Consumer Behavior and the Consumer Price Index (Preliminary)

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2008 World Congress on National Accounts and Economic Performance Measures for Nations

- Long literature in IO and Marketing that examines consumer demand including
 - substitution between products;
 - heterogeneity;
 - stockpiling and inter-temporal substitution;
 - non-linear pricing;
 - store choice;
 - coupons;
- Equally long literature on price indices that has only partially included the above effects (some notable exceptions!);
- Dramatic increase in food prices in the past few months;

- We have two large consumer panels for the US and UK in which panelists scan (at home) their food purchases;
- Our long term goals are (among others):
 - bring closer the two parts of the literature discussed above;
 - compare behavior across countries and its implications
 - "rip off Britain" campaign
 - difference in health outcomes
- In the short term more modest goals
 - How much do consumers "save" by optimizing in different dimensions?
 - How does this vary with demographics (income, age, race)?
 - What implication does this have for the measurement of the CPI?

Today I will follow an even more modest outline

- Data sets
- Implications of consumer behavior for measurement of price changes;
 - Stockpiling: the difference between consumption and purchase incidence;
 - Search and store choice
- Evidence
- Where to next

Data Sets: Nielsen Homescan and TNS Homescan

- 2 unique data sets that record food purchases of participating households;
- In both countries we have multiple years;
- Nielsen Homescan: 61,000 US panelists, mainly in big markets. (15,000 of those also record produce and other fresh food). "Static" sample: approx 40K (8K).
- TNS Homescan: roughly 15,000 active panelists every week;
- In principle ... all grocery shopping trips should be recorded, including a gum they buy at the movies.
- Overall, quite unique data. Main advantages over alternatives (e.g., POS data, loyalty-card panels, competitors data):
 - multiple stores and mass merchants (e.g., Wal-mart)
 - many households with variation in location and demographics
 - many product categories including random weight and fresh food

- The data are self reported by scanning products at home;
- The self reporting process raises two common concerns:
 - Is the sample of households representative of the population of interest?
 - Do the panelists record their purchases properly?
- Nielsen and TNS go to great length to assure the sample is representative (confirmed by work done at the USDA);
- Einav, Liebtag and Nevo (2007) examine mis-recording in the Nielsen Homescan panel;

- A typical price pattern for food includes frequent price reductions (see graph)
- A large fraction of purchases are on sale;
- Furthermore, many products exhibit non-linear prices (see table);
- There is plenty of evidence that the additional purchases are at least partially going to inventory;
- Stockpiling behavior varies across households and markets (see table);

Typical Pricing Pattern



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	Print (Discourt	Quantity	Weeks	Average Sale	Quantity	Genia
	Price/Discount	Sold on Sale	on Sale	Discount	Share	Savings
	(\$/%)	(%)	(%)	(%)	(%)	(%)
Detergents						
32 oz.	1.08	2.6	2.0	11.0	1.6	4.3
64 oz.	18.1	27.6	11.5	15.7	30.9	1.3
96 oz.	22.5	16.3	7.6	14.4	7.8	10.0
128 oz.	22.8	45.6	16.6	18.1	54.7	18.6
256 oz.	29.0	20.0	9.3	11.8	1.6	_
Yogurt						
6 oz.	1.39	37.8	23.6	19.7	27.4	13.7
6 * 4.4 oz.	7.8	19.4	15.2	18.5	12.4	8.9
8 oz.	9.3	25.3	14.4	21.9	40.4	7.2
16 oz.	9.9	1.1	1.8	16.6	5.7	1.3
32 oz	28.3	15.9	10.8	13.0	12.9	3.0
Soft drinks						
1 can	1.07	24.3	19.4	21.9	6.8	6.3
6 cans	2.3	59.5	34.3	35.4	16.8	21.8
12 cans	14.7	72.8	43.9	22.0	21.8	17.2
24 cans	34.4	78.3	41.7	20.8	54.5	17.6

TABLE 3 Quantity Discounts and Sales

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	Dried Pasta	Plain Rice	Biscuits/ Cookies	Canned Cola	Yoghurt/Yog urt	Frozen Veg	Frozen Pizza	Ice Cream
UK Data								
Number of Households	6,366	3,029	11,977	2,523	11,449	11,709	5,711	9,264
Number of Shopping Trips	55,464	20,937	187,454	28,279	217,566	157,056	57,464	107,250
Quantity purchased per trip	28.71oz	40.42oz	17.43oz	149.42fl oz	30.65 oz	56.83 oz	24.55 oz	45.68fl oz
Days until next purchase	32.5	42.4	17.5	21.8	14.2	21.5	26.7	21.3
US data								
Households	5,254	1,317	6,894	3,688	4,939	6,236	3,853	6,413
Trips	33,221	4,660	84,937	42,209	56,397	52,301	28,038	56,882
Quantity purchased per trip	32.17oz	77.53oz	22.68oz	279.77fl oz	38.34oz	45.08oz	36.44oz	85.45fl oz
Days until next purchase	56.9	62.2	22.6	26.3	22.9	51.7	33.5	27.5

Proportion of expenditure on own label (as opposed to branded)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	biscuits	vegetables	yoghurt	rice	pasta	pizza	ice cream	cola
Britain	32.57	61.79	28.96	81.60	73.60	40.61	48.20	12.39
US	18.16	45.27	23.36	32.51	26.98	10.61	6.13	0

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- When consumers stockpile there is a difference between acquisition price and consumption price;
- Consumption price is a shadow price:
 - equals acquisition price in periods of purchase, if decisions are continuous;
 - equals shadow price of inventory in periods of no purchase (lower than the market price);
- Implications for COLI;
- Also practical implications for CPI;

- Evidence that consumers shop at different stores;
- Literature that relates this behavior to sales and loss leaders;
- Like stockpiling this has theoretical implications for the COLI and practical implications for the CPI;

variable	all	small trips (<5 items)	med trips (5-9 items)	big trips (10+ items)
# of trips	4,605,731	2,518,535	1,032,007	935,339
# of HH	39,572	39,500	39,320	38,343
avg # of trips per HH	116.4	64.8	26.2	24.4
avg exp per trip (\$)	19.28	6.70	19.00	52.36
avg # of items per trip	7.0	2.1	6.6	20.2
avg annual exp by household (\$)	2,244.1	426.5 (19.0%)	495.6 (22.1%)	1,322.0 (58.9%)

Summary Stats of Homescan Data

variable	all	small trips (<5 items)	med trips (5-9 items)	big trips (10+ items)
avg # of stores visited	12.9	11.5	5.4	3.8
avg annual exp per store (\$)	173.5	37.2	91.8	352.2
avg # of chains visited	11.4	10.5	4.8	3.3
avg annual exp per chain (\$)	197.3	40.9	104.1	414.8
avg HH-level C1	0.55	0.41	0.55	0.69
avg HH-level C2	0.74	0.61	0.77	0.88
avg HH-level C3	0.83	0.73	0.87	0.94
avg HH-level C4	0.88	0.81	0.93	0.97
avg HH-level HHI	0.41	0.28	0.43	0.58

Household Level Concentration Measures

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variable	all	small trips (<5 items)	med trips (5-9 items)	big trips (10+ items)
# of household-weeks	1,725,770	1,213,018	780,315	879,253
avg # of weeks per HH	43.6	30.7	19.8	22.9
avg HH-week C1	0.80	0.82	0.92	0.96
avg HH-week C2	0.95	0.96	0.99	1.00
avg HH-week C3	0.99	0.99	1.00	1.00
avg HH-week C4	1.00	1.00	1.00	1.00
avg HH-week HHI	0.73	0.77	0.91	0.95

Household Weekly Concentration Measures

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- Key: requires (high frequency) quantity data;
- Preferably consumer level data;
- Hasuman and Leibtag (NBER 2004) show how to use a model of store choice to compute a price index that accounts for shopping at supercenters;
- The results in Nevo and Hendel (2006) can be used for a similar computation of the impact of stockpiling.

- Compute a measure of "saving" from various dimensions of behavior;
 - compare actual to "random" choices;
 - compare actual to CPI sampling;
- Correlate these measures with demographics;
- These allow us start quantifying the relevance of consumer behavior for the computation of price indexes;