A Workshop on the Use of Scanner Data in Policy Analysis

A Workshop Organized by the
Economic Research Service, USDA, and the Farm Foundation

Waugh Auditorium, 3rd Floor, Economic Research Service, USDA
1800 M Street NW, Washington, DC 20036
Monday, June 9, 2003

Agenda

8:00 to 8:15 Continental Breakfast

8:15 to 8:30 Welcome and Introduction

a) Mark Denbaly

8:30 to 10:30 Addressing Policy Issues Using Micro Scanner Data

a) Moderator: Harry Kaiser, Cornell University
   i) Panel 1:
      (1) Helen Jensen, Iowa State University – Demand for Enhanced Foods and the Value of Nutritional Enhancements of Food Summary
      (2) James Binkley, Purdue University – Determinants of Functional Food Consumption Summary
      (3) Cesar Costantino, Univ. of Maryland – Consumer Search Inside the Supermarket Summary
      (4) Key Points from Discussion of First Three Presentations
   ii) Panel 2:
      (5) Oral Capps, Texas A&M University – Demand Projections Segmented by Income for the Highly Competitive Non-Alcoholic Beverage Complex Using the A.C. Nielsen HomeScan Panel Data Summary
      (6) Steven Yen, University of Tennessee – Demand for Fruits and Vegetables: An Analysis of HomeScan Data Summary
      (7) Jeff Perloff, University of California, Berkeley – Use of Demand Estimation for Policy Simulation Summary
      (8) Key Points from Discussion of Second Three Presentations

10:30 to 10:45 Break

10:45 to 12:00 Panel Discussion: Scanner Data and Price Indices

a) Moderator: Ephraim Leibtag, Economic Research Service
   i) Presentations:
      (1) Mick Silver, Cardiff University Summary
      (2) Walter Lane, Bureau of Labor Statistics Summary
   ii) Roundtable Discussion Summary
      (1) Mick Silver, Cardiff University

(2) Marshall Reinsdorf, Bureau of Economic Analysis
(3) Walter Lane, Bureau of Labor Statistics

12:00 to 1:00 Lunch

Methodological and Data Challenges of Using Scanner Data

a) Moderator: David Davis, Economic Research Service

1:00 to 2:00 Properties of Scanner Data

i) Presentations
   a) Properties of Scanner Data, Mike Harris – Economic Research Service Summary
   b) The Importance of Sales in High Frequency Supermarket Scanner Data, Dan Hosken– Federal Trade Commission Summary

2:00 to 2:15 Break

2:15 to 3:15 Aggregating Scanner Data

i) Presentations
   a) Aggregating Scanner Data, Oral Capps – Texas A&M University Summary

3:15 to 3:30 Break

3:30 to 4:30 Estimation Using Scanner Data

i) Presentations
   a) Tirtha Dhar – University of Wisconsin Summary
   b) Mick Silver – Cardiff University Summary

A Summary of the Presentation: ***Demand for Enhanced Foods and the Value of Nutrition Enhancements of Food: The Case of Margarines***

by
Helen H. Jensen
Iowa State University

Research co-author, Sonya K. Huffman.

New production and processing methods have led to significant changes in foods in response to consumer preferences for health-promoting attributes in foods. Changes in observed food prices reflect changes in the market for existing foods as well as the added value from new foods (foods with new product attributes). As with other new or changed product introduction, the different values in the market pose a problem for understanding what the observed product price means and whether consumer welfare has improved with the introduction of the new product.

The introduction of new margarine products provides an example of a nutritionally-enhanced food. In May 1999, the Food and Drug Administration approved the sale of Take Control and Benecol margarines. The products include components that block the absorption or re-absorption of cholesterol. Product sales reached a level of $27 million in 2000. In this paper, we model the consumer food choices based on economic, ethnic and other socioeconomic characteristics with respect to butter, regular margarine, diet margarines, regular and diet blends, regular and light Benecol and Take Control. We use the hedonic method to estimate consumer values of various attributes of the products applied to data from the 1999 HomeScan retail scanner data panel.

There were 6,607 households in the panel that purchased dairy products during 1999. Most (98 percent) households consumed one of the dairy spread products. Sixty one percent of the sample purchased butter and 34 percent of the households purchased some diet margarine or spread. Over 70 percent of butter purchasers also purchased special, light or diet spreads. The products of particular interest in this study were Benecol and Take Control; 7.2 percent of the households purchased these products during 1999, after their introduction in May. For all dairy spreads, the average expenditure per month was $3.03 with an average unit value of $1.23 per pound. For Benecol and Take Control, the average monthly expenditure by consuming households was $4.52, with an average unit value of $7.55 per pound.

The hedonic estimation was based on the unit value paid by the household for butter, margarine and spreads. The unit value was computed as the ratio of the household monthly expenditure on butter, margarine and spreads (in dollars) and the household monthly quantity purchased (in pounds). The results of the hedonic estimation showed that households were willing to pay 4% more for a diet product, 76% more for butter, and 44% more for blend compared to the margarine. The value of Benecol/Take Control increased by 131.6% compared to the margarine. In addition to characteristics variables in the hedonic equation, we included dummy variables for the four regions, and for urban residence. We also estimated the hedonic equation with a selection term, and, although the selection term was statistically significant, the estimated coefficient results were similar.

Finally, we estimated single probit equations for butter, margarine and spreads, and Benecol/Take Control as a function of the demographic characteristics of the households and income. Income, college education and age were statistically significant in most of the estimations. Income and age over 50 had a positive effect on butter and on Benecol/Take Control and a negative effect on margarine consumption. The estimation established a positive value for nutritional enhancement, although the purchases of both butter and diet spreads suggest that the consumer choice on nutritional attributes is relatively complex.

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A Summary of the Presentation: *Determinants of Functional Food Consumption*

By
Dr. James Binkley
Purdue University

Research co-authors:
Sharon Abbott, Dr. Christine Wilson, Dr. Kevin McNamara

Objective

The focus of this study is functional foods, an increasingly popular--though not well-defined--concept in the food industry. Functional foods are foods with a perceived nutritional component, but the line between functional foods and foods that are simply nutritious is somewhat blurred. For example, in the case of cereals, plain bran flakes, however nutritious they may be, would generally not be considered a functional food, while Fiber One, which is enhanced with extra fiber of varying types and which was introduced after a link between fiber and cancer was identified, would be so considered. But 100% Bran, an old cereal with standard wheat bran as a major ingredient, is ambiguous. In this study we regard functional foods to be food products having a salient nutritional characteristic that has been added (or removed) during manufacture and for which there are very close substitutes lacking (having) that characteristic.

The objective of this project is to identify the characteristics of consumers who purchase functional foods. Specifically, this research will focus on identifying both the socioeconomic characteristics and the shopping basket characteristics—the purchase patterns--of consumers who buy certain categories of functional foods. The relationship between functional foods and traditional foods in consumer diets will be analyzed. Whether or not consumers who purchase functional foods consistently eat a healthy diet or only eat well in certain product categories, perhaps to compensate for consuming foods with questionable nutrient merit will also be considered. Socioeconomic characteristics such as education, income, and household size will also be analyzed in order to better understand their influence on functional food consumption decisions.

Hypotheses Investigated

A general hypothesis of the study is that consumers who buy functional foods have characteristics similar to those who buy 'traditional' nutritious foods. Previous research on characteristics of those with more nutritious diets suggests that more educated consumers, because they will be more aware of functional food attributes, are more likely to purchase functional foods than are less educated buyers. Similarly, older consumers are more aware of the diet/health relationship and therefore are inclined to purchase more healthful products such as functional foods. Women, especially those with young children, have been found to be more aware of food attributes and the importance of nutrition, making them more likely to purchase functional foods.

It is natural to expect that buyers of functional foods includes most people who buy minimally processed healthy foods such as fresh produce and whole grain breads, and this will be tested.

However, some functional foods, rather than adding healthy components to 'normal' foods, remove components viewed as unhealthy, or at least as non-nutritious. The main examples are reduced fat and fat-free products and products using sugar replacements. Consumers may use these as a means to compensate for their otherwise unwholesome choices, possibly resulting in an overall less healthy diet. The study will examine this question.

Functional foods are often more expensive than standard counterparts, either in terms of shelf price or infrequency of price promotion. This reflects possibly higher production costs, but also discriminatory pricing due to manufacturers' perceptions of less elastic demand. Higher prices suggest that income may be an important factor in demand for functional foods. In addition, careful (i.e. cheap) shoppers---as measured by coupon use, buying on special, buying private labels, shopping at multiple stores, etc---may be discouraged from buying functional foods. These issues will be considered.

Methodology

In order to address the above issues, data on individual household grocery purchase patterns, together with demographic characteristics of the households making the purchases, are needed. Thus, the AC Nielsen HomeScan Data is well suited for the project. We have found that the data is not difficult to deal with, although without software such as SAS (which is what we use) it would be nightmarish.

Generally, the project is being based on annual totals for the 7195 Nielsen households (in terms of expenditures and quantities) for selected categories and subcategories. Foods with functional food attributes are identified, and then the characteristics of consumers who purchased those products are examined. There are numerous specific products in the data base that can be considered functional foods. However, despite the seeming enormity of the data, a large number of these have few purchases. At this point the focus is on reduced fat and fat free products, which easily comprise the most important class of functional foods. Foods considered include milk, yogurt, and cheese (cultured, processed and natural); ice cream; salad dressings; snacks; and processed meats. Other categories that will certainly be considered in the project will include beef, pork, poultry, fish, bacon, fresh vegetables by type, fresh fruit by type, frozen vegetables by type, bottled water, soft drinks, and fruit juice. In some cases these involve important functional foods, but they also involve foods perceived to be especially nutritious or seriously lacking in nutrition, and we wish to study their relation to purchases of functional foods. Given the ease of aggregating over time, it is likely that all categories will be included in some manner.

The major data problems we have encountered involves aggregating and disaggregating across products. The Nielsen data contains several variables meant to measure product characteristics (brand, flavor, formula, etc). However, for any product many of these are zero and are uninformative. The major problem is that in general they are set up somewhat whimsically. Regular and reduced fat salad dressing each has its own category. This is not true of the various milks, but we found it easy to disaggregate the milk category into whole milk, skim milk, etc., for the types are clearly defined using the 'formula' descriptor. But in general, descriptors such as Low-Fat, Skim, Fat-Free, and Lean were found in different variables for different categories

of foods. For some cases there are none. In the case of mayonnaise, all types are included in the same category, and the only way to distinguish, e.g., Kraft regular mayonnaise from the fat free version (other than using UPC codes, which are unique for every conceivable size) is via the UPC description variable, which contains 'FF' for the fat-free version. Similar methods must be used throughout the cookie and crackers modules, and most other snacks. Since the descriptions often vary by brand, different codes might mean the same thing: 'LC' for 'less calories' rather than 'RF' for 'reduced fat.' And 'FF' need not mean fat free; it is also used for "Fancy Feast," the feline favorite. In short, in some cases aggregating products into functional food classes is very difficult, due to the absence of appropriate descriptors.

A category of particular interest is breakfast cereal, because it contains products distributed across the nutritional spectrum. Most of the variation is associated with sugar and fiber content. The cereals will be aggregated into a small number of subgroups based on these components. To do this we will merge the Nielsen cereal data with brand specific USDA nutritional contents data for cereals. This is a cumbersome process, due to the large number of branded cereals. At this time, only the top 100 sellers are being considered, for the nutrition data does not include minor cereals, and for private label brands it only has data for basic varieties, such as corn flakes.

An additional data limitation that may be a problem for this study pertains to the demographics of the sample. First of all, the sample may not be representative of the population. For example, 83% of the households are white and 30% have children under the age of 18. According to the 2000 Census, 75% of households were white and 35% have children under the age of 18. Secondly, the measures used are not very detailed. In particular, income is categorized, despite the fact that there does not seem to be any possibility of disclosure problems. While the market area is in most cases identified, there are large differences in sample size (e.g. six households for Little Rock, 189 for Atlanta). Nonmetropolitan household are all aggregated into a single region. It would be much better if zip codes or county FIPS codes were provided, for then interesting geographical aggregates would be possible. Store chain identifiers would also be valuable.

We anticipate using different statistical methods in the study. In view of study objectives, it is necessary to go beyond standard regression estimation. Theoretical models are not of interest; the study is more of a search for patterns in consumer behavior. This suggests the use of cluster analysis, which will be used to form groups of households that purchase similar products. The clusters will then be profiled using the demographic data in order to determine the characteristics of households that purchase certain functional food products in addition to other products that are purchased. Cluster analysis is regarded as a component of the growing field known (not pejoratively) as "data mining," and other data mining methods are being investigated.

Public Policy Issues

Nutrition has become a major policy focus of the USDA. In particular, considerable efforts are being made to raise the nutritional awareness and improve the diets of the American public. As a result, consumers are becoming more concerned about diet/health relationships, and typically express a desire for healthier food products. Food companies have responded with hundreds of food products designed with a specific nutritional purpose, and these have met with varying degrees of success. Despite this trend, there is little evidence of dietary improvement, and

obesity has become one of the nation's most serious health problems. Determining the characteristics of households that do and do not purchase functional foods can guide policy designed to encourage consumers to choose more nutritious foods, as well as improve the marketing practices of manufacturers of foods with specific nutritional qualities.

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A Summary of the Presentation: *Consumer Search Inside the Supermarket*

by:

Cesar Costantino

University of Maryland

Manufacturers, retailers and policymakers need to understand the effects of advertising on consumer demand. Lately the literature in applied microeconomics has focused on trying to identify these effects by means of a variety of strategies (e.g., Modjuska et al. 2001, Ackerberg 2001, Murthi and Srinivasan 1999, Allenby 1995, Jain, Vilcassim and Chintagunta 1994, Guadagni and Little 1983). In this paper, I use a discrete choice model to estimate the effects associated with advertising a brand, in the form of newspaper and/or store circular features, on consumer search behavior and on brand choice inside the refrigerated orange juice category.

When estimating discrete brand choice models, it is usually assumed that each consumer searches all the relevant information, such as price and other marketing variables, on every purchase occasion (e.g., Guadagni and Little 1983; Jain, Vilcassim and Chintagunta 1994; for an exception to this claim see Murthi and Srinivasan 1999). However, this assumption is restrictive. Consumers may restrict their choice sets before acquiring information if searching is a costly activity (Stigler 1961, Rothschild 1974, Weitzman 1979, Ratchford 1982, Carlson and Gieseke 1983). Advertising can affect the economic returns from searching and then the size of the choice set finally considered.

In dealing with our main question, I address two related queries. First - Do consumers actually make their choices after searching only a restricted set of alternatives? We find evidence that this is the case even when the number of alternatives is not large.

Second - How does each consumer decide what alternatives to include in the choice set he will finally search? There are many reasons why a consumer might not include all the alternatives in his choice set. Some consumers might dislike a brand so much that they will not include it no matter what value its marketing variables take. Then we could have consumers picking from a restricted set even when they know all the characteristics associated to each alternative. Although the discrete choice model I use will capture the behavior of such consumers, my results suggest that in deciding what alternatives to screen out of his choice set some consumers may not use all the current available information. This finding is consistent with optimal search behavior.

The type of distribution services provided by the retail system and the advertising policy of the manufacturer can have an impact on the search effort, by providing economically relevant information in a convenient way (Betancourt and Gautschi 1988), and on the probability of choosing a particular alternative by “persuading” (Galbraith 1976) consumers to buy a particular brand or through “prestige” effects associated to a particular brand (Stigler and Becker 1977, Becker and Murphy 1993).

Relevant to the former argument is the finding by Dickson and Sawyer (1990) that consumers spend an average of 13 seconds in selecting a brand out of the shelf. This is a very short time for a consumer to incorporate all the often-available marketing information associated to a given

product category offered by a typical supermarket. Then, retailers and manufacturers' efforts to make available as much information as possible in a convenient way could lead consumers to make better decisions. Among the marketing tools that manufacturers and retailers often use we will analyze the effect of featuring a brand in newspapers and/or store circulars.

Finally, the main research question then arises – Is there a link between advertising and search activity/brand choice? The empirical evidence is mixed at best. Findings by Ackerberg (2001) and Murthi and Srinivasan (1999) suggest that advertising increases the size of the choice set searched by the consumers. On the other hand, Allenby (1995) finds that advertising's main effect is to persuade the exposed consumers to reduce search outside the choice set made of the advertised brands. My previous results suggest that search costs might be one of the reasons why some consumers restrict their choice sets. If advertising reduces search costs theory predicts, ceteris paribus, an increase in the probability that consumers search larger choice sets. Regarding brand choice, if advertising increases the utility associated to the featured brand (Becker's "prestige effect") then, ceteris paribus, we should see an increase in the probability that consumers purchase the featured brand. In sequential search models (e.g., Weitzman 1979), an increase in the utility associated with an alternative can reduce the returns from searching an additional alternative if the increment is high enough. Then, a strong "prestige effect" can have a negative effect on choice set size.

I identify both effects by proper parameterization of the probability of purchase associated with each brand and the probability associated with each possible choice set. My results show that featuring increases the probability of purchase associated with the featured brand and the probability that consumers search larger choice sets.

In order to obtain the results I used the GenL model, due to Swait (2001), in which choice probabilities associated to each brand and to each possible (latent) choice set are estimated from the sampled purchases. The model belongs to the Generalized Extreme Value family of discrete choice models and is a generalization of the Nested Multinomial Logit (NML) model (Daly and Zachary 1978, McFadden 1978, and Williams 1977). I implement a variation of this model where consumers are allowed to pick their choice sets using less information than available.

A discrete choice model seems appropriate for the product category I have information about since households typically buy only one brand in each purchase occasion. In the sample, households bought only one brand in 96% of the purchase occasions.

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Key Points from Discussion of First Three Presentations

How Representative are Scanner Data?: The period began with a discussion about how representative scanner data were. Helen Jensen noted that she compared the data used in her analysis with Census population characteristics. She found that the scanner data usually reflected consumers that had higher incomes than the population in general, and were more likely to be married. Mick Silver noted that the problem may be more serious than just measuring scanner data against Census benchmarks. He noted that the HomeScan data are subject to a host of complications due to a lack of knowledge about the nature of the selection of program participants and their dedication to faithfully, and regularly record their purchases (Dr. Silver kindly put his concerns in writing which can be found in the Supplemental Comments on the use of point-of-sale Scanner Data).

Prices of Substitute Goods: A next line of discussion centered on the ability to identify prices of substitute goods that consumers face. Jeff Perloff noted that the specially constructed IRI data set he had purchased allowed him to identify the stores where consumers purchased items. This allowed him to identify the prices of a set of substitute goods even if the consumer did not purchase the items. Without this information there are two ways to deal with missing prices of substitutes. The first is to use an average price of substitute products, and a second was to use auxiliary regressions to generate prices of substitute products. Oral Capps used auxiliary regressions to generate substitute prices. Steven Yen stated that in his work using the Nielsen HomeScan data set he calculated the average price of substitutes using the cross sectional geographic variation in the data.

Data Biases: It was noted that computing prices for items was complicated as one aggregates over several individual items into broad aggregates. This process of aggregating products creates a problem of endogenous quality.

It was noted that the companies capturing scanner data (IRI and Nielsen) are moving to HomeScan type systems in order to get more complete coverage of retail outlets. When consumers record their purchases, data spans all retail outlets including supermarkets, convenience stores, and discount stores. Other methods of recording point-of-sale data may not include convenience stores or discount stores, and instead include only supermarket data.

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Summary of the Presentation*: Demand Projections Segmented by Income for the Highly Competitive Non-Alcoholic Beverage Complex Using the A.C. Nielsen HomeScan Panel* Data

by Oral Capps, Jr.

Professor and Holder of the
Southwest Dairy Marketing Endowed Chair,
Texas A&M University

The four objectives of this study are to identify the consumption patterns of non-alcoholic beverages, to identify some nutrient (calories, calcium, vitamin C and caffeine) intakes from non-alcoholic beverages, to identify the drivers of demand for non-alcoholic beverages, and to conduct these analyses with regard to whether a household is above or below the poverty level.

An important issue to consider when doing analysis with scanner data is coping with the voluminous nature of the data. For this project, the data set could have been organized with as many as 4 million records. In this project, these 4 million records were compiled into 77 beverage groupings. Another issue is reducing the various product forms into a common unit measure. Some products are measured in quarts, some in gallons, and some in concentrated ounces. In this study, researchers chose to convert all values to gallon measures.

Preliminary results from this analysis suggest that 10 percent of the recommended daily intake of calories come from non-alcoholic beverages, 20 percent of the daily intake of calcium come from non-alcoholic beverages, and 70 percent of recommended daily intake of vitamin C comes from non-alcoholic beverage consumption. It also appears that daily intake levels for below and above poverty households are the same for calories and calcium. However, caffeine and vitamin c intake is lower in below poverty households than in above poverty households.

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Summary of the Presentation: ***Demand for Fruits and Vegetables: An Analysis of HomeScan Data***

by
Steven Yen
University of Tennessee

This presentation began with a review of fruit and vegetable consumption using data from the CSFII. The authors note that only about 18 percent of the population meets the daily recommended consumption of fruit and only about 31 percent of the population is meeting the daily recommended daily intake of vegetables.

The objective of this research, which is in its initial stages, is to analyze methods to promote fruit and vegetable consumption. A question is whether price is a factor. The literature suggests that demand for fruit and vegetables is own-price inelastic, or that large price decreases will have only small effects on consumption. Finally, the research will seek to identify the welfare implications of price changes.

The research will estimate a demand system, compute price elasticities for different income groups, and conduct welfare analysis.

There are a number of data issues to consider. First, the data do not include food consumed away from home. It is difficult to identify and therefore include in the analysis the amount of fruits and vegetables included in "mixture" products. Therefore, these products will not be included in the analysis. It is necessary to develop a method to aggregate the various items. Methods examined include aggregating over product form (e.g., fresh, frozen, canned) and aggregating according to nutritional content. It is also necessary to account for data censoring, which is more serious as products are less aggregated.

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Summary of the Presentation: ***Use of Demand Estimation for Policy Simulation***

by
Jeff Perloff
University of California, Berkeley

The University of California Berkeley has two cooperative agreements with the Economic Research Service for policy evaluation using scanner data. One examines federal milk marketing orders and another examines the effectiveness of taxes on fats and sugars. The University of California Berkeley is also conducting a study of sales using scanner data.

The policy simulations require two types of information; demand studies based on scanner data, and supply side, or equilibrium pass-through information. The presentation today focuses on the demand side.

Several types of data are used in these analyses. Information on the various policies that will be examined must be incorporated into the analyses. Furthermore, aggregate data (for example CPI, wholesale price of milk), market structure data, nutrition information, and household level scanner data are necessary components of these analyses.

Nutrition information are from Shirley Gerrior and Lisa Bente at the Center for Nutrition Promotion and Policy (CNPP) who hand calculated 17 nutrient percentages in 21 foods for the period 1909-2000. Nutritional information includes data on calories, protein, cholesterol, fat, carbohydrates, minerals (calcium, phosphorous, iron, magnesium, and zinc) and vitamins (A, thiamin, riboflavin, niacin, B6, B12, and C).

These analyses intend to utilize a specially constructed IRI scanner data. This data set merges household and store-level information. That is, prices and quantities are available at both levels. The data set is weekly transactions from 24 cities, with approximately 170 stores, for the time period 1997-1999.

So far, analysis has centered on simulating the effect of fat and sugar taxes. Many countries, states, counties, and cities have them or are considering them. For example, U.S., Canada, U.K., Australia have or are considering soft drink and "Twinkie" taxes. In 2002, LA and several other school districts banned soft-drink sales.

The common justification for such taxes (Jacobson and Brownell, 2000) is that 310,000-580,000 deaths annually due to cancer, cardiovascular diseases, and diabetes caused by poor diet and physical inactivity. The economic cost of diet-related diseases is at least $71 billion annually. These taxes have been a large source of tax revenues (CA soft-drink tax: $218 million/year), that can be used in campaigns to promote the health consequences of physical activity and better diet. However, these revenues have to be measured relative to advertising on restaurants (greater than $3 billion), soft drinks ($600 million), M&M candies ($67 million), Lay's potato chips ($56 million), and Kool-Aid ($19 million).

There have been difficulties using the IRI household data. However to facilitate discussion, and to provide cross-price elasticities for foods not included in the IRI database, analysis has

proceeded using aggregate, farm disappearance data. The data are for 1919-1941 and 1947-1999, and researchers estimate a demand system based on Beatty and LaFrance, "Structure of U.S. Food Demand: 1919-1999."

With the results of the demand estimation two experiments were conducted, a 10% ad valorem tax on butter and a 10% ad valorem tax on fats (similar to a carbon tax). Simulating the effect of a 10% tax on butter reduces the quantity purchased of fresh milk, cream, and yogurt by 1.2%, butter by 1.9%, cheese and cottage cheese by 0.1%, frozen dairy products by 0.6%, and canned and powdered milk by 2.2%.

The results from imposing a 10% tax on fat content had the following effects. Per capita total food expenditure increased 1.06% from $379 to $383 ($1967 constant). Total fat intake (lbs/person/year) decreased by –0.887 pounds from about 132 pounds to about 131 pounds. Thus, the fat demand price elasticity is about -0.09.

It is important to realize the estimation based on micro data will likely show substantially larger effects. This is a benefit of using scanner data for policy analysis. The researchers will be able to model substitutions between disaggregate products. For example, the imposition of a tax on fat will lead some consumers to switch from a higher fat version of a product to a lower fat version of the same product. Pass through implications may increase or decrease the effectiveness of taxes, as taxes may be over- or under- shifted to prices. Finally, taxes on fat content, or other unhealthy attributes may cause food manufacturers to reformulate their products away from the offending attribute. Researchers have not decided whether to model the product reformulation effects

Future work will incorporate demand estimation using scanner data. However, applying the model using scanner data has encountered problems. Moderately serious problems include missing data and data that are inconsistent between the store-level and household-level data sets. More serious problems arise because for many shopping trips, families do not buy certain products. Thus, we need to deal with the estimation problems due to "zeros".

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Key Points from Discussion of Second Three Presentations

Categorical income: Discussion for this second set of presentations began by revisiting the issue of categorical income and the ability to divide the sample by income. There is a concern that program participants might underreport their income levels. Many researchers on the discussion panel reported adjusting the categorical income levels to a continuous measure by using the midpoint of the categorical income ranges. It was noted that using this method resulted in 5.9% of households in the data set below the poverty level, which approximately matches the proportion of households below the poverty level in census data. It was mentioned that underreporting was less likely to be an issue because program participants were asked only to report their income category, rather than their actual income. A comment was made that while asking consumers to report bracketed income is likely better than asking consumers to report actual income, there is still the possibility of underreporting. It was felt that poverty analysis should include a caveat that income may be underreported.

It was also noted that research is underway at the University of California Berkeley on categorical income. The results of this research suggest that the income brackets contain information to accurately recover the income distribution. However, this does not address the issue of underreporting and bias.

It was also noted that the measure of income is not as important in demand analysis, categorical income levels may be all this is needed, but a better measure of income is needed to do welfare analysis.

How representative are scanner data: It was noted that consumers recruited into the data set may be more price sensitive than other consumers. Also, the data are primarily from supermarkets, and shoppers at supermarkets are likely to be more price sensitive. Finally, households rotate in and rotate out of the sample. Each of these issues is a source of bias in demand analysis. Jeff Perloff noted that an examination of consumers who switched products against consumers who did not switch products revealed that those who switched were more price sensitive than those who did not switch.

There was a concern that in the HomeScan data, there may be an underreporting of fresh fruit and vegetable purchases, because these products are often sold unpackaged without scanning codes attached. The HomeScan system allows program participants to scan a code in book which facilitates recording fresh fruit and vegetable (and similar) purchases, and do reduce the underreporting of these products.

Fat taxes: The purpose of the fat tax presented by Jeff Perloff was questioned. It was noted that some fat is necessary in a diet, and, for example, fat in some fish has health benefits. It was thought that to the knowledge of the panelists, most taxes aimed at high-sugar or high-fat foods are intended to affect consumption, and not to raise revenues. Of course, any tax could be designed to exempt fish. The analysis suggests very small effects in any regard. The purpose of the exercise was to examine whether a tax on fat would affect behavior.

A question was raised about the effectiveness of fat taxes. It was noted that a tax on butter allowed for a substitution toward other products, notably margarine, and that fat consumption may not be affected. In contrast, a tax on fat content may not allow for such substitutions. Jeff Perloff replied that without analysis using micro scanner data, such a hypothesis could not be confirmed.

A question was raised about whether it made sense to increase the amount of the fat tax greater than 10%, in order to increase effectiveness. The answer was that that was possible, but the researchers were afraid that such an exercise would be outside the observable range of price changes.

Outlet type Bias: It was noted that there are differences in store services that are likely to be reflected in food prices. This may create biases if aggregates are constructed across stores. It was noted that in some research, failing to control for this issues proved important in regression analysis.

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Panel Discussion: Scanner Data and Price Indices

With presentations by:
Mick Silver, Cardiff University
And
Walter Lane, Bureau of Labor Statistics

Followed by a roundtable discussion with:
Mick Silver, Walter Lane, and Marshall Reinsdorf, Bureau of Economic Analysis

Summary of the Presentation: *Scanner Data and Price Indices*

By
Mick Silver
Cardiff University

The data used in these analyses are different that the HomeScan and loyalty card data discussed in the workshop to this point. These data are point-of-sale data complied from the bar-code readers of retailers' scanners supplemented by store surveys. These data contain no demographic information. However, data are available on values, volumes, unit values (price), outlet (type), time (month), brand and other 'quality' characteristics of the vast majority of transactions of a product.

Some recent empirical work uses monthly scanner data for television sets from January 1998 to March 200. For the 51 months of January 1990 to March 2002 there were 73,020 observations which covered 10.8 million transactions worth £3.9 billion on up to 100 variables. There is variation in price across models and over time.

The data have the following benefits. They include market share (weights) at elementary aggregate levels. They represent unit values (prices) on transactions, which are not, for example, mid-month quotes as would be recorded in a price survey. They cover a broad range of items, and not just sampled or representative items. They include data on quality characteristics for quality adjustment. They are timely, in an electronic form, and represent actual transactions prices, and not offered prices.

However, the data are not always clean and can have some major inconsistencies. Coverage can be compromised because some stores do not cooperate or withdraw.

Calculation of price indices can be complicated because products are terminated and product characteristics change over time. Solutions include using only matched data, or data for products that are not eliminated and do not change characteristics over time. However, hedonic regression methods exist to estimate price changes for the unmatched non-comparable replacement products, or the replacement universe. In addition, it is possible to use hedonic regression methods on the double universe, including data on the matched and unmatched data.

Scanner data are useful for the matched models. Scanner data provide monthly, timely weights at an elementary level for use in superlative indices. They provide great coverage of price data with less sampling error.

Scanner data can also help in sampling methods to calculate price indices. Scanner data are used to validate the sampling procedures used to collect item prices.

The hedonic estimation approach involves the estimation of the implicit shadow prices of the quality characteristics of a product. Products are often sold by a number of manufacturers who brand them by their 'make'. Each make of product is usually available in more than one model, each having different characteristics. A set of (z_k = 1,….K) characteristics of the models are identified and data over i=1,…N models are collected. A hedonic regression of the price of model i, p_i, on its set of quality characteristics z_{ki} is given by:

$$1\text{n } p_i = \beta_0 + \sum_{k=1}^{K} \beta_k z_{ki} + \varepsilon_i$$

The β_k are estimates of the marginal valuations the data ascribes to each characteristic.

To calculate price changes, the hedonic regressions are supplemented with time dummy variables.

$$\ln p_i^t = \beta_0 + \beta_1 D^t + \sum_{k=2}^{K} \beta_k z_{ki}^t + \varepsilon_i^t$$

The coefficients on the dummy variables are quality adjusted price changes. Alternatively, hedonic imputation methods can be used to create indices.

It can be shown that using different data (matched, non-matched, and double-universe) can affect the estimated change in prices.

These methods can also be used to examine quality adjusted price dispersion.

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Summary of the Presentation*: Point of Sale Scanner Data*

by
Walter Lane
Bureau of Labor Statistics

There are two main types of scanner data: point of sale data and household data. These are available at the micro data level and at more aggregate level. Micro point-of-sale data are typically store based data macro data ranges up to the national level data. There are multiple sources for these data. As mentioned in earlier presentations, data are available for purchase from vendors (Nielsen, IRI). It is also possible for BLS to directly collect the scanner data from outlets and for BLS to organize and clean the data themselves. Finally, it is possible for BLS staff to use scanner technology to collect data.

Point of sale scanners collect product codes. These are unique product identifiers, not prices and not a classification system. There is no reference book. Knowing the code does not immediately reveal the item's description or even its category. Stores use several types of codes. Universal Product Codes (UPC) are manufacturer assigned codes usually consisting of 12 digits. Five digits identify the manufacturer, who chooses another 5—usually sequentially. Price Look Up (PLU) codes are store or chain assigned codes generally for variable-weight packaged fresh meat, deli, and bakery ("random weight" items). PLUs have digits for the product and the individual package's price, and are also used for weigh-at-checkout codes for loose produce. Stock Keeping Units (SKU) are store or chain assigned codes and are defined according to whatever the store wants.

Stores have 2 files that use these codes for sale transactions. The host file is the input file that contains: the product code, the product description (free text), and the price. There is a record for each product offered for sale in the store/chain, but it will include items not in the store (e.g., out-of-stock, only in larger stores in the chain). The transactions file contains the code for each product sold during a period (almost always a week), the number of units sold, the total receipts for those sales, the Unit Value = "Price" = receipts / units sold. There is a record for each product for which there was a sale. If there was no sale, the item is not in this file. The checkout scans the code, looks up the description and the price on the host file, prints the receipt with the description and the price, and updates the transaction file.

BLS has been studying using scanner data in the calculation of the CPI since 1994. BLS collects some UPCs for some items in the CPI, and in the future will likely use computer assisted data collection (CADC) scanning wants to aid their price collection personnel. There are several benefits from using scanner data in CPI calculation. There is a greater precision or lower variance, actual transactions prices are used, there is a greater commodity detail, and current weights are available and superlative indexes can be implemented.

On the other hand, there are several minuses from using scanner data. The outlet coverage is restricted to stores using scanner technology, which may not include convenience stores and mom-and-pop stores. Product or item coverage may also be limited. Calculated unit values may differ from the actual prices paid by consumers, and some products can have multiple UPCs. Sometimes there is a problem of UPC churn, when products change but UPCs do not. Also, point-of-sale scanner data cover what is bought in a particular area rather than what people who live in the area buy.

POS scanner data purchased from one of the vending companies (IRI, Nielsen), has pluses and minuses. The biggest pluses are that vendors would edit or clean-up, and classify the data. The vendors also can track UPC "churn" and are able to aggregate over UPCs.Minuses from purchasing scanner data from a vendor include the inability to control the "sampling scheme." BLS would also be reliant on the vendor to deliver the data on schedule. This could greatly affect BLS's ability to meet their CPI reporting deadlines if data delivery schedules were not met. Another problem arises because data vendors would also have pre-release knowledge of CPI information, which tightly protected at BLS. Data vendors also have geographic gaps in their coverage. Notably, Alaska is not covered. Vendors have confidentiality limits, and cannot reveal store locations. Without store locations, it is difficult for BLS to apply sales taxes. And, purchasing scanner data would be very expensive.

BLS engaged in an experiment to create a Breakfast Cereal price index to judge their ability to create an index with purchased scanner data. They concluded that it was possible to create an index, however it was prohibitively expensive. Furthermore, there was nothing demonstrably wrong with the current index.

It is also possible for BLS to directly collect scanner data instead of purchasing from a vendor. This is actually done in the Netherlands, but the process is facilitated by the fact that there are only two supermarket chains in the Netherlands, and they actively cooperate in the process If BLS collected the data directly, then they could control the sample collected, would be able cover the whole month of data, can apply the appropriate sales tax, and can address confidentiality concerns. This may also be done at less cost. However, the process would be dependent on respondent cooperation. BLS would also be burdened with cleaning and classifying the data. BLS would also have to track UPC churn, address UPC aggregation, and coordinate several different systems not designed for their purposes.

BLS could also utilize a scanner assisted data collection. In this case, scanner wands would be added to computer assisted data collection machines. A large benefit of this technique is that it might be possible for BLS to ask respondents to provide prices on some occasions. Then, for example, price collectors would only have to make site visits half as often.

BLS also conducted some analysis using scanner data to examine how well the CPI sample represented what was purchased according to the scanner data. For the items they examined, they found that their sample closely resembled the scanner data. However, for flour and prepared flour mixes there were some discrepancies which BLS is attempting to address.

BLS also provides estimates of average prices for some items. They have used scanner data to compare their estimated average prices to average prices estimated from scanner data. The early indications are that the CPI average price data generally tends to exceed the result obtained from scanner data. This is not unexpected, since weights from scanner data would account for volume shifts from sales, whereas the BLS average price weights reflect quantities at the time the quote was initiated.

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Key points Discussed During Panel Discussion

Coupons: Coupons are included in the CPI if they are on or with the product so that price collectors can see them.

Hedonic Regression: It is important to account for channel or outlet changes in hedonic regression. Results differ when based on different outlet types.

Superlative Index and Sales: Sales can have a large effect on superlative index calculation. The timing of advertising may cause the index to place too small of a weight on the price decrease.

Unit Value Calculation: Unit values are used to approximate price, and are calculated as expenditures / # of units. It is possible for this value to change without price changing. For example, suppose there is a high price store and a low price store, and consumers make half their purchases at the high-priced store and half at the low-priced store in period one. If in period two, more consumers find out about the low-priced store and make more of their purchases there, so that say, 70% of purchases are made at the low-priced store, the average unit value will change even though price has not changed. This is arguably a legitimate price change in that the average prices consumers are actually paying changes. This is even a more important problem if the high-price store is also higher service. If consumers desire the higher service level, and switch from low-priced stores to higher service, higher-priced stores, unit-values can also change, although prices have not changed. However, in this case the price change indicates an increase in utility, not solely a change in price.

New Products: BLS makes efforts to account for new products, by substituting new products for old products and adjusting for quality. A real benefit of scanner data is that it keeps up to date with changes in purchasing patterns, and keeps up with new products, and also identifies when products disappear.

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Summary of the Presentation: ***Properties of Scanner Data***

by
J. Michael Harris
Economic Research Service

There are several types of scanner data sets. The term "scanner" arises from the technology used to capture the information. The first type of data, referred to as retail scan data, are captured at the point of sale by the scanning technology used at a store when an item is sold. These data have been available for some time, but they are not consumer panel data. Consumer panel data sets are only recently available, and match scanner data with consumer information (card data) or consist of panels where each household reports purchases (purchases).

Information Resources Incorporated data are available for 266 product categories (e.g., breakfast cereal, ice cream) and, within those categories, 800 product types of UPC coded products. My understanding is that random weight (non-UPC coded) products are also available in their point of sale data. The data include category information, product type information, brand level information, and UPC or item level information. The IRI panel data does not contain information on random weight products.

A.C. Nielsen data are available for about 571 product modules in both their point-of-sale and panel data. In our panel data set purchased from Nielsen, we have 43 random weight product modules in addition to the basic product modules. There are brand identifiers, and UPC or item level information available in both the retail and panel data. The panel data also contains demographic information about the households in the panel. Individual observations detail individual product purchases by panel households and can be aggregated up to the brand or product module level if desired. Researchers can also do custom aggregations using available item, brand, product module, or attribute.

The Economic Research Service's HomeScan data set include data on 43 dairy modules, 410 dry grocery modules, 21 UPC produce models, 84 frozen food modules, 13 UPC meat modules, and 43 random weight modules. As you can see the size of panel data sets can be large, and, in fact, voluminous. For example, in 1999 for the 7,195 households, there are over 4,000,000 dry grocery purchase transactions in the data set. This example is significant since the ERS data set is only a subset of the total panel which numbers over 50,000 households.

UPC information is available to allow researchers to aggregate to the brand or category level. Attributes are also available in product descriptions. However, caution must be used when aggregating across modules due to aggregation issues and estimation. Caution also must be taken when examining measure units. For example, some products' quantities are measured in more than one unit. In some cases, an item may be measured in dry ounces, but other similar products may be measured in counts (e.g., in one product module cookies may be measure in ounces, while in another module cookies may be measured by count).

Categorical variables do not always provide a good description of the household composition. For example, the data identifies age brackets of children in the households but not their specific ages. The entry and exit of households can also be an issue. In the HomeScan data set only 12,000 households reported both UPC and random weight purchases. However, if you restrict the sample to households present in the data for 10 of 12 months in 1999, only purchases for 7,195 households are available. Indeed, it is clear that all households are not present in the purchase data for every month. This situation can potentially create estimation problems for researchers and can magnify the censoring problem, especially when individual products are examined.

Key Points of Discussion of Harris Presentation

Household Participation: It is not known why participation is low in some months. It is noted that participation seems to be lowest in months associated with major holidays (November, December, January), and that time constraints may be a factor.

It is also noted that population characteristics may differ when samples are restricted. For example, the characteristics of the sample of those present 10 of 12 months may be different than the characteristics of those present for all 12 months.

Store Information: It was discussed whether data were available for random weight items with store identifiers. There was no definitive answer, except that it seemed that it would take a specially constructed data set.

Data Use: ERS is able to share these data with experts who are solicited to examine issues important to the USDA. Furthermore, the first publication from the analysis must be an ERS publication.

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Summary of the Presentation: *The Importance of Sales in High Frequency Supermarket Scanner Data*

By Daniel Hosken
Bureau of Economics
Federal Trade Commission

Disclaimer: These are the opinions of the speaker and should not be viewed as those of the Federal Trade Commission, its staff, or any of its individual Commissioners.

A large fraction of observed retail price variation is the result of temporary price discounts; that is, retail sales. Using retailer-level data, we typically observe very large price discounts (20%-50%) and very large quantity responses (100%-400%). What is the correct interpretation of the elasticities estimated using retail scanner data?

There are two main bodies of research which develop theories of retail sales. In the first, retailers are seen as selling one good to two types of consumers: those that shop for a low price (shoppers), and those that do not (non-shoppers). In these theories, retail sales are generated by competition between retailers for shoppers. In equilibrium, retailers play a mixed strategy in prices. This results in each retailer's prices changing every period. This line of research was introduced by Varian in 1980.

The second line of research examines how retailers use sales to price discriminate over time. In these models there are two types of consumers: high-willingness-to-pay consumers (who are not willing to wait for a sale), and low-willingness-to-pay consumers (who are willing to wait for a sale). In these models, retail prices are high most of the time, interrupted by short periods of deep discounts. Papers examining this issue include: Sobel (1984), Conlisk, Gerstner and Sobel (1984), and Pesendorfer (2002). Hosken and Reiffen (2001, 2003) combine elements of both types of models using a multiproduct retailer.

There is a related line of research that examines how retailers set margins on specific items when consumers purchase multiple items on a shopping trip. In these models, advertising and shopping are costly. As a result, consumers purchase bundles of goods from a given retailer. Lal and Matutes (1989, 1994) develop a model where retailers charge different margins on different items. This model provides a rationale for loss-leader pricing. Hosken and Reiffen (2004a) extend the model and show that retailers will offer low margins on products that are the most popular with consumers. As products become more popular in periods of high demand (for example, turkeys at Thanksgiving) they are more likely to be sold at a low margin (placed on sale).

There have been some empirical studies of sales. Hosken and Reiffen (2004b) find that sales are an important source of annual retail price variation, generating from 20%-50% of the total price variation. In addition, most products have a regular price and are at that price most of the time (50-70% of the time). They also find that most price deviations from a product's regular price are negative (price decreases), and that pricing distributions do not support the Varian model in

which prices change every period. Empirical pricing distributions look more like those predicted by price discrimination models. However, they find similar pricing patterns for goods where retailers cannot price discriminate over time! That is, they tend to find the same pricing pattern for storable and non-storable products.

Other empirical work, finds that products have lower average prices and are more likely to be on sale during periods of high demand (MacDonald (2000), Chevalier, Kashyap and Rossi (2003), Hosken and Reiffen (2004a)). Products *within* a category that are more popular are more likely to go on sale (Hosken and Reiffen (2004a)). Evidence suggests that the pricing strategies of retailers selling bundles of products will differ from those of single product retailers (products that have higher demand appear to have lower average margins).

At this point, several conclusions can be drawn from the available evidence.

1. Consumers appear to buy for household inventory during sales; that is, current purchases are larger than current consumption. Nevo and Hendal (2003), Pesendorfer (2002).
    - Purchase elasticity is different from consumption elasticity.
    - This suggests that estimated own- and cross-price elasticities are "too large."
2. The correct demand model is likely dynamic, however, currently these models are hard to estimate, e.g., Nevo and Hendal 2003.
3. If price discrimination over time is an important determinant of sale behavior, then the homogenous consumer model of demand may yield misleading estimates.
4. Pricing behavior is different for "Important" and "Unimportant" products.
5. Sales are more likely in periods of peak demand (as a category becomes more important to consumers).
6. Only a fraction of products in a category, e.g., ketchup or margarine, ever go on sale.
7. Products with high market shares are more likely to be on sale.
8. This implies that the variance of price and quantity of "important" products will be higher than "less important" products.

Promotional variables also may be an important consideration in demand analysis. Products that go on sale receive other types of promotional support, e.g., advertising in a supermarket's circular or increased in-store exposure. In some circumstances, these factors greatly increase the quantity sold during a sale. Variables for these promotions are commonly included in studies in the marketing literature. However, their economic interpretation is unclear. There is a need to build shelf space, promotion, and advertising into a consumer demand model.

Key Points of Discussion of Hosken Presentation

Consumption versus Purchase Elasticity: It was noted that the scanner data measures purchases and not consumption. In demand models, consumption is what is typically being modeled. If consumers are purchasing for inventory, then in empirical demand analysis an endogeneity issue is created because demand shifts in every period in which there is not a sale. That is, the pattern of prices over time affects the position of the demand curve.

A potential solution for the problem was suggested. Aggregating to less-frequent time duration would affect results. However, if there are two types of consumers, then this method would give an estimate of their average price elasticity, when the estimates of interest would be the elasticity for each group of consumers.

There was also a general discussion of the various theoretical models that explain pricing strategies of retailers and manufacturers. The point was made that the relationships are complex and difficult to model.

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Summary of the Presentation: ***Aggregating Scanner Data***

By Oral Capps, Jr.

Professor and Holder of the
Southwest Dairy Marketing Endowed Chair,
Texas A&M University

June 9, 2003

"Things should be made
as simple as possible,
but not any simpler."

-Albert Einstein

Aggregating Scanner Data

Executive Summary

Scanner data allow advances in understanding food marketing because analysts can now estimate firm-, brand-, and commodity-level demand models. Scanner data are available for thousands of products at the store, regional, and national level on daily, weekly, biweekly, and monthly frequencies.

A number of econometric considerations arise from scanner data use in demand analyses. Aggregation issues are the heart of appropriate model specifications. This presentation focuses on aggregation across geographic, time, and commodity dimensions.

Geographic or spatial aggregation often is based on convenience for addressing specific research objectives, for example, to determine differences (or similarities) of own-price, cross-price, and expenditure (or income) elasticities across different markets. Scanner data from either Information Resources, Inc (IRI) or AC Nielsen are available on a regional basis. For illustrative purposes, work by Seo and Capps (1997) on spaghetti sauce was used to demonstrate that own-price elasticities vary significantly by region and by brand.

In considering the effect of time, two opposing forces exist influencing the elasticity of demand, namely storage activity and product substitution. Shorter-term elasticities are likely to be greater than longer-term elasticities because of storage activities. Shepherd (1963) argues that own-price elasticities have a U shape when plotted against the time frequency of the data. Inventory adjustment and habits also depend on the time dimension as well as on the specific commodity.

Work by Capps and Nayga (1990), through the use of Houthakker-Taylor State Adjustment Model, was reviewed to show that elasticities indeed are a function of the time frequency of the data. Using weekly, biweekly, and monthly scanner data for disaggregate beef and round cuts, but they provide evidence of the U shape in own-price elasticities for ground beef and rib cuts. Additionally, Capps and Nayga (1990) find that the importance of inventory adjustment relative to habit formation diminishes with longer time periods.

Multicollinearity, degrees-of-freedom issues, and computational limitations necessitate aggregation across commodity dimensions. The usual ways to address commodity aggregation issues are as follows: (1) invoke the assumption of weak separability; and (2) assume a multi-stage decision process. Capps and Love (2002) examine commodity aggregation by building on Lewbel's (1996) generalized composite commodity theorem (GCCT). The GCCT provides conditions for aggregating commodities based on relatively straight-forward test procedures involving time-series properties of scanner data. Using weekly data of prices and purchases of chilled and shelf stable fruit juice and drink products, the work by Capps and Love was used to demonstrate the use of the GCCT in the construction of aggregate products and to compare the elasticities obtained from this construction to these estimated using multi-stage budgeting. With the use of the GCCT, commodity aggregation reduces the number of precuts to be considered without much effect on key demand elasticities.

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Key Points of Discussion of Capps Presentation

Time Aggregation: The presentation pointed out that a U-shape should be apparent in elasticities of demand if plotted against time frequency. A question was raised about the effect if quarterly data were available. While the analysis was conducted using weekly, bi-weekly and monthly frequencies, no analysis was done on a quarterly frequency and no speculation was offered on the effect of a longer time frequency. Another issue is how to reconcile the differences in elasticity dependent on the time frequency of the data. It is difficult to do, but it is important to realize that differences do exist, and elasticities can, in part, be determined by data frequency.

Consequences of time frequency for Household data sets: The same issues should apply to the household data sets that are being discussed in today's conference. In commodity aggregation, it would be appropriate to check for correct aggregates using the Lewbel procedure, even in household data.

In current analysis, Dr. Capps aggregated to an annual frequency, generating, in effect, a cross-section of household data. This decision will likely affect the elasticity estimates produced.

It was also noted that aggregating over time, while solving some problems, also failed to consider available information. Perhaps, a dynamic model is a way to incorporate all available information.

Commodity Aggregation: Aggregation will also generate price variability. For example, products have different sizes, and different prices based on size. Therefore, aggregating over products of different sizes will create price variability. A question was raised whether this would affect results. Dr. Capps discussed a potential project that would examine price elasticities based on different container sizes of milk.

Ideally, one would like to account for many factors when conducting analysis using scanner data. For example, couponing and promotional activity are important to consider. However, these are difficult to incorporate when commodities are aggregated. While possible, it greatly includes the programming involved in creating a data set.

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A Summary of the Presentation: *Estimation Using Scanner Data*

By
Tirtha Dhar
Food System Research Group, University of Wisconsin- Madison

Two types of scanner data are frequently used for industrial organization analysis. Market-level data aggregate store-level data, while household data record household purchases. Market data can be plagued by the endogeneity of price and income, producing inconsistent parameter estimates. It is also noted that controlling for endogeneity can improve the efficiency of estimates. Also, as has been mentioned, there can also be data aggregation problems. Indeed, aggregating products can create endogeneity, because typically, quality differences, and strategic interactions are not addressed when aggregating. Market-level data are also characterized by unbalanced panels of branded products as new products are introduced, and old products are discontinued. This is not a problem if one models staple brands which are continually present in the data.

Household level data can also provide challenges to use. First, as has been mentioned earlier there is the zero purchase scenario, creating a censored data problem. Household data sets also are plagued by missing prices. For example, if a household does not purchase a particular item, or does not purchase from a particular store, then the substitute price is not observable for that product or store for that household.

There are two basic demand models commonly used in industrial organization models. There is the representative consumer model and the address or location based model. The representative consumer model can be estimated by specifying the appropriate demand system (AIDS, Q-AIDS, Translog). Address or location based models are usually estimated with logit, nested logit, or random coefficient discrete choice models.

Both methods have advantages and disadvantages. Discrete choice models solve the dimensionality problem. If one is estimating models of brand interactions, then the number of parameters to be estimated increases exponentially with the number of brands examined. However, discrete choice models are also disadvantaged because they implicitly assume consumers purchase only a single unit. This seems an especially limiting assumption given that retailers frequently conduct sales, and as has been discussed, these sales create large increases in the quantity purchased.

In contrast, the representative consumer model has strong theoretical underpinnings. However, this model is limited by the assumption of the representative consumer. That is, they do not allow for heterogeneous consumers. Aggregation can be a problem in these models, and unlike discrete choice models, there is an exponential expansion of the parameters to be estimated when the number of brands modeled increases.

Demand models can be used for policy relevant research. Correctly specified demand models can be used in antitrust simulation, (Hausman, Leonard and Zona; Cotterill, Franklin and Ma;

Nevo), in CPI construction and consumer welfare analysis (Hausman; Nevo), in examinations of brand-level strategic behavior (Chintagunta, Kadiyali, Rossi), and in modeling channel behavior (Zhao and Vilas-Boas; S. Vilas-Boas).

A key issue to consider when conducting IO analysis is defining the appropriate market. For example, is it appropriate to model only the leading five brands, or are more brands needed to adequately capture the market. It is also important to consider the appropriate choice of demand and cost specifications. Most work assumes a constant marginal cost, but a different assumption may provide alternative conclusions. Most models assume Bertrand competition, but other choices of game theoretic models in the strategic interactions of firms are also important considerations.

To date, there are few studies that dynamically model the introduction of new products. Most studies have been limited to a set of pure strategy games. Other strategic interactions may provide useful insights. Also, relaxing the assumption of constant marginal costs, and modeling the inventory behavior of consumers are heretofore relatively unexplored areas.

Another fruitful area for future research includes examining the marketing channel. It is difficult to model processor to retailer relationships. Most studies infer market power of the processor from retail data, which is problematic. Finally, a very important policy issue is the rate of cost pass through to prices. Farmers frequently complain that retail price increases are not fully passed on to producers in the form of higher farm prices.

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A Summary of the Presentation: *Estimation Using Scanner Data*

by
Mick Silver
Cardiff University

Scanner data possess three important characteristics:

- information on prices of all models/outlet-type on a monthly basis
- Information on volumes/expenditures
- Information on characteristics.

As the sample 'churns', average price change is tainted by quality-mix change. An adjustment requires a marginal valuation of each characteristic and information on the characteristics. Hedonic regressions provide the former.

The hedonic approach involves the estimation of the implicit, shadow prices of the quality characteristics of a product. Products are often sold by a number of manufacturers who brand them by their 'make'. Each make of product is usually available in more than one model, each having different characteristics. A set of (z_k = 1,….K) characteristics of the models are identified and data over i=1,…N models are collected. A hedonic regression of the price of model i, p_i, on its set of quality characteristics z_{ki} is given by:

$$1\text{n } p_i = \beta_0 + \sum_{k=1}^{K} \beta_k z_{ki} + \varepsilon_i .$$

The β_k are estimates of the marginal valuations the data ascribes to each characteristic.

Rosen (1974) showed that they can be equated in economic theory to a mapping of the equilibria in characteristic space of production possibility curves and indifference curves of specific distributions of optimizing consumers and producers with respective varying tastes and technologies.

Griliches (1988: 120) states, "My own view is that what the hedonic approach tries to do is to estimate aspects of the budget constraint facing consumers, allowing thereby the estimation of "missing" prices when quality changes. It is not in the business of estimating utility functions *per se*, though it can also be useful for these purposes….what is being estimated is the actual locus of intersection of the demand curves of different consumers with varying tastes and the supply curves of different producers with possible varying technologies of production. One is unlikely, therefore, to be able to recover the underlying utility and cost functions from such data alone, except in very special circumstances."

However, while seemingly straightforward, a number of technical issues arise in hedonic estimation. Unresolved issues from the ABS Ottawa Group include whether weighting is appropriate. Is it appropriate to weight a least squares hedonic estimator? If weighted, there is a choice between volume (transaction) or expenditure weights. Some form of weighting is desirable, though it is argued that if a function is properly specified and in hedonic equilibrium it

should not matter. The evidence on the matter is mixed. If representativity is a criterion, then weighting is best.

In the transactions approach, observations are repeated, which is equivalent to WLS. With volume weights, too little weight is placed on high priced items for decomposition of value changes. Value weights are preferred, and for time dummy variable, value *shares* for homoskedastic residuals.

Weighting can also influence estimates. For example, it is first noted that an OLS vector of **β** estimates is a weighted average of the individual **p** elements, the prices of individual models,

$$= (\mathbf{X}^{\mathbf{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathbf{T}}\mathbf{p} \qquad \textbf{(1)}$$

where the matrix **X** are the explanatory variable and $(\mathbf{X}^{\mathbf{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathbf{T}}$ are the implicit weights given to the prices. Equation (1) clearly shows that the estimate is a weighted average of prices, **p**. Consider also a WLS estimator where the explicit weights are expenditure shares,

$$= (\mathbf{X}^{\mathbf{T}}\mathbf{W}\mathbf{X})^{-1}\mathbf{X}^{\mathbf{T}}\mathbf{W}\mathbf{p} \qquad (2)$$

It is apparent from (1) and (2) that outliers with unusual values of **X** will have a stronger influence in determining**β**, than observations which are one of a group clustered in a small area. Furthermore, equation (2) shows that the imposition of weights **W** allows the influence to vary with **W**.

The hedonic time dummy variable model is:

$$\ln p_i^t = \beta_0 + \beta_1 D^t + \sum_{k=2}^{K} \beta_k z_{ki}^t + \varepsilon_i^t$$

Hedonic imputation indices include:

base-period imputations,

$$P_{HB-GMB} = \frac{\left[\prod_{i=1}^{N} h_i^t\left(z_i^0\right)\right]^{s_i^0}}{\left[\prod_{i=1}^{N} h_i^0\left(z_i^0\right)\right]^{s_i^0}}$$

current-period imputations,

$$P_{HC-GMC} = \frac{\left[\prod_{i=1}^{N} h_i^t\left(z_i^t\right)\right]^{s_i^t}}{\left[\prod_{i=1}^{N} h_i^0\left(z_i^t\right)\right]^{s_i^t}}$$

and geo-mean,

$$P_{HBC-Tornq} = \sqrt{P_{HB-GMB} P_{HB-GMC}}.$$

When comparing dummy time (DT) versus hedonic imputations (HI), what is not clear is that HI relies on instability of coefficients, while paradoxically DT constrains them. HI provides two estimates, but this gives an indication of spread. It is a change in characteristic mix, not instability that gives rise to the spread.

For missing observations, DT uses constrained coefficients to estimate, while HI uses period specific. Chaining allows coefficients to be updated and more representative of the path consumption expenditures have followed.

The main contenders for functional form are linear, semi-log, double log. With the linear, there is the possibility of heteroskedasticity. The semi-log is more practical with dummy variables.

The research questions are:

- Is the spread of the base to current period hedonic imputed indexes (say to) large? If so either current period hedonic imputed indexes or base period hedonic imputed indexes are not justifiable?
- Does chaining minimise the spread?
- Does weighting matter?
- The base-current period hedonic spread is governed by the stability of the coefficients. What is the evidence on this?
- Are the results from the time dummy method similar to those from hedonic imputed indexes?
- Does weighting for the time dummy variable method matter?
- On a technical note, does the correction using the standard error for the bias in the coefficients from an estimated semi-logarithmic hedonic regression matter?
- On a technical note does the correction for leverage effects matter?
- How does everything compare to Fisher and Törnqvist?

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