Effects of Container Size on Overconsumption of Carbonated Soft Drinks

Xiaoyong Zheng
North Carolina State University

Chen Zhen
RTI International

and

Michael Wohlgenant
North Carolina State Unviersity

Please do not quote without permission

Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Orlando, FL, July 27-29, 2008.

Effects of Container Size on Overconsumption of Carbonated Soft Drinks*

Xiaoyong Zheng, Chen Zhen and Michael Wohlgenant†

May 5, 2008

Abstract

We take a structural approach to examine the effects of larger container size on consumption of carbonated soft drinks—using Nielsen Company's Homescan data on household purchases for the years 2004 through 2006. Our results show that by removing the price discount implicit in packages with larger container size, the average unit price the two households pay for CSD products increase and hence both households (both the low income and the high income) reduce their annual consumption of soft drinks by about 75%. This reduction is due to a combination of reduced number of purchases and switching to products with less number of bottles/cans.

*We thank Shawn Karns for wonderful assistance in cleaning the data.

†Zheng: Department of Agricultural and Resource Economics, North Carolina State University. Email address: xzheng@ncsu.edu. Zhen: RTI International. Email address: czhen@rti.org. Wohlgenant: Department of Agricultural and Resource Economics, North Carolina State University. Email address: michael_wohlgenant@ncsu.edu.

1 Introduction

Food manufacturers sell packaged foods in a variety of package sizes. Food manufacturers generally price packaged foods so that larger packages have lower per unit prices compared to smaller packages. Although there is little discussion on the benefits and costs to consumers of different package sizes in the economics literature, there has been some research conducted in the marketing (nutrition) science on the role of package (portion) size in influencing usage volume (energy intake).

Recent laboratory and field experiments suggest that larger packages may increase usage volume for a number of consumer goods. Wansink (1996) found that the implicit price discounts for larger packages led subjects to use more cooking oil, spaghetti, bottled water, and detergent. In another experiment, Wansink and Kim (2005) reported that movie goers consumed more free popcorn when it was distributed in large containers than in small containers. Rolls, Roe, and Meengs (2006) showed that there is a significant effect of portion size on energy intake. In their experiments, there was no evidence that excess energy intake from consumption of large portions resulted in a reduction in energy intake in subsequent meals. Based on this research, we hypothesize that consumers who purchase larger package sizes for foods that are high in calories, sugar, fat and other undesirable nutrients may overconsume these foods which could ultimately contribute to poor health outcomes such as overweight and obesity.

To date, studies on package size have been limited to experimental and clinical settings. Although lab experiments provide useful insights about human behavior, they are not designed to recover deep structural parameters of consumer preferences (Levitt and List, 2006). The structural preference parameters are essential in quantifying behavioral response of the general population to changes in economic conditions. In other words, as long as the environment in the lab differs systematically from that in the natural setting, results do not need to correspond inside and outside the lab.

We take a structural approach to examine the effects of larger container size on consumption of carbonated soft drinks—using a large-scale panel of households in natural settings.

As the panel is designed to be nationally representative, we will be able to examine the differences in unhealthy food consumption behavior by household income. Quantitative measures of the contribution of large container size to overconsumption of carbonated soft drinks are needed to help inform academics, public health officials, and government regulators concerned with obesity issues.

We conduct econometric analyses of household demand for carbonated soft drinks using The Nielsen Company's Homescan data on household purchases for the years 2004 through 2006. Households in the Homescan panel are provided with a handheld scanner to record purchase information and upload all information on a weekly basis to Nielsen. Besides price and quantity information, the data contain information on container size, multipack, and a number of household demographic characteristics. This information will be used in estimating a dynamic multinomial logit discrete choice model of household demand for carbonated soft drinks. It is also planned that the econometric model to be extended to be a dynamic nested logit model with unobserved household characteristics similar to Shum (2004) who studied consumption dynamics of breakfast cereals using household scanner data. The estimated preference parameters are then be used to simulate the impact of removing the per unit price difference between soft drinks in larger containers and smaller containers.

Our results (based on the multinomial logit model) show that by removing the price discount implicit in packages with larger container size, the average unit price the two households pay for CSD products increase and hence both households (both the low income and the high income) reduce their annual consumption of soft drinks by about 75%. This reduction is due to a combination of reduced number of purchases and switching to products with less number of bottles/cans.

The rest of the paper is organized as follows. Section 2 describes the data. The empirical model and estimation method are presented in Section 3 and 4 respectively. Section 5 is devoted to the discussion of results. Results from counterfactual analyses are reported in Section 6. Plans for future extensions are detailed in Section 7. The final Section concludes.

2 Data

The data employed in this study consist of individual household purchase histories in supermarkets, weekly market-level prices, household characteristics and physical product characteristics. The data come from Nielson, covering the 25 major US markets for the years 2004, 2005 and 2006. Our sample includes information on the purchases of carbonated soft drinks by 1,000 households on a weekly basis. 500 households are from the low income class and the other 500 are from the high income class.

In this study, a product is defined as a UPC (Universal Product Code) to distinguish among different package sizes of a given brand. Different package sizes of a brand are treated as different products due to the significant differences in storability of, for instance, small aluminum cans and plastic bottles. This definition also distinguishes between diet versus regular (e.g., diet Coke is a different product than Coke Classic), and caffeine-free versus regular (e.g., Caffeine-Free Coke is different than Coke Classic). The definition of a brand differs from that of a product. A given brand, such as Coke Classic, is available in three different pack sizes: 12-pack of cans, 6-pack of cans, and a 2-liter bottle. In the CSD category, we also see brand extensions such as Diet Coke and Caffeine-free Diet Coke. Even though these bear the Coke name, they are priced and promoted differently. Hence, for the analysis below, we treat these brand extensions as separate products. In the data, there are about 3,052 different UPCs, or products. To simplify the analysis, we consolidate the number of products as follows. First, for the 45 products that have at least 0.5% of the aggregate sales volume share (in oz), we include them in the analysis, without any consolidation. For the remaining products, we consolidate them into 17 different aggregate products by whether the product is diet or not, the number of packs in the product and the volume in oz per pack. Table 1 provides the list of the products used in the analysis and their characteristics.

The household panel consists of 1,000 households' shopping histories (including trips during which no CSDs were purchased) in the 25 major U.S. markets during the sample period. Each household also has a corresponding set of reported demographic variables that are used to control for heterogeneity in tastes. In this study, we use the household size and the household income to control for such heterogeneity. For each household, the data only reports the income bracket in which the household income falls into. To convert this information to be a continuous income variable, we take the mean value of the two bounds of the income bracket and apply the logarithm transformation. In addition, in our analysis, a shopping trip is defined as one visit to a supermarket where a product of CSD is purchased or no CSD products is purchased. Please note that if a household purchased more than one unit of the CSD product or more than one CSD product during one visit, it is treated as multiple shopping trips. As a result, for some households, the number of observed shopping trips is larger than the number of weeks during the sample period. Table 2 provides summary statistics for household characteristics and their shopping trips, by income class. The total number of shopping trips observed for these 1,000 households is 155,555. On average, high income households made 152 shopping trips during the sample period and a CSD product is purchased in 74 of these trips. On the other hand, low income households made 160 shopping trips during the same time period and a CSD product is purchased in 85 of these trips. Therefore, it indicates that low income households tend to make slightly more shopping trips and buy CSD products slightly more frequently.

To conduct the analysis, we need price data for all the products in all the markets for all the weeks. We use weekly household purchase data to calculate the average weekly price for a product in a Nielsen major market. This price is taken to be the prevailing price for the week and market faced by households who did not purchase the product. Although we focus on the 25 major markets, there were still approximately 40,000 missing weekly prices due to nonpurchases. These account for about 16 percent of the 243,350 market/week/product prices needed to estimate the discrete-choice model. We regressed the observed weekly price on indicator variables for market, week, brand, multipack, volume, whether it is regular or diet and whether it is caffeine free or not, and used the predicted price to replace the missing prices. Using regional average prices to impute prices faced by nonconsuming households is common in empirical applications (Dong, Gould, and Kaiser 2004; Yen, Lin, and Smallwood 2003). For empirical studies of censored demand using unit values, two biases are possible. One is the bias from the simultaneity of unit value with expenditure. The other is the selectivity bias due to economic nonconsuming. Because we use UPC-level prices, the simultaneity bias may be less likely to be a major concern. The selectivity bias may be relevant if the missing prices are due to nonconsuming in response to higher prices. To confront this issue, one has to either have weekly store-level price data (e.g. Dubé 2004) or treat prices as endogenous (and estimate simultaneous equations with the demand model (see Wales and Woodland 1980 and Dong and Kaiser 2005 for models with one endogenous price). Given the large number of UPCs, joint estimation of quantity purchased and price paid is less likely to be empirically feasible. However, this appears to be a good topic for future research. The last column of Table 1 provides the average price across markets and time periods for all the products.

We measure household product loyalty by households' past purchases. Specifically, we create two indicator variables to distinguish two kinds of product loyalty. The first variable is $\text{Pastuse}_{ijt}^{\text{brand}}$, which takes the value of 1 if household i purchased at least a product of the same brand (no matter which package size) as product j in the previous 12 weeks. This measures households' brand loyalty. The second variable is $\text{Pastuse}_{ijt}^{\text{size}}$, which takes a value of 1 if household i purchased at least a product of the same package size (no matter which brand) as product j in the previous 12 weeks. This captures the households' loyalty or habit formation for a certain package size.

Finally, since CSD products can be easily stored in households, it seems natural that at a weekly level, the utility a household derives from a CSD purchase depends on the stock available. To capture this effect, we create another variable Stock_{it}, which takes the value of 1 if the household purchased any CSD product during the previous 2 weeks.

3 The Empirical Model

Following the Berry, Levinson and Pakes (BLP 2005) literature, the indirect utility for household i in market m to choose product j in week t is assumed to be

$$u_{ijmt} = \delta_{ijmt} + \varepsilon_{ijmt} \text{ for } j = 0, 1, ...J$$

where δ_{ijmt} is the deterministic component of the utility and ε_{ijmt} is the stochastic component. 0 denotes the outside choice, that is, the household made a shopping trip but no CSD product is purchased. $j = 1, ..., J$ are the indices for the 62 included products discussed above. Both δ_{ijmt} and ε_{ijmt} are observed by the households when they decide which product to purchase. On the other hand, only δ_{ijmt} is observed by the econometrician. δ_{ijmt} is specified to be

$$\begin{aligned}\delta_{ijmt} &= x_j\beta_0 + x_{ijt}\beta_1 + x_{it}\beta_2 + \theta_1 \text{Pastuse}_{ijt}^{\text{brand}} + \theta_2 \text{Pastuse}_{ijt}^{\text{size}} \\ &+ \left(\alpha + \theta_3 \text{Pastuse}_{ijt}^{\text{brand}} + \theta_4 \text{Pastuse}_{ijt}^{\text{size}} + x_{it}\beta_3\right) p_{jmt} \text{ for } j = 1, ..., J.\end{aligned}$$

x_j is a vector of product dummies, one for each product (does not include the constant to avoid multi-collinearity). The inclusion of the product dummies allows us to control for the effect of unobserved product characteristics on households' utility. These unobserved product characteristics are also likely to be correlated with the price variable in the utility function. Hence, failing to control for these unobserved product characteristics could lead to endogeneity bias.

x_{ijt} is a vector of interaction variables between household-specific demographics (Famsize_{it}, Inc_{it}) and product-specific characteristics (Multi_j, Volume_j, Diet_j). In particular, x_{ijt} includes $\text{Famsize}_{it}\text{Multi}_j$, $\text{Famsize}_{it}\text{Volume}_j$, $\text{Famsize}_{it}\text{Diet}_j$, $\text{Inc}_{it}\text{Multi}_j$, $\text{Inc}_{it}\text{Volume}_j$ and $\text{Inc}_{it}\text{Diet}_j$. These interaction variables capture the fact that different households value the same product characteristics differently. x_{it} is a vector of variables that vary by household and time periods, including Famsize_{it}, Inc_{it} and Stock_{it}. Finally, p_{jmt} denotes the price for product j in market m during week t in terms of dollars per ounce. One thing to note here is that we allow the time varying household characteristics and loyalty variables to affect the utility in two ways. First, they enter the utility specification directly. Second, they also affect the slope (with respect to price) of a product's utility. To complete the model, we also need to specify δ_{i0mt}, the deterministic component of the utility when household i in market m purchased no CSD product in week t. Following the literature, it is normalized to be 0.

In period t, household i in market m chooses the product j that maximizes its utility, that is,

$$\max_{j \in [0,1,...,J]} u_{ijmt}.$$

4 Estimation

Assume that ε_{ijmt} follows an i.i.d. (across i, j, m and t) type I extreme value distribution, the likelihood for household i in market m to purchase product j in period t can be written as

$$l_{ijmt} = \frac{\exp\left(\delta_{ijmt}\right)}{1 + \sum_{k=1}^{J} \exp\left(\delta_{ikmt}\right)},$$

which implies the log likelihood function for all the observations can be written as

$$L = \sum_{i=1}^{N} \sum_{m=1}^{M} \sum_{t=1}^{T_{im}} \sum_{j=0}^{J} d_{ijmt} \log\left(l_{ijmt}\right).$$

d_{ijmt} equals 1 if household i in market m purchased product j in period t and 0 otherwise. N is the total number of households, M is the number of markets and T_{im} is the observed number of shopping trips by household i in market m during the sample period.

5 Results

5.1 Parameter Estimates

Table 3 collects the estimation results from the multinomial logit model. Most of the parameters have the expected sign. For example, households with more family members are willing to pay more for CSD products (β_{31}), and they prefer a product with more packs (β_{11}), larger container (β_{12}) and not diet (β_{13}). Also, households with more income are less likely to purchase CSD products (β_{22}), are willing to pay less for CSD products (β_{32}), and they prefer a product with more packs (β_{14}), but smaller container (β_{15}) and diet (β_{16}). This can be explained by the fact that high income households are more aware of the adverse health effects of consuming CSD products. Therefore, when they purchase CSD products, they prefer those packaged in smaller containers and diet products instead of regular ones.

Turning to the product loyalty variables, consistent with our prior expectations, households tend to form habit over both the brand (θ_1) as well as the package size (θ_2), that is to say, they are more likely to purchase products of the same brand and packaged the same.

More interestingly, the two loyalty variables have different effects on households' willingness to pay. Households seem to be willing to pay less now for the products of the same brand as those products they consumed in the past 12 weeks (θ_3), but are willing to pay more for products of the same package size as those products they consumed in the past 12 weeks (θ_4), though both variables are only significant at the 10% level.

Finally, the estimated fixed effects are all significant. The average value across the 62 included products is -7.0352, with a standard deviation of 1.7296.

5.2 Elasticities

Next, we use the estimated structural parameters to compute the aggregate own and cross price elasticities for the 62 included products. Given the model specifications above, the own price elasticity of product j for household i in market m in period t can be calculated using

$$e_{imt,jj} = \frac{\partial l_{ijmt}}{\partial p_{jmt}} \frac{p_{jmt}}{l_{ijmt}} = (1 - l_{ijmt}) \left(\alpha + \theta_3 \text{Pastuse}_{ijt}^{\text{brand}} + \theta_4 \text{Pastuse}_{ijt}^{\text{size}} + x_{it}\beta_3 \right) p_{jmt}.$$

As a result, the average own price elasticity across all the observations is $\frac{1}{N}\sum_{i=1}^{N}\frac{1}{M}\sum_{m=1}^{M}\frac{1}{T_{im}}\sum_{t=1}^{T_{im}} e_{imt,jj}$. Similarly, the cross price elasticity between product j and k for household i in market m in period t can be written as

$$e_{imt,jk} = \frac{\partial l_{ijmt}}{\partial p_{kmt}} \frac{p_{kmt}}{l_{ijmt}} = -l_{ikmt} \left(\alpha + \theta_3 \text{Pastuse}_{ikt}^{\text{brand}} + \theta_4 \text{Pastuse}_{ikt}^{\text{size}} + x_{it}\beta_3 \right) p_{kmt}$$

and hence average cross price elasticity is $\frac{1}{N}\sum_{i=1}^{N}\frac{1}{M}\sum_{m=1}^{M}\frac{1}{T_{im}}\sum_{t=1}^{T_{im}} e_{imt,jk}$. One thing worth mentioning is that it is a well known fact that the multinomial logit model suffers the Independence of irrelevant alternatives (IIA) problem, that is, by construction, $e_{imt,jk} = e_{imt,j'k}$ for any j and j' not equal to k. Intuitively, we would expect that $e_{imt,jk} > e_{imt,j'k}$ if product j is a closer substitute to product k than product j'. Given this restriction of the multinomial logit model, results obtained here need to be interpreted with caution. As described in Section 7, we plan to explore alternative models that relax this restriction in future extensions.

Table 4 collects the average own and cross price elasticities for all the included 62 products. The own price elasticities for the 62 products range from -1.1884 to -0.2081, with an average at -0.4263 and standard deviation at 0.1752, indicating that demand for CSD products are inelastic. The cross price elasticities range from 0.0003 to 0.0321, with an average at 0.0037 and standard deviation at 0.0053. This indicates that CSD products are substitutes to one another, as expected. However, the demand for an individual CSD product only weakly responds to changes in the prices of other CSD products.

6 Counterfactual Analysis

As mentioned above, the motivation for this study comes from the fact that different CSD products are sold in different package sizes and products with larger container size charges a lower unit price. This can be easily seen from Tables 5 and 6, which represents the average unit prices for different CSD products organized by package size. Table 5 is for products packaged in plastic bottles and Table 6 is for products packaged in cans. For products packaged in plastic bottles, it is clear that as the per bottle size goes up, the average unit price goes down, with the exception of the 20oz×1 package and the 33.8oz×1 package, both of which are more likely to be sold in convenience stores rather than in supermarkets. For products packaged in cans, the same trend is observed. Therefore, we have plenty evidence showing that indeed soft drinks companies offer a discount in unit price for products packaged in larger contained size.

The discounts for products in larger containers have profound impacts on consumers' demand for different CSD products. Estimation results above show that product loyalty variables (both brand and size) are significant determinants of consumers' demand. In one period, if a household is induced to purchase a CSD product packaged in a large container over a product packaged in a small container due to the implicit price discount for the former, then it is likely that this household will form habit or product loyalty for this product and as a result, in the long run, this household will consume a lot more CSD products if it purchased a product packaged in a small container.

To empirically quantity this effect, we conduct a counterfactual experiment using the estimated model. The experiment is conducted as follows. We simulate a household's purchasing behavior for an entire year, that is, the year 2005. During any week in that year, the price discounts contained in products packaged in large container size are removed. For example, for products packaged in plastic bottles, in market m during week t, unit prices for the 16.9oz $\times$ 6 package, the 24oz $\times$ 6 package and the 101.4oz $\times$ 1 package are reset to be the same as that charged for the 67.6oz $\times$ 1 package during that week in that market. The unit prices for the 20oz $\times$ 1 package and the 33.8oz$\times$1 package are left unchanged as the prices for these two products do not follow the same trend and only constitute small market shares in the CSD market. Similarly, for products packaged in cans, in market m during week t, unit prices for the 12oz $\times$ 1 package, 12oz $\times$ 24 package and 12oz $\times$ 36 package are reset to be the same as that charged for the 12oz $\times$ 12 package during that week in that market. The unit prices for the 12oz $\times$ 1 package is left unchanged as the price for this package do not follow the same trend and only constitutes a small market share in the CSD market.

We conduct the experiment for two households, one from the high income class (household id 2073807) and one from the low income class (household id 2006190). Before running the counterfactual experiment, we first examine their observed purchasing behavior in 2005. This information is collected is Table 7. Both households have 5 household members in 2005. During the year, the two households purchased similar number of CSD products, 41 and 40 respectively. The low income household purchased CSD products with more bottles or cans, and hence consuming more soft drinks in terms of total volume. A little bit surprising is the fact that the high income household purchased products packaged in larger containers and as a result, pay a low unit price on average.

We perform the counterfactual experiments for the two households and the results are collected in Table 8. The results are based upon 200 dynamic paths for the selected household and the averages are reported. Comparing results in Table 8 with those of Table 7, we found that by removing the price discount implicit in packages with larger container size, the average unit price the two households pay for CSD products increase and hence both households (both the low income and the high income) reduce their annual consumption of soft drinks by about

75%. This reduction is due to a combination of reduced number of purchases and switching to products with less number of bottles/cans.

7 Future Extensions

As mentioned above, the multinominal logit model imposes a counter-intuitive cross price elasticities structure onto the data (the IIA property). In future extensions of this study, we plan to use alternative discrete choice models to relax this restriction. One such model is the nested logit model proposed by McFadden (1981). A two-level nested logit model (McFadden 1981) assumes that $\varepsilon_{i0mt}, \varepsilon_{i1mt}, ..., \varepsilon_{iJmt}$ follow the joint distribution

$$F\left(\varepsilon_{i0mt}, \varepsilon_{i1mt}, ..., \varepsilon_{iJmt}\right) = \exp\left\{-\sum_{s=1}^{S}\left[\sum_{j\in B_s}\exp\left(-\frac{1}{1-\sigma_{it}}\varepsilon_{ijmt}\right)\right]^{1-\sigma_{it}}\right\},$$

where S is the number of nests and B_s is a collection of indices for products in nest s. $0 < \sigma_{it} < 1$ is a parameter that determines the correlations among the errors and can be interpreted as the larger substitutability within than across nests. Note that when σ_{it} goes to 0, the model is reduced to the standard multinomial logit. The two-level nested logit model assumes that households make decisions sequentially. First, they group all the products into several groups and choose the group. Then, conditional on their group choice, they choose which product in that group to consume.

In our study, we assume for each household in week t, there are three nests. The first nest is the outside choice by itself. The second nest includes all the products that the household has purchased recently, that is, within w (=12) weeks. The third nest includes the rest of the products that the household has not purchased recently. Then, the likelihood for household i in market m to purchase product j that belongs to nest s in period t can be written as

$$l_{ijmt} = \frac{\exp\left\{\delta_{ijmt} - \sigma_{it}\log\left[\sum_{k\in B_s}\exp\left(\delta_{ikmt}\right)\right]\right\}}{1+\left[\sum_{k\in B_2}\exp\left(\delta_{ikmt}\right)\right]^{1-\sigma_{it}} + \left[\sum_{k\in B_3}\exp\left(\delta_{ikmt}\right)\right]^{1-\sigma_{it}}},$$

which implies the log likelihood function to be

$$L = \sum_{i=1}^{N}\sum_{m=1}^{M}\sum_{t=1}^{T_{im}}\sum_{j=0}^{J} d_{ijmt}\log\left(l_{ijmt}\right).$$

In our estimation, we plan to specify $\sigma_{it} = \frac{\exp(\sigma_0+\sigma_1 \text{Famsize}_{it}+\sigma_2 \text{Inc}_{it})}{1+\exp(\sigma_0+\sigma_1 \text{Famsize}_{it}+\sigma_2 \text{Inc}_{it})}$.

The nested logit model allows more flexible substitutions between more familiar (to the household) products and less familiar products. Although within a nest the IIA property still applies for cross-price elasticities of individual households, it is not the case for aggregate cross-price elasticities. This is because different households have different nests in different time periods, the aggregate substitution pattern between products and is more heavily influenced by households whose preferences exhibit closer substitution between and than those that do not. Hence the IIA property for the basic logit models is unlikely to be an issue for aggregate elasticities in nested logit models.

8 Conclusions

We take a structural approach to examine the effects of larger container size on consumption of carbonated soft drinks—using Nielsen Company's Homescan data on household purchases for the years 2004 through 2006. Our results show that by removing the price discount implicit in packages with larger container size, the average unit price the two households pay for CSD products increase and hence both households (both the low income and the high income) reduce their annual consumption of soft drinks by about 75%. This reduction is due to a combination of reduced number of purchases and switching to products with less number of bottles/cans.

References

Berry, S., J. Levinson, and A. Pakes (1995): "Automobile Price in Market Equilibrium," Econometrica, 63, 841-90.

Dong, D. and H.M. Kaiser. 2005. "Coupon Redemption and Its Effect on Household Cheese Purchases." American Journal of Agricultural Economics 87: 689-702.

Dubé, J-P. 2004. "Multiple Discreteness and Product Differentiation: Demand for Carbonated Soft Drinks." Marketing Science 23: 66-81

Dubé, J.-P., 2005, "Product Differentiation and Mergers in the Carbonated Soft Drink Industry." Journal of Economics and Management Strategy, 14, 879-904.

Levitt, Steven D., and John A. List, 2006, "What Do Laboratory Experiments Tell Us About the Real World?" working paper, Department of Economics, University of Chicago.

McFadden, D. L. (1981): "Econometric Models of Probabilistic Choice," in *Structural Analysis of Discrete Data with Econometric Applications*, ed. C. F. Manski and D. L. McFadden. Cambridge, MA: MIT Press, 198-272.

Rolls, B. J., Roe, L. S., & Meengs, J. S. (2006). Larger portion sizes lead to a sustained increase in energy intake over 2 days. Journal of the American Dietetic Association, 106, 543-549.

Shum, M. 2004, "Does Advertising Overcome Brand Loyalty? Evidence from the Breakast-cereals Markets." Journal of Economics and Management Strategy, 13, 241-272.

Wales, T.J. and A.D. Woodland. 1980. "Sample Selectivity and the Estimation of Labor Supply Functions." International Economic Review 21: 437-468.

Wansink, Brian, 1996, "Can Package Size Accelerate Usage Volume?" Journal of Marketing, 60, 1-14.

Wansink, Brian, and Junyong Kim, 2005, "Bad Popcorn in Big Buckets: Portion Size Can Influence Intake as Much as Taste," Journal of Nutrition Education and Behavior, 37, 242-245.

Yen, S.T., B-H Lin, and D.M. Smallwood. 2003. "Quasi- and Simulated-likelihood Approaches to Censored Demand Systems: Food Consumption by Food Stamp Recipients in the United States." American Journal of Agricultural Economics 85: 458-478.

Table 1 List of Products and Their Characteristics

index	product name	type	volume	# of packs	ave. price
1	COCA-COLA CLASSIC R	regular	67.6	1	0.0164
2	COCA-COLA CLASSIC R	regular	16.9	6	0.0264
3	COCA-COLA CLASSIC R	regular	12	12	0.0216
4	COCA-COLA CLASSIC R	regular	12	24	0.0194
5	PEPSI CAFFEINE FREE R	regular	12	12	0.0213
6	PEPSI R	regular	67.6	1	0.0157
7	PEPSI R	regular	24	6	0.0199
8	PEPSI R	regular	12	12	0.0210
9	PEPSI R	regular	12	24	0.0190
10	SPRITE R	regular	67.6	1	0.0161
11	SPRITE R	regular	12	12	0.0215
12	DR PEPPER R	regular	67.6	1	0.0160
13	DR PEPPER R	regular	12	12	0.0217
14	DR PEPPER R	regular	12	24	0.0193
15	MOUNTAIN DEW R	regular	67.6	1	0.0155
16	MOUNTAIN DEW R	regular	24	6	0.0200
17	MOUNTAIN DEW R	regular	12	12	0.0212
18	MOUNTAIN DEW R	regular	12	24	0.0190
19	SEVEN UP R	regular	12	12	0.0206
20	A & W R	regular	12	12	0.0211
21	CTL BR R	regular	67.6	1	0.0099
22	CTL BR R	regular	101.4	1	0.0100
23	CTL BR R	regular	12	12	0.0141
24	CTL BR R	regular	12	24	0.0145
25	Aggregate-Reg Soda 1	regular	12	1	0.0340
26	Aggregate-Reg Soda 2	regular	20	1	0.0533

Table 1 Continued

index	product name	type	volume	# of packs	avg. price
27	Aggregate-Reg Soda 3	regular	33.8	1	0.0286
28	Aggregate-Reg Soda 4	regular	67.6	1	0.0153
29	Aggregate-Reg Soda 5	regular	101.4	1	0.0110
30	Aggregate-Reg Soda 6	regular	16.9	6	0.0262
31	Aggregate-Reg Soda 7	regular	24	6	0.0188
32	Aggregate-Reg Soda 8	regular	12	12	0.0209
33	Aggregate-Reg Soda 9	regular	12	24	0.0184
34	Aggregate-Reg Soda 10	regular	12	36	0.0180
35	COCA-COLA CAFFEINE FREE DT	diet	67.6	1	0.0163
36	COCA-COLA CAFFEINE FREE DT	diet	12	12	0.0215
37	COCA-COLA DT	diet	67.6	1	0.0161
38	COCA-COLA DT	diet	16.9	6	0.0263
39	COCA-COLA DT	diet	12	12	0.0216
40	COCA-COLA DT	diet	12	24	0.0193
41	PEPSI CAFFEINE FREE DT	diet	67.6	1	0.0154
42	PEPSI CAFFEINE FREE DT	diet	12	12	0.0210
43	PEPSI DT	diet	67.6	1	0.0157
44	PEPSI DT	diet	24	6	0.0201
45	PEPSI DT	diet	12	12	0.0209
46	PEPSI DT	diet	12	24	0.0188
47	DR PEPPER DT	diet	12	12	0.0219
48	MOUNTAIN DEW DT	diet	67.6	1	0.0157
49	MOUNTAIN DEW DT	diet	12	12	0.0214
50	A & W DT	diet	12	12	0.0213
51	DIET RITE PURE ZERO DT	diet	12	12	0.0210
52	CTL BR DT	diet	33.8	1	0.0178

Table 1 Continued

index	product name	type	volume	# of packs	avg. price
53	CTL BR DT	diet	67.6	1	0.0099
54	CTL BR DT	diet	12	12	0.0144
55	CTL BR DT	diet	12	24	0.0145
56	Aggregate-Diet Soda 1	diet	12	1	0.0383
57	Aggregate-Diet Soda 2	diet	20	1	0.0536
58	Aggregate-Diet Soda 3	diet	67.6	1	0.0153
59	Aggregate-Diet Soda 4	diet	16.9	6	0.0253
60	Aggregate-Diet Soda 5	diet	24	6	0.0191
61	Aggregate-Diet Soda 6	diet	12	12	0.0215
62	Aggregate-Diet Soda 7	diet	12	24	0.0181

Table 2 Household Characteristics

	mean	std. dev.	min	max
high income class				
family size	2.24	1.10	1	7
log income	10.88	0.53	9.77	11.70
# of shopping trips	152.55	56.52	46	506
# of shopping trips that a CSD product bought	74.47	75.11	1	505
low income class				
family size	2.07	1.49	1	9
log income	9.30	0.53	7.82	10.53
# of shopping trips	160.43	80.15	32	843
# of shopping trips that a CSD product bought	85.45	101.53	1	843

Table 3 Estimation Results from Multinomial Logit Model

	estimate	std. err.	t-stat		estimate	std. err.	t-stat
β_1				β_3			
$\text{Famsize}_{it}\text{Multi}_j$	0.0102	0.0006	17.3671	Famsize_{it}	2.3426	0.2809	8.3384
$\text{Famsize}_{it}\text{Volume}_j$	0.0030	0.0002	18.2157	Inc_{it}	-1.8805	0.4679	-4.0189
$\text{Famsize}_{it}\text{Diet}_j$	-0.2382	0.0053	-44.8562	Stock_{it}	5.0252	0.7262	6.9203
$\text{Inc}_{it}\text{Multi}_j$	0.0047	0.0010	4.7640	α	-9.3156	5.0579	-1.8418
$\text{Inc}_{it}\text{Volume}_j$	-0.0013	0.0003	-4.8445	θ_1	2.1556	0.0402	53.5588
$\text{Inc}_{it}\text{Diet}_j$	0.2020	0.0081	25.0252	θ_2	2.3257	0.0248	93.9537
β_2	9.30	0.53	7.82	θ_3	-3.3113	1.9256	-1.7196
Famsize_{it}	0.0134	0.0149	0.8977	θ_4	1.4902	0.8825	1.6886
Inc_{it}	-0.1066	0.0240	-4.4363	β_0	average	-7.3052	
Stock_{it}	0.5043	0.0198	25.4379		std. dev.	1.7296	

Table 4 Own and Cross Price Elasticities

index	own price	cross price	index	own price	cross price	index	own price	cross price
1	-0.3340	0.0032	27	-0.6609	0.0083	53	-0.2106	0.0025
2	-0.5587	0.0021	28	-0.3250	0.0127	54	-0.3059	0.0026
3	-0.4355	0.0054	29	-0.2473	0.0009	55	-0.3140	0.0005
4	-0.3955	0.0010	30	-0.5921	0.0029	56	-0.8179	0.0112
5	-0.4330	0.0008	31	-0.4249	0.0010	57	-1.1884	0.0182
6	-0.3183	0.0041	32	-0.4445	0.0109	58	-0.3270	0.0089
7	-0.4176	0.0014	33	-0.4060	0.0008	59	-0.5706	0.0013
8	-0.4221	0.0046	34	-0.3937	0.0004	60	-0.4312	0.0013
9	-0.3871	0.0012	35	-0.3335	0.0013	61	-0.4572	0.0093
10	-0.3139	0.0012	36	-0.4359	0.0025	62	-0.3977	0.0015
11	-0.4182	0.0014	37	-0.3259	0.0036			
12	-0.3165	0.0013	38	-0.5543	0.0010			
13	-0.4223	0.0026	39	-0.4355	0.0056			
14	-0.3778	0.0003	40	-0.3939	0.0012			
15	-0.3077	0.0010	41	-0.3156	0.0015			
16	-0.4066	0.0005	42	-0.4259	0.0012			
17	-0.4144	0.0016	43	-0.3174	0.0021			
18	-0.3737	0.0003	44	-0.4239	0.0008			
19	-0.3997	0.0010	45	-0.4218	0.0032			
20	-0.4081	0.0012	46	-0.3831	0.0008			
21	-0.2081	0.0046	47	-0.4269	0.0014			
22	-0.2233	0.0008	48	-0.3092	0.0011			
23	-0.2992	0.0046	49	-0.4201	0.0007			
24	-0.3127	0.0007	50	-0.4132	0.0008			
25	-0.7222	0.0149	51	-0.4051	0.0015			
26	-1.1591	0.0321	52	-0.3989	0.0077			

Table 5 Average Prices for Products Packaged in Plastic Bottles

product name	16.9oz × 6	20oz × 1	24oz × 6	33.8oz × 1	67.6oz × 1	101.4oz × 1
COCA-COLA CLASSIC R	0.0264				0.0164	
PEPSI R			0.0199		0.0157	
SPRITE R					0.0161	
DR PEPPER R					0.0160	
MOUNTAIN DEW R			0.0200		0.0155	
CTL BR R					0.0099	0.0100
Aggregate-Reg	0.0262	0.0533	0.0188	0.0256	0.0153	0.0110
COCA-COLA CAF FR DT					0.0163	
COCA-COLA DT	0.0263				0.0161	
PEPSI CAF FR DT					0.0154	
PEPSI DT			0.0201		0.0157	
MOUNTAIN DEW DT					0.0157	
CTL BR DT				0.0178	0.0099	
Aggregate-Diet	0.0253	0.0536	0.0191		0.0153	

Table 6 Average Prices for Products Packaged in Cans

product name	12oz × 1	12oz × 12	12oz × 24	12oz × 36
COCA-COLA CLASSIC R		0.0216	0.0194	
PEPSI CAFFEINE FREE R		0.0213		
PEPSI R		0.0210	0.0190	
SPRITE R		0.0215		
DR PEPPER R		0.0217	0.0193	
MOUNTAIN DEW R		0.0212	0.0190	
SEVEN UP R		0.0206		
A & W R		0.0211		
CTL BR R		0.0141	0.0145	
Aggregate-Reg	0.0340	0.0209	0.0184	0.0180
COCA-COLA CAFFEINE FREE DT		0.0215		
COCA-COLA DT		0.0216	0.0193	
PEPSI CAFFEINE FREE DT		0.0210		
PEPSI DT		0.0209	0.0188	
DR PEPPER DT		0.0219		
MOUNTAIN DEW DT		0.0214		
A & W DT		0.0213		
DIET RITE PURE ZERO DT		0.0210		
CTL BR DT		0.0144	0.0145	
Aggregate-Diet		0.0215	0.0181	

Table 7 Observed Purchase Behavior for Households in Counterfactual Experiments

household id	2006190	2073807
number of products purchased	41	40
average bottle/can per product	8.98	2.65
total volume (oz)	5494.8	3031.6
average bottle/can size	14.93	28.60
average unit price (dollar/oz)	0.0219	0.0180

Table 8 Purchase Behavior for Households from Counterfactual Experiments

household id	2006190	2073807
number of products purchased	24.67	16.66
average bottle/can per product	1.68	2.55
total volume (oz)	1037.9	786.92
average bottle/can size	28.47	25.64
average unit price (dollar/oz)	0.0294	0.0279