Brand and Category Influences on the Difference between Store and Household Data

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Abstract

This paper investigates brand and category effects on the differences in the price elasticity estimates obtained from store level and household level data using a methodology proposed by Gupta and colleagues (1996). We analyze four product categories and find that household price elasticity estimates are substantively more elastic compared to store level data. We also find that the differences between the two data sources vary considerably across brand-sizes and across categories. A demographic analysis using data from the U.S. Census indicates that panel households are more middle income, have a larger household size and have younger household members. Statistical tests indicate that a higher proportion of household purchases are on deal but there is considerable variation across brand-sizes and categories.

We develop propositions about brand-size and category influences on the differences. We test these propositions in a cross brand-size cross category model, including data obtained from IRI's Marketing Factbook. The model provides a very good fit to the data. We find that household data tend to be more elastic for categories with lower penetration rates, and for brand-sizes with higher price elasticity and higher promotion frequency. A reanalysis of the results reported by Gupta and colleagues are consistent with these findings. We conclude with a discussion of the practical implications for retailers and manufacturers including the promise of a de-biasing procedure.

Introduction

Both store and household level data have been used extensively to model response to price elasticities.[1] Retailers have access to both types of data. Retailers capture store level data using point of sale systems. Retailers get access to household data through manufacturers and are also able to directly capture household data with loyalty card programs.

Store and household level data might provide very different price elasticity estimates. For example, as shown later in this paper, for an Orange Juice Brand-size, household data might provide a price elasticity estimate of -3.02, whereas the estimate from store data might be -2.04, a difference of 48%. The differences in estimates for other brand-sizes or product categories might be much smaller. If the retailer knew when the differences between store and household data will be large, they would know when to invest resources in analyzing both data sources.

Gupta and colleagues (1996), in a groundbreaking study, propose a methodology to compare the price elasticity estimates from store and household data. Gupta and colleagues analyze two product categories and find small differences between the two data sources. Gupta and colleagues do not investigate when the magnitude of the differences between store and household data will be large and what factors influence these differences.

This paper investigates brand and category influences on the differences in price elasticity estimates obtained from store and household data. We implement the methodology proposed by Gupta and colleagues on data for 23 brand-sizes from 4 product categories. We find that the differences can be quite large (e.g. 48%) in some cases and quite small (e.g. 0.5%) in others.

A demographic analysis using data from the U.S. Census indicates that panel households are more middle income, have more household members, and younger household members. We reason that these demographic differences predispose the households to be more price sensitive. Further we reason that this predisposition is amplified when household price sensitivity is high and promotions are frequent, a situation that allows households to exhibit price sensitive behavior. Hence we propose that a brand-size's price elasticity and promotion frequency contribute to the difference in price elasticities, and that category penetration provides a measure of the predisposition.

We empirically test these propositions by estimating a cross-brand cross-category model that includes data obtained from IRI's Marketing Handbook. The model provides a very good fit to the observed differences between the data sources. The results support the notion that household price elasticity estimates will be more elastic in categories with low penetration rate and for brand-sizes with higher price elasticity and higher promotion frequency. We expand our data set to include the estimates reported Gupta and colleagues. A reanalysis of the results presented by Gupta and colleagues supports our findings. We conclude with a discussion of the practical implications for retailers and manufacturers including the promise of a de-biasing procedure.

[1] For a review of this literature see Blattberg and Neslin (1990).

Testing for Differences in Price Elasticity Estimates

Methodology

We briefly review the methodology proposed by Gupta and colleagues for comparing price elasticities from store and household data. Brand-size choices of households are modeled using the multinomial logit model:

(1) $$P_{ist} = \frac{\exp(X'_{ist}\beta)}{\sum_{j=1}^{J}\exp(X'_{jst}\beta)},$$

where P_{ist} is the probability of choice of brand-size i in store s in week t, given the marketing variables X_{ist} and β denotes the effects of marketing variables for the panel households. The likelihood function for household data is given by

(2) $$L_{HH} = \prod_{t}\prod_{s}\prod_{i} P_{ist}^{q_{ist}},$$

where q_{ist} is the total number of purchases of brand-size i by the panel households at store s in week t.

For the store level data,

(3) $$\tilde{P}_{ist} = \frac{\exp(X'_{ist}\gamma)}{\sum_{j=1}^{J}\exp(X'_{jst}\gamma)},$$

where $\tilde{P}_{ist}$ is the probability of choice of brand-size i at store s in week t, given the marketing variables X_{ist} and γ denotes the effects of marketing variables. The likelihood function for the store level data is given by

(4) $$L_{ST} = \prod_{t}\prod_{s}\prod_{i} \tilde{P}_{ist}^{\tilde{q}_{ist}},$$

where $\tilde{q}_{ist}$ is the number of units of brand-size i sold in store s at week t.

We note several key aspects of this methodology. First, as highlighted by Gupta and colleagues, the likelihood functions for household (equation (2)) and store data (equation (4)) are equivalent. Second, the models are specified at the weekly level. Promotional activities are also conducted on a weekly basis in our product categories and time aggregation problems do not arise here. Finally, the model is specified at the brand-size level (SKU level) not at the brand level. Hence problems due to aggregation over brands do not arise.

Price elasticities can be computed using the parameter estimates from the household and store data (See Appendix A for details). A statistical test of equality of the price elasticities derived from the maximum likelihood estimates of β and γ provides a measure of equivalence (See Gupta and colleagues, pp. 387). To summarize, the methodology proposed by Gupta and colleagues is implemented as follows:

1. Estimate β in equation (1) using choice data obtained from households,
2. Compute household price elasticities using β,
3. Estimate γ in equation (3) using data obtained from the corresponding stores
4. Compute store price elasticities using γ,
5. Evaluate equivalence with a statistical test of the equality of the price elasticities based on β and γ.

Data Description & Household Selection

We analyzed scanner data from four product categories: Orange Juice, Caffeinated Ground Coffee, Red Drinks (Cranberry blend drinks) and Ketchup. Table 1 provides a summary of the databases and Tables 2-5 present summary statistics for the household and store data for each product category. The first row of Table 1 indicates the source of the data. Collectively, the databases represent three suppliers (IRI, A. C. Nielsen, and SAMI) of household panel data.

In each category, we selected a subset of the brand-sizes (SKUs) for analysis. The subset of the brand-sizes retained comprised over 80% of the total purchases. Consistent with the household selection approach[2], we then select those households who only purchased the subset of brand-sizes.

Empirical Results

In each product category, maximum likelihood estimates of β and γ were obtained from household and store data respectively. In all of the categories the estimate of the price coefficient had a negative sign and was statistically significant. Feature and display estimates had positive signs and were also statistically significant. Price elasticities computed using these estimates are reported in Table 6. For ease of interpretation we report the absolute value of price elasticity. Hence a larger elasticity means a more negative elasticity. A multivariate paired difference test (Johnson & Wichern, 1988, p.213, see Appendix B for details) was used to test for statistical differences between the household and store elasticities in each category. For all four categories, the test rejects the null hypothesis of equality of the elasticities. So the differences in the price elasticities are statistically significant.

For the Orange Juice SKU's, the price elasticity estimates from the household data are always higher than the store data estimates. The largest difference is for

[2] A unique aspect of household data is that they allow us to study differences in purchase behavior across households and within households across time. Household data also allow us to make targeting decisions at the level of the household. In order to do these types of analysis across households and across time, it is important to include all the purchases of a selected household. This approach, which is common in the marketing literature (e.g. Guadagni and Little, 1983; Kamakura and Russell, 1989; Jain, Vilcassim and Chintagunta, 1994), is called household selection.

Tropicana Regular, for which the store estimate is 2.04 whereas the household estimate is 3.02, a difference of 47.9%. Differences of about 20% are observed for three brand-sizes and about 6% for the remaining two brand-sizes. In the Orange Juice Category, the household elasticities are 20.2% higher on average.

For Ground Coffee, the price elasticity estimates from the household data are also higher than the store data. The largest difference in this case is 22.3% for Folgers 1lb. Differences of comparable magnitudes are observed for the other SKU's. In the Ground Coffee Category, the household elasticities are 20.5% higher on average.

The results for the Red Drink SKUs are similar to Ground Coffee. Again, the price elasticity estimates from the household data are higher than the corresponding store estimates for all the brand-sizes. The largest difference is 45.6% for Cranberry 48oz whereas the smallest difference is 16.8% for Cranberry 64oz. The household elasticities are 34.8% higher on average, which is much larger than the differences observed for the Orange Juice and Ground Coffee SKU's.

In the Ketchup category, for Heinz 32oz, the store estimate is higher than the household estimates by 8.8%. For the other Ketchup SKUs the household estimates are higher than the store estimates. The differences in this category are more modest, ranging from 0.5% for Heinz 28oz to 7.5% for Heinz 14oz. The average difference for this category is 2.8%, which is the lowest among the categories analyzed. This low average is partly due to the negative difference for Heinz 32oz.

A summary of the results is as follows:

1. Across four product categories, for 22 of the 23 brand-sizes examined, the absolute value of the price elasticities from the household data are larger in magnitude than

estimates obtained from store data. This finding is directionally different from Gupta and colleagues who find that in the two product categories they analyzed, household selection produces lower price elasticity estimates compared to the store data. This fact is summarized in the first row of Table 8.

2. There is considerable variation in the magnitude of the differences across brand-sizes within a category,
3. There is considerable variation in the magnitude of the differences across categories.

Brand and Category Influences on the Differences

We first conduct statistical tests for differences between the household and store data with respect to (1) demographics and category penetration and (2) purchases on deal. We then formulate propositions about brand-size and category specific influences on the differences and empirically test these propositions with a cross-brand cross category model.

Propositions

Demographics & Category Penetration

Previous research (Hoch et al., 1995, Kalyanam and Putler, 1997) has demonstrated that Income, Size, Age, Racial composition and Education of the households in the geographic area are related to price sensitivity. For two of the household panels (SAMI, Kansas City MO,[3] A. C. Nielsen, Sioux Falls SD.), we have information on these demographic variables for the households. We compare the household demographics to information with the U.S. Census for these geographic areas

[3] Documentation provided by SAMI indicates that the suburbs of Kansas City in which the panel operated are Lenexa and Shawnee in Johnson County, KS and Grandview and Independence in adjoining Jackson County, MO. The U.S. Census data presented in Figures 1 and 2 for Kansas City are for these geographic areas.

to ascertain if the panel households are systematically different from the population. Figures 1 and 2 present these comparisons.[4] In our discussion, we focus on one demographic variable at a time, but make comparisons across both panels to see if there are any common patterns.

Figures 1A and 1B graph income of the panel households versus the U.S. Census of Kansas City (1980) and Sioux Falls (1990). The numbers displayed on the graphs are the percentage of households in each category. For example, 10% of households in the panel in Figure 1A had an annual income of less than $10,000, whereas the corresponding number for the U.S. Census is 20%. A χ^2 test rejects the hypotheses that the household panel and census proportions are equal.[5] Both household panels have fewer lower income and higher income households.

Figures 1C and 1D present data on household size. χ^2 tests reject the hypotheses that the household panel and census proportions are equal. Both household panels have fewer one person households, are reasonable at representing 2 person households, but have significantly higher households with more than 2 persons in them. In terms of Household Income and Size, our findings support the results reported by Gupta and colleagues. These findings are summarized in rows 2 and 3 of Table 8.

Figures 2A and 2B present data on the distribution of age for all household members in the household panel and the U.S. Census. For both household panels, χ^2 tests reject the hypothesis that the proportions are equal. Both household panels have more people who are below 18 years of age and fewer people in the 19-24 range. The

[4] SAMI and A. C. Nielsen use different demographic categories, hence the differences in the demographic categories across the two geographic areas. In those instances where the panel and census categories did not match, we grouped them till they matched.

[5] All of our tests are conducted at the 99% level.

difference is quite large for the Sioux Falls panel. Both household panels have fewer people who are over 24 years of age.

Figure 2C and 2D present data on both race and education. Both household panels have higher proportions of non-white households and χ^2 tests reject the null hypothesis. With respect to educational attainment in Kansas City, the panel and census proportions match almost exactly. The Sioux Falls panel has a slightly higher proportion of households in the 4 years or more college education category. However, this difference is not statistically significant. Thus, both panels are representative of the population in terms of educational attainment. Rows 4 to 6 in Table 8 summarize these findings. The similarity in the patterns across both household panels is interesting given that different firms operated these household panels, in different time periods, and in different geographic areas. Table 8 also indicates that some of these demographic variables were not analyzed by Gupta and colleagues.

In summary, households in both panels are more middle income, larger in size and have younger household members when compared to the population. Previous research (Hoch et al., 1995, Kalyanam and Putler, 1997) has demonstrated that each of these variables influences price sensitivity of households. We conclude that the demographic differences between the panel households and the population predispose them to be more price sensitive.

In order to directly incorporate demographic differences between the panel households and the population in a cross-brand cross-category analysis, we need information regarding demographics at the category or brand-size level for the population and the panel households. Demographic information for the population at the level of brand-sizes and SKU's are not readily available in these types of scanner data sets[6]. However, we were able to obtain from IRI's Marketing Factbook[7] category penetration rate *PENET%(c)*, defined as the percentage of households purchasing from the product category. Among our product categories, Ketchup had the highest penetration rate (74%) followed by Orange Juice (67%) and Coffee (64%). Red Drinks had the lowest penetration rate of 41%.

Our interest is in the potential linkage between the penetration rate and the magnitude of the difference in price elasticites. We conjecture that, with lower penetration rates, it is more difficult to get households that have higher incomes to participate. This leads to the following proposition:

P1: The percentage difference in price elasticities between household and store data and the category penetration rate are inversely related.

Deal Proneness, Price Elasticity and Promotion Intensity of Brand-Sizes

In addition to the differences in demographics or penetration, household price elasticities will be higher if households are more price sensitive regarding the brand-size in question and have more opportunities to show their price sensitivity. Increase in deal frequency increases such opportunities. Tables 2 to 5 also provide information on the percentage of sales that occurred on a deal (a deal being defined as a price cut or a feature) for the household and store data. We computed a χ^2 statistic of equality of binomial proportions to test the null hypothesis that the percentage sales on deal for the

[6] While the census provides the demographics of a geographic area, it does not provide demographics at the brand level. Hence it is not possible to compute demographic differences at the brand level between the household and the population and hence we are unable to include them in our analysis.

household and store data are equal. We conducted this test at the brand-size level, and the category level (presented in the last row of the last column). As Tables 2 to 5 indicate, the χ^2 values for the category level tests lead to a rejection of the null hypothesis in all four categories.

Statistically significant brand-size level tests are marked in the last column with a $^+$ symbol. At the brand-size level, household deal purchases exceed the corresponding proportions at the store for 13 of the 23 brand-sizes. In seven cases the differences are statistically significant. In summary the panel households tend to be more deal prone and there is considerable variation in this tendency across brand-sizes within a category and across product categories. Row 7 in Table 8 summarizes this result.

Intuitively, it seems reasonable to expect that we will observe more of the households' deal prone behavior in purchase situations where the households: (1) are sensitive to the price of the product in question and (2) have opportunities to take advantage of deals because they are prevalent for the brand-size. In other words, the extent of deal prone behavior depends on price sensitivity and promotional intensity. This leads to the following propositions:

P2: The higher the price elasticity for a brand-size, the higher the percentage difference in the price elasticity estimates between household and store data.

Further, the greater the promotional intensity, the greater is the opportunity to observe deal prone behavior by the households. Consequently:

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[7] The Marketing Factbook also reports information on several other category characteristics like % volume sold with price reductions, etc. We did not introduce these variables because many of them are highly correlated with price elasticity and Feature %, which are also included in our model.

P3: The higher the promotional intensity for a brand-size, the higher the percentage difference in the price elasticity estimates between household and store data.

Empirical Tests

Cross Brand Cross Category Model

The propositions are empirically tested with a cross-brand cross-category model. Our measure for the dependent variable is *PEDIF%(ic)*, the percentage difference between household and store elasticity[8] for brand-size i in category c, shown in the last column of Table 6. Following P1-P3, the variables on the right hand side of the model are category penetration rate, brand-size price elasticity and brand-size promotion intensity. As described earlier, we obtained the category penetration rate (*PENET%(c))*, defined as the percentage of households purchasing from the product category, from IRI's Marketing Factbook.

In our data, household price elasticity is the most direct measure of the household's price sensitivity for a brand-size. Hence, our measure for the price elasticity in Proposition 2 is the price elasticity estimate for brand-size i obtained from the households (*PEHH(ic)*), shown in the third column of Table 6. We use the percentage of weeks that the brand-size was featured (*FEAT%(ic)*) as a measure of promotional intensity. We use this measure because it is consistently available for all the product categories analyzed. Across the four product categories, we have 23 observations (brand-sizes).

[8] Computed as a % of the store elasticity.

Based on a visual examination and specification test[9], we selected a specification incorporating linear specifications for *PENET%(c)* and *FEAT%(ic)* and a logarithmic transformation of *PEHH(ic)* as follows:

$$(5) \qquad PEDIF\%(ic) = \beta_0 + \beta_1\ PENET\%(c) + \beta_2\ LN(PEHH(ic)) + \beta_3\ FEAT\%(ic) + \varepsilon_{ic}$$

According to our propositions P1 - P3, our expectations for the signs of coefficients are $\beta_1<0$, $\beta_2>0$, and $\beta_3>0$.

With respect to the error term ε_{ic}, the price elasticities for the brand-sizes within a category are computed on a common set of parameters estimates (see β and γ in equations (1) and (3)) and have a non-zero covariance structure. Since the data from each category was obtained from different panels we assume that the estimates across categories are not correlated. These assumptions imply that the error term $\varepsilon_{ic} \sim N(0, \Sigma)$, and

$$(6) \qquad \Sigma = \begin{bmatrix} \Omega_1 & 0 & 0 & 0 \\ 0 & \Omega_2 & 0 & 0 \\ 0 & 0 & \Omega_3 & 0 \\ 0 & 0 & 0 & \Omega_4 \end{bmatrix},$$

where Σ is a block diagonal matrix with each block consisting of Ω_c the variance covariance matrix for the observations in category c. For each category, Ω_c was obtained using the bootstrap procedure described in Appendix B.

9 We selected the logarithmic specification over the linear based on the Schwartz Criterion, (Schwartz, 1978).

Estimation Results

Equation 5 was estimated using a restricted maximum likelihood procedure[10]. We obtained an R Square of 71.3%. Table 7 contains the estimation results. The second column of Table 7 reports the estimated coefficients and standard errors using data from the four categories analyzed in this paper. All the coefficients have the hypothesized signs. The coefficient for *PENET%* is negative and statistically significant at the 10% level, providing empirical support for P1. This suggests that a lower penetration rate for a product category might make it more difficult to get participation from higher income households. The estimated coefficient for *LN*(*PEPN)* has a positive sign and is significant at the 1% level. This provides empirical support for P2. The implication is that, as hypothesized, higher price elasticity for a brand-size leads to an increase in the percentage difference between the household and store data. This increase occurs at a diminishing rate. The coefficient for *FEAT%* is positive and statistically significant at the 1% level, providing empirical support for P3. Higher promotion intensity leads to higher percentage differences between household and store data.

Reanalysis of the Estimates Reported by Gupta and Colleagues

In their paper, Gupta and colleagues report estimates for the Detergent and Peanut Butter categories. In order to directly verify that the results from these categories are consistent with our cross-category model, we created data[11] from the estimation results reported in their paper. We appended this data to those obtained from our product

[10] The variance-covariance matrix for one of the product categories was not positive definite and resulted in an infinite likelihood. Hence we used the diagonal variance terms in a weighted least squares procedure.

[11] All price elasticity estimates are based on household selection. Some of the data was obtained from the paper. We are grateful to Sachin Gupta for providing additional data.

categories and re-estimated Equation 5[12]. Gupta and colleagues provide estimates for 17 brand-sizes, which along with our 23 brand-sizes gives us a total of 40 observations. The estimation results for Equation (5) are shown in the third column of Table 7. The R-Square of the model improves from 71.3% to 87.7%. *PENET%, LN(PEPN), and FEAT%* and are all statistically significant at the 1% level. The coefficient for *PENET%* is negative, *LN(PEPN)* is positive and FEAT% is positive, providing empirical support for all three propositions. The finding suggests that empirical support for the three propositions is robust across the estimates reported in both studies[13].

The reanalysis also helps reconcile our findings with those of Gupta and colleagues. Specifically, Gupta and colleagues find that household elasticities (based on household selection) are lower than store elasticities. Our results are quite different in that we find the household elasticities are mostly *higher*. The price elasticity estimates reported by Gupta and colleagues indicate that the Detergent and Peanut Butter categories that they examine are at the lower end of the spectrum in terms of price sensitivity. The Marketing Factbook indicates that Detergent and Peanut Butter categories have the highest penetration level among all 6 categories. With respect to promotion intensity, Detergents were featured on average only 2% of the weeks and Peanut Butter was featured on average about 2% of the weeks. In contrast the Orange Juice brand-sizes were featured on average 13% and the Ground Coffee brand-sizes were featured 14%. From P1 P2 and P3, we know that higher penetration, lower elasticities and lower

[12] Bootstrap variance estimates were not available for the Detergent and Peanut Butter category, and Equation 5 was estimated using ordinary least squares.

[13] We also examined the robustness of the results to a specification of the dependent variable that calculates price difference as a % of the household elasticity. We also used linear, logarithmic and inverse transformations for price elasticity using data from our categories and a more comprehensive data set that included the results from Gupta. The two dependent variables, three functional forms and two data sets

promotion intensity will result in the similar price elasticities for store and household data. Hence the results obtained by Gupta and colleagues.

Practical Implications

Our findings can inform retailers as to when they should expect large differences between store and household data. In product categories like Ketchup, where price elasticities and promotion frequencies are low and penetration is high, retailers should expect the magnitude of the differences between store and household data will be small. On the other hand, with product categories like Red Drinks, which have higher price elasticity and low penetration, retailers should expect larger differences between store and household elasticities. In such product categories, retailers should be cautious is using household data to make store level decisions. In such product categories, additional investments in analyzing two data sources might be justified.

Improving Household Participation

For retailers who have implemented loyalty card programs and for suppliers of household panel data, our results suggest several avenues for improving household participation. Our analysis indicates demographic differences between the households and the population. Implementing stratified sampling on the demographic variables using the census data as a sampling frame (Cornish, 1989) may reduce these differences. While retailers might not be able to control which households sign up for a loyalty card program, they might appropriately sample from the participating households.

Our analysis indicates that the pattern of demographic differences with the population was very similar for two panels. The fact that this is the case for two different

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lead to a total of 2x3x2 models. The empirical support for the propositions was generally robust across all models. The one exception was PENET%, which was not significant in three of the estimated models.

panels, across two different time periods operated by different firms suggests that there may be a natural ceiling with respect to the number of households with certain demographic characteristics (e.g., high-income) that will participate in panels.

Another factor to consider is that in a typical use of household data, multiple product categories are tracked using the same set of households. Even if the households are overall representative of a particular geographic area, it does not mean that they will be representative of every product category that is being tracked. Hence there may be diminishing returns to investments made towards improving household participation

De-biasing Household Elasticities

In product categories where we expect large differences, one potential solution is to de-bias the household estimates. A debiasing procedure would adjust the household estimates to the expected value of the store estimates using predicted values obtained from Equation (5).

Once Equation (5) is estimated, a debiasing approach can be implemented for brand-sizes in a product category (even if the store estimates are not available) using the following two steps: (1) Substitute the values of the independent variables for the brand-size in Equation (5) and obtain a predicted value. (2) Use this predicted value as a debiasing adjustment to the household estimates as outlined below. The expression for *PEDIF%(ic)* is

(7) $$PEDIF\%(ic) = \frac{PEHH(ic) - PESTR(ic)}{PESTR(ic)}$$

Manipulating and changing sides we get,

(8) $$PESTR(ic) = \frac{PEHH(ic)}{PEDIF\%(ic) + 1}$$

Let *PEDIF%(ic)** be the predicted value of *PEDIF(i)* obtained in step 1. Substituting *PEDIF%(ic)** in the right hand side of (8) along with the actual value of *PEHH(ic)* yields *PESTR(ic)**, which is the expected value of the store elasticity and is equivalent to the de-biased estimate of household elasticity.

Figure 3 provides a scatter plot of the de-biased estimates and household estimates versus the actual store elasticity. The closer the points on the scatter plot lie to the diagonal line the smaller is the magnitude of the differences between store and household estimates. Figure 3 shows that many of the de-biased estimates are closer to the diagonal line compared to the household estimates. This indicates that differences between de-biased estimates and store estimates are smaller than the differences between household estimates and store estimates. We note that in order to implement the de-biasing procedure we need the household elasticity estimate, promotion intensity and category penetration for each brand size, all of which can be obtained from the household data.

Conclusions, Limitations and Future Research

This paper has investigated brand and category influences on the magnitude of the differences between store and household data. Our key findings, summarized in Table 8, are:

1. For 22 of the 23 brand-sizes examined across our four product categories, household data based on household selection, produce higher price elasticity estimates compared to store data.
2. The differences in price elasticities show some variation across brand-sizes within a category.

3. The differences in elasticities show considerable differences across categories ranging from about 34% for the Red Drink brand-sizes to about 3% for the Ketchup brand-sizes.
4. A demographic analysis using data from the U.S. Census indicates that participating panel households are more middle income, larger in size and the household members are younger in age when compared to the population. Notably, we find the same patterns across two panels that were operated by different firms, in different geographic areas and in different time periods.
5. At the brand-sizes level, the household's purchases on deal exceed the corresponding proportions for the population for 13 of the 23 brand-sizes. In 7 cases the differences are statistically significant.

Based on these findings, we developed three propositions about the variation in the magnitude of the difference in price elasticities across brand-sizes and categories. The intuition behind our propositions is that certain patterns of demographic differences predispose participating households to be more price sensitive, and this effect is more salient for categories with lower penetration rate and for brand-sizes with higher price elasticity and higher promotion frequency. Empirical tests with a cross-brand cross-category model provide support for all three propositions. Specifically, the results indicate that the difference between store and household data:

1. Increases with increase in category penetration,
2. Decreases at a decreasing rate with the price elasticity obtained from household data,
3. Decreases with the increase in promotional intensity of the brand-size.

These findings are generally robust across alternative specifications of the dependent variable, functional forms, our categories and an expanded dataset based on 6 categories and 40 brand-sizes that included the results reported by Gupta and colleagues.

Our results show that retailers and manufacturers have less reason to be concerned about product categories like Ketchup, where the price elasticity is low and penetration is high. On the other hand, in product categories like Red Drinks, which have higher price elasticity and lower penetration, our results show that retailers and manufacturers should be concerned about the difference between store and household data. In such situations our analysis shows that a de-biasing approach might be promising.

Census data regarding the demographics of a brand-size were not available for our analysis. Hence we were unable to directly examine the effect of demographic differences on the differences in price elasticity, instead relying on a proxy such as category penetration. Future research can address this limitation. While this paper explored the potential of de-biased estimates, an alternative approach might be to develop an appropriate weighting scheme for households that would result in more consistent price elasticity with the estimate obtained from store data. Future research might examine the development of such weighting schemes.

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Table 1: Summary of the Databases

	Orange Juice	Ground Coffee	Red Drinks	Ketchup
Data Source	IRI	SAMI	IRI	A.C.Neilsen
No. of Weeks	78	65	104	138
No. of Stores	5	4	11	13
No. of Brand-sizes	6	6	5	6
No. of Households	200	663	123	258
No. of Purchases	2307	6879	513	2857

Table 2: Description of the Orange Juice Brand-sizes

Brand-sizes (64 oz)	Share %		Average	Feature	% Sales on Deal	
	Store	Household	Price*	Weeks %	Store	Household
Regional	15.9	15.4	1.67	16.5	22.4	28.6+
Citrus Hill	33.5	32.9	1.83	6.3	29.9	31.8
Minute Maid	24.6	22.5	1.92	14.4	46.4	53.1+
Private Label	8.8	11.7	1.41	7.7	9.4	8.6
Tropicana-Regular	13.9	13.7	1.71	27.3	36.6	46.3+
Tropicana-Premium	3.3	3.9	2.30	5.1	17.8	19.1
χ^2	---	17.0+	---	---	---	10.2+

* ($)Volume weighted average computed from store data.

+Chi square significant at α=0.01.

Table 3: Description of the Ground Coffee -sizes

Brand-sizes	Share %		Average	Feature	% Sales on Deal	
	Store	Household	Price*	Weeks %	Store	Household
Butternut 1 lb	17.7	18.8	2.91	15.6	32.6	34.6
Butternut 3 lb	6.3	4.1	2.81	14.1	56.1	62.5+
Folgers 1 lb	41.2	41.8	3.03	15.6	31.9	44.3+
Folgers 3 lb	9.4	10.1	3.08	14.1	28.0	44.9+
Maxwell Hs. 1 lb	21.1	18.6	3.00	17.2	38.1	36.1
Maxwell Hs. 3 lb	4.3	6.5	2.92	7.9	37.3	39.7
χ^2	---	22.4+	---	---	---	30.2+

* ($ per lb.) Volume weighted average computed from store data.

+Chi square significant at α=0.01.

Table 4: Description of the Red Drink Brand-sizes

Brand-sizes	Share %		Average	Feature	Display	% Sales on Deal	
	Store	Household	Price*	Weeks %	Weeks %	Store	Household
Pvt. Label 48 oz	15.1	14.5	4.36	1.9	2.3	11.7	11.9
Cranapple 48 oz	19.3	12.4	4.69	5.0	12.8	26.1	41.7^{+}
Cranberry 32 oz	18.6	15.2	5.43	0.0	0.0	11.6	0.0^{+}
Cranberry 48 oz	32.4	32.1	4.69	6.0	13.3	30.2	26.9
Cranberry 64 oz	14.6	25.9	4.53	2.2	4.2	32.8	24.0^{+}
χ^2	---	33.5^{+}	---	---	---	---	10.8^{+}

* ($ per package) Volume weighted average computed from store data.

+Chi square significant at α=0.01.

Table 5: Description of the Ketchup Brand-sizes

Brand-sizes	Share %		Average	Feature	Display	% Sales on Deal	
	Store	Household	Price*	Weeks %	Weeks %	Store	Household
Del Monte 32	7.2	4.7	3.23	11.9	3.9	50.1	48.9
Heinz 14	6.6	8.0	5.64	0	0.2	0.1	0
Heinz 28	26.3	26.2	4.56	14.9	10.7	42.4	39.1
Heinz 32	38.1	45.8	3.46	15.5	5.9	38.9	30.8^{+}
Heinz 48	5.9	4.1	4.71	4.8	5.5	24.3	28.2
Hunt 32	15.9	11.3	3.40	9.6	6.2	41.0	35.7
χ^2	---	132.4^{+}	---	---	---	---	29.7^{+}

* ($ per package) Volume weighted average computed from store data.

+Chi square significant at α=0.01.

Table 6: Price Elasticity Estimates from Brand-size Choice Model

Brand-size	Store	Household	Difference %
Orange Juice			
Regional	3.22	3.84	19.3
Citrus Hill	1.92	2.33	21.3
Minute Maid	2.14	2.64	23.4
Private Label	1.26	1.34	6.0
Tropicana Regular	2.04	3.02	47.9
Tropicana Premium	3.05	3.22	5.5
Average	**2.27**	**2.73**	**20.2**
Ground Coffee			
Butternut 1 lb	2.70	3.27	20.9
Butternut 3 lb	3.30	3.98	20.4
Folgers 1 lb	2.38	2.91	22.3
Folgers 3 lb	3.58	4.31	20.4
Maxwell Hs. 1 lb	2.83	3.37	18.9
Maxwell Hs. 3 lb	3.43	4.12	20.1
Average	**3.04**	**3.66**	**20.5**
Red Drinks			
Private Label 48 oz	2.25	3.12	39.7
Cranapple 48 oz	2.84	3.93	38.4
Cranberry 32 oz	3.04	4.08	34.4
Cranberry 48 oz	2.29	3.34	45.6
Cranberry 64 oz	2.69	3.14	16.8
Average	**2.62**	**3.52**	**34.8**
Ketchup			
Del Monte 32 oz	1.45	1.51	3.8
Heinz 14 oz	2.61	2.80	7.5
Heinz 28 oz	1.50	1.51	0.5
Heinz 32 oz	0.95	0.86	-8.8
Heinz 40 oz	2.02	2.16	7.2
Hunt 32 oz	1.30	1.39	6.6
Average	**1.64**	**1.71**	**2.8**

All entries are absolute values of price elasticities.

Table 7: Estimation Results for Cross-Brand Cross-Category Model

	4 CATEGORIES (OUR DATA)	6 CATEGORIES (OUR DATA +GUPTA DATA)
INTERCEPT	0.409 (0.299)	0.177 (0.231)
PENET%	-0.007 (0.004) *	-0.010 (0.003) ***
LN(PEHH)	0.151 (0.046) ***	0.380 (0.063) ***
FEAT%	0.010 (0.003) ***	0.018 (0.004) ***
NUMBER OF OBSERVATIONS	23	40
R SQUARE	71.3%	87.7%

Standard errors in paranthesis

***Significant at 1%.

**Significant at 5%.

* Significant at 10%

Table 8: Summary of Findings

Description	Variable Analyzed	Finding in this Paper	Gupta et. al Findings
Price Elasticities	Brand Choice	Absolute value of household elasticities are *higher* than store elasticities	Absolute value of household elasticities are *lower* than store elasticities
Demographics	Household Income	Household panel under-represents lower and higher income households, over-represents middle income households	Same
	Household Size	Household panel under-represents 1 person households, is representative of 2 person households and over-represents households with greater than 2 persons	Same
	Age of Household Head	Household panel over-represents under 18 age group, under-represents older households	Not analyzed
	Race of Household Head	Household panel has a larger % of non white households	Not analyzed
	Education of household head	Household panel is representative	Not analyzed
Deal Purchases	Purchases on Deal	% of sales on deal is higher for household data	Same
Brand and Category Influences on Difference (Propositions)	Penetration	P1: Higher penetration leads to lower difference.	Not analyzed
	Price Elasticity	P2: Higher price elasticities lead to more difference with a diminishing rate.	Not analyzed
	Deal Frequency	P3: Higher deal frequencies lead to less difference.	Not analyzed

Figure 1: Comparison of Income and Size of Panel Households with U.S. Census

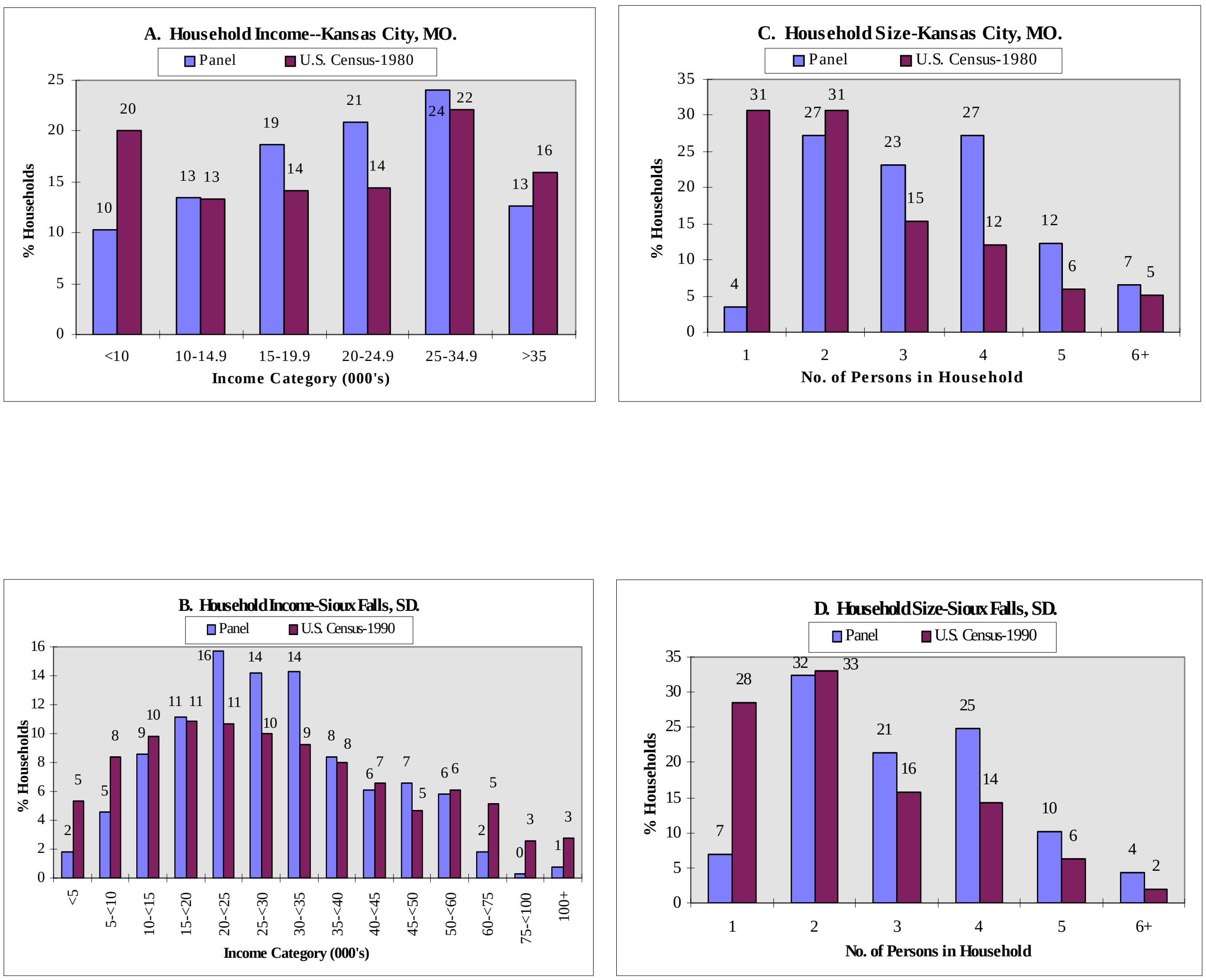


Figure 2: Comparison of Age, Race and Education of Panel Households with U.S. Census

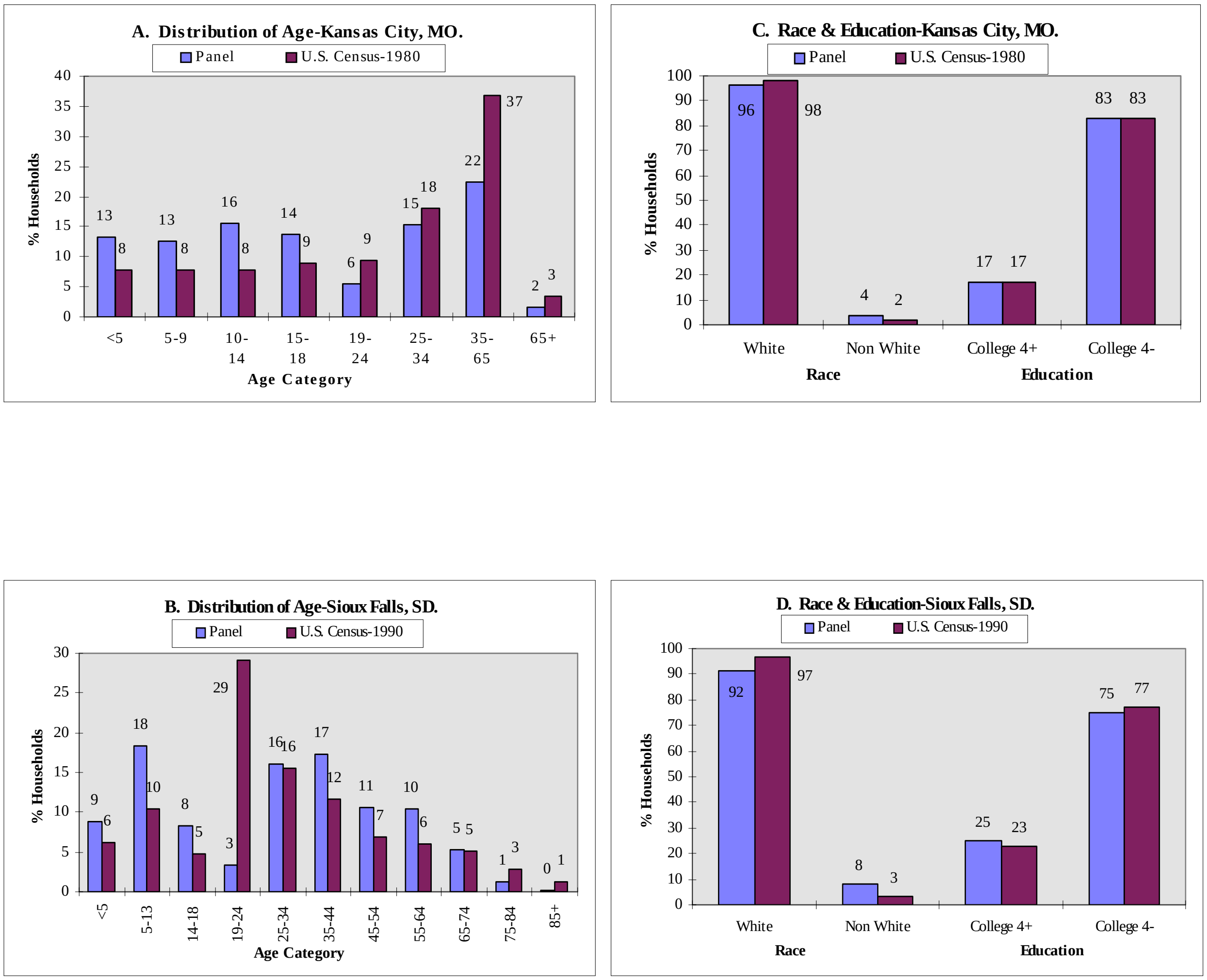
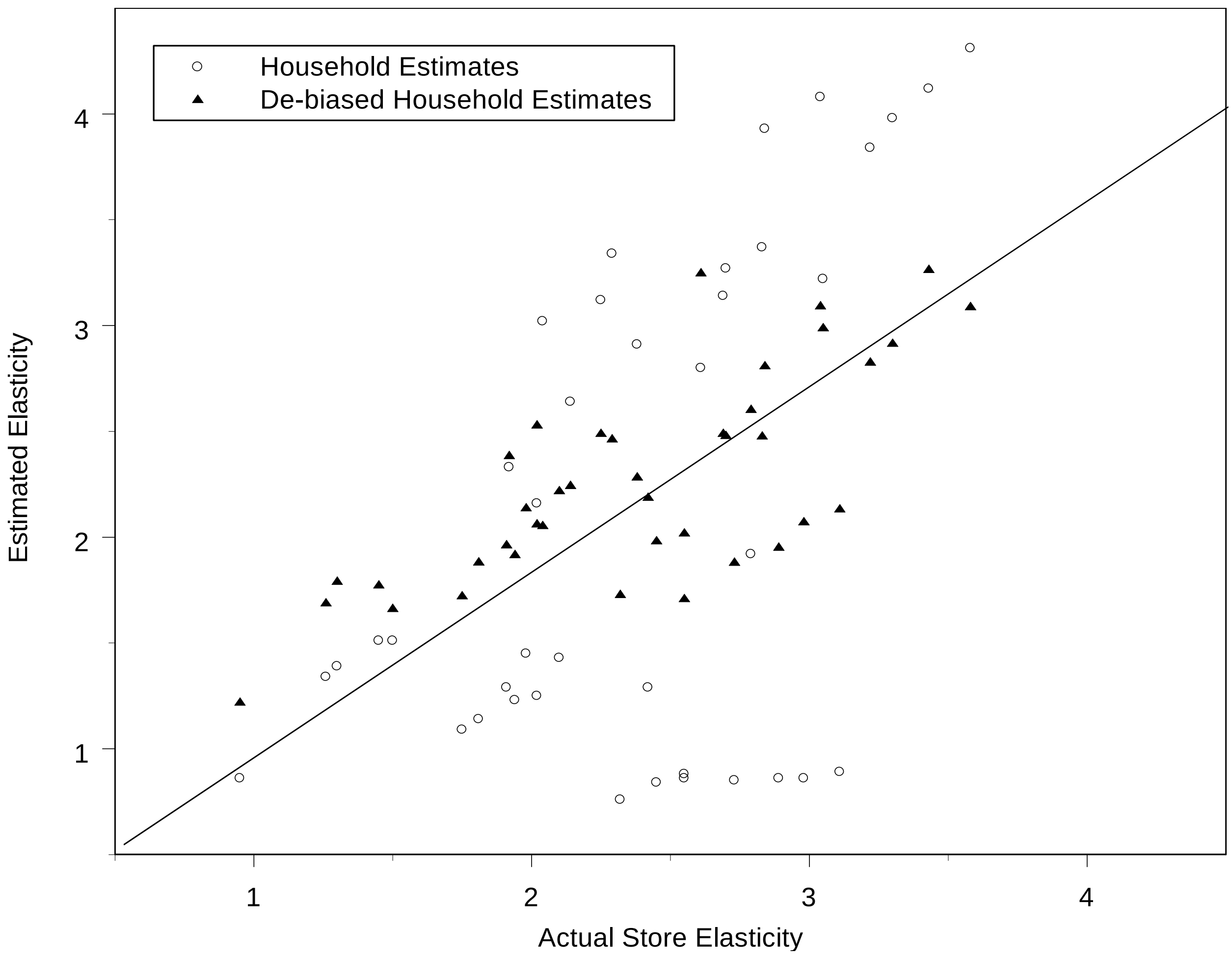


Figure 3: Illustration of De-biased Household Elasticities



APPENDIX A: Formula for Price Elasticity

The price elasticity of brand-size j on the share of brand-size i in store s during week t for household data is obtained by differentiating Equation (1) with respect to price x_{jst} as

$$E_{x_{jst}}^{P_{ist}} = \frac{\partial P_{ist} / P_{ist}}{\partial x_{jst} / x_{jst}} = \beta_p x_{jst} \left(\delta_{ij} - P_{jst} \right).$$

where β_p is the price coefficient. Note that it follows the IIA property at the individual brand-size-store-week level. Now, the volume weighted store-week level share in the aggregate share is obtained as follows.

$$\overline{P}(i) = \frac{\sum_s \sum_t q_{st} P_{ist}}{Q} \qquad \text{where } q_{st} = \sum_i q_{ist} \quad \text{and} \quad Q = \sum_s \sum_t q_{st} .$$

q_{st} is the number of units bought at store s during week t. Hence, the aggregate elasticity is

$$E_{x_j}^{\overline{P}(i)} = \frac{\partial \overline{P}(i) / \overline{P}(i)}{\partial x_j / x_j}$$

$$= \frac{\frac{1}{Q} \sum_s \sum_t q_{st} \frac{\partial P_{ist} / P_{ist}}{\partial x_{jst} / x_{jst}} P_{ist}}{\overline{P}(i)}$$

$$= \frac{\sum_s \sum_t q_{st} P_{ist} E_{x_{jst}}^{P_{ist}}}{\sum_s \sum_t q_{st} P_{ist}} \qquad \text{where } \frac{\partial x_j}{x_j} = \frac{\partial x_{jst}}{x_{jst}} \text{ is assumed for all } s,t.$$

Likewise, working on Equation (3), price elasticity for store data can be derived with the appropriate notational change.

APPENDIX B: Multivariate Paired Difference Test

Because price elasticity estimates for all brand-sizes in a product category are obtained from the parameter estimates of the same model, they are not statistically independent. Hence a multivariate test should be used in lieu of a univariate test. Formally, let E_P and E_S be the $i \times 1$ vectors of elasticity estimates for the i brand-sizes in a product category from household panel and store data, respectively. Let $D = E_P - E_S$ and $Var(D) = S_D$. Under the null hypothesis, H_o: D ~ N(δ, Σ), the test statistic $T^2 = n(D-\delta)' S_D^{-1}(D-\delta) \sim \left[\frac{(n-1)i}{(n-i)}\right] F_{i,n-i}(\alpha)$, where n is the sample size and $F_{i,n-i}(\alpha)$ is the upper (100α)-th percentile of an F-distribution with i and $n-i$ degrees of freedom[14]. For large samples, $\left[\frac{(n-1)i}{(n-i)}\right] F_{i,n-i}(\alpha) \cong \chi_i^2(\alpha)$ and the normality need not be assumed (See Johnson and Wichern, 2002, p. 272). Because price elasticity is a nonlinear function of the model parameters (see the appendix), S_D is a complicated nonlinear function of the variance-covariance matrix of the MLE of the model parameters. Thus we employ the following bootstrap-like procedure to obtain an estimate of S_D empirically (and to compute the test statistic T^2):

Step 1: Make a random draw of a set of coefficients from the sampling distribution of the maximum likelihood parameter estimates of the household panel and store models.

Step 2: Using the coefficients drawn in step 1 above, compute price elasticities, E_{Pb} and E_{Sb}, from the formulae in the appendix for the store and household panel models, where b denotes the random draw.

Step 3: Compute the difference in elasticities, $D_b = E_{Pb} - E_{Sb}$.

Step 4: Repeat steps 1-3 for $b = 1,..., B$ (B = 100 in our case).

Step 5: Compute $\overline{D} = \frac{1}{B}\sum_{b=1}^{B} D_b$, $S_D = \frac{1}{B-1}\sum_{b=1}^{B}(D_b - \overline{D})(D_b - \overline{D})^t$ and T^2.

[14] For the problem at hand, our interest is whether δ = 0.