Do Differences in Reported Expenditures between Commercial Household-based Scanner Data and Government Surveys Matter in a Structural Model of Food Demand?

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Abstract

Commercial household-based scanner data have advantages in the degree of granularity and length of time that food purchases are tracked compared to government paper-and-pencil expenditure surveys. In addition to their use in marketing science for understanding food consumption and consumer behavior, these data have the potential to inform government policies related to food and nutrition. This study examine whether differences in the level of reported consumer food expenditures between the IRI's Consumer Network household-based scanner data and the paper-and-pencil U.S. Bureau of Labor Statistics' Consumer Expenditure Survey (CES) lead to important differences in estimated price and income elasticities.

In this study, consistent with results in Zhen et al. (2009), we found reported scanner-data expenditures to be lower than reported government survey expenditures in general. We estimated the Exact Affine Stone Index (EASI) demand system (Lewbel and Pendakur, 2009) for 18 food-at-home categories using 2008-2012 Consumer Network and CES data using panel price indices created from retailer scanner data from IRI's InfoScan. We focus on households in 21 metropolitan areas that are identified in the public-use CES data. We account for censored purchases using Tobit regression and impose theoretical restrictions on the demand parameters using minimum distance.

The results of this study provide an opportunity for discussion of (1) the characteristics of commercial household-based scanner data compared to government consumer expenditure data and (2) how the data can be applied in analyzing consumer food purchase behavior considering estimated price and income elasticities.

Keywords: food demand, structural model, household-based scanner data, econometric estimation, demand elasticities

Topic: Models of food consumption behavior and their predictive power

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Introduction

Proprietary commercial data on household food purchases collected through in-home barcode scanning are becoming more available and affordable to researchers in the United States and European countries. These data are particularly well-suited to analyzing consumer food purchase behavior in more depth than is possible through more traditional or more limited data sources. In particular, household-based scanner data have advantages in the degree of granularity in product detail and length of time that purchases are tracked compared to government paper-and-pencil expenditure surveys. In addition to their use in marketing science for understanding food consumption and consumer behavior, household-based scanner data have the potential to inform government policies related to food and nutrition. In comparison to store scanner data, household-based scanner data have the advantage of being linked to characteristics of the households that purchased the products. However, the data collection process for household-based scanner data could influence consumer purchase decisions, the households that choose to participate in the panel may have different characteristics compared to the general population, and the methods that are used to prepare the data may affect the generalizability of results of analyses.

Numerous papers have used household-based scanner data collected and prepared by The Nielsen Company (specifically, Homescan data) to analyze various policies and issues concerning foods and beverages (a recent example is Zhen et al. 2014). Household-based scanner data have also been used to better understand markets for consumer products and consumer behavior in general. For example, Aguiar and Hurst (2007) used Nielsen Homescan data and time diaries to estimate the degree of substitution between time spent on shopping and home production and prices paid for food. Broda and Weinstein (2010) examined entry and exit in product markets and found that net product creation is strongly procyclical. Bronnenberg, Dube, and Gentzkow (2012) examined the evolution of brand preferences for consumer packaged goods over time and found brand preferences to be highly persistent and influenced by geography. Handbury and Weinstein (2015) examined sources of bias in developing spatial price indexes and found heterogeneity bias arises from comparing different goods in different locations, and variety bias arises from not correcting for the fact that some goods are unavailable in some locations; eliminating these biases reverses the common finding that prices are higher in larger cities. In general, these studies demonstrate the broad applicability of household-based scanner data in studies that have implications for understanding consumer behavior.

Several prior studies have compared Nielsen Homescan household-based scanner data with other data sources. Zhen et al. (2009) found discrepancies in reported expenditures between Nielsen Homescan and U.S. Bureau of Labor Statistics Consumer Expenditure Survey (CES) for the years 2002 to 2005 with the largest differences found in unpackaged foods without a barcode. Einav, Leibtag, and Nevo (2010) compared purchase transactions recorded in Nielsen Homescan and in a large grocery chain's database of the same households and found the degree of measurement error in Homescan prices to be similar to those identified in other data sets commonly used by social scientists. Comparing results from two choice-based conjoint experiments, Lusk and Brooks (2011) found IRI Consumer Network and Nielsen Homescan respondents to be slightly more price-sensitive than a random sample of the U.S. population. Finally, Boonsaeng and Carpio (2014) estimated a structural food demand system for eight food-at-home categories using Homescan and CES over the 2002 to 2006 period and found that estimated demand curves based on Homescan are more price elastic than those based on CES.

Now that IRI Consumer Network data are being used increasingly by researchers, it is important to also gain a more thorough understanding of these data. Although the methodology used for developing the Nielsen Homescan and IRI Consumer Network data are similar, and they both rely on the same initial data reported by a panel of households, each has unique attributes that could influence the results of analyses. The specific objective of this study is to examine whether differences in the level of reported consumer food expenditures between the IRI's Consumer Network household-based scanner data and the paper-and-pencil U.S. Bureau of Labor Statistics' Consumer Expenditure Survey (CES) lead to important differences in estimated price and income elasticities. Different psychological processes underlie the data collection process for each data set because one is a lower burden but continuous effort over a long time period and the other is higher burden but short duration effort. Results of this study, in addition to other analyses, can aid in developing a fuller understanding of how these data can best be used for a wide range of marketing and policy analysis topics related to food consumption. This paper is a contribution to the set of studies that have examined household-based scanner in general, but also begins the process of examining the IRI data.

Analysis and Modeling Methods

We focused the analysis on 18 food categories that encompass all foods at home using the 2008-2012 Consumer Network and CES data shown in Table 1. These 18 food categories comprise over 640,000 unique products or Universal Product Codes (UPCs) with the highest numbers in bakery products, sugar and sweets, and nonalcoholic beverages. First, we compared mean expenditures, including both UPC and random weight products, between Consumer Network (the household scanner data) and CES in levels by product category. Mean expenditures were weighted by survey weights in each dataset to be nationally representative. Next, to compare price and income elasticities between the two data sources, we estimated the Exact Affine Stone Index (EASI) demand system (Lewbel and Pendakur, 2009) for the 18 food-at-home categories and a *numéraire* category capturing all other goods and services. Because of censored purchases, we estimated the approximate version of the EASI model using one dataset (i.e., Consumer Network or CES) at a time as follows:

$$(1) \qquad w_{hi}^{*} = \sum_{j=1}^{J}\left(a_{ij}\ln p_{hj} + a_{ijy}y_h \ln p_{hj}\right) + \sum_{r=1}^{L} b_{ir}y_h^r + \sum_{k=1}^{K} g_{ik}d_{hk} + u_{hi}\,,\ h = 1,\ldots,H;\, i = 1,\ldots,J-1$$

where w_{hi}^{*} is the latent budget share of food category i for household h; J is the number of categories in the demand system including the J th *numéraire* category; H is the number of households; y_h is real household income; L is the empirically determined highest order of polynomial in y_h; p_{hj} is a price index for category j facing household h; d_{hk} is the k th household demographic variable; a_{ij}, a_{ijy}, b_{ir}, and g_{ik} are parameters; and u_{hi} is the residual. Eq. (1) is an unconditional demand model in that demand is not conditional on total food expenditure, which we know is lower in Consumer Network than in CES.

Household demographic variables include household size, average age of household heads, indicators for Census region, season (spring, summer, and fall), presence of female household head, college educated female household head, presence of children, and black and Hispanic household head. These variables serve two purposes. First, they serve as demand shifters. Second, to a certain extent, they control for some of the differences in reported expenditures between the two datasets (Zhen et al. 2009).

The latent budget share w_{hi}^{*} maps to the observed budget share w_{hi} through $w_{hi} \equiv \max\{0, w_{hi}^{*}\}$, where w_{hi} equals to food category expenditure divided by nominal household income. Estimation of the EASI model is a two-step process (Perali and Chavas 2000; Meyerhoefer et al. 2005). In step one, we accounted for censored w_{hi} using a singleequation Tobit model. In step two, cross-equation correlations and theoretical restrictions of homogeneity and symmetry on latent demand are imposed using the minimum distance estimator. Real income y_h is calculated as $\ln x_h - \sum_{j=1}^{J} w_{hj} \ln p_{hj}$, where x_h is nominal weekly household income. In theory, y_h is endogenous because of w_{hj} in the formulation. However, Lewbel and Pendakur (2009) and Zhen et al. (2014) showed that this source of endogeneity is quantitatively trivial.

There are two alternative approaches to getting the price indices p_{hj}. First, in their comparison of Homescan and CES, Boonsaeng and Carpio (2014) created Fisher Ideal price indices for Homescan households using Homescan prices and Stone-Lewbel price indices (Holderlein and Mihaleva 2008) for CES households using item-level monthly consumer price index-average price data from Bureau of Labor Statistics. Unlike the Fisher Ideal price index that requires both item-level prices and quantities as inputs, the Stone-Lewbel price index only needs item budget shares and market-level item prices to create a price index that exhibits variations across households in the same market. A higher price variation helps identify the price coefficients in the demand model. However, this approach does not work for our purpose, which is to examine whether differences in reported expenditures lead to differences in elasticities, ceteris paribus. Because CES households do not report prices or purchase quantities, it is reasonable to expect that the Stone-Lewbel price indices created for these households are measured with more error than the Fisher Ideal price indices created for Homescan households. Because measurement error causes attenuation bias, estimated Homescan-based demand should be more price-elastic than estimated CES-based demand, which is what Boonsaeng and Carpio (2014) discovered.

The second approach creates a common category price index for Consumer Network and CES households in the same market. When the same price is used to estimate both demand systems, we can attribute differences in estimated elasticities between datasets to expenditure differences. To create the category price index, p_{hj}, we use barcode-level volume and dollar sales from InfoScan, an IRI retail scanner database developed *independent* from Consumer Network data collection.

To increase comparability, we focused on Consumer Network and CES households in 21 metropolitan areas that are identified in the public-use CES data (that is, "A" size PSUs or MSAs with greater than 1.5 million population). Each p_{hj} is a panel rolling-window GEKS weekly price index (base = 2008) that maximizes the number of matched barcodes between two periods and minimizes chain drift in high-frequency price index. The same price indices are linked to both Consumer Network and CES households based on week and metropolitan area.

Data Description

For the models and comparison methodology described above, we rely primarily on three data sources: IRI Consumer Network household-based scanner data, IRI Infoscan store-based (or point-of-sale) scanner data for constructing price indices, and the Bureau of Labor Statistics CES household purchase diary data. We describe these data below.

Consumer Network household-based scanner data. IRI derives the Consumer Network data product from the National Consumer Panel (NCP), which is an operational joint venture equally owned by IRI and The Nielsen Company (IRI, 2015a). Households are recruited to the NCP through multiple mechanisms and are provided incentives to record all of their UPC-based consumer product purchases, regardless of where purchased, with a handheld in-home scanning device (IRI 2015a). The panel comprises approximately 120,000 households that rescan and record their food purchases on an ongoing basis. A subset of these households, nearly 80,000 households in 2012, also record random weight purchases such as loose fruits and vegetables and meats and cheese packaged in the store. IRI and Nielsen strive to match the demographics of the panel to U.S. Census Bureau targets, but some types of households are more inclined to join the panel and to be consistent reporters of purchases.

Of the 120,000 or so households in the panel, approximately half report data consistently enough throughout the year to be included in the static panel that are produced annually for use in analysis. The proportion of households with data of sufficient quality to be included in the status panel for random weight foods is somewhat less than for the all products. Note that IRI and Nielsen use different criteria for determining whether a household will be included in the static panel. In the case of IRI, a household has to meet specific thresholds for expenditures based on household size. Specifically, they must report purchases at least monthly for most months of the year, and purchases must exceed thresholds established for 1-person, 2-person, or 3- or more person households.

The data contain food purchase information by UPC code including quantities, prices, discounts, and coupons along with a set of household demographic information including household size, household income, age of household head, ethnicity, race, and presence of children. IRI assigns prices to each UPC-level transaction using their weekly point-of-sale data for the store chain or the outlet types, or they use the price that households inputs during the reporting process if they shop at a store that is not represented in the IRI point-of-sale data. In addition, IRI also tracks nutrition values and label claims that can be linked by UPC code for high volume products.

Table 2 compares the distribution of key household demographics for the IRI panel, the CES panel, and the American Community Survey conducted by the U.S. Census Bureau. The weighted American Community Survey can be considered the true benchmark because it is an annual survey used to determine distribution of federal and state funds under numerous programs (U.S. Census Bureau, 2015). IRI weights the Consumer Network data to match precisely the Census targets using the iterative proportional fitting (IPF) method and therefore we do not present the weighted Consumer Network proportions here. The weighted and unweighted proportions for CES are similar to each other and therefore we present the weighted estimates here.

In general, the households in the static panel for the Consumer Network data tend to be considerably older, have higher incomes, are less likely to be Hispanic or black, and are less likely to have children compared to the U.S. population as represented in the American Community Survey. These differences are generally similar when compared to CES households except that CES households appear to have substantially lower income. This result could be due to differences in how income is defined and thus we are continuing to explore use of other measures in the CES data. The weighting procedures for the Consumer Network data account for the differences in household characteristics, but examining the differences is informative for understanding the types of households participating in the panel. Also, differences in the household characteristics between the static panel and the remainder of households that did not provide data of sufficient quality to be included in the static panel provide insights into which types of households are better reporters. In particular, the following types of households appear to be less likely to be included in the static panel: one-person households, younger households (less than 35 years of age), the lowest and highest income households, non-Hispanic households, and households with children. In some cases, this means that purchases are being projected from a relatively small proportion of reporting households (particularly younger households). Households that meet the requirements for the static panel in these lower reporting categories have not only different reporting behaviors but could also have different purchasing behaviors in general.

IRI InfoScan store-based scanner data. In contrast to the Consumer Network data collected from households, InfoScan data are collected directly from stores through an automated process. IRI has established agreements with the majority of grocery, drug, mass merchandise, club, and other types of retailers to provide point-of-sale (POS) scanner sales and promotional data. The primary purpose of the data are for manufacturers, retailers, sales and marketing agencies, and financial institutions to conduct analyses of sales by brand, category, promotion type, and industry (IRI, 2015b). The dataset used in our analysis contains “census” stores that have agreed to supply IRI all of their sales data, which IRI estimates includes approximately three-fourths of U.S. grocery retailers and nearly all drug stores and mass merchandisers. As with the household data, the store data are also disaggregated to the UPC level with detailed product information including number of units sold and average prices and are provided on a weekly basis. In some cases, the data are provided at the store level and, in other cases, the data are provided at a retailer marketing area (RMA) level. However, the data are not tied to information on who purchases the products as with the household-based data. In addition, the data are not weighted because they represent a census of stores.

U.S. Bureau of Labor Statistics CES purchase diary data. The CES program consists of two surveys—the Quarterly Interview Survey and the Diary Survey—that provide information on the buying habits of American consumers, including data on their expenditures, income, and consumer unit (similar to the concept of a household) characteristics (U.S. Department of Labor, Bureau of Labor Statistics, 2015). As described in Zhen et al. (2009), two independent samples are maintained for these surveys, but our focus is on the Diary Survey which is a cross-sectional data collection in which households keep one-week expenditure diaries for two consecutive weeks. Households record food expenditures by food category but do not record quantities purchased. Approximately 14,000 households participate on an annual basis, and their demographic characteristics fairly closely track the distribution of households in the American Community Survey (see Table 2) with the exception of household income.

Results of Analyses and Estimation

In this study, consistent with results in Zhen et al. (2009), we found reported scanner-data expenditures to be substantially lower than reported government survey expenditures. Table 3 shows results of comparisons of total expenditures and per-household expenditures by food category for IRI and CES in 2012. Note that these results are similar across the 2008 to 2012 time period used for estimating demand and expenditure elasticities by food category. Over all product categories, estimated per-household weekly expenditures total $58 for the IRI panel and $74 for the CES panel; thus, IRI expenditures are approximately 78% of CES expenditures. Per-household weekly expenditures for CES exceed IRI for all categories with exception of “other” dairy products and sugar and other sweets; for these categories, the estimates are very similar. The largest differences appear for fresh fruits and fresh vegetables. These products have higher burden associated with reporting in the IRI panel because a larger proportion of these products do not have a scannable UPC code and therefore must be hand-keyed. In comparing fresh fruits and fresh vegetables to their processed counterparts, all of which have UPC codes, the differences between IRI and CES are considerably lower (less than half the differences). In comparing the results to Chen et al. (2009), beef, poultry, and pork previously had the largest differences between the two data sources; these categories continue to have large differences but are now no longer among the top.

The own-price and expenditure elasticity estimates by food category for each data source will be shown in Table 4 (still in process). These estimates will help determine if using one data source or the other results in important differences regarding how consumer purchases respond to changes in prices or income (expenditure shares). Results of estimation will be available prior to the conference.

Conclusions

Analyses of consumer demand for food products have benefited from the availability of detailed, high frequency consumer purchase data that can be tied to household demographics. However, a number of factors may affect its representativeness, particularly because of the types of households likely to participate and provide data of sufficient quality to be included in the dataset, the potential effects of the data recording process itself, and the methods that are used to assign prices in the dataset. Therefore, in considering how to use the data for better understanding consumer purchase decisions, it is important to understand the properties of the data. This will help ensure that the results of analyses using the data are appropriately applied for marketing purposes or for informing food policy.

After final estimates are available, we will provide a recap of the results and discuss conclusions based on the results.

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Table 1. Description of Food Groups Used for Comparing IRI Household-based Scanner Data and CES Diary-based Data (Preliminary)

CES Product Categories	Types of Products from IRI Consumer Network	Number of IRI UPCs
Cereal and Cereal Products	Baking mixes, dry noodles, dry rice, and breakfast cereals	36,552
Bakery Products	Fresh, refrigerated, and frozen baked goods; cookies, crackers, and bread	87,370
Beef	Refrigerated and frozen beef	2,895
Pork	Refrigerated, frozen, and canned pork, ham, and pork sausage	10,561
Other Meats	Refrigerated, frozen, and shelf-stable deli meats and frankfurters	9,855
Poultry	Refrigerated and frozen poultry	4,969
Fish and Seafood	Refrigerated, frozen, and canned seafood	14,549
Eggs	Fresh eggs and egg substitutes	3,531
Fresh Milk and Cream	Refrigerated and shelf-stable milk and creamers	14,349
Other Dairy Products	Cheese, yogurt, ice cream, and butter	55,573
Fresh Fruits	Fresh fruits (uniform weight)	6,810
Fresh Vegetables	Fresh vegetables (uniform weight)	10,595
Processed Fruits	Refrigerated, frozen, and canned fruits and juices and dried fruits	24,308
Processed Vegetables	Refrigerated, frozen, and canned vegetables and dried beans	29,552
Sugar and Other Sweets	Candy, gum, jam, jelly, preserves, and syrups	72,492
Fats and Oils	Cooking oils, sandwich spreads, and salad dressings	16,025
Nonalcoholic Beverages	Carbonated beverages, coffee, tea, and juice drinks and mixes	64,267
Miscellaneous Foods	Fresh, frozen, and shelf-stable prepared meals; seasonings and sauces; snack foods; and baby foods	178,884
Total		643,137

Table 2. Characteristics of the IRI Household Panel Versus the American Community Survey, 2012 (Preliminary)

	Households in Static Panel (Unweighted)	Households not in Static Panel (Unweighted)	CES (Weighted)	American Community Survey (Weighted)
Household Size				
1 person	24.7%	14.5%	28.8%	32.8%
2 persons	43.5%	29.9%	32.9%	31.0%
3-4 persons	24.8%	39.8%	28.8%	27.3%
5+ persons	7.0%	15.8%	9.5%	9.0%
Age of Household Head				
<35 years	5.9%	81.1%	24.4%	18.5%
35-44 years	13.5%	5.1%	17.8%	18.0%
45-64 years	55.1%	10.6%	37.8%	40.2%
65+ years	25.5%	3.2%	20.0%	23.3%
Annual Household Income				
<$15,000	6.5%	9.1%	33.8%	13.2%
$15,000-$34,999	22.1%	22.9%	15.9%	20.8%
$35,000-$69,999	35.7%	36.6%	23.9%	28.8%
$70,000+	35.7%	31.4%	26.4%	37.2%
Ethnicity				
Non-Hispanic	94.7%	90.6%	86.6%	85.1%
Hispanic	5.3%	9.4%	13.4%	14.9%
Race				
Black	9.9%	11.4%	13.1%	14.3%
Non-Black	90.1%	88.6%	86.9%	84.7%
Presence of Children				
Yes	21.2%	47.3%	31.9%	32.9%
No	78.8%	52.7%	68.1%	67.1%

Table 3. Total and Mean Weekly Household Food Expenditures Using IRI Household-based Scanner Data Versus CES Diary-based Data, 2012 (Preliminary)

Food Category	IRI Total ($1,000s)	IRI Per House-hold	CES Total ($1,000s)	CES Per House-hold	IRI - CES (Total)	IRI – CES (per HH)
Cereal & Cereal Products	$295,756	$2.85	$432,482	$3.50	-$136,723	-$0.65
Bakery Products	$551,411	$5.20	$845,582	$6.84	-$294,171	-$1.64
Beef	$319,454	$2.98	$538,328	$4.35	-$218,875	-$1.37
Pork	$237,848	$2.23	$393,804	$3.18	-$155,956	-$0.95
Other Meats	$211,370	$1.99	$290,538	$2.35	-$79,168	-$0.36
Poultry	$253,654	$2.41	$379,268	$3.07	-$125,614	-$0.66
Fish and Seafood	$146,280	$1.38	$297,525	$2.40	-$151,246	-$1.02
Eggs	$59,738	$0.56	$125,985	$1.02	-$66,247	-$0.46
Fresh Milk and Cream	$243,716	$2.30	$361,308	$2.92	-$117,592	-$0.62
Other Dairy Products	$547,529	$5.19	$635,191	$5.13	-$87,661	$0.06
Fresh Fruits	$296,123	$2.73	$620,273	$5.01	-$324,150	-$2.28
Fresh Vegetables	$243,868	$2.27	$536,602	$4.34	-$292,734	-$2.07
Processed Fruits	$171,901	$1.64	$269,982	$2.18	-$98,081	-$0.54
Processed Vegetables	$165,230	$1.58	$308,679	$2.50	-$143,449	-$0.92
Sugar and Other Sweets	$300,938	$2.84	$348,747	$2.82	-$47,809	$0.02
Fats and Oils	$162,047	$1.55	$271,180	$2.19	-$109,133	-$0.64
Nonalcoholic Beverages	$613,830	$5.85	$879,344	$7.11	-$265,513	-$1.26
Miscellaneous Foods	$1,303,625	$12.42	$1,661,258	$13.43	-$357,633	-$1.01
Total	$6,124,322	$57.97	$9,196,078	$74.34	-$3,071,756	-$16.37

Table 4. Estimated Own-Price and Expenditure Elasticities Using Weekly IRI Household-based and CES Data, 2008-2012

Note: Estimation is underway and estimates will be available prior to the conference.

	CES			IRI Consumer Network		
Food Category	**Hicksian Own-Price Elasticity**	**Marshallian Own-Price Elasticity**	**Expend-iture Elasticity**	**Hicksian Own-Price Elasticity**	**Marshallian Own-Price Elasticity**	**Expend-iture Elasticity**
Cereal & Cereal Products						
Bakery Products						
Beef						
Pork						
Other Meats						
Poultry						
Fish and Seafood						
Eggs						
Fresh Milk and Cream						
Other Dairy Products						
Fresh Fruits						
Fresh Vegetables						
Processed Fruits						
Processed Vegetables						
Sugar and Other Sweets						
Fats and Oils						
Nonalcoholic Beverages						
Miscellaneous Foods						