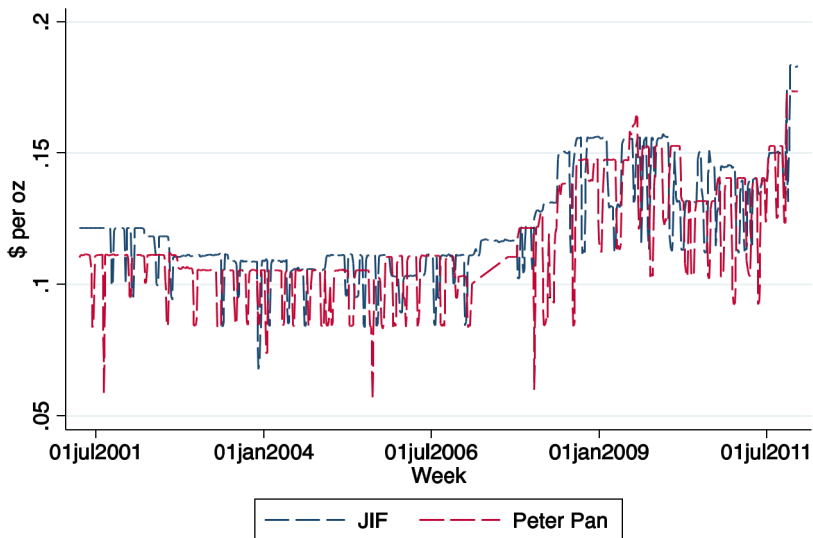
Results and Testable Predictions

- 1 Unit value (nearly) traces the cost of achieving a given level of utility over time. Outcome of price discrimination.
- 2 A disproportionate fraction of goods are sold at temporary discounts.
- 3 A unit value price index should be well-approximated by a linear combination of a fixed weight index and the best available price. The weights are the shares of each type.
- 4 A geometric mean aggregation will not adequately account for the migration of consumers to the 'best price'.

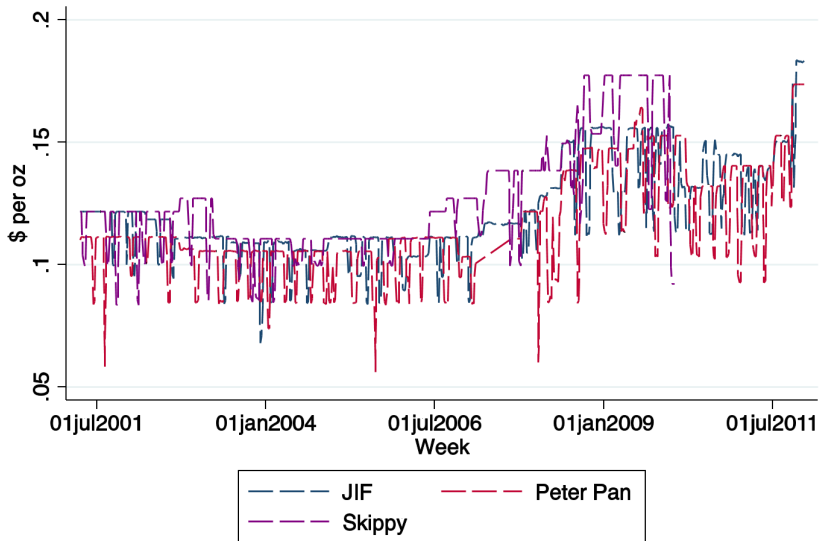
Data

- IRI marketing data set, 2001 to 2011
- Choose products where IRI classification matches a BLS classification: peanut butter, ground coffee.
 - Reasonably representative. Median IRI category has 37 of volume sold on deal. Coffee 40.8%, 32.9% peanut butter.
 - Also have an agricultural commodity as primary input
- Part 1: data from 9 cities, one from each of 9 Census divisions. Typically sample from largest chain.
 - String together UPC fragments and aggregate
 - Define “sales” using modified Kehoe-Midrigan definition
- Part 2: partially mimic BLS procedures and construct national price aggregates
 - 23 products

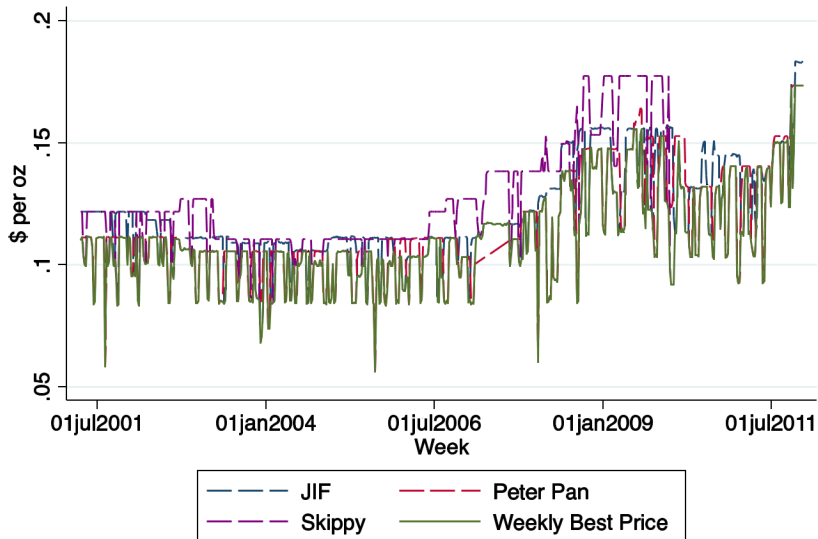
Observed and Best Prices



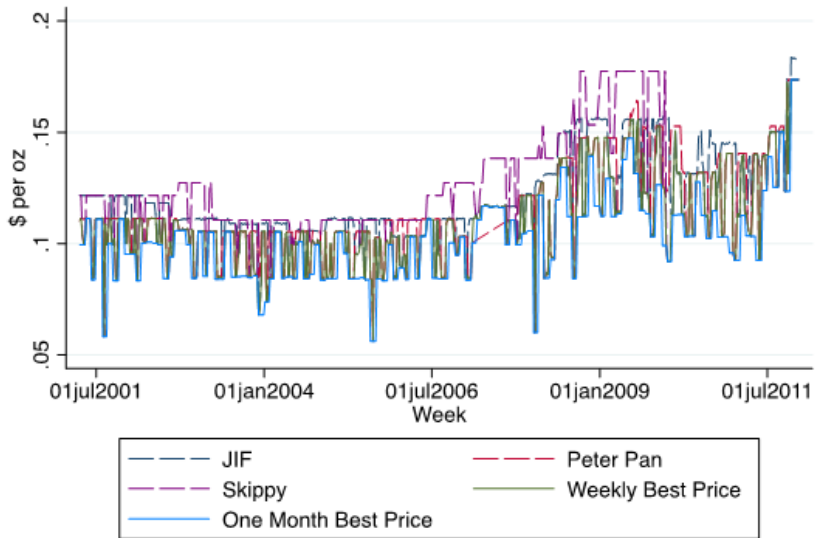
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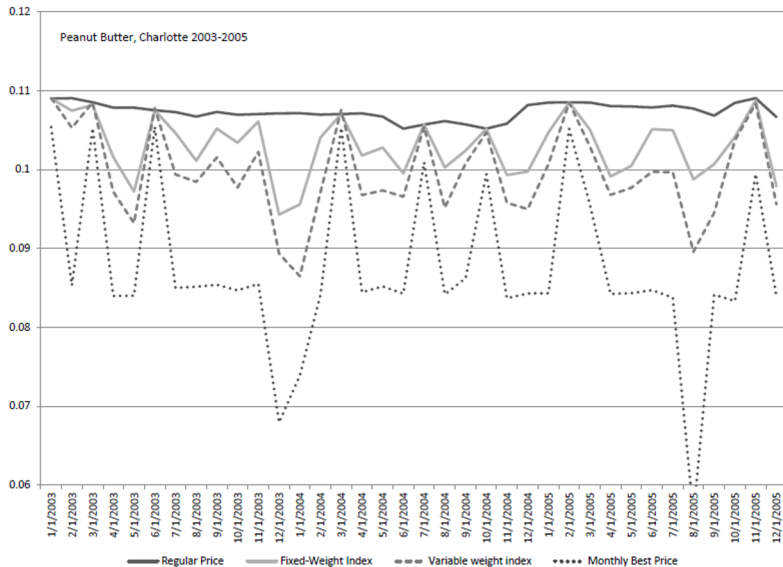


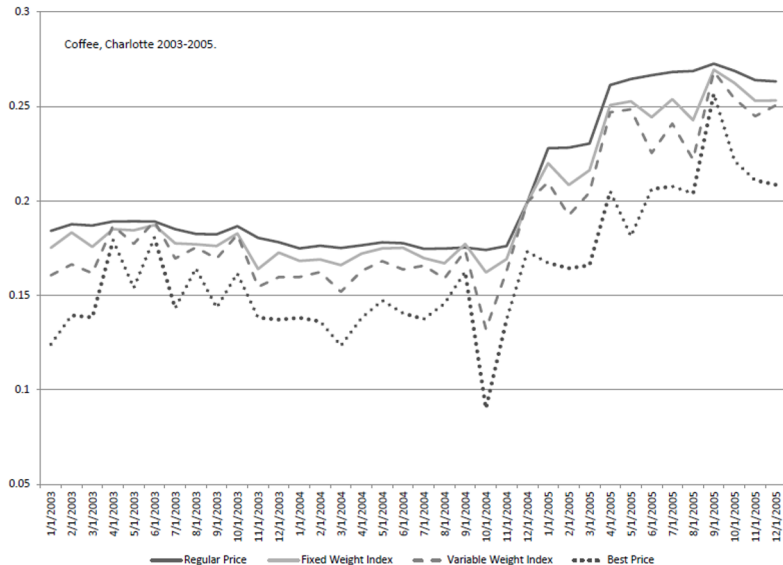
Observed and Best Prices



Observed and Best Prices







Confirmation that discount prices are disproportionately important for determining amounts sold

Share of Ounces Sold and Share of Weeks at Regular and Sale Prices: Totals for Sample Cities

Product		Ounces sold		Regular price	Weeks	
		Regular price	Sale price		Sale price	Average Disc
<i>Peanut butter</i>	Charlotte	60.03%	39.97%	75.91%	24.09%	17%
	Chicago	33.92%	66.08%	59.17%	40.83%	21%
	Hartford	50.08%	49.92%	92.45%	7.55%	27%
	Houston	63.49%	36.51%	74.57%	25.43%	12%
	Knoxville	65.24%	34.76%	73.19%	26.87%	11%
	Los Angeles	49.49%	50.51%	65.83%	34.17%	13%
	New York	37.49%	62.51%	78.63%	21.37%	21%
	St Louis	34.88%	65.12%	67.73%	32.27%	26%
	West Tx-New Mexico	46.26%	53.74%	68.60%	31.40%	19%
	AVERAGE	48.99%	51.01%	72.89%	27.11%	19%
<i>Coffee</i>	Charlotte	31.51%	68.49%	54.23%	45.77%	9%
	Chicago	43.272%	56.73%	52.01%	47.99%	13%
	Hartford	18.56%	81.44%	49.01%	50.99%	12%
	Houston	42.89%	57.11%	57.83%	42.17%	6%
	Knoxville	44.59%	55.41%	56.10%	43.90%	7%
	Los Angeles	41.48%	58.52%	50.42%	49.58%	14%
	New York	13.16%	86.84%	43.79%	56.21%	16%
	St Louis	31.88%	68.12%	52.71%	47.29%	11%
	West Tx-New Mexico	40.32%	59.68%	50.98%	49.02%	9%
	AVERAGE	34.18%	65.82%	51.90%	48.10%	11%

Summary Statistics–City Data

	Charlotte	Chicago	Hartford	Houston	Knoxville	Los Angeles	New York	St Louis	West Tx
<i>Peanut butter</i>									
Unit Value Price	0.116	0.140	0.126	0.118	0.118	0.162	0.123	0.117	0.138
Fixed Weight Price	0.119	0.151	0.140	0.121	0.120	0.165	0.240	0.129	0.148
Monthly Best Price	0.101	0.118	0.108	0.104	0.108	0.141	0.101	0.097	0.113
Geometric Mean Price	0.118	0.150	0.138	0.121	0.120	0.164	0.139	0.128	0.147
Total Ounces Sold	8,073	4,277	12,898	2,414	4,501	4,576	9,218	9,233	2,692
Observations	129	129	129	127	129	129	129	129	121
<i>Coffee</i>									
Unit Value Price	0.248	0.315	0.224	0.274	0.248	0.325	0.221	0.275	0.314
Fixed Weight Price	0.257	0.328	0.266	0.277	0.253	0.341	0.279	0.288	0.321
Monthly Best Price	0.214	0.250	0.186	0.245	0.220	0.258	0.177	0.239	0.252
Geometric Mean Price	0.256	0.325	0.264	0.276	0.252	0.338	0.275	0.286	0.319
Total Ounces Sold	3,431	1,221	10,522	2,538	2,800	6,339	15,538	3,339	1,391
Observations	129	129	129	127	129	129	129	129	121

Structural Estimates of Price Coefficients

	Charlotte	Chicago	Hartford	Houston	Knoxville	Los Angeles	New York	St Louis	West Tx New Mexico
<i>Peanut butter coefficients</i>									
FWI*	0.804 (0.024)	0.542 (0.032)	0.484 (0.044)	0.646 (0.045)	0.664 (0.037)	0.687 (0.047)	0.414 (0.037)	0.808 (0.073)	0.669 (0.067)
Best price	0.234 (0.022)	0.548 (0.039)	0.587 (0.029)	0.319 (0.030)	0.289 (0.032)	0.316 (0.032)	0.590 (0.040)	0.403 (0.045)	0.401 (0.044)
cons	-0.0038 (0.002)	-0.006 (0.003)	-0.005 (0.004)	0.0065 (0.004)	0.007 (0.003)	0.0042 (0.004)	0.005 (0.004)	-0.0258 (0.007)	-0.007 (0.007)
<i>Coffee coefficients</i>									
FWI	0.737 (0.038)	0.648 (0.031)	0.437 (0.035)	0.831 (0.017)	0.678 (0.028)	0.716 (0.038)	0.348 (0.043)	0.646 (0.023)	0.915 (0.031)
Best price	0.292 (0.040)	0.386 (0.042)	0.667 (0.038)	0.206 (0.017)	0.306 (0.031)	0.291 (0.033)	0.697 (0.047)	0.375 (0.020)	0.183 (0.026)
cons	-0.0040 (0.004)	0.0058 (0.006)	-0.0162 (0.005)	-0.007 (0.002)	0.0086 (0.002)	0.0053 (0.008)	0.0009 (0.008)	-0.002 (0.003)	-0.0257 (0.006)

*Fixed Weight Index

- Model predictions: 1) Sum of fixed weight and best price ≈ 1 ; 2) Constant close to 0; 3) High R^2 . Note there are lots of reasons why these could fail to hold.

Geometric Mean vs. Best Price

	Charlotte	Chicago	Hartford	Houston	Knoxville	Los Angeles	New York	St Louis	West Tx New Mexico
<i>Peanut butter coefficients</i>									
Geomean	0.827 (0.024)	0.593 (0.033)	0.503 (0.045)	0.683 (0.044)	0.689 (0.038)	0.732 (0.046)	0.441 (0.038)	0.825 (0.070)	0.726 (0.066)
Best price	0.209 (0.022)	0.493 (0.039)	0.571 (0.030)	0.290 (0.030)	0.270 (0.032)	0.276 (0.032)	0.567 (0.039)	0.373 (0.045)	0.353 (0.044)
cons	-0.0037 (0.002)	-0.007 (0.003)	-0.0053 (0.004)	0.005 (0.004)	0.006 (0.003)	0.0029 (0.004)	0.004 (0.004)	-0.024 (0.006)	-0.009 (0.007)
<i>Coffee coefficients</i>									
Geomean	0.743 (0.039)	0.694 (0.031)	0.453 (0.036)	0.863 (0.017)	0.699 (0.028)	0.756 (0.038)	0.373 (0.044)	0.672 (0.023)	0.937 (0.030)
Best price	0.284 (0.041)	0.336 (0.042)	0.649 (0.039)	0.173 (0.017)	0.285 (0.032)	0.248 (0.033)	0.668 (0.048)	0.346 (0.020)	0.146 (0.026)
cons	-0.003 (0.003)	0.005 (0.005)	-0.0162 (0.005)	-0.007 (0.002)	0.0086 (0.002)	0.0051 (0.007)	0.0005 (0.008)	-0.0016 (0.003)	-0.022 (0.006)

- Confirmation that substitution patterns are not well captured: 1) Best price still matters controlling for geometric mean; 2) Best price coefficients are almost the same as with the fixed weight index.

Best Fit CES Specifications (α being elasticity parameter)

	Charlotte	Chicago	Hartford	Houston	Knoxville	Los Angeles	New York	St Louis	West Tx New Mexico
<i>Peanut butter coefficients</i>									
α	4.5	8	10	8.5	8	6.5	9.5	10	7
CES α	0.893 (0.027)	0.899 (0.040)	0.624 (0.052)	0.852 (0.049)	0.818 (0.044)	0.85 (0.050)	0.692 (0.053)	0.778 (0.063)	0.925 (0.066)
Best price	0.136 (0.025)	0.167 (0.044)	0.456 (0.036)	0.123 (0.034)	0.171 (0.036)	0.15 (0.037)	0.377 (0.047)	0.252 (0.051)	0.105 (0.051)
cons	-0.0027 (0.002)	-0.006 (0.003)	-0.0066 (0.004)	0.0053 (0.003)	0.0031 (0.003)	0.0036 (0.004)	-0.0057 (0.004)	-0.009 (0.005)	-0.0027 (0.005)
<i>Coffee coefficients</i>									
α	2	7	10	5	8.5	4.5	10	4.5	3.5
CES α	0.748 (0.041)	0.98 (0.031)	0.562 (0.042)	0.998 (0.019)	0.873 (0.035)	0.844 (0.041)	0.484 (0.047)	0.755 (0.031)	0.993 (0.033)
Best price	0.276 (0.043)	0.026 (0.039)	0.525 (0.045)	0.032 (0.019)	0.118 (0.039)	0.128 (0.036)	0.523 (0.053)	0.239 (0.029)	0.0544 (0.029)
cons	-0.0021 (0.004)	0.0052 (0.004)	-0.013 (0.005)	-0.0066 (0.002)	0.0068 (0.002)	0.014 (0.007)	0.009 (0.006)	0.0075 (0.003)	-0.0158 (0.006)

- Confirmation that substitution patterns are not well captured: 1) Best price also is significant controlling for the optimal CES elasticity of substitution; 2) Tornquist is significantly related to best price, even when controlling for geometric mean.

Results

- Our “structural” model fits well.
 - The unit value is approximated by the fixed weight and the best price
 - Coefficients nearly summing one
 - Constant = 0.
- The geometric mean is not a sufficient statistic for the unit value.
- Even the best fit CES index is not a sufficient statistic for the unit value (except for coffee in Chicago). See Shapiro and Wilcox, 1997.

National inflation

- Possible that our findings matter in levels, but aren't that informative about rates of change.
 - High frequency price variation strategies constant through time, shopping behavior constant through time, etc.
- Kryvstov and Vincent (2014), Wong and Nevo (2014), Handbury Watanabe and Weinstein (2013), and Basker (2013) make us suspect this isn't true.
- Constructed price aggregations by following BLS sampling procedures as closely as possible for 23 grocery products in our data.

Estimation for 23 products

$$\ln(\text{unitvalue}_t) - \ln(\text{unitvalue}_{t-1}) = \gamma + \ln(\alpha \text{fixedweightagg}_t + (1 - \alpha) \text{bestprice}_t) - \ln(\alpha \text{fixedweightagg}_{t-1} + (1 - \alpha) \text{bestprice}_{t-1}) + \epsilon_t$$

Estimation for 23 products

If our strategy well-approximates the unit value changes:

- α should be between 0 and 1 and represent the share of loyals
- γ should be zero
- Fit should be good

Results:

- Alpha coefficients range from 0.2 to 0.7
- Constant terms are small
- Explanatory power is high
- Implies that unit value is tracked very well by our simple formulation.

Implications for price measurement- Discussion for FESAC

- Our empirics/model highlight the outsized importance of the ordinally lowest price/promoted price in a narrow product category.
- Scanner data is used to parameterize as simple substitution model, but our ongoing methodology relies on enumerator collecting TWO prices for an item per outlet.
 - The sampling selected product the enumerator would ordinarily collect
 - The best special or deal in the product category
- Proposed methodology similar to (my understanding of) BLS airline ticket methodology
- Particularly important if promotional intensity/frequency varies over the cycle/ across outlets aimed at different demographics