An Empirical Analysis of Socio-Demographic Stratification in Sweetened Carbonated Soft-Drink Purchasing

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Abstract

Caloric soft drinks are the number one source of added sugars in U.S. diets, and are associated with many health problems. Three recent years of household purchase, household demographic, and industry advertising data allow Heckit estimation to identify how specific demographic groups vary in their purchase response to marketing of sweetened carbonated soft drinks (**sCSDs**) at the product category level. Empirical results reveal unique non-linear patterns of household purchase response to sCSD-industry price, sale, and advertising signals that vary significantly by specific demographic characteristics. Isolating the effects of either price, sale, or advertising on household purchase, highest education level of high school or less for the household head tends to be the most robust predictor of higher sCSD purchase, followed by household income at or below the poverty level for a family of four. The novel approach and results here contribute to the literature by estimating how rising education level for a fixed level of household income will variously affect sCSD purchase quantity depending on the ethnicity of the household, and does the same fixing education level across rising income level. Econometric controls are used to avoid estimation and inference errors the literature warns commonly accompany the Heckman specification.

Keywords: sugar-weetened beverages, Heckit, scanner data, demographic sub-groups

JEL Codes: D12, C33, C34, Z18

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I. Introduction

Figures relating the rapid expansion of overweight and obesity in the American population over recent decades have been cited so often that they may have begun to lose their power to alarm. But the numbers depicting epidemic rises in diet-related health problems when understood in their proper context cannot fail to alarm, once one admits that the term "epidemic," is appropriate, as the U.S. Centers for Disease Control and Prevention (CDC) does (cdc.gov website, accessed November 2011). Defining *obesity* as having a body-mass index (BMI[2]) over 30, 2010 numbers from the CDC for persons over 20 years indicate that 33.9% of Americans are obese, and an additional 34.4% are overweight, leaving but one-third of Americans at or below "normal" weight. Every state in the U.S. has an obesity rate over 20%, with 12 states having obesity prevalence of over 30%. For reference, not a single state had obesity prevalence over 14% in 1990.

While marketed to the consumer for their flavor, effervescence, kick (caffeine), color, and overall enjoyability, most sugar-sweetened beverages enter the digestive track as nutrient-deficient simple sugars in a form and quantity the human body did not evolve to tolerate well (Wolf , Bray, and Popkin: 2007). Sugar-sweetened beverages (**SSBs**), and particularly sweetened carbonated soft-drinks (**sCSDs**), the largest category by consumption within SSBs, have a special place at the head of the line when the medical community attributes factors associated with overweight, obesity, and dietary-based illness. The first reason is that the sheer quantity of SSBs in the American diet has been increasing for decades, nearly tripling the calories from SSBs from 1977 to 2001 (Nielsen & Popkin: 2004), and accounting for 50% of the rise in average daily calorie intake over the past 30 years (Johnson, et al.: 2009). Sweetened CSDs are "the main contributor of added sugars in the diet of all age/gender groups" (Marriott, et al.: 2010), and account for about 1/3 of all added sugars (Krebs-Smith: 2001; USDA & US Dept. HHS: 2010; *added sugars* are those not naturally occurring, but introduced in processing). Ogden, et al.

[2] Body Mass Index, or BMI, is calculated in standard American measure as: weight (lbs.) / [height (in.)]^2} x 703; and in metric units as weight (kg) / [[height (m)]^2. Thus a 5-foot five-inch person weighing 150 lbs. has a BMI of 24.96, on the very cusp between "normal" (18.5-24.9), and "overweight" (25-29.9). Any BMI below 18.5 is considered "underweight." "BMI is calculated the same way for both adults and children," http://www.cdc.gov/obesity/data/trends.html, or http://www.cdc.gov/nchs/fastats/overwt.html , accessed 19 November 2011.

(2011) find *every* age group of males from adolescence to the age of 60 derive more than 150 kcals/day from SSBs. This is notable as 150 kcals/day is the American Heart Association's recommended limit for adult males from added sugars in a day from all sources, and the 100 kcals/day recommended cap for adult females is also exceeded by SSB consumption alone (Stanhope, et al. : 2011).

The second reason is the class of biological effects of the sugars in SSBs. Dietary added sugars from SSBs/sCSDs are associated with dental caries, weight gain and obesity (Bleich, et al.: 2009; Malik, Schulze, and Hu: 2006), adult-onset/Type II diabetes (Vartanian, Schwarz , and Brownell: 2007), upset of blood-fat balance and cardiovascular disease (directly, by Malik, et al.: 2010 and Bray: 2010, and indirectly by the volume of sugar affecting triglyceride and HDL cholesterol levels, by Johnson and Yon: 2010, and by Lustig Schmidt and Brindis: 2012), inadequate nutrient intake (Marriott, et al.: 2010),. As strong inflammatory agents (Ludwig: 2002, Malik, et al.: 2010), high dietary added-sugar intake also associates with many cancers (Anand, et al.: 2008, citing Harvard's Walter Willett). Lustig Schmidt and Brindis (2012) attack added sugars as "toxic" given their extreme effects on the liver.

Elliott, et al. (2002), conduct a review finding that high-fructose corn syrup (HFCS), the primary added sugar in most SSBs and almost all American sCSDs, especially effects the liver, where fructose is primarily digested. Insulin resistance, hypertension, impaired glucose tolerance, and higher triglyceride levels all pronounce more than for glucose or sucrose consumption. Elliott, et al., called for more human trials, and results from Stanhope, et al. (2008), and Stanhope, et al. (2011), associate worse health effects with dietary fructose or HFCS more than with dietary sucrose or glucose.

Evidence is growing that added sugars may affect brain reward-center pathways in addictive-like ways that could in turn affect consumer choice (Lutter and Nestler: 2009; Bernheim and Rangel: 2004; Levine, Kotz, and Gosnell: 2003; Wang, et al.: 2004; Avena, Rada, and Hoebel: 2009; Fullerton, et al.: 1985).

II. Literature Review

Industry structure of the sCSD or SSB industry is not a focal point of this work. Some indications of industry structure and power are present in order to establish a general background before examining sCSD purchases by demographic type at the household level.

The Coca-Cola Company (Coca-Cola), founded some 125 years ago in 1886 and now based in Atlanta, is the most successful soft-drink company. It began when an Atlanta pharmacist combined a caffeinated kola nut from Africa with coca leaves from South America, putting together a spiced sugar-sweetened water-based "tonic." Coca-Cola calculates that across its beverage line, worldwide customers now consume 1.8 billon servings per day – nearly one for every 3 people on the planet. Coca-Cola now boasts 49 consecutive years of stock dividend share increases, indicating they well know their products and how to market them and their brand.

PepsiCo, building from the 1898 formulation of Pepsi Cola, is based in New York state, and is the only clear rival to Coca-Cola for market share in the sCSD industry. PepsiCo has diversified much further into snack and other food market divisions, having developed or acquired hundreds of brands, many easily recognizable in U.S. stores, and perhaps not associated with PepsiCo (Quaker Oats, Lay's, Aunt Jemima, etc.).

Some estimates attribute these two companies with controlling roughly three-quarters of the world beverage market (Sharma, et al.: 2010).

The Coca-Cola Company (40%) and PepsiCo (33%) dominate the flavoring syrup and concentrate manufacturing industry (North American Industry Classification System: 311930, comprised of 151 companies in the U.S.), for use in fountain drinks, manufactured soft drinks, and powdered concentrates. These two manufacturers *alone* define an industry Herfindahl–Hirschman Index, or HHI, of over 2500, designating it a *highly concentrated industry* (>2500).

The soft-drink manufacturing industry (NAICS: 312111, comprised of 1,209 companies in the U.S. that blend flavorings and water, then package and distribute soft drinks) is dominated by the Coca-Cola Company (28.6%), PepsiCo (26.8%), and Dr Pepper Snapple Group, Inc. (8.6%). These three manufacturers alone manifest an HHI of over 1610, defining a *moderately concentrated industry* (1500-2500). While less concentrated than the flavoring syrup and concentrate industry, this number may seem counterintuitively low, as the HHI covers all six soft-drink categories as defined by the Federal Trade Commission.[3] Negative consumption trends in sCSDs give way to profitability for other soft-drink categories, often among brands owned by

[3] These categories are: sCSDs (43% by industry revenue), fruit beverages (15.2% by revenue), bottled waters (12.6%, including spring, with flavoring, and vitamin and mineral enhanced), functional beverages (11.3%, including energy drinks, and ready-to-drink teas and coffees), sports drinks (8.7%, including liquid and powdered formulas), and an "other" category (7.2%, including ices, dairy-based drinks, and soy-based drinks) (NPLAN: 2011). If one removes waters, "other," and teas and coffees (but not energy drinks), the HHI for soft-drink manufacturing begins to edge higher. Coca-Cola and Pepsi are dominant in multiple soft-drink categories, including bottled water.

the majors that dominate sCSD market share. This has been occurring for at least a decade, since around 1997.

A 1999 FTC report indicates “rapid structural change that transformed” the sCSD industry in the 1980s and early 1990s. The FTC had challenged large horizontal integrations of franchises and bottlers, but not vertical acquisitions. Beyond the FTC merger enforcement activities, the Department of Justice (**DoJ**) leveled price-fixing cases in the mid-to late 1980s “against CSD bottlers affiliated with each of the leading concentrate firms” (Saltzman, Levy, and Hilke: 1999, p vii). The same report notes that DoJ investigations and indictments led to “guilty pleas or convictions for price fixing between and among CSD bottlers” (p 2).

The sCSD/SSB industries are rich fields for the study of market power issues, both for price and industry structure, but also for the effects of persuasive advertising for an industry able to get its products into basically any public forum that might allow commercial food sales. Manufacturers of sCSDs are the largest marketer of any food product to children, and the number one advertiser to children in schools, with over 60% of total spending (NPLAN: 2011, p 23, 25, figures based on FTC: 2008).

Outside the sCSD industry and marketing literature, associations between demographic factors, SSB consumption, and health literacy bear on household sCSD purchase. Socio-demographic factors are associated with differences in dietary choice. Deshmukh-Taskar, et al. (2007), find that food group consumption varies by socioeconomic, demographic, and lifestyle factors. Stevens-Garmon, Huang, and Lin (2007, using Nielsen HomeScan data for organic produce) show that the direction of ethnic influence is not always predictable. Remember from Marriott, et al. (2010) that high added-sugar intake is associated with lower intake of many micronutrients. Kant and Graubard (2007) use dietary recall data in conjunction with serum blood tests, finding that ethnicity and education level are stronger independent predictors of micronutrient intake than income level, and that after controlling for income and education levels, ethnic differences persist as independent predictors. This suggests that ethnic grouping could explain more variance in household sCSD purchase than differences in household income or head-of-household education level, a testable hypothesis here. Kranz and Siega-Riz (2002) find that ethnicity, income, and level of the female head of household’s education are among the determinants of added sugar intake for 2-to-5-year-old preschool children. This links purchaser decisions to added sugar intake, and suggests that policies that effectively reduce the head of household's purchase may help reduce sugar intake for non-shoppers in the household.

Soederberg Miller, et al. (2011), define **health literacy** as "to the ability to obtain, process, and use health information in managing one's health." Health literacy for many Americans remains consistently low over time, despite generations of rising average incomes and educations (Kumanyika: 2009, responding to Popkin, Siega-Riz, Haines: 1996). Beydoun and Wang (2008) measure nutrition knowledge and beliefs about the importance of nutrition, finding that higher diet quality and higher education or higher income are significantly correlated at high levels of nutrition knowledge and beliefs, but not at low levels of nutrition knowledge and nutrition beliefs. This suggests that empirical identification of sCSD purchase by education and income level (or by implication racial group, age, or presence of children in the household) will not be fully identified, because nutrition knowledge and beliefs are not observed for this quantitative analysis. To the degree that sCSD purchase behavior does not closely proxy nutrition knowledge and beliefs, there will be an implicit grouping of potentially identifiable knowledge and belief levels within education and income levels in estimation here.

Beydoun and Wang use cross-sectional data, and do not use race as a factor, so the implementation of panel data on purchase for a particularly unhealthful food (sCSDs) in this study has the potential to satisfy or fail to satisfy predictions that follow from Beydoun and Wang's results that associate lower diet quality with lower education or lower income. We would expect from Beydoun and Wang's results a higher sCSD purchase response to advertising (at least, possibly also less negative response to rising price) for lower-education and lower-income groups.

Zoellner, et al. (2011), claim to be the first to account for demographic differences in a sample population while also examining the association between health literacy skills, healthy eating, and SSB consumption. They find that a one-point rise in health literacy score (Newest Vital Sign, 0 to 6) is associated with intake of 34 fewer SSB calories per day. The non-significant positive associations they find between education and income categoric variables and Healthy Eating Index (**HEI**) score (where health literacy is significant) importantly indicate that increasing education or income alone are inadequate to predict a healthy eating profile. They conclude that a measure of health literacy is a better predictor of HEI scores and SSB consumption than education or income, and consequently caution against using income and education status as proxies for health literacy. My quantitative work does not use any direct measure of health understanding, and by necessity proxies household application of nutrition knowledge by the HHH education variable.

However, Zoellner et al.'s results are compromised by the fact that they only regress education and income as categoric variables. It is my precise hypothesis that there is non-linearity across income and education levels, and across these levels within ethnic groups. If proven, this non-linearity would compromise the statistical significance of a linear regression fit.[4] Their caution is well taken and I cannot claim that regressing on levels of income or education would lead to statistically significant associations with health literacy. But from their results, a useful conclusion emerges that speaks to my hypothesis that sCSDs are so unhealthful that heavy household purchase naturally proxies for poor nutrition knowledge. Zoellner, et al., find significant inverse relationships between HEI scores and SSB kcals/day for health literacy scores, age (by year), and sex, as well as a significant inverse relation between the categoric variable education and SSB consumption. So while not tying my household-purchase data with nutrition knowledge is a limitation, it is one mitigated by the overlap of relevant results with those found when health literacy scores are accounted when determining demographic associations with diet quality.

I have found one study that presages some of my methodology and research goals. Thompson, et al. (2009), use many similar categories for demographic variables, across a nationally representative population, and with interaction of demographic terms, from a 29,000-person National Health Interview Survey (**NHIS**) to assess "interrelationships of" added sugar intake, socioeconomic status, and race/ethnicity in U.S. adults. They claim theirs is the first study to associate demographic factors with added sugar intake as a means to "formulate effective nutrition intervention programs" (p 1377).[5] The variant work with a marketing orientation here appears to be the second. The NHIS is a cross-sectional study

[4] Results indicate latent non-linearity of fit does compromise the statistical significance of a linear regression fit.
[5] Thompson, et al., regress age, income and education levels, and ethnic/racial groups, along with an interaction of education level with racial groups and by U.S. region, on a transformed dependent variable representing dietary intake of added sugars. Separate regressions are run for men and women. For Age, there are 3 groups, 18-39, 40-59, and 60+ years; for Race, non-Hispanic Whites, African Americans, and Asians, as well as Hispanics, and American Indian/Alaskan Natives; for education level, less than high school, high school, some college, and college or greater; for (family-size adjusted) income less than 200% of the poverty level, 200-299%, 300-399%, 400-499%, and 500%+. Interaction is only reported for education and race/ethnicity variables.

conducted annually by the National Center for Health Statistics, and consists of a clustered, randomized sample of U.S. households.

Thompson, et al., find significant inverse associations between sugar intake and education level or income levels for men and for women. Race/ethnicity groups significantly differ, with Asian Americans the lowest consumers, and African Americans the highest. For race interacted with education level, Thompson, et al., find significant drops in sugar intake with rising education level for Whites, African Americans, Hispanic men, and American-Indian/Alaskan-Native men. The order of sugar intake by ethnic group does not change between males and females, the education and income effects were linear, and the interacted education-ethnic effects were linear for all groups except non-Hispanic Asians and Hispanic women. "Groups with low income and education are particularly vulnerable to diets high in added sugars. However, there are differences within race/ethnicity groups that suggest that interventions aimed at reducing the intake of added sugars should be tailored to each group" (p 1382). Thompson, et al., note that while there are strong independent relationships between demographic factors and added sugar intake, environmental factors, including "greater advertising" may also affect outcomes. Their results fulfill the prediction of Beydoun and Wang that low income and low education will be associated with lower diet quality, in the form of higher added sugar intake. These are strong results that suggest comparisons and research questions for the contribution to the literature provided by the quantitative work here.

Dietary recall survey methods are frequently cited for self-underreporting of food consumption Huston and Finke (2003). I use three years of actual household purchase data rather than single- or two-day dietary recall, as every other study does. This removes one type of bias (dietary recall reporting), while perhaps introducing others (non-random sample, adjusted to reflect a random sample by Nielsen methodology[6]). Nielsen HomeScan has its own underreporting issues that rise with large families and female heads of household (Zhen, et al.: 2009).

[6] Einav, Leibtag, Nevo, 2010 indicate this is not likely to be a problem.

III. Research Objectives

Existing literature strongly supports the efficacy of examining purchases patterns over a multi-year panel to identify how demographic sub-groups respond to marketing of unhealthful foods. I find no evidence that anyone has done this using purchase data rather than dietary recall for sCSDs.

By focusing on sCSDs, I study the “worst” of the added sugar products by volume and by single-product health effect. The scope of the effect of sCSD consumption on American health, the diversity of the U.S. population, and existing evidence from a range of academic literatures present many questions that may be addressed using three years of marketing data for and household purchase of sCSDs – particularly when demographic information is available for all households in a demographically-weighted sample. We have just seen evidence that the consumption of sCSDs has risen more than for any other food group in the last thirty years. Is the rise uniform throughout the population? Does everyone drink many more ounces than before?

Research already confirms that people vary widely in their nutrition knowledge, beliefs, and choices (Variyam and Golan: 2002; Guthrie and Variyam: 2007; Neff, et al., 2009; Powell and Chaloupka: 2009). This variety is partially accounted by differences in sex, age, income, education, and ethnicity. Analysis is limited to characteristics we can observe or infer. But even within these limitations, consumers are combinations of characteristics. Researchers may regress on categoric variables such as age or income, but ultimately individuals exist in multiple dimensions, and the higher-income young may not behave as the higher-income old, in ways that can significantly differ from linear estimation results based on age or income alone. Demographic variables alone may never explain a large portion of household differences in tastes (Zhen, et al.: 2009). Estimations based on broad averages may poorly identify associations of high variability.

While some behavioral trends may be roughly identified by broad isolated characteristics, combinations of observable characteristics are more likely to identify trends at an interesting level. Of course sCSD purchase rises with household size. Similarly, people expect sCSD demand to vary by income level, education level, and racial group, and probably by the sex of the head of household. But why should any difference in purchase across changing household income be strongly similar across racial groups, or across levels of education? Might it not be the case that a college education would affect one's response to a price or advertising change differently if they were earning $20k/yr. versus $100k/yr. – whether for a luxury car, frozen chicken, or for sCSDs? By interacting demographic variables to identify specific demographic sub-groups, my objective is to determine if purchase responses to sCSD industry ***marketing variables*** – price, sale/price promotion, and advertising – differ significantly in ways that analysis using categoric variables would necessarily be constrained to overlook.

Formally and first, I seek to determine which household-level demographic characteristics are associated with the strongest sCSD-purchase response to sCSD industry marketing variables, and by identifying these characteristics to a more precise level, examine consumer behavior in more detail. This method implicitly checks for the relative robustness of effects already identified in the literature across other characteristics. For example if lower-educated households eat more added sugar relative to higher-educated households, is it true that lower-educated Hispanic households buy more sCSDs than higher-educated Hispanic households when they are on sale? If so is the difference greater or less than the difference for Asian households?

The same work can address numerous other questions. When deriving estimates for finer levels of demographic characteristics, interacted across income or education levels, are responses linear – which would validate a categoric variable approach – or non-linear, which would suggest that marketing strategies or policy proposals based on broad categoric data may prove inefficient? There is an existing literature associating demographic characteristics with high added-sugar consumption or high SSB or sCSD consumption, but from my search, the entire literature derives from single- or two-day dietary recall surveys. Compared to these results, does behavior identified by a three-year panel confirm, dispute, or add useful gradients to current findings? Specifically, studies with fewer demographic categories find that higher levels of family income or of formal education are associated with higher diet quality, and less added sugar intake.

Medical/nutrition literature using dietary recall data for added sugars generally do not interact education and income to control for education effects within income effects (and vice-versa), and only Thompson, et al. (2009), interact either variable type with racial group. If there are ethnically-based differences in purchase of sCSDs, the difference in purchase associated with rising education or income may not be identical between racial groups, and Thompson, et al., find differences from their nutrition survey data. By interacting purchase reactions with various marketing variables within education-racial-group or income-racial-group bands, the robustness of education or income effects to sub-cultural tastes may be implicitly checked. Delineated by demographic characteristic, are the same people that nutritionists, psychologists, and behavioral economists (including decision theorists) suggest would be poor food decision makers the same ones that respond least to price incentives, and most to sale and advertising incentives for sCSD purchase?

By interacting each group with sCSD industry-level marketing variables, it is possible to identify certain environmental factors contributing to sugar overconsumption that Thompson, et al., cannot account for.

Thus the analysis here may confirm or refute the findings of Thompson, et al., (and Beydoun and Wang) as they apply to the #1 source of added sugars in the U.S. diet. This analysis can further explore the robustness of demographic associations with one type of sugar intake in at least two ways. First, it can identify whether these demographic associations hold at more refined demographic levels, and whether effects are generally linear across categoric variables. Second, it can identify the degree to which these demographic associations with sCSD intake are associated with specific marketing tools (price, sale, or advertising). From specific demographic sub-group responses to marketing variables, we may infer policy strategies specific to the marketing that seems to affect those groups "particularly vulnerable to diets high in added sugars," to use the phrasing of Thompson, et alia.

I also explore all of the above for difference in the sex of heads of household, including in the presence of children. Do poorer or less educated parents buy more sCSDs than better-educated or higher-income parents? Are either group more reactive to sCSD advertising on television, to price promotions? Does ethnicity affect these reactions? Which household characteristics are associated with the highest reaction to all marketing variables, when children are present in the household? Which the least? Which households will tax-based policies likely effect most, which will education-based policies effect most, which will advertising restrictions effect most?

Broadly: will this deeper analysis, derived from panel data and household responses to industry marketing confirm, refute, or expand existing understanding in meaningful ways?

There is more than one valid perspective on whether sCSDs are normal economic goods, or inferior economic goods. They are highly palatable, and their consumption has doubled with rising incomes in the U.S. since the 1960s. Use is high enough that many people clearly do not treat sCSDs as a rare treat, despite strong suggestions to this effect from repeated iterations of the USDA's Dietary Guidelines (and food pyramid). This suggests sCSDs are a normal good. However, medical/nutrition literature using dietary recall data for added sugars generally (Thompson, et al.: 2009) and for SSBs (Zoellner, et al.: 2011) finds that consumption falls in rising income, suggesting that sCSDs are an inferior good. What will analysis based on actual purchase history suggest about the basic nature of sCSDs as an economic good?

IV. Methodology and Model

I conduct multivariable regression on demographic and marketing variables, the *dependent variable* being quantity of sCSDs purchased by a household in a week. There is a limited dependent variable problem, as the ease of household stocking of sCSDs enables multiple zero-purchase weeks. Because non-purchase in a week may result from not being in the market for sCSD purchase in a week (the household never considers purchase that week), or from a rejection of the marketing variable profile that week (the household considers purchase, but does not locate a satisfactory product, price, etc.), there is a sample selection problem when regressing marketing variables on household purchase. There is no certain means of identifying whether a zero-purchase week results from non-participation in the market or rejection of the market profile for sCSDs in a week. The sample-selection problem is thus with "being in the market" for sCSDs, not with household selection into the data sample. Heckman modeling (1979) to correct for self-selection bias is an accepted method for the data type used here (Zhen, et al.: 2009).

The Heckman two-step model establishes two equations, a *selection equation* assessing the probability of market participation in a given observation period, and an *outcome equation* gauging the quantitative result of participation. In this application, the first equation assesses the probability that a household selects into the market in a given observation period (modeling purchase decisions), and the second equation gauges the purchase quantity resulting from participation (modeling expenditure decisions). The dependent variable in the selection equation is a probit probability variable, 1 if purchase occurred and 0 otherwise. The dependent variable in the expenditure equation is ounces purchased by a household in a period, contingent on participation in the market. In the selection equation, purchase is equated with market participation, so the dependent variable does not fully reveal the latent variable of probability of market participation (as distinct from non-participation, which also generates a 0 observation).

By Heckman's design, using parameter estimates and variance from the selection model to inform estimation of the expenditure decision attempts to correct for the latency of the dependent variable in the expenditure equation. As participation in the market is only observed when there is positive purchase, there are no zero-purchase observations directly used in estimation of the second-stage, the expenditure equation. Existence of correlation between the error terms in the two equations itself confirms that selection into the market occurs in part from unobservables (Cameron and Trivedi, 2005: 552). As long as this covariance is non-zero, selection bias is a problem, and ordinary least squares (OLS) regression will not yield consistent estimates, due to likely nonlinearity and likely heteroskedastic error.

The covariance between the errors for the purchase (probit) and expenditure (OLS) equation estimations is the inverse Mills ratio (IMR), introduced as a missing regressor into the second equation to correct bias. Influence of the IMR requires that coefficients from estimation be modified to appreciate true marginal effects (Breen: 1996). Explanation of and equations for conditional expectations associated with the Heckman estimation process and conversion of coefficient results to true marginal effects are available upon request (the most relevant one is in the Technical Appendix). The Heckman two-step ("Heckit") estimator, is an efficient estimator of the explanatory variable set in the expenditure equation (Cameron and Trivedi: 2005).[7] "Exclusion restrictions" are variables that exist only on the probit side of the model, intended to explain selection into the market without necessarily explaining quantity purchase once commitment to purchase is certain. Exclusion restrictions help to more robustly identify the model, without relying solely on the nonlinearity of the functional form (Cameron and Trivedi, 2009: 546, 543).

The explanatory variable set for the reduced-form model will interact demographic characteristics with marketing variables. Observations are at the household level for one week, with the subscripts "H" (household) and "t" (time period = one week). Demographic and marketing variables exist in both equations, with seasonal binaries in the expenditure equation,

[7] The two-step model offers some advantages to the maximum likelihood estimation of Heckman when data are problematic and for large datasets (StataCorp. 2007. Stata Statistical Software: Release 10. College Station, TX: StataCorp LP: 560.)

and exclusion restriction variables in the selection equation. The single exception to this is the variable for purchase on Discount/Sale (price promotion), which cannot be regressed properly on the probit side, because the variable exists only when purchase occurred, by the data structure (further explanation when the variable is defined, in the Data section). By decomposing a hypothetical explanatory variable set $\mathbf{x}$, into demographic ($\tilde{\mathbf{x}}$) and non-demographic ($\bar{\mathbf{x}}$) component vectors, we can simplify notation:

$$y_{Ht} = \alpha_0 + \tilde{\mathbf{x}}_{Ht}^{'}\beta + \bar{\mathbf{x}}_{Ht}^{'}\gamma + v_{Ht} \; , \tag{1}$$

where α_0 is the intercept, belonging to neither the demographic parameter set β , nor the non-demographic parameter set γ, the unscripted coefficient vectors for their respective explanatory variable sets, and v_{Ht} is the additive error term. Interaction of the demographic explanatory variable set with each of the three marketing variables – Price, Sale, Advertising, where each exists individually in the non-demographic variable vector – involves a simple replication of the demographic component vector for each marketing variable. Thus the second right-hand-side term in (1) and in (2) also appears in the third, fourth, and fifth terms in (2):

$$y_{Ht} = \alpha_0 + \tilde{\mathbf{x}}_{Ht}^{'}\beta + P * \tilde{\mathbf{x}}_{Ht}^{'}\beta + Sale * \tilde{\mathbf{x}}_{Ht}^{'}\beta + Adv * \tilde{\mathbf{x}}_{Ht}^{'}\beta + \bar{\mathbf{x}}_{Ht}^{'}\gamma + v_{Ht} \; . \tag{2}$$

The purchase equation can be conceived as (1), and the expenditure equation in the models of estimation can be conceived as (1) or (2). Identification of purchase responses to the three marketing variables for particular demographic characteristics is possible only through the interaction of demographic and marketing terms in (2). In all the models, interaction between the demographic variables and each of the marketing variables is introduced only in the expenditure/outcome equation.

Preliminary regressions used a BASIC model where all relevant demographic variables were categoric, and a BROAD model, where categoric demographic variables were decomposed to *level* variables within the *categories*. Education variables for head of household (**HHH**) by level are: Less than High School (including grade school or less), High School, Some College, College, and Post-College. Income may similarly be a categoric variable or decomposed to levels. Variables for ethnic groups could not exist as levels, but could be interacted with income or education levels, and of course with marketing variables. “Race” when capitalized refers to the original data variable: White, African American, Asian, or Other Race. “Racial groups” or “ethnic groups” capitalized or not, refer to the set of five groups, adding Hispanic to the original set, with the implicit understanding that when reference groups are chosen, “Race” uses White, while “Hispanic” implicitly uses non-Hispanic.

This paper focuses on a result subset from a REFINED model, where all demographic variables are the interaction of at least one variable level and another demographic characteristic. Any demographic “group” in the REFINED model here is thus relative to any category level in fact a ***sub-group***, which exists at a level for each of two combined categories. For example when the group “female head of household whose education level is high school” is interacted with the six levels of household income, this generates six sub-groups for that education level. Similarly, interacting a single household income level with any of the female head of household education levels generates five sub-groups.

Levels comprise the following seven combined categories, where ***HH*** designates “household,” and ***HHH*** designates “head of household”:

- *Income x (Male/Fem HHH) Education*
- *Income x Race (/Hispanic)*
- *Income x HH Size*
- *Income x # of Kids in HH*
- *Income x (Male/Fem HHH) Age*
- *(Male/Fem HHH) Educ x Race (/Hispanic)*
- *(Male/Fem HHH) Educ x # of Kids in HH*.

The high number of coefficients resulting from this specification allow the identification of marginal effects specific to precise demographic sub-groups, and comparison of results in multiple configurations (e.g., across levels of Income and separately across number of children in the household at each Income level), for deeper insight into real-world behavior. Income or Education effects (which are generally expected to conflict if sCSDs are a normal good) can be checked for their robustness across Race, Number of Children, or Age.

Within each of the bulleted combined categories, a reference sub-group is dropped to avoid the dummy variable trap, so every variable in any category combination is estimated as the marginal effect versus the reference sub-group. This allows for comparison of a ***set*** of marginal effects that all reflect to the same reference group (a set spans all combinations of the two demographic groups that are interacted in sub-groups from the BROAD model). Comparison of sets occasionally establishes a level of consistency enabling some comparison of results across different demographic-demographic category combinations – a method that introduces another level of analysis for marginal effects on marketing-variable interaction variables. However, because the combination of two categories establishes a second-tier dummy-variable trap, beyond dropping the reference sub-group, one level of one of the categories cannot be combined with all of the levels of the other category in the combination. Summary statistics, and previous iterations of estimation informed the choices for which category levels to simply list as variables in the equation of estimation, rather than including them in the combined category sets.[8] Little inference is done on these variables, which are included in the estimation because dropping them entirely would resign their effects into the reference groups, rather than controlling for their effects.

V. Data and Empirical Implementation

Data are from AC Nielson, weekly HomeScan, spanning three years from February 2006 through to December 2008 (152 weekly "Process Periods"), and 16 Designated Marketing Areas (DMAs): Atlanta, Baltimore, Boston, Chicago, Detroit, Hartford & New Haven, Houston, Kansas City, Los Angeles, Miami – Ft. Lauderdale, New York, Philadelphia, San Francisco – Oakland – San Jose, Seattle – Tacoma, Springfield – Holyoke (MA), and Washington D.C. DMAs are defined by the spatial range of metropolitan commercial television broadcast markets to the county level, and thus extend across urban households to suburban and some rural households. This data set combines specific purchase information, recorded after purchase by household members, with the demographic information of the participating household. Because some households end HomeScan participation and others enter in a given year, the number of households (HHs) in each annual panel varies: 17,278 households in 2006; 17,883 in 2007; 17,772 in 2008; for an average 17,628 households in an annual panel. After data management procedures that included totaling daily purchases to the weekly level, there were 459,392 non-zero purchase observations within the sweetened carbonated soft-drink product category, across all HHs over the three years. About 48% of all SSBs are purchased in supermarkets and general merchandise stores (and would hypothetically enter this data set), with the balance from restaurants (12%) and convenience stores and vending machines (20%) (Ogden, et al.: 2011; NPLAN: 2011). Findings here represent a lower limit on the purchase effects of marketing

[8] Because Income and Education are the primary interacted categories, the category level drops are taken from the other five categories: No Male HHH, No Female HHH, Other Race, 4 Kids or more, Female Age greater than 65, Male Age greater than 65, and HH Size 5 or more. The un-combined category levels listed here, from the second-tier dummy variable trap, were not interacted with marketing variables.

variables, but nothing specific to this data set or empirical methodology allows inference as to the linear or nonlinear application of these marketing variable responses to away-from-home purchase decisions or consumption.

Also from Nielsen are sCSD (television) advertising data corresponding to Nielson DMAs. The television advertising industry has defined standard units known as “gross rating points” (GRPs) that measure a target audience’s viewing exposure to specific advertising within a broadcast market Nielsen advertising data categorizes the DMA-level GRPs to a certain level of demographic granularity. For example the entire data set includes age-specific GRPs for children. For variable construction here, this enables calibration of mean advertising exposure to the age-specific number of individuals in a household.

Raw data from Nielsen offers a “projection-factor weighting” number for each household in each year. This number is computed using a proprietary Nielsen methodology to weight each HH so that the dimensions of particular demographic characteristics can be treated as proportionally representing true population frequencies within the DMA.[9] Nielsen-assigned Projection Factors at the HH level are used to weight the data in this study, so that inference on estimation results applies to populations, rather than merely to Nielsen sample-household behaviors. Assuming that Nielsen’s Projection Factor methodology is sound, the particular 16-DMA sample here implies that for this study there was effective sampling from roughly one-third of the U.S. population. With proper econometric application, estimation results should prove statistically and economically robust.

This analysis is structured to use household observations to address effects at the product-category level rather than to identify brand-specific reactions to price sale or advertising, as the biological effects of sCSD consumption are not brand-specific. The three marketing variables defined below are not product specific, but each yields a coefficient that can be interpreted in ounces per week, once multiplied by some selected level – here average value of the continuous marketing variable across the final data configuration.

The Price variable here is an index, in dollars per ounce. It is constructed in multiple steps – designed to insulate against any potential endogeneity between the Price Index and HH

[9] For example, given the relatively few sampled HHs with household heads under 30 years of age, the Projection Factor associated with such a household would be higher than for a household with a head between 50 and 65 years, but the same Projection Factor assigned to the HH would also be weighted to reflect Income, Race, and other demographic characteristics, in order to make the HH representative of households similar to others in the DMA by any of a range of measures.

quantity purchased. DMA-week brand prices are weighted by "U.S."-brand-market shares (across the 16 DMAs), and averaged, retaining the plausibility of both the average price and the average market share for the product-category. This protects against endogeneity with household-level purchase quantity and provides Price values for weeks in which a HH does not purchase. All Price Index values are adjusted for inflation across the three-year data span, using a Consumer-Price-Index monthly adjustment factor from the U.S. Bureau of Labor Statistics.

While the construction of the Price Index is consistent with targeting consumer response to the entire product-category, the coefficients of estimation on the price variable may depict less quantity response than they would if prices were constrained to the specific products an individual HH routinely considers purchasing, but these cannot be completely identified. We may expect price-response coefficients to be of lower magnitude than if the coefficients corresponded to prices on household-selected products rather than on the full product category. This would be an effective damping of the signal conveying price-reactivity in household purchasing, because category prices are regressed on what ultimately must be household purchases of a limited number of actual products whose specific prices do not exist as unique regressors.[10]

The ***Discount/Sale*** variable is not an index, it simply identifies any type of HomeScan-coded "Sale" or price promotion from the many types that Nielsen defines. If the HH noted that the item was discounted in price, (without specifically identifying a coupon application exclusively), the variable is non-zero. The "Disc/Sale," or "Sale," variable exists only when purchase occurred, a one-to-one correspondence from the data structure. This forces linear combination within the explanatory variable set in the selection (probit) equation, and standard error approaching infinity, as well as artificially deflating the IMR, given the false impression that presence of Sale is invariable. The Disc/Sale variable is easily omitted from the probit (purchase) equation, once we realize that if the information that something is on sale *can* impact the decision-making process, then one is already considering or amenable to purchase, and is

[10] It is important to remember that because the Price Index here is built from actual purchases rather than the actual choice set, it is likely to favor by inclusion more price-competitive products, products on sale, and possibly more heavily advertised products than the entire population might buy, particularly if brands not well-represented in the national market share constructed here proved to be consistently significant and higher in DMA-market share than they appear to be here. Compared to constructions built from fully-known shelf availability, prices, and documented promotions, the estimated mean prices for the sCSD category here may well be lower, the estimated mean percentage of the category on sale may be higher, and the effect of advertising may be higher than if these variables could be regressed on a full-information price-product set.

therefore already in the market. Buying something on Sale cannot be a determinant of market participation, because it follows from market participation. So exclusion of the Disc/Sale variable in probit estimation is reasonable on strictly logical grounds, given that this dataset does not identify price promotions without there having been purchase.

The Advertising variable (generally designated “Adv” or “Advert” in Results tables) is also an index, and its units are in GRPs at a household level, specific to a particular DMA in a given week. The specific advertising data configuration used here is GRP exposures for a DMA-week combination, across types of television broadcast (cable, network, syndicated, and spot television placements), for each of five age categories: 2-5 years, 6-11 years, 12-17 years, 18-24 years, and 25+ years; thus presenting 20 GRP numbers for each DMA-week. I calibrate household-specific GRP exposure to the number and age of HH members by adding the GRP exposure types into a HH weekly total according to demographic data listings for age and number of each household member. Thus the advertising observation for a specific household in a week is that household’s estimated exposure to television advertising of any sCSD, with GRP exposure based on the number and age of that HH’s members, and on the original DMA-week GRP exposure indexes compiled from Nielsen.

As with the Price Index, the construction of the Advertising Index is consistent with targeting consumer response to the entire product-category, so the coefficients of estimation on Advertising variables may depict less quantity response than they would if advertising were examined for the specific products an individual HH routinely considers purchasing. Identifying these is outside the scope of analysis of consumer types to product-category-level marketing variables. Paralleling the potential effect associated with the Price Index, there could be an effective damping of the signal conveying advertising-reactivity in household purchasing, because category–level advertising is regressed on what ultimately must be household purchases of a limited number of actual products whose specific advertising GRPs do not exist as unique regressors.

A dataset consisting of only purchase observations cannot directly represent the choice not to purchase as a valid response to a price promotion or increased advertising. So regressing on only positive observations with no other modeling correction would mis-specify a model seeking to answer these research questions. It is therefore necessary to balance the panel with demographic information fully listed for every week in which households are in the panel, including weeks without purchase. The integrity of the Nielsen data-gathering process ensures that these filled-in zeros are actual purchase observations for the household for the week. As the Price and Advertising Indexes are constructed so that they have non-zero values in non-purchase weeks for every household, the "fill-in" expands the ability of the existing dataset to characterize real-world behavior. With every house existing in the Nielsen panel during a year now having an observation – zero or positive purchase – every week, the number of observations rises to 2,666,124. With the filled-in zeros, non-purchase observations represent 82.8% of all observations. The post fill-in data configuration reveals in a way that is less obvious before the fill in, that given the extremely shelf-stable nature of the product, HHs do appear to engage in stocking behavior, and purchase at supermarkets usually to replace consumed HH stocks of sCSDs.

The filled-in zero-purchase observations created cell space in the data for implementation of the "household stocking variable" to be used as an exclusion restriction variable (section 3.1). Based on tabulated HH-average annual frequency of purchase numbers (10.16, stand. dev. 0.046) frequency of purchases greater than 67 ounces (third line in Table 1, below), and previous iterations of the model, the six-week degrading stock variable fit best. The "MovingAvgHHstock6" variable begins with the week's purchase in ounces, and subtracts one-sixth of the volume for each subsequent week, with the process of addition and stock subtraction overlapping with any new purchase.

VI. Results

Descriptive Statistics, Selected Race-/Hispanic-Specific Means, and Mean Purchase By Demographic Variables Decomposed to Category Levels

Table 1 presents descriptive statistics for the dependent and explanatory variables, with many demographic variables here covering an entire demographic category. Category-spanning variables will be decomposed into category levels for more complex versions of the model. Across all observations, including zero-purchase weeks for households, the weekly HH-average purchase total (the dependent variable) is 47.8 ounces, the equivalent of two now standard-sized 20-ounce bottles, plus a 1960's standard-serving-sized 8-ounce bottle. The standard deviation over three times the mean indicates the extreme variation in purchase quantity when over 80% of observations are zero purchase. So it is useful to see how the purchase statistics change when only positive purchase observations are considered, the next line in the table. Counting only the

HH weekly observations for which purchase occurred, the average rises over five times to 277.4 ounces, the equivalent of four two-liter bottles, again plus a 1960's standard-serving-sized 8-ounce bottle. For this amount, the standard deviation has dropped to roughly 110% of the mean, depicting far less variance than for the zero-purchase-inclusive average. The mean number of weeks in a year that HHs purchase more than a two-liter bottle (a six-pack of 12-ounce cans is more fluid than a two-liter bottle; variable depicted "WksHHTotOzGrtr67", the first exclusionary restriction, in probit estimation results) is 7.77, with a standard deviation roughly 120% of the mean, again depicting large variance in HH behavior. These basic statistics support the observation that sCSDs are routinely purchased in quantities greater than for immediate consumption, stocked, and consumed over a period of time.

The Price and Advertising variables are each indexes, constructed across all sCSDs to a weekly level within each DMA. So the mean price in $/oz across all DMAs for all weeks is 2.2 cents per ounce, with a standard deviation around one-tenth that. The following line reflects prices adjusted for inflation using the Bureau of Labor Statistics' Consumer Price Index tables. The standard deviation, at almost half the mean, is much larger than for the unadjusted mean.[11]

The ratio of standard deviation to the mean of average HH advertising exposure in GRPs is less than 100%, indicating far less variance than for the purchase and purchase frequency variables above. The minimum and maximum do show there is a wide range in weekly sCSD-advert GRPs from the most to least saturated markets.

The portion of observations that Nielsen HomeScan participants indicated were on sale in some form is 5.3%, once again with a relatively large standard deviation across weekly averages, perhaps indicating the periodic nature of company-sponsored sales. Restricted to positive-purchase observations, the percent purchased on sale jumps to 30.5%, which indicates something about the timing of purchases, or as can be inferred by the mean of weeks-per-year-greater-than-67-ounces, the timing of household re-stocking purchases. Again, a standard deviation greater than the mean for the percentage of positive purchases on sale indicates high variability in sale purchase – a single standard deviation defines purchase-on-sale frequency from 0 to 75 percent. The number of ounces purchased on average under a promotional price discount (sale) is 328.5, with a relatively miniscule standard deviation. As might be expected, mean purchase on sale is

[11] For this second mean price-per-ounce, the maximum value is forcibly determined by excluding prices per ounce above $0.50, as this is over twenty times the mean and many standard deviations away, suggesting errors in data entry by participating households.

more than the 277.4-ounce mean for positive purchases broadly, by some 50 ounces, or about 2/3 of a two-liter bottle.

Moving to the demographic variables, the sixteen Nielsen categories for household income range from “Under $5000” to “$100,000 & Over.” The mean HH Income of 20.8 in this dataset indicates around $50,000 per year, although the standard deviation indicates little population concentration around this mean – note that plus one standard deviation pushes to the $70,000 range, and minus one standard deviation pushes to the $25,000 range.

Education levels and Age levels are for the household head. There may be a single head of household (HHH, male or female), or two heads of household (both male and female). All HHH-identified Nielsen variables apply to a single sex. For either sex of HHH, there are six levels within the category that can define the highest level of education completed, and a null option indicating there is no HHH of that sex in the home. The higher mean education level for Female HHHs falls between High School graduate and Some College, as it also does for Male HHHs. The variance suggested by adding or subtracting a standard deviation indicates little concentration around the mean, and greater variation in the Male HHH education level.

Under Nielsen’s “Race” variable there are four groups, and the portion of each in the sample is reported by the mean here: White 76.1%, African American 13.4%, Asian 4.6%, Other Race 5.9%. Whether a HHH identifies as Hispanic is identified with a binary question separate from the Race question. It is therefore possible to be non-Hispanic, or White-, AfrAm-, or Asian-Hispanic, and all of these combinations exist in the data.[12]

Mean household size is 2.4, but again, the standard deviation suggests little clustering around the mean. 26.9% of households have one or more children. When children are in the home, the HH purchase average including zero-purchase weeks is 50% higher than the overall HH purchase average mean, but across only positive purchases, the mean with children is only 10% higher. The HHH average Age for females (~45 years) is higher than for males (~40 years), but the dispersion is again high, and higher for male HHHs.

The mean values for the seasons represent their proportion in the data, and reflect that the first weeks of January 2006 are not in the dataset.

[12] The only way to not be one of these is to identify as Other Race and select Hispanic versus non-Hispanic. Other Race would also include any other group not self-identifying as White or Asian, including Hawaiians and other indigenous peoples of the Americas or elsewhere. So there is no pre-determination of strongly correlated behavior between the Other Race group and the group identifying as Hispanic versus non-Hispanic. Of the sampled households, 7.7% self-identify as Hispanic, but these are necessarily all distributed across the four Race categories.

It will prove useful in analysis of model results to have benchmark comparisons of Income, Education level, and HH Size averages across racial groups, and the lower portion of Table 1 offers these.[13] The average income for White HHs is close to the whole-sample average, with almost the same standard deviation. African-American and Other Race averages are lower, with African American HH incomes being a bit more dispersed. Hispanic average HH incomes are greater than White HHs, and Asian average HH incomes are much higher than for all other groups, with the least dispersion. This higher income corresponds with outstandingly higher level of Education, averaged across Male and Female HHHs, for Asian HHs. Again self-identified Hispanic HHs top White HHs, which also place lower than Other Race HHs in average HHH Education level. African-American households have the lowest average Education level (High School), just greater than one entire level (of the 6) below the Asian average (of almost halfway between Some College, and College). Whites maintain the smallest average HH Sizes at between 2.25 and 2.5, with an increase in size and dispersion for African American average HH Sizes, also under 2.5. For other non-White groups, there is an increase in average household size relative to White HHs, all of these being closer to 3 than to 2 or 2.5. On average, Hispanics maintain the largest HHs. Dataset frequency distributions for demographic variables are available upon request.

For the demographic variables that were category-wide in Table 1, **Table 2** decomposes the category variables, as well as Race, Hispanic, and a few additional variables at the end of the table, for reference. For each level of these variables, statistics for mean weekly HH purchase in ounces are listed (zero-purchase weeks excluded, similar to the adjustment in the expenditure equation within Heckit estimation). Bold numbers indicate the highest mean within the category cluster. Income levels are relative to the federally-defined poverty level for a family of four (**Pov4Inc**), which is in the $20,600 range from 2006-2008.[14] Income is decomposed into the following levels: from zero to half the Pov4Inc, half the Pov4Inc to Pov4Inc, from Pov4Inc to twice Pov4Inc, etcetera, through to 5 times the Pov4Inc and higher. The highest income category in Nielsen's raw data is "$100,000 and above." This notation referencing the poverty level for a

[13] All of these demographic numbers specifically correspond to the Nielsen sample, and are calculated *before* application of Nielsen's Projection Factor, which is used to generalize purchase behavior to the larger populations of the sampled DMAs. From a previous note: "Racial groups" capitalized or not, refer to the set of five groups, adding Hispanic to the original "Race" variable set, with the implicit understanding that when reference groups are chosen, "Race" uses White, while "Hispanic" implicitly uses non-Hispanic.

[14] U.S. Department of Health & Human Services website, accessed 5/19/2011: http://aspe.hhs.gov/poverty/figures-fed-reg.shtml . 2006: $20,000; 2007: $20,650; 2008: $21,200.

U.S. family of four over the data period will be applied in future tables and results, sometimes with variants of shorter notation, such as: "**x3PovInc**" or "**HfPvInc**" or even "**x2Inc**." Because the highest mean weekly purchase by one of these groups is for x4Pov4Inc, it is immediately clear that consumption is unlikely to increase or decrease in a linear fashion across all the income levels.

Defining five levels of education for HHHs of either sex, we see that across both sexes there is a strict fall in weekly purchase for each discrete category-level rise in education for the HHH, from over 315-oz/wk. down to under 250-oz/wk.

At 286.7 ounces/purchase-wk, Asian HHs have the highest average weekly purchase by Race, with African American HHs over 40-oz/purchase-wk lower. As when the same figures are run including zero-purchase weeks, Asian HHs show the lowest purchase (one-third below African-American HHs; figures available on request), this contrast indicates high-quantity, infrequent purchase by Asian HHs relative to all other HH types by ethnic group.

Ounces purchased per week do strictly rise in Household Size and in Number of Children, but not by equal increments – per capita purchase actually falls as the number of people in the home (by either measure) rises.

For either sex of HHH, the age level with the highest weekly purchase is 40-50 years. This fact corresponds well to HHH-Age breakdowns by HH Size and presence of children (figures available on request).

For reference, mean weekly ounces purchased for only Male HHH ("No Fem Hd") and only Female HHH ("No Male Hd") are included. Male-only HHH homes average higher, consistent with the fact that, except for the lowest level of Female Education, households with Male heads (or both) buy more on average than households with Female heads (or both) at every level of Education and Age. The Male- and Female-only averages are less than the general HH average because they tend to have smaller household sizes.

As expected, controlling for no other factors, the highest mean weekly purchase is in Summer, followed by Autumn, Spring, then Winter – basically dropping with average seasonal temperature for the U.S.

Estimation Results

The REFINED model specification of focus here allows degrees of estimated effects to vary across levels within one category while remaining fixed in another, rather than being fixed increments independent of another category, as they are in the BASIC and BROAD models. Thus the REFINED model enables observation of how for example Whites and Asians may differ in purchase response to rising sCSD Price as HH Income rises for each from low to high levels. To reiterate, the *dependent variable* in the outcome/expenditure equation is: weekly purchase of sCSDs at the HH level, in ounces (for weeks that purchase occurs).

For all regression results, heterogeneity is controlled for with proactive use of robust estimators, and endogeneity between the price vector and purchase quantity (dependent variable) vectors is rejected by hypothesis testing (see Technical Appendix). Standard goodness-of-fit measures of model comparison such as R^2 and Akaike or Bayesian information criterion do not apply for the two-stage Heckman ("Heckit" model), but as model sophistication goes up (more explanatory variables in the REFINED than the BROAD model, and in the BROAD versus the BASIC model), the magnitudes of "catch-all" constants, binaries, seasonal variables, and un-interacted continuous marketing-mix variables all fall. This provides some empirical evidence that the most complex models (with interaction of demographic variables defining analysis to the sub-group level, and interacting these further with marketing-mix variables) fit the data best, with the sub-group variables explaining more variation in the dependent variable than the aggregate variables. The models all fit well with expectations for simple (un-interacted) variables, indicating a robust overall modeling structure. While only the REFINED model is suitable for addressing the primary research questions of interest here, there is compelling evidence that allowing for flexibility in degree of effect within levels of a demographic variable category does provide further defensible analytical insights beyond the useful results inferable from the BASIC and BROAD models.

All heckman estimation model results confirmed significant (non-zero) correlation between the selection and outcome equations. Thus a selection model is appropriate, and a simple OLS, Tobit, or Two-Part model would be mis-specified if applied to this data configuration. Further, in all the models, the Inverse Mills Ratio (IMR) is significant to below the 1% level, suggesting that the appropriate correction factor for the OLS equation is transferred through the two-step estimation process.[15]

[15] As the regression output table for the REFINED model is 25 pages long, it is omitted, but is available upon request, as are output tables from the BASIC and BROAD configurations.

Despite the need to correct for marginal effects to conduct proper inference on the households that select into the market (see Technical Appendix), the non-mfx-adjusted OLS-side coefficient estimates still represent the marginal effects of variables on the population as a whole. So we must expect at the least that estimated coefficients for the marketing-mix variables remain of expected signs (negative on Price, positive on Sale and Advertising) for the unadjusted OLS-side coefficient estimates. Along with the constant, seasonal dummies, and the two exclusion-restriction variables, the OLS-side marketing-mix variables are of the expected sign in all estimated versions of the model, confirming to an extent the choice of specification of models, variables, and estimators. All nine of these variables are significant to better than 1% significance in all estimations of the model, with the exception of Disc/Sale in REFINED, which is better than 10% significance.[16]

All results discussed from this point are for household purchase response associated with a particular demographic characteristic to a particular sCSD industry marketing-mix variable (Price, Sale, or Advertising), unless otherwise noted. No single estimation coefficient is used in isolation to infer purchase behavior for a demographic group or sub-group. (Again, a sub-group is a slice of a group defined by a particular characteristic, as for example, lower-educated Asian HHs within Asian HHs or within lower-educated HHs.) Thus, instead of interpreting the heckman-adjusted marginal effects for any group or sub-group alone, a group/sub-group marginal effect is combined with a marketing-variable-specific marginal effect, so that reported values are Combined Marginal Effects (**CMEs**).

After estimation, prediction is conducted, with **Prediction Tables** constructed so that each table cell represents a predicted weekly HH purchase quantity for a single representative HH type, comprised of estimation results for specific characteristics. (Hundreds of such household-representative combinations may be constructed from the regression results of the REFINED model.) Each HH type must exist in all demographic dimensions upon which regression was conducted: Income, (Female/Male HHH) Education level, racial group, HH size, # of Kids in HH, (Female/Male HHH) Age. Thus, with sex of HHH difference, there are seven characteristics that can vary. All prediction tables reported here are fixed in HHH Age, at 40-50 years, and the reference season spring is assumed for all prediction table cells. One table type has

[16] This higher variance may be expected for a binary variable that has had much of its variation explained (controlled for) through its interaction with some 250+ specific demographic sub-groups.

Male and Female HHHs, and two children, for a HH size=4. There is one variant of each, so that either there is a single Male or single Female HH head, with all other characteristics the same (HH size=3). This isolates sex-of-HHH-specific parenting choices reflected in sCSD purchase for two-child single-parent homes. Fixing certain demographic characteristics enables analysis according to variation in other characteristics, particularly variation in the primary variables of interest to the core research questions here: Income level, Education level, and racial group. Secondarily, the sex of the HHH is compared for purchase-reactivity to marketing variables.

The REFINED model prediction tables with reactions to rising Price for HH Size=4 show a flexibility in response across Income and Education levels by racial group that exposes weaknesses in assumptions implicit in models such as the BASIC and BROAD that do not refine analysis to the demographic sub-group level, and therefore constrain estimable reactivity. One measure of this is the span from lowest to highest cell value in Prediction Tables for HH purchase reactions to a rise in the Price variable (an index). The span for the BASIC and BROAD prediction tables (not presented), were 148 and 222 ounces, respectively for HH size=4. For the REFINED model prediction tables, HH size=4 in rising Price or Advertising, or purchase on Sale, the span in each is over 600 ounces. In the REFINED specification, each sub-group reacts independently of other sub-groups, even if they share common elements. Responses different from base-group assumptions stand now in sharper relief, with many individual cells breaking from the reference-sub-group levels by over 350 and even over 550 ounces (in the BASIC there were none over 350 ounces, and in the BROAD only a few cells at HH size=4).

In the top half of prediction tables, Income level varies across one of two fixed Education levels (one low, one high) and across racial groups. In the bottom half of prediction tables, Education level varies across one of two fixed Income levels (one low, one high) and across racial groups. It is then possible to determine whether one HH type is predicted to buy more than a reference group, or to compare a set of HH types to another set. For example one common comparison is *whether the two lowest-Income HH types buy more or less than the two highest-Income HH types for a fixed level of education*. If they do, I refer to this as HH purchase "**rising in Income**." The vocabulary mirrors for falls and across education levels. The result can easily be compared across racial groups, given the construction of the table. This checks the robustness of any (expected positive) income or (expected negative) education effect across sub-cultural categorization, similar to the way that breaking the Income and Education categoric variables into levels allows a check for the robustness of income or education effects. I will use the term the "income effect *dominated* the education effect" to mean that one set of variables' directions and magnitudes appear to overwhelm another variables' set of directions and magnitudes. This result can be *weak* or *strong domination*, based on multiple comparisons enabled by the structure of prediction tables, where levels of one variable (Income or Education) differ while held fixed at a low or high level of another variable level (Education or Income).

Prediction Tables 3a – 3c represent predicted HH purchase in ounces for purchase weeks, including the reaction to a rise in the Price index variable. All the tables hold the number of Kids=2, and Age of HHHs Fem/Male=40-50 fixed, and include the constant in every cell. Cells differ by Income level, Education level, and racial group, depending on their placement in the grid. The unique combination of reference-sub-group assumptions to which all the cells are relative is not a combination presented in any of the prediction table configurations: x5PvInc, (Fem/Male) Post College, White, Non-Hispanic, HH Size=1, No Kids, (Fem/Male) Age 50-65. The reference group for season, "spring" is assumed. Changing the season to summer would raise every number in the table by 26.7 ounces. Prediction Table 3a is for HHs with a Male and Female HHH, for HH size=4, while 3b drops the Male HHH, and 3c instead drops the Female HHH. In cells, relative to reference-sub-group reactions, 40%-shaded totals are 550+ ounces given weekly purchase, 25%-shaded totals are 350+ ounces, 10%-shaded totals are under 100 ounces, and bold totals are negative. A detailed analysis of prediction table 3a is offered to demonstrate the interpretive method for and the richness of these prediction tables, then less comprehensive commentary is offered for later tables.

By percentage of cells shaded in (half-)column or (half-)row, Hispanic HHs (vs. non-Hispanics) are the big purchasers when accounting for reaction to higher Price. There is a clear insensitivity to Price in Hispanic HHs that was not clear in less sophisticated (BASIC or BROAD) specifications. Next by percentage in column or row it is clear that Less High School HHs are least Price-sensitive of the Education levels, with HS a distant second: lower Education HHHs are least Price-sensitive. Even the Price-insensitive Hispanic HH reaction strictly becomes less positive in rising Education in the bottom half of the table (without falling from HS to Some College at x4PvInc). This is a gradient display of the rough effect evident in the top half of the table where Hispanic HS Ed has 4 of 6 Income levels 25%-shaded, and Hispanic College has but 1 of 6.

Next by percentage in column or row are HfPvInc x HS Ed (3 of 4), and x5PvInc x HS Ed (3 of 4), both in the upper-left quadrant. Both Income levels are insensitive to Price, but the average of the four cells at HfPvInc is over 20 ounces higher (377 versus 355) than the x5PvInc average. x1- and x2PvInc each have 2 cells over 350 across the row, whereas x3- and x4PvInc do not. Lower-Income HHs are less Price sensitive than middle-Income HHs, but not less Price sensitive than upper-Income HHs ($100k/yr+). Perhaps the upper Income HHs no longer consider sCSDs to be a portion of the HH budget worthy of concern, or perhaps they do not let Price increases on so small a budgetary item affect their purchase schedule or purchase whims as middle-Income HHs relatively seem to. It is possible that the lower-Income HHs behavior is not economically rational, because it is so much less Price responsive than the reference sub-group, and this might indicate habitual behavior trumping economic behavior. It is also possible that the behavior is rational in buying more at a higher relative price, because the higher margin paid is less than the search cost of matching a lower price given a pre-existing commitment to purchase.

Next by percentage in column or row is White in HS Ed (3 of 6), whose cell values are higher than African-American (Afr-Amer) HHs at every row in the table, so White HHs are less Price-sensitive than Afr Amer HHs. White HHs are less Price-sensitive than Asian HHs at lower Income levels, and more Price-sensitive at higher levels. Asian HHs are exceptionally Price sensitive for the lower three Income levels at fixed College Education, and at the upper three education levels in fixed x1PvInc, falling below 100 in these combinations (the 54 value is a duplicate, for 5 cells in Asian <100 ounces; 10%-shaded cells). At the higher fixed level of Income, Hispanic HHs have an extreme taper in higher Education levels, generating the only other sub-100 CME in 3a. The combination of high Income and high Education triggers a reversal of purchase response in Hispanic HHs from the highest value in the table at Less HS x1PvInc, to one of the lowest in the table at x4PvInc Post College. Comparing changes in Income level versus changes in Education level in Hispanic half-columns, the education effect is the stronger driver of this extreme taper in predicted quantity.

Moving from the prevalence of exceptional predicted quantities to within- and cross-quadrant analysis, in fixed HS Ed & fixed College Ed across Income levels (top half of table) all racial group HHs are less Price-sensitive (have higher average quantities) at the lower three Incomes than the higher three, except Asian HHs. This may indicate stronger habit in purchase behavior or reduced access to price-competitive purchase venues. In Price sensitivity, the income effect is negative for all racial group HHs but Asian HHs. Asian HHs are more sensitive to Price at higher education levels, and far less sensitive at either lower education levels or higher (top three) Income levels. Separating sex of HHH will provide more evidence to analyze this apparently anomalous Asian HH behavior. By Income-level-racial-group combination, every CME is greater in HS (top-left) than College (top-right), with drops of 150 ounces common, strongly underscoring an education effect. There are 10 CMEs in fixed HS over 350, but only 1 in fixed College. Averaging the values in the top-left (HS) quadrant and subtracting the average from the top-right (College) quadrant, HS-educated HHs buy 114 more ounces when they buy than do College-educated HHs.

In the lower-left quadrant there is a strong education effect, but short of a strict fall in CME in Price for any racial group but Hispanic. In the lower-right quadrant, there is also a strong education effect, but short of a strict fall in CME in Price for any racial group but White, with a plateau between two Hispanic Educ levels. All racial groups have much higher CMEs comparing the lowest two Educ levels to the top two, for x1 or x4PvInc quadrants (the gap is smaller in Afr-Amer at x4PvInc).

The difference in averages between these two bottom quadrants is poverty-level-Income for a family of four HHs buying 57 more ounces at purchase than HH Incomes four times the poverty-level-Income for a family of four. If the HS-to-College gap can be directly compared to a 4-times-HH-Income gap, we can say by these differences in average that the education effect in HHs with both sexes of HHHs is dominant, nearly twice the income effect on purchase – and that is allowing that the income effect in Price is the *reverse* economic expectation (i.e., in the same direction as the education effect).

In fixed Educ level across Income levels (top half), the first observation is that the effect across Income levels is certainly not linear, and in fact peaks in the HS quadrant at three different Income levels for four racial groups. This is a strong indictment of the validity of the BASIC model, and questions the soundness of the BROAD model. Across the rows, every racial group except Asian HHs falls significantly in CME value from x2- to x3PvInc, and from x3- to x4PvInc, and every group including Asian HHs rises significantly from x4- to x5PvInc. White and Afr-Amer HHs fall significantly from HfPv- to x1PvInc, but Asian and Hispanic HHs do not. Except Hispanic HHs all racial groups rise in CME from x1PvInc to x2PvInc. The middle Income levels seem most Price reactive (fewest 25%-shaded boxes in these rows in top half).

There is a twist to the argument for an unexpectedly negative income effect. Splitting the three lower-Income-level HHs as a separate group from the three upper-Income-level HHs, there is a positive income effect *within* the three-level Income groupings for White and Afr-Amer HHs at either fixed education level, and for Hispanics at the College level. This suggests a possible spline in behavior between the lower groups and upper groups in Income for certain racial groups.

Which racial group buys most by quadrant and overall when accounting specifically for Price reactivity in the HHsize=4 combination? For the left quadrants (HS and x1PvInc) Hispanic HHs buy more than White HHs. The most reactive is Afr-Amer HHs in HS Ed, and Asian HHs in College Ed. For the right quadrants (College and x4PvInc): White HHs are less reactive than Hispanic HHs, with Asian HHs most reactive in College Ed, and Afr-Amer HHs most reactive in x4PvInc. Table-wide, from HHs from highest-to-lowest cell average (least to most Price reactive): Hispanic, White, Afr-Amer, Asian. Comparative to a common reference sub-group, Asian HHs therefore seem the most economically rational in Price reaction, and Hispanic HHs least.

Table 3b compares the HHsize=3, Two Kids, for Female ONLY HHHs. There are now only four cells over 350 ounces, and twice as many values under 100 ounces, in addition to the first four negative-value cells. Whereas the HHsize=4 table-wide span was 616 ounces, the table-wide span here has shrunk to (402-[-65]=) 467 ounces, meaning that Female HHHs are less different in their Price response than dual-sexed HHH households. In HHsize=4, Hispanics were the least responsive group. Now Hispanic HHs (2 of 22) are second to HfPvInc x HS Ed (3 of 4, with HfPvInc in fixed College also relatively high) as least responsive to Price rises. As in HHsize=4, Hispanic HHs at the three lowest Income levels tend to have high relative values, as do Hispanic HHs at all Education levels. The average for the first column Hispanic (fixed HS and fixed x1PvInc, 255) is slightly higher than the HfPvInc average cross fixed HS and College Educ levels (251). Less HS was second highest by cell values after Hispanic HHs before, and remains high in fixed x4PvInc, but not very high in fixed x1PvInc. The gap between White and Afr-Amer HHs has narrowed considerably from dual-sexed HHs to Female only HHs with Two Kids. Asian HHs with Female only HHHs are now by far the most responsive in Price of any group, having only 6 of 22 cells across the four half-columns over 100 ounces, and four cells more responsive than the base sub-group (with one duplicate). For Female HHHs Asian HHs are the most responsive in Price, Hispanic HHs the least, and the difference between White and Afr-Amer remains significant, but has shrunk.

As in the HHsize=4 table, across Income levels there is obviously no linear trend, and the lowest three Income groups are much less responsive (have higher cell values) than the higher three Income levels. The exception is for Asian fixed College, for which there is a clear reversal of this rule. Also as in Table 3a, all but Asian HHs rise from x3- to x4PvInc. Except for White (and arguably Afr-Amers) HHs in fixed College, there is a large rise in ounces from x4- to x5PvInc.

All racial groups fall in 2x2 comparison of lowest to highest Education levels, except for fixed x1PvInc Asian HHs, and a flatness in Afr-Amer at x4PvInc. This indicates a solid education effect. But whereas in Table 3a the span in ounces between lowest and highest Educ levels (lower half) was much larger than the span in ounces across Income levels (upper half), this is no longer true in Female only HHHs. Again, the Female only HHHs are more responsive than dual-sexed HHHs outside of HfPvInc, but the income effect presents stronger than before, larger than the education effect in at least this measure. Comparing the x1PvInc quadrant to the x4PvInc quadrant shows a rise in CME cell values in the three Race groups, further supporting a stronger income versus education effect in Female HHHs. For Hispanic HHs, the negative income effect observed in Table 3a still holds.

Comparing cell values in the HS quadrant versus the fixed College quadrant, values uniformly fall for White and Afr-Amer HHs, indicating a solid education effect, but tend to rise for Asian and Hispanic HHs, failing to support an education effect in this comparative dimension. The exception to the rule for higher-Income highest-education Afr-Amer Female HHHs – who only in Post College have the highest value across the racial groups – may suggest a sub-cultural influence that could make education-based policy mechanisms insufficient for some sub-groups.

For Female only HHH households, the order of totals by racial group across the quadrant remains as for table 3a: Hispanic, White, Afr-Amer, Asian. But in contrast Asian Female HHHs are most responsive in every quadrant, by a large margin, and Hispanic Female HHHs are relatively even less Price reactive than in dual-sexed HHH households, dominating 3 of the 4 quadrants. This has policy implications.

Table 3c compares the HHsize=3, Two Kids, for Male ONLY HHHs. Whereas the HHsize=4 table-wide span was 616 ounces, Male HHHs vary from highest-Income Asian HHs (707), to highest-Education Hispanic HHs (38), for a table-wide span of 669, meaning Male HHHs differ more in their Price responses than dual-sexed or Female only HHH households.

The striking result is that where before Asian Female HHHs were extremely Price reactive, Asian Male HHHs are the least Price reactive of any group in the prediction tables, with only 6 of 22 cells *below* 350, and four of these are paired duplicates, one pair at 349. They are much more Price responsive at the higher two levels of education (2x2 and fixed College versus fixed HS), but nonetheless display the first very strong positive income effect (3 low vs. 3 high) yet seen. The only other 350^{+}-ounce cells are at lower Income and lower Education levels for Hispanic HHs. The other racial groups join Asian in a clear education effect in 2x2 comparison (Less HS and HS versus College and Post College, lower half). While not uniformly falling cell-by-cell between fixed HS and fixed College across Income levels and racial groups, Male HHHs more consistently fall for this fixed incremental rise in Education than do Female HHHs, demonstrating a solid education effect (weakest at HfPvInc). All racial groups in Male HHH fall from HS to Some College, and all fall from College to Post College (except Asian at x4PvInc, to a level well below Less HS and HS), further supporting an education effect.

Except for Asian HHs, racial groups fall in the upper three Income levels versus the lower three. Mixed results across quadrants and racial groups do not suggest that the education or income effect clearly dominates the other in magnitude, but the results are more mixed in assessing a strong income effect (try to assess a clear income effect from the lower-left to lower-right quadrants), giving the edge to the more stable education effect.

For Male only HHH households, the order of totals by racial group across the quadrant strongly turns. For Male only HHHs, now Asian HHs stand apart as by far the least responsive in every quadrant, and overall, Afr-Amer HHs stand apart as by far the most responsive to Price rise. Asian Male only HHHs do not care about Price rises, Afr-Amer Male only HHHs do. Hispanic and White HHs are closer in behavior as measured by quantity purchase to Afr-Amer HH behavior than to Asian HH behavior.

Similar detail in analysis has been conducted for Tables 4a – 5c, but I forego recounting this to focus on result highlights. The power and breadth of the method has been effectively demonstrated.

VII. Overall Results Summary

There are many possible ways to report results across HH characteristics and their responses to individual marketing variables, as well as many possible ways to construct HH types for prediction analysis, even for the few HH-type combinations presented here. Every choice to group results in one way forces a division, and a consequent need to refer back across dividing lines to a previous variable group. Here is one method.

Marketing Variables

There is clear evidence of large purchases when there is a price-promotion event, and strong evidence of household stocking behavior. In the REFINED model, *HHs tend to respond with purchase to Sale or Advertising incentives in at least the same magnitude as to Price incentives*. It is important to remember that weekly Price and Advertising data are weighted averages across the entire sCSD industry within the same DMA in which HH-level observations are collected, so by construction, these cannot be particularly flexible to a weekly change in price for a particular HH's preferred brand(s).[17] The magnitude of the response to changes in weekly Advertising is against my expectation that it might have a small effect on purchase, given that most of the effects from sCSD-industry advertising may well have accumulated over many years. There was no evidence from graphing Advertising exposure against quantity purchased across the entire population that weekly advertising strongly motivated increased purchase in the same week or the next few weeks, but certain sub-groups have high purchases correlated with increased exposure to Advertising (graph omitted for space, but available upon request).

Income

In the REFINED model, middle-income HHs (from twice through four times the poverty level for a family of four) seem most responsive to Price change, while the lowest- and highest-income HHs are least Price-sensitive (have the highest purchase in ounces). This result may be motivated by a strong habit of regular purchase behavior, such that Price changes do not provoke much purchase change at these income levels. In addition, the lowest-income HHs may have reduced access to price-competitive purchase venues, and the highest-income HHs may have

[17] The orientation at the product category rather than product brand level is motivated by medical/nutrition and decision-theory/behavioral-economic literature, where the influence of caloric sweeteners on choice behavior and health are not dependent on brand. It is beyond the scope of this work to defend the degree to which positive consumer associations developed by one product's advertising campaign may spill over to other brands, but the effect is documented for soft drinks (Zheng, Yuqing and Kaiser, Harry M. Advertising and U.S. Nonalcoholic Beverage Demand. *Agricultural and Resource Economics Review*, 2008, vol. 37, issue 2, pp. 147-159.)

even less concern for the price of sCSDs as a portion of their HH budget than other income levels. *HHs with lower Income in combination with lower Education display a strong pattern of least response to rising Price, indicative of stronger habit in purchase.* Across the four racial groups (White, Afr-Amer, Asian, Hispanic) in the prediction table, all purchase more in rising Price at the highest HH income level versus the second highest, indicating an insensitivity to Price that may be Income- or habit-based. As occurs in most prediction tables, Asian HHs present some exceptions to other behavior described.

Because response to Price is lowest at the lowest Income level, is higher in middle Income, and is low again at the highest level of Income (with HS Education the fixed level across these Income levels), the income effect is clearly not linear, as determined by the BASIC model. Extreme differences in purchase reaction between Income levels within a racial group indicate that the uniform changes across Income levels within a racial group as constrained by the BROAD model similarly do not hold. *The REFINED model indeed discovers differences in purchase response that the BASIC and BROAD models are incapable of identifying.* Income effects are less clear than education effects in Sale, and for White and Afr-Amer HHs the income effect is actually negative, meaning that the education effect is clearly dominant. For Hispanic HHs, the education effect is less dominant, and for Asian HHs, it is weakly dominant.

For response in weekly purchase to increased Advertising, lower-income HHs are more responsive than higher-income HHs. The effect is fairly robust across racial groups except Asian HHs, being particularly strong in Hispanic HHs. For Female Only and Male Only HHHs in rising Advertising, lower-Income HHs are more responsive generally versus higher Income (in all but Asian HHs), but the differences are smaller than in Price and Sale prediction tables, suggesting that *any positive Advertising effect is more universal in overall effect than Price or Sale effects*.

With exceptions for Male HHH Asian HHs, results comparing the lower two with the highest two income levels in Price, Sale, and Advertising tend to favor a negative income effect. *This offers broad evidence that sCSDs are an inferior good.*

Education

In rising Price, REFINED model prediction tables demonstrate a clear strong education effect that dominates any (expected positive) income effect. *Fixed HS Educ across Income levels is dramatically larger than fixed College Educ across Income levels, averaging over 110 oz/week* *and often much more, across all racial groups*. In the Price prediction tables, Male Only HHH HHs have a more consistent education effect than Female Only HHs, as only White and Hispanic HHs demonstrate a strong education effect in Female Only HHs.

In rising Sale, REFINED model prediction tables (HH Size=4) show that HHs with Less-than-HS Educ are extremely responsive to Sale (followed by lowest Income level), with a marked drop off even to HS Educ. Beyond this *there is a strong education effect favoring higher Sale response at lower Educ levels*. In the Sale prediction tables, neither the education nor the income effect clearly dominates in its expected direction for Female Only HHs, but education dominates income in Male HHs.

In rising Advertising, REFINED model prediction tables show that Less HS Educ is again the most positive in purchase reaction. Once again, *the education effect dominates any positive income effect across all racial groups (although weakly for Asian HHs)*. In the Advertising prediction tables, the education effect dominates the income effect for Female Only HHs, but less robustly than in the Price and Sale tables. For Male Only HHs responding to Advertising, the education effect again dominates any positive income effect (even for Asian HHs, which demonstrate a clear positive income effect).

Given the strength in direction and magnitude of the fall in sCSD purchase in rising Education, *there appears to be sufficient support for the assumption that the level of formal education of the HHH can effectively proxy for the critical thinking necessary for nutrition awareness to apply to actual purchase.* The evidence is neither linear nor overwhelming.

Racial Group

Each of the four racial groups whose behavior is predicted from estimation results reacts to marketing variable changes in a unique way. For the REFINED prediction table in rising Price (also HH Size=4), *some racial group rankings change with the quadrant of the table, indicating exactly the variability in response by racial groups at different Education and Income levels that I originally hypothesized.* For example, in the low-(fixed)Education, and low-(fixed)Income quadrants, Hispanic HHs purchase more than White HHs in rising Price, and Afr-Amer HHs are the most Price reactive; whereas for the high-(fixed) Education and high-(fixed)Income quadrants, Asian HHs are the most reactive in high Education, and Afr-Amer HHs are the most reactive in high Income. Across the REFINED Price prediction table, Hispanic > White > Afr-Amer > Asian. For Female Only HHH the order is the same, again suggesting that Asian HHs are the most negative in responsive to Price rise, and Hispanics the least responsive. For Male Only HHH: Asian > Hispanic > White > Afr-Amer.

For the REFINED prediction table in rising Sale, HH Size=4 with both sexes of HHHs: White > Asian > Afr-Amer > Hispanic, indicating a strong Sale preference for White HHs (although Hispanic HHs are quite high in Sale at x1PvInc). For Female Only HHHs: Afr-Amer > White > Asian > Hispanic – the only table-wide dominance of Afr-Amer response to a marketing variable. Quadrants with fixed lower Educ and Income levels show very low response to Sale by Asian Female HHHs. For Male Only HHHs: Asian (by a vast amount) > White (by a lot) > Afr-Amer > Hispanic.

For the REFINED prediction table in rising Advertising, HH Size=4: Hispanic > White > Afr-Amer > Asian. This identical ordering represents a direct inversion to the Price response, such that *Hispanic HHs (HH Size=4) are the least responsive in rising Price, the most responsive in rising Advertising, and the least responsive in rising Sale, i.e. the least economically rational of any racial group, and most indicative of habitual purchase behavior.* In contrast, *Asian HHs (HH Size=4)* being nearly the opposite in response and ranking to Hispanic HHs (edged out by White HHs in high Sale response), *are the most economically rational to marketing variable incentives*.

Beyond the summary results here, discussion by racial group is omitted for space, but available upon request, as are tables presenting the straightforward calculations by which the rankings were established.

Indicators of Parental Choice by Income Level or Sex of HHH

While all results so far discussed refer to HH-characteristic mixes across all regressed characteristics (seven dimensions, as in prediction tables), analysis was conducted on combinations of demographic characteristics in response to marketing variable changes, without establishing full-profiles (two dimensions.) The interaction of Income level with # of Kids in HH, and Educ level of HHH-sex with # of Kids in HH were a few of many combinations analyzed using sets of combined marginal effects.

HHs with Income level Half-, x1-, or x2Pv4Inc demonstrate *rising* sCSD purchase in rising Price as the # of Kids in HH increases, indicating strongly habitual purchase favoring sCSD consumption in lower-Income HHs with more children. However, for the x3-, x4-, and x5Pv4Inc (and above) HHs, purchase tends to *fall* in rising Price as the # of Kids in HH rises.

This may indicate a difference in parenting style by broad HH income category (having controlled for education and other effects), with higher-Income HHs less favorable to sCSDs.

A range of results using the same method for Education level of a single sex HHH with # of Kids indicate that *in response to each of the marketing-mix variables tested here, Male Only HHHs tend to purchase less in response to these than Female Only HHHs do, when children are present in either HH. This effect overrides the* ***general*** *tendency of Male Only HHHs to purchase more than Female Only HHs, an effect robust across racial groups. When facing similar Pricing, Sale, and Advertising incentives, single fathers seem to be more strict against sCSD purchase than single mothers.*

Age / HH Size / Sex of HHH

Age is a very general category, although not so general as HH Size, from which little policy-relevant results may be derived, despite HH Size results conforming closely with economic expectations in every version of every model. Larger HHs purchase more and are Price sensitive, although, perhaps counterintuitively, smaller HH sizes are more Sale sensitive, perhaps indicating less habitual purchase.

Female HHH Age results (again, a general characteristic) for the REFINED model CMEs confirm that *lower-Income Female Only HHH HHs are less responsive to Price increase and more responsive to Sale and to Advertising, matching the highly habitual consumer profile* of Hispanic Female HHHs, and are thus appropriate targets for any policy intervention to reduce consumption. This is exactly the type of effect this empirical approach can identify, despite the very general and robust effect that Male Only HHHs purchase more sCSDs than Female Only HHHs. Older Female HHHs buy more when they buy, independent of any Price or Sale effects, possibly associated with older children.

Male HHHs are, contrary to Female HHHs by Age group, more responsive to Price. Younger Male HHHs generally tend to be more responsive to Sale (than older Male HHHs), while lower-Income Male HHHs respond more to Sale in higher Age brackets. Response to Advertising is mixed across Male HHH Age brackets, but there is weak support for the contention that lower-Income HHs are more responsive to Advertising (in the same direction but with a weaker effect than for Female HHHs).

Female HHHs react to marketing variables more similarly to each other than do Male HHHs or HHs where both sexes head the household. This may imply that policies targeting

Female HHH shoppers may have more focused effect toward intended goals than broad campaigns, or campaigns targeting Male HHHs.

VIII. Limitations and Future Research

The reduced-form approach here, regressing product-category marketing variables on household-level purchases is uncommon in consumer economics or marketing, but allows for interesting results. Results are constrained both by natural limitations in the data, including the fact that estimation across the SSB category may have been more informative, and limitations resulting from the choice to regress at the product category level (all sCSDs). Other works I have found that examine soft-drink consumption by demographic group use dietary survey recall data. While those data sets have their own limitations, including the holistic inability to identify economic responses, they do offer the advantage of being at the individual rather than at the household level, at which I am constrained to report.

To the degree that sCSD purchase behavior does not closely proxy nutrition knowledge and beliefs, there will be an implicit grouping of potentially identifiable knowledge and belief levels within education and income levels in the empirical work of this study. Results indicate this may not be a serious limitation.

Aggregating Price and Advertising variables to category-wide indexes minimizes identification of HH reactions to particular favored products. This was a trade-off for focusing on the category as generally undifferentiable in health effects across calorically sweetened carbonated soft drinks.

Future research may involve any of the many specific comparisons that can be made across household types using the very rich set of results, given the many coefficients identified by REFINED model demographic variable interaction. For example, simply by changing the fixed and variable dimensions in a prediction table, analyzing the difference in HH purchase responses by number of children in the home within one or more racial groups is quite tractable. It is also enticing to run the model for diet soft drinks, and compare results, or for other snack foods (salty snacks or candy) to compare consumer reactions to marketing variables for these products which are similar in some dimensions. Isolating DMAs based on natural experiments in local soft-drink policies and comparing results is also an achievable extension.

While a few policy implications have been identified here, a parallel project of mine indicates that politically achievable sCSD or SSB per-ounce taxes or standard methods of providing consumers with more product information as a means of education are unlikely to effectively dissuade purchase to a degree likely to significantly improve health outcomes. This parallel work is large enough to be an independent piece, so I am constraining discussion here of the critical policy questions and novel approaches which apply to any attempt to lower average sCSD consumption levels below sCSDs being the single product type by which many Americans exceed recommended daily limits to added-sugar intake. The following paragraph is an inadequate overview.

Results suggest that nutrition education policies will benefit all demographic groups, but that some are in more dire need than others. Advertising restrictions should be considered. Tax-per-ounce policies may be effective in alerting consumers to the fact that the USDA is interested in discouraging consumption of sCSDs (SSBs), and any device that raises consumer awareness that the product is unhealthful when consumed daily in common container sizes is likely to affect purchase more than simple taxation on any scale currently proposed. Per-ounce soft-drink taxes are unlikely to significantly dissuade purchase for committed buyers, who by numerous household-realistic profiles already demonstrate habitual sCSD purchase, even when the outlay appears to be four times the percentage of the household budget of higher-income households (refer to prediction tables). I propose based on empirical results and established peer-reviewed findings from other fields that sCSD-industry advertising budgets (across all media) be scaled and matched into a fund that is pre-designated for use to generate and air public-service announcements educating the public to the dangers of products and diets high in added sugars.

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Table 1. Descriptive Statistics – Variables for BASIC Model†

Variable	Mean	Std. Dev.	Min	Max	Number of obs.
Wkly HH Purchase Total (oz.)	47.8	163.6	0	12235.6	2,666,124
Wkly HH Purchase Total (oz.)^	277.4	302.8	8	12235.6	459,392
# of Weeks/yr. HH Purchases $\geq$ 67 oz.	7.77	9.167	0	52	2,666,124
Avg Price in \$/oz. in a DMA / wk	0.022	0.0025	0.0095	0.0336	2,666,124
2006-8 Real Avg Price in \$/oz. in a DMA / wk+	0.0233	0.0103	0	0.4922	2,666,124
HH Avg. Advert Exposure (GRPs)	1181.4	872.2	6.2	5841.3	2,666,124
On Sale, portion of all observations*	0.053	0.223	0	1	2,666,124
On Sale, portion of positive purchases^*	0.305	0.460	0	1	459,392
On Sale^	328.5	0.835	326.9	330.1	140,000
HH Income	20.848	5.829	3	27	2,666,124
Female Head of HH Edu	3.782	1.697	0	6	2,666,124
Male Head of HH Edu	3.149	2.133	0	6	2,666,124
White*	0.761	0.426	0	1	2,666,124
African American*	0.134	0.341	0	1	2,666,124
Asian*	0.046	0.209	0	1	2,666,124
Other Race*	0.059	0.235	0	1	2,666,124
Hispanic*	0.077	0.266	0	1	2,666,124
HH Size	2.416	1.341	1	9	2,666,124
No Kids in HH*	0.731	0.443	0	1	2,666,124
Kids in HH*	0.269	0.443	0	1	2,666,124
Kids in HH, Wkly HH Purchase Total (oz.)	69.1	0.235	68.6	69.5	716,708
Kids in HH, Wkly HH Purchase Total (oz.)^	301.8	0.792	300.2	303.3	164,012
Female Head of HH Age	5.819	2.814	0	9	2,666,124
Male Head of HH Age	4.908	3.387	0	9	2,666,124
Ssn1 / Spring*	0.231	0.422	0	1	2,666,124
Ssn2 / Summer*	0.256	0.437	0	1	2,666,124
Ssn 3 / Autumn*	0.263	0.440	0	1	2,666,124
Ssn 4 / Winter*	0.250	0.433	0	1	2,666,124
Race-/Hispanic-Specific Means:					
White - Income	20.808	5.826	3	27	2,029,492
African Amer. - Income	20.236	5.995	3	27	358,168
Asian - Income	23.413	4.742	3	27	121,560
Other Race - Income	20.785	5.740	3	27	156,904
Hispanic - Income	21.251	5.690	3	27	204,748
White - Educ Level (avg Fem & Male)	3.46	.	0	6	2,029,492
African Amer. - Educ Level (avg Fem & Male)	3.17	.	0	6	358,168
Asian - Educ Level (avg Fem & Male)	4.33	.	0	6	121,560
Other Race - Educ Level (avg Fem & Male)	3.53	.	0	6	156,904
Hispanic - Educ Level (avg Fem & Male)	3.67	.	0	6	204,748
White – HH Size	2.361	1.303	1	9	2,029,492
African Amer.– HH Size	2.407	1.434	1	9	358,168
Asian– HH Size	2.795	1.298	1	8	121,560
Other Race– HH Size	2.858	1.497	1	9	156,904
Hispanic– HH Size	2.970	1.433	1	9	204,748

† Default reference quantities are for averages that include all observations, inclusive of zero-purchase weeks.

^ Indicates mean in ounces calculated for positive purchase weeks only; not averaged across zero-purchase weeks.

+The fifth row is calculated from the data configuration for the BROAD model, and represents inflation-adjusted statistics. The small number of prices per ounce in the data registering above \$0.50/oz, this being over twenty times the average, were discarded as faulty data entries, generating the \$0.492 maximum price per ounce in the inflation-adjusted price set. Zero price in this row is possible , given rare and restrictive promotion campaigns.

* Indicates a binary variable (min=0, max=1). Reported means present the portion of this variable (=1) within the full-sample category.

Table 2. Decomposition of Demographic Variables to Category Levels – Mean Value of HH Total Oz Purchased in a Week, Purchase Observations Only

Variable	mean Wkly HH Buy in Oz.	Std. Err.	[95% Conf.	Interval]	Number of Obs.
HalfPov4Inc	262.624	2.158	258.395	266.853	17,347
x1Pov4Inc	267.300	1.494	264.372	270.229	43,271
x2Pov4Inc	270.755	0.904	268.984	272.526	104,465
x3Pov4Inc	285.142	0.887	283.404	286.880	122,750
x4Pov4Inc	**285.759**	1.018	283.764	287.755	96,633
x5Pov4Inc	272.526	1.040	270.489	274.564	74,926
Fem LessHS	**318.998**	2.676	313.753	324.242	15,405
Fem HS	307.187	0.982	305.262	309.111	109,477
Fem SomCollg	280.665	0.798	279.100	282.230	135,431
Fem Collg	263.727	0.864	262.033	265.421	114,064
Fem PostCollg	246.893	1.424	244.101	249.684	39,736
Male LessHS	312.754	2.281	308.283	317.226	19,794
Male HS	**314.752**	1.145	312.509	316.996	89,414
Male SomCollg	290.227	0.898	288.467	291.986	112,908
Male Collg	266.422	0.939	264.581	268.263	100,703
Male PostCollg	261.029	1.413	258.259	263.799	41,227
White	284.196	0.520	283.177	285.216	347,300
African American	242.562	1.034	240.536	244.589	66,578
Asian	**286.717**	2.984	280.868	292.566	14,605
Other Race	271.848	1.693	268.529	275.167	30,909
Hispanic	263.580	1.413	260.811	266.350	40,668
HH size 1	214.016	0.878	212.296	215.736	78,724
HH size 2	268.090	0.729	266.661	269.520	163,396
HH size 3	289.340	1.037	287.307	291.373	86,917
HH size 4	308.645	1.143	306.404	310.886	78,325
HH size 5+	**335.663**	1.537	332.650	338.675	52,030
No Kids	263.876	0.536	262.825	264.926	295,380
One Kids	294.807	1.150	292.553	297.061	75,160
Two Kids	304.538	1.294	302.001	307.075	61,265
Three Kids	312.842	2.382	308.173	317.510	19,800
4 Kids+	**319.462**	3.861	311.894	327.030	7,787
Fem Age <30	255.002	2.268	250.557	259.447	12,792
Fem Age30-40	276.784	1.123	274.582	278.986	66,647
Fem Age40-50	**295.245**	0.935	293.413	297.077	127,181
Fem Age50-65	284.038	0.756	282.556	285.520	153,020
Fem Age 65+	251.962	1.160	249.688	254.237	54,473
Male Age <30	259.750	3.119	253.635	265.865	7,594
Male Age30-40	282.056	1.285	279.539	284.574	52,722
Male Age40-50	**297.694**	0.998	295.737	299.650	107,372
Male Age50-65	293.162	0.845	291.506	294.818	143,269
Male Age65+	261.554	1.182	259.238	263.871	53,089
No Fem HH Hd	242.799	1.400	240.056	245.543	45,279
No Male HH Hd	238.573	0.856	236.896	240.250	95,346
Ssn1 / Spring	264.399	0.857	262.719	266.078	107,472
Ssn2 / Summer	**292.589**	0.938	290.751	294.427	123,566
Ssn 3 / Autumn	279.207	0.897	277.450	280.965	117,586
Ssn 4 / Winter	271.201	0.859	269.518	272.884	110,768

Bold numbers indicate highest mean in category.

REFINED Combined Marginal Effects – PRICE, Table 3a: Across major Race groups & Hispanic, compare 2 Educ Levels across Income Levels, and 2 Income Levels across same M/F HHH Educ Levels, given HHsize=4, Two Kids, M/F Age=40-50 yrs^

cell units =	White*	Afr Am*	Asian*	Hispanic	White*	Afr Am*	Asian*	Hispanic
oz./purchase	HS Ed	HS Ed	HS Ed	HS Ed	Collg Ed	Collg Ed	Collg Ed	Collg Ed
HfPvInc	427	369	252	459	273	226	12	277
x1PvInc	329	234	227	474	242	158	54	360
x2PvInc	370	329	236	402	292	262	73	296
x3PvInc	326	252	458	288	260	196	307	194
x4PvInc	291	201	249	237	238	160	110	157
x5PvInc	362	297	405	355	270	216	227	235
	x1PvInc	x1PvInc	x1PvInc	x1PvInc	x4PvInc	x4PvInc	x4PvInc	x4PvInc
Less HS	410	230	373	628	333	160	357	353
HS	329	234	227	474	291	201	249	237
Sm Collg	217	132	51	404	249	170	143	237
Collg	242	158	54	360	238	160	110	157
Post Collg	167	158	90	289	135	131	118	58

^ For every cell, Male & Female HHH, both age 40-50 yrs, HHsize=4, #Kids=2. Column cells vary by Race/Hispanic, upper columns by level of education, lower columns by level of income. HH size, number of Kids, and HHH Age(s) are held fixed for all similar tables to allow comparison across levels of the estimation model in the variables designated by rows, columns, and half-columns. Dropping one HHH lowers HHsize by one. 40%-shaded totals are 550+ ounces at positive weekly purchase, 25%-shaded totals are 350+ ounces, 10%-shaded totals are under 100 ounces, **bold** totals are negative.
* Races are non-Hispanic, base for est. was White; for Hispanic, base was non-Hispanic.

REFINED Combined Marginal Effects – PRICE, Table 3b: Across major Race groups & Hispanic, compare 2 Educ Levels across Income Levels, and 2 Income Levels across ONLY Female HHH Educ Levels, given HHsize=3,Two Kids, Fem Age=40-50 yrs^

cell units =	White*	Afr Am*	Asian*	Hispanic	White*	Afr Am*	Asian*	Hispanic
oz./purchase	HS Ed	HS Ed	HS Ed	HS Ed	Collg Ed	Collg Ed	Collg Ed	Collg Ed
HfPvInc	402	388	68	389	229	237	35	271
x1PvInc	196	145	**-65**	296	146	117	24	301
x2PvInc	248	251	**-44**	235	197	222	44	239
x3PvInc	142	112	116	59	125	116	238	96
x4PvInc	216	170	15	117	177	154	116	133
x5PvInc	265	244	149	212	173	174	197	175
	x1PvInc	x1PvInc	x1PvInc	x1PvInc	x4PvInc	x4PvInc	x4PvInc	x4PvInc
Less HS	191	53	50	341	247	114	165	198
HS	196	145	**-65**	296	216	170	15	117
Sm Collg	142	103	**-15**	299	194	160	97	152
Collg	146	117	24	301	177	154	84	133
Post Collg	121	125	**-27**	259	134	143	47	73

^ For every cell, Female HHH, age 40-50 yrs, HHsize=4, #Kids=2. Column cells vary by Race/Hispanic, upper columns by level of education, lower columns by level of income. HH size, number of Kids, and HHH Age(s) are held fixed for all similar tables to allow comparison across levels of the estimation model in the variables designated by rows, columns, and half-columns. Dropping one HHH lowers HHsize by one. 40%-shaded totals are 550+ ounces at positive weekly purchase, 25%-shaded totals are 350+ ounces, 10%-shaded totals are under 100 ounces, **bold** totals are negative.
* Races are non-Hispanic, base for est. was White; for Hispanic, base was non-Hispanic.

REFINED Combined Marginal Effects – PRICE, Table 3c: Across major Race groups & Hispanic, compare 2 Educ Levels across Income Levels, and 2 Income Levels across ONLY Male HHH Educ Levels, given HHsize=3,Two Kids, Fem Age=40-50 yrs^

cell units =	White*	Afr Am*	Asian*	Hispanic	White*	Afr Am*	Asian*	Hispanic
oz./purchase	HS Ed	HS Ed	HS Ed	HS Ed	Collg Ed	Collg Ed	Collg Ed	Collg Ed
HfPvInc	301	257	563	367	320	264	356	303
x1PvInc	199	118	533	378	162	70	272	259
x2PvInc	216	189	519	282	189	151	267	172
x3PvInc	180	120	749	176	131	60	476	44
x4PvInc	193	118	588	173	179	93	349	76
x5PvInc	228	176	707	254	227	165	482	171
	x1PvInc	x1PvInc	x1PvInc	x1PvInc	x4PvInc	x4PvInc	x4PvInc	x4PvInc
Less HS	285	206	565	486	205	132	546	208
HS	199	118	533	378	193	118	588	173
Sm Collg	141	59	307	305	173	97	400	138
Collg	162	70	272	259	179	93	349	76
Post Collg	112	62	358	230	119	75	425	38

^ For every cell, Male HHH, age 40-50 yrs, HHsize=4, #Kids=2. Column cells vary by Race/Hispanic, upper columns by level of education, lower columns by level of income. HH size, number of Kids, and HHH Age(s) are held fixed for all similar tables to allow comparison across levels of the estimation model in the variables designated by rows, columns, and half-columns. Dropping one HHH lowers HHsize by one. 40%-shaded totals are 550+ ounces at positive weekly purchase, 25%-shaded totals are 350+ ounces, 10%-shaded totals are under 100 ounces, **bold** totals are negative.

* Races are non-Hispanic, base for est. was White; for Hispanic, base was non-Hispanic.

REFINED Combined Marginal Effects – SALE, Table 4a: Across major Race groups & Hispanic, compare 2 Educ Levels across Income Levels, and 2 Income Levels across same M/F HHH Educ Levels, given HHsize=4, Two Kids, M/F Age=40-50 yrs^

cell units =	White*	Afr Am*	Asian*	Hispanic	White*	Afr Am*	Asian*	Hispanic
oz./purchase	HS Ed	HS Ed	HS Ed	HS Ed	Collg Ed	Collg Ed	Collg Ed	Collg Ed
HfPvInc	402	372	401	94	385	307	246	**-2**
x1PvInc	279	253	184	274	286	212	51	202
x2PvInc	359	278	302	161	343	214	146	66
x3PvInc	271	206	516	218	245	131	351	113
x4PvInc	275	200	397	221	252	128	234	118
x5PvInc	330	327	532	392	245	194	308	229
	x1PvInc	x1PvInc	x1PvInc	x1PvInc	x4PvInc	x4PvInc	x4PvInc	x4PvInc
Less HS	513	416	348	642	389	242	440	468
HS	279	253	184	274	275	200	397	221
Sm Collg	291	259	**-11**	278	303	221	217	240
Collg	286	212	51	202	252	128	234	118
Post Collg	242	267	**-22**	197	271	246	224	176

^ For every cell, Male & Female HHH, both age 40-50 yrs, HHsize=4, #Kids=2. Column cells vary by Race/Hispanic, upper columns by level of education, lower columns by level of income. HH size, number of Kids, and HHH Age(s) are held fixed for all similar tables to allow comparison across levels of the estimation model in the variables designated by rows, columns, and half-columns. Dropping one HHH lowers HHsize by one. 40%-shaded totals are 550+ ounces at positive weekly purchase, 25%-shaded totals are 350+ ounces, 10%-shaded totals are under 100 ounces, **bold** totals are negative.

* Races are non-Hispanic, base for est. was White; for Hispanic, base was non-Hispanic.

REFINED Combined Marginal Effects – SALE, Table 4b: Across major Race groups & Hispanic, compare 2 Educ Levels across Income Levels, and 2 Income Levels across ONLY Female HHH Educ Levels, given HHsize=3,Two Kids, Fem Age=40-50 yrs^

cell units =	White*	Afr Am*	Asian*	Hispanic	White*	Afr Am*	Asian*	Hispanic
oz./purchase	HS Ed	HS Ed	HS Ed	HS Ed	Collg Ed	Collg Ed	Collg Ed	Collg Ed
HfPvInc	445	489	223	69	415	468	365	64
x1PvInc	184	232	**-133**	110	212	270	69	164
x2PvInc	274	268	**-5**	8	290	293	184	49
x3PvInc	218	227	242	97	236	254	432	140
x4PvInc	210	209	110	87	184	192	257	86
x5PvInc	222	294	203	217	155	236	308	175
	x1PvInc	**x1PvInc**	**x1PvInc**	**x1PvInc**	**x4PvInc**	**x4PvInc**	**x4PvInc**	**x4PvInc**
Less HS	260	255	17	341	274	219	246	305
HS	184	232	**-133**	110	210	209	110	87
Sm Collg	191	240	**-35**	159	220	220	211	139
Collg	212	270	69	164	184	192	223	86
Post Collg	168	206	**-13**	126	193	182	229	102

^ For every cell, Female HHH, age 40-50 yrs, HHsize=4, #Kids=2. Column cells vary by Race/Hispanic, upper columns by level of education, lower columns by level of income. HH size, number of Kids, and HHH Age(s) are held fixed for all similar tables to allow comparison across levels of the estimation model in the variables designated by rows, columns, and half-columns. Dropping one HHH lowers HHsize by one. 40%-shaded totals are 550+ ounces at positive weekly purchase, 25%-shaded totals are 350+ ounces, 10%-shaded totals are under 100 ounces, **bold** totals are negative.

* Races are non-Hispanic, base for est. was White; for Hispanic, base was non-Hispanic.

REFINED Combined Marginal Effects – SALE, Table 4c: Across major Race groups & Hispanic, compare 2 Educ Levels across Income Levels, and 2 Income Levels across ONLY Male HHH Educ Levels, given HHsize=3,Two Kids, Fem Age=40-50 yrs^

cell units =	White*	Afr Am*	Asian*	Hispanic	White*	Afr Am*	Asian*	Hispanic
oz./purchase	HS Ed	HS Ed	HS Ed	HS Ed	Collg Ed	Collg Ed	Collg Ed	Collg Ed
HfPvInc	170	164	973	**-69**	184	120	675	**-159**
x1PvInc	68	66	776	132	46	**-13**	443	6
x2PvInc	36	**-21**	782	**-93**	4	**-110**	438	**-229**
x3PvInc	122	81	1171	138	78	**-21**	815	**-9**
x4PvInc	7	**-44**	932	21	10	**-99**	623	**-80**
x5PvInc	31	52	1036	163	13	**-23**	707	41
	x1PvInc	**x1PvInc**	**x1PvInc**	**x1PvInc**	**x4PvInc**	**x4PvInc**	**x4PvInc**	**x4PvInc**
Less HS	226	206	791	269	57	**-13**	839	51
HS	68	66	776	132	7	**-44**	932	21
Sm Collg	73	64	483	88	25	**-34**	652	**-10**
Collg	46	**-13**	443	6	10	**-99**	623	**-80**
Post Collg	47	106	451	40	20	29	640	**-37**

^ For every cell, Male HHH, age 40-50 yrs, HHsize=4, #Kids=2. Column cells vary by Race/Hispanic, upper columns by level of education, lower columns by level of income. HH size, number of Kids, and HHH Age(s) are held fixed for all similar tables to allow comparison across levels of the estimation model in the variables designated by rows, columns, and half-columns. Dropping one HHH lowers HHsize by one. 40%-shaded totals are 550+ ounces at positive weekly purchase, 25%-shaded totals are 350+ ounces, 10%-shaded totals are under 100 ounces, **bold** totals are negative.

* Races are non-Hispanic, base for est. was White; for Hispanic, base was non-Hispanic.

REFINED Combined Marginal Effects – Advertising, Table 5a: Across major Race groups & Hispanic, compare 2 Educ Levels across Income Levels, and 2 Income Levels across same M/F HHH Educ Levels, given HHsize=4, Two Kids, M/F Age=40-50 yrs^

cell units =	White*	Afr Am*	Asian*	Hispanic	White*	Afr Am*	Asian*	Hispanic
oz./purchase	HS Ed	HS Ed	HS Ed	HS Ed	Collg Ed	Collg Ed	Collg Ed	Collg Ed
HfPvInc	430	391	255	492	284	233	42	319
x1PvInc	349	268	228	514	267	175	79	404
x2PvInc	379	353	246	388	291	253	90	272
x3PvInc	328	264	454	282	276	200	334	202
x4PvInc	297	229	244	231	245	165	125	152
x5PvInc	361	313	393	346	268	208	233	226
	x1PvInc	x1PvInc	x1PvInc	x1PvInc	x4PvInc	x4PvInc	x4PvInc	x4PvInc
Less HS	456	265	396	697	377	198	384	387
HS	349	268	228	514	297	229	244	231
Sm Collg	248	158	71	445	260	182	150	225
Collg	267	175	79	404	245	165	125	152
Post Collg	215	200	133	367	143	140	129	65

^ For every cell, Male & Female HHH, both age 40-50 yrs, HHsize=4, #Kids=2. Column cells vary by Race/Hispanic, upper columns by level of education, lower columns by level of income. HH size, number of Kids, and HHH Age(s) are held fixed for all similar tables to allow comparison across levels of the estimation model in the variables designated by rows, columns, and half-columns. Dropping one HHH lowers HHsize by one. 40%-shaded totals are 550+ ounces at positive weekly purchase, 25%-shaded totals are 350+ ounces, 10%-shaded totals are under 100 ounces, **bold** totals are negative.

* Races are non-Hispanic, base for est. was White; for Hispanic, base was non-Hispanic.

REFINED Combined Marginal Effects – Advertising, Table 5b: Across major Race groups & Hispanic, compare 2 Educ Levels across Income Levels, and 2 Income Levels across ONLY Female HHH Educ Levels, given HHsize=3,Two Kids, Fem Age=40-50 yrs^

cell units =	White*	Afr Am*	Asian*	Hispanic	White*	Afr Am*	Asian*	Hispanic
oz./purchase	HS Ed	HS Ed	HS Ed	HS Ed	Collg Ed	Collg Ed	Collg Ed	Collg Ed
HfPvInc	400	397	68	406	221	233	45	290
x1PvInc	215	172	**-62**	325	155	126	33	326
x2PvInc	257	268	**-33**	210	212	237	77	227
x3PvInc	146	120	116	44	135	122	259	94
x4PvInc	220	189	11	99	181	164	127	122
x5PvInc	276	265	152	206	184	188	216	176
	x1PvInc	x1PvInc	x1PvInc	x1PvInc	x4PvInc	x4PvInc	x4PvInc	x4PvInc
Less HS	231	86	95	397	274	142	206	209
HS	215	172	**-62**	325	220	189	11	99
Sm Collg	155	116	**-1**	327	197	171	109	138
Collg	155	126	33	326	181	164	117	122
Post Collg	148	147	9	306	140	151	68	67

^ For every cell, Female HHH, age 40-50 yrs, HHsize=4, #Kids=2. Column cells vary by Race/Hispanic, upper columns by level of education, lower columns by level of income. HH size, number of Kids, and HHH Age(s) are held fixed for all similar tables to allow comparison across levels of the estimation model in the variables designated by rows, columns, and half-columns. Dropping one HHH lowers HHsize by one. 40%-shaded totals are 550+ ounces at positive weekly purchase, 25%-shaded totals are 350+ ounces, 10%-shaded totals are under 100 ounces, **bold** totals are negative.

* Races are non-Hispanic, base for est. was White; for Hispanic, base was non-Hispanic.

REFINED Combined Marginal Effects – Advertising, Table 5c: Across major Race groups & Hispanic, compare 2 Educ Levels across Income Levels, and 2 Income Levels across ONLY Male HHH Educ Levels, given HHsize=3,Two Kids, Fem Age=40-50 yrs^

cell units =	**White***	**Afr Am***	**Asian***	**Hispanic**	**White***	**Afr Am***	**Asian***	**Hispanic**
oz./purchase	**HS Ed**	**HS Ed**	**HS Ed**	**HS Ed**	**Collg Ed**	**Collg Ed**	**Collg Ed**	**Collg Ed**
HfPvInc	278	250	551	383	311	257	361	326
x1PvInc	200	131	526	407	178	83	282	296
x2PvInc	225	210	539	276	181	140	272	143
x3PvInc	169	117	742	165	128	50	479	35
x4PvInc	199	141	592	175	185	103	357	73
x5PvInc	231	194	710	258	229	166	487	167
	x1PvInc	**x1PvInc**	**x1PvInc**	**x1PvInc**	**x4PvInc**	**x4PvInc**	**x4PvInc**	**x4PvInc**
Less HS	292	213	538	518	225	158	538	220
HS	200	131	526	407	199	141	592	175
Sm Collg	160	76	308	335	184	113	400	129
Collg	178	83	282	296	185	103	357	73
Post Collg	133	88	361	279	125	91	420	40

^ For every cell, Male HHH, age 40-50 yrs, HHsize=4, #Kids=2. Column cells vary by Race/Hispanic, upper columns by level of education, lower columns by level of income. HH size, number of Kids, and HHH Age(s) are held fixed for all similar tables to allow comparison across levels of the estimation model in the variables designated by rows, columns, and half-columns. Dropping one HHH lowers HHsize by one. 40%-shaded totals are 550+ ounces at positive weekly purchase, 25%-shaded totals are 350+ ounces, 10%-shaded totals are under 100 ounces, **bold** totals are negative.

* Races are non-Hispanic, base for est. was White; for Hispanic, base was non-Hispanic.

X. Technical Appendix

Despite a construction that makes unlikely the simultaneous solution of price and quantity at the same level of decision-making, the small chance of price being an endogenous regressor makes hypothesis testing prudent. It is worth noting that the standard Hausman test for endogeneity tests two variants of a model, but on the assumption that one of the estimators (the OLS without an instrumental variable) is consistent and fully efficient. But the sample-selection model is used precisely because without it, OLS estimation is inconsistent and biased (Cameron and Trivedi, 2005: 546, Breen: 36). So the standard Hausman test of endogeneity [estimator: $V(b_0) – V(b_1)$] is econometrically inappropriate for any of these models. Use of the "seemingly unrelated estimation" command in STATA allows estimation of b_0 against b_1 in a way that is always defined. It estimates $V(b_0 – b_1)$ by $V(b_0) – cov(b_0, b_1) – cov(b_1, b_0) + V(b_1)$, instead of the questionable standard Hausman (STATA 10, Reference Q-Z: 352-354).

I generate a lagged Price Index, and regress separately to generate the "consistent" (i.e., non-endogenous) b_0 to compare against the previous regression results b_1 (note that no independent OLS regression is conducted here). The test is whether b_0 and b_1 are the same. With 41 degrees of freedom, the chi-square statistic is 29.84. The exact level of significance (p-value) on the assertion that the test statistic is in the critical region above the critical value for a χ^2 distribution with 41 degrees of freedom (roughly 52) is 0.902, so we cannot reject the equality of the common coefficients across b_0 and b_1. To be certain, I also add to this test a test of whether the means of the two Price Indexes (lagged and not) are different. With 41 degrees of freedom, the chi-square statistic is 30.28. The exact level of significance (p-value) on the assertion that the test statistic is in the critical region above the critical value for a χ^2 distribution with 41 degrees of freedom (roughly 52) is 0.911, so we again cannot reject the equality of the common coefficients across b_0 and b_1 and particularly across the differing Price Indexes. Therefore b_1 (the default vector of coefficient estimates across any of the models reported here) does not display price-quantity endogeneity, as hypothesized from the particular construction of the Price Index. Lagging the Price vector in anticipation of endogeneity would be redundant.

Hypothesis testing is done on second-stage OLS coefficient estimates after two-step Heckman estimation, with marginal effects (**MEs**) interpreted only after a further stage of adjustment that conforms to:

$$\frac{\partial E(y_2 \mid y_1^* > 0)}{\partial x_k} = \beta_{2k} - \sigma_{12}\lambda(\mathbf{x}_{1k}^{'}\beta_{1k})[\mathbf{x}_{1k}^{'}\beta_{1k} + \lambda(\mathbf{x}_{1k}^{'}\beta_{1k})] \ , \tag{3}$$

which is the conditional probability of the outcome equation dependent variable based on a positive selection equation variable, adjusting outcome-equation coefficients, using the IMR, error correlation between the two estimation equations, and probit equation coefficients. I will refer to this as "***mfx adjustment***." Direct inference on OLS variables common to the probit equation is inappropriate to describe the behavior of those who have selected into the market.[18] Practical application of this correction involves construction of the elements of equation (3) from estimation results, in a formula that yields a result to which the delta method may be applied "to compute the [standard error] of a non-linear function for which it is too complex to analytically compute the variance." The delta method uses a Taylor series to linearly approximate a non-

[18] "As is well-documented in the theoretical literature but rarely applied in the applied literature, the calculation of these marginal effects must be adjusted to account for sample selection bias" (Vance: 1418). Vance offers an example in his paper where failure to apply the mfx adjustment led to "misleading inferences …[being] drawn with respect to the precision of the estimated coefficients" in other authors' peer-reviewed published work.

linear function, then this linear-approximate result is used to compute variance for inference on the relevant estimate, whose distribution is the function of multiple parameters (Vance: 1416, including quote). The difference between the mfx adjustment numbers used for inference and the original OLS coefficient estimates are ultimately not predictable in linear fashion. This mfx adjustment process of defining linear approximate solutions for multiple parameter distributions yields marginal effects that are often 20-35% smaller than the original OLS-side coefficient estimates (selection into the market is a restriction), but some of which fall by more than 90%, and a few of which rise in size. Signs of the marginal effects rarely flip from original OLS-side coefficient estimate signs, but this does occur with numbers relatively close to 0 in magnitude.[19]

The final "coefficient estimates" vector for inference is thus a combination first of coefficient estimates taken directly from OLS estimation, for variables unique to the OLS equation, and second of products of the mfx adjustment process (adjusted MEs), for variables existing in the OLS and probit equations. Within this vector, the "coefficient estimates/MEs" on demographic variables (including demographic-demographic interaction variables), on the constant, and the seasonal binaries are directly interpretable in ounces purchased – but not weekly. Remembering that the OLS-side estimation is for positive-quantity observations only, these are quantities *when the HH buys sCSDs*, not weekly (for all but a very few HHs). Within the same vector, all estimates/MEs that are – or are interacted with – the continuous marketing-mix variables (Price, Advertising) must be multiplied by some value for the continuous variable to be interpreted in ounces. For all inference, the data-wide average value of each continuous marketing-mix variable is used to calculate marketing-mix variable MEs in ounce-equivalents.

Standard errors for the mfx-adjusted ME estimates generated from the delta method application are almost uniformly too similar to the original variance-covariance matrix values associated with OLS-side output to significantly affect the results of hypothesis testing, such as for simple z-scores and critical p-values.[20] OLS standard errors are used for hypothesis testing.

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[19] Rare exceptions include x2PvIncxFmPCollg & x1PvIncxSmCollg in the REFINED model.

[20] Standard errors (even heteroskedasticity-robust ones) may vary from OLS results because an estimate of the IMR is used, so the estimate brings its own standard error into an already heteroskedastic model. As with the coefficients versus marginal effects on variables common to both equations of estimation, whether the variance is higher or lower is not predictable (Cameron & Trivedi, 2005: 550; Vance: 38). Greene states that there are also unknown parameters of the IMR, in addition to its heteroskedasticity (Greene, 2003: 785). While checking for differences between the adjusted and unadjusted standard errors is driven by statistical theory (Cameron & Trivedi, 2005: 550), in practice here, the effective mathematical differences between the adjusted and unadjusted standard errors proved almost uniformly negligible in their ultimate effect on z-scores or p-values, as differences are routinely under 2% of the absolute value of the standard error. To be clear, z-scores and p-values may differ between OLS estimates and mfx-adjusted ME values for identical variables, but the standard error value strongly tends to be identical to within 2%, regardless of the estimate or corresponding mfx-adjusted value. For the REFINED model, delta-method-generated standard errors are identical to the OLS-side standard errors for all un-interacted variables (i.e., all the variables for which such calculation is appropriate). So using the OLS variance-covariance matrix on the mfx-adjusted vector is extremely unlikely to change significance calculations for any single un-interacted variable, and because much relevant inference is done on combinations of estimates/MEs, any possible effect is diminished further. References exist that directly assert that STATA automatically does the standard error correction properly, meaning that any further delta-method correction would yield very similar results (https://files.nyu.edu/mrg217/public/selection.pdf, accessed 26 August, 2011).