The Effect of Consumer Learning Behavior on the Rising Bottled Water Consumption

Lu Huang
Department of Agricultural and Resource Economics
University of Connecticut
lu.huang@uconn.edu

Yizao Liu
Department of Agricultural and Resource Economics
University of Connecticut
yizao.liu@uconn.edu

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Abstract

This paper examines the impact of consumer learning behavior on the rising bottled water consumption. Consumers are assumed with initial prior beliefs about the distribution of health effect of beverages and update their beliefs using health information in a Baysian manner. We find that the health effect perception for bottled water is much higher than for sugar sweetened soft drinks, which can explain the increase in bottled water consumption over time. According to our findings, health information can promote healthy diet and reduce sugar intake through consumers' learning behavior. This finding helps policy makers develop more effective obesity control programs.

Keywords: Consumer learning, Information Economics, Bottled Water

JEL classification: D12, D83

1 Introduction

Bottled water consumption has been increasing consistently over the last several decades in the United States, with a per capita consumption rising from 1.6 gallons in 1976 to 29.2 gallons in 2011. As a result, bottled water has become the fastest growing segment of non-alcoholic beverages, representing an overall share of 30 % in the liquid refreshment beverages market in 2010, comparing to 11.6% in 1995 (Beverage Marketing Corporation,2011). On the contrary, carbonated soft drinks (CSDs) demand has been declining since 2005. Figure 1 shows the changes in percapita consumption of several beverages.

High water consumption has been proved to be an aid to weight control (Popkin et al, 2005). Obesity is commonly acknowledged as the leading public health crisis in the United States, with an estimated social cost of approximately $120 billion a year (Rowley, 2004). And CSDs, known as the single largest source of calorie intake in the U.S., are believed to be responsible for the epidemic of obesity. As more and more consumers use bottled water as substitutes for CSDs and other sugar filled beverages, the healthy drinking habit is expected to play a role in promoting a healthy diet, lowering the rate of obesity, and reducing the associated social costs. Facing the fact that two out of every three adults are either overweight or obese in the U.S., the knowledge of the determinants of healthy and unhealthy food and beverage choices over time will shed light on factors that affect obesity, and help policy makers in developing programs to effectively improve healthy diet.

Some studies have tried to model the demand for healthy and unhealthy beverages to examine U.S. consumer preferences and analyze how these preferences are linked to an apparently higher incidence of obesity in this population. For example, Yen et al (2004) estimated a demand system for U.S. household beverage consumption including milk, juice, coffee, tea and soft drinks and found that price plays an important role in the declining consumption of healthy beverage (milk) and rising consumption of unhealthy beverage (soft drinks). But these studies mainly focus on the role of relative prices and find mixed results.

Our explanation of consumers switching from CSDs to bottled water is that they have been aware of the health effect of drink these beverages. Increasing evidence about obesity and other negative health outcomes caused by CSDs has been issued under continuing research. Consumers learn information about the association between health outcomes and consumption behaviors from many sources and modify their beverage choices accordingly. The seminal paper in this area is the Brown and Schrader (1990). They use the number of journal articles with the key word "cholesterol" to build indices as a proxy for health information and find that cholesterol information reduces U.S. egg demand by 19 %. Following studies use more sophisticated ways to build information indices (McGuirk et al. 1995, Burton and Young, 1996, Verbeke and Ward, 2001, Chang and Just, 2007, Kinsey et al. 2009). They incorporate information from different sources, use computer-coded content analysis, take the decaying effect of information on consumer behaviors into account, and find health information decrease the consumption of food contains "bad" nutrients.

Different from aforementioned studies, we use a structural approach (Erdem and Keane, 1996) to model the impact of health information through consumer learning behaviors. Due to the feature of our data, a random coefficient logit model is used following the framework of Berry, Levinsohn and Pakes (1995, henceforth BLP). Compare to other demand systems, this approach can handle a large number of product choices in the beverage market, utilize the aggregated data, allow for flexible substitution pattern, generate realistic distribution of consumer preferences among heterogeneous consumers, and deal with endogenous prices. We incorporate the consumer learning process into the demand model following Narayanan, Manchanda, and Chintagunta (2005), and find that the health information influences the substitution between bottled water and CSDs significantly.

2 Consumer Learning Process

Consumers are assumed with initial prior beliefs about the distribution of health effect of beverages. In each period, consumers update their prior beliefs using health information from the current period to form a set of posteriors in a Bayesian fashion. They make purchase decisions conditional on this set of posteriors and use it as a prior in the next period. The expectations of the posterior beliefs of health effect enter the market share equations and take place of the brand intercept terms. It is impossible to include all the information obtained by consumers, and we use proxies.

3 Data

The main data employed in this research is ScanTrack data obtained from the Nielson Company. It covers sales data of bottled water and carbonated soft drinks from 12 Designated Market Areas (DMAs) including Atlanda, Boston, Chicago, Dallas, Detroit, Hartford, Los Angeles, Miami, New York, San Francisco, Seattle, and Syracuse. Our sample period begins from January 2008 and ends in June 2012, during which there is a noticeable growth in bottle water consumption. We choose top 26 bottled water brands and top 18 carbonated soft drink brands based on their market shares. Table 1 lists all the brands included and table 2 shows some summary statistics.

Search volumes of health information from Google Search are employed as a proxy to capture the health information received by consumers. Searching a specific keyword on google implies that the user is gethering information about the object, indicating that search volumes are a reasonable proxy for the information flow. Search volumes used in this study are acquired from Google Trends, a public web site which shows how often a term is searched over time. The search volume data provided has been normalized and displayed on a scale of 0 to 100. Figure 2 shows the search volume of keyword "benefits of water" between 01/2008 and 07/2012. We can see that people were increasingly concerned with the benefits from drinking water during this period.

4 Model Specification

4.1 Learning About The Health Effect

We assume that consumers have an initial prior belief about the health effect of the beverage at the beginning of the period, which is normally distributed. Let $\widetilde{H}_{ij0}$ denote the consumer i's initial belief about the mean health effect of beverage j, where

$$\widetilde{H}_{ij0} \sim N(H_0, \sigma^2_{H_0}). \tag{1}$$

Due to the data availability, information on the beverages introduction is lack. We assume that the distributions of initial belief are the same for all the beverages, which means they have the same mean and variance.

Let ns_{jt} denote the amount of health information in period t (search volumes of health information at this point) and H_j denote the true mean health effect of the beverage. Since consumers may treat the same health information in different manners, the nth health effect signal received by consumer i in market t for beverage j is assumed normally distributed around the true value:

$$R_{nijt} = H_j + \nu_{nijt}, \quad \nu_{nijt} \sim N(H_j, \sigma^2_\nu) \tag{2}$$

At the beginning of each time period, consumers update their beliefs about the health effect of the beverage with the information available at that time. Because the normal distribution is self-conjugated and the initial prior ($\widetilde{H}_{ij0}$) is assumed to be normally distributed, the posterior belief at the beginning of each period is given by.

$$\widetilde{H}_{ijt} \sim N(\bar{H}_{ijt}, \sigma^2_{H_{jt}}). \tag{3}$$

The mean and variance of the postior are derived as:

$$\bar{H}_{ijt} = a_{jt}\bar{H}_{ij(t-1)} + b_{jt}\bar{R}_{ijt} \tag{4}$$

$$\sigma^2_{H_{jt}} = \frac{1}{1 + \sum\limits_{\tau=1}^{t} \frac{ns_{j\tau}}{\sigma^2_\nu}}, \tag{5}$$

where

$$a_{jt} = (\frac{1}{\sigma^2_{H_{j(t-1)}}})/(\frac{1}{\sigma^2_{H_{j(t-1)}}}) + \frac{ns_{jt}}{\sigma^2_\nu}), \tag{6}$$

$$b_{jt} = (\frac{ns_{j(t-1)}}{\sigma^2_\nu})/(\frac{1}{\sigma^2_{H_{j(t-1)}}} + \frac{ns_{jt}}{\sigma^2_\nu}), \tag{7}$$

$$\bar{R}_{ijt} = \sum_{n=1}^{ns_{j(t-1)}} \frac{R_{nijt}}{ns_{jt}} \sim N(H_j, \frac{\sigma^2_\nu}{ns_{jt}}), \tag{8}$$

4.2 Utility Function

We use a mixed logit discrete choice model following the framework of BLP (1995). And we incorporate the learning process into the demand model following the procedure developed by Narayanan, Manchanda and Chintagunta (2005). They replace the brand intercept term in a typcal descrete choice model with a composite term of learning process:

$$\widetilde{U}_{ijt} = \widetilde{H}_{ijt} + r\widetilde{H}^2_{ijt} + \beta X_{jt} + \xi_{jt} + \varepsilon_{ijt}, \tag{9}$$

where r is the measure of risk aversion; $r > 0$ means consumers are risk seeking, $r = 0$ means risk consumers are risk neutral, and $r < 0$ means consumers are risk averse.

In our case, however, the identification of this risk aversion parameter is problematic. If consumers are risk averse, the adoption rate of a newly introduced product would be lower than it is for risk neutral consumers. But we do not observe any introductions of beverage in our sample period, so we cannot identify this parameter. Instead, we assume consumers are risk neutral (in fact, Narayanan, Manchanda and Chintagunta reported that the estimate of the risk averse parameter is not significant), and the utility function is specified as follows:

$$\widetilde{U}_{ijt} = \widetilde{H}_{ijt} + \beta_i X_{jt} + \xi_{jt} + \varepsilon_{ijt}, \tag{10}$$

where X_{jt} includes the observed characteristics of non-alcoholic beverages such as calories, sodium, sugar, coffeine, etc. And it also includes prices, region dummies, time trend, seasonal dummies, and firm dummies. β_i is a vector of coefficients including consumer-specific coefficients for product characteristics and prices. ξ_{jt} is the unobserved product characteristic and ε_{ijt} is an i.i.d error term.

Because consumers are uncertain about the true health effect of beverages, they maximize the expected value of the utility function. The expectation is over the distribution of the health effect

$$\begin{aligned} E[\widetilde{U}_{ijt}] &= E[\widetilde{H}_{ijt}] + \beta_i X_{jt} + \xi_{jt} + \varepsilon_{ijt}. \\ &= \bar{H}_{ijt} + \beta_i X_{jt} + \xi_{jt} + \varepsilon_{ijt}. \end{aligned} \tag{11}$$

where $\bar{H}_{ijt}$ is defined in equation (4).

To allow for the category expansion, we define the utility from consuming outside good (other non-alcoholic beverages such as tea, juice, coffee, etc) as follows:

$$U_{i0t} = -\kappa t + \varepsilon_{i0t}. \tag{12}$$

The time trend is included in the utility function of the outside good to account for the overall trend of beverage consumption.

As in BLP (1995), we assume that the i.i.d error term is Gumbel distributed. The market share of product j in market t is given as

$$s_{jt} = \int \frac{exp(\bar{H}_{ijt} + \beta_i X_{jt} + \xi_{jt})}{1 + \sum_{k=1}^{J} exp(\bar{H}_{ikt} + \beta_i X_{jt} + \xi_{jt})} \mathrm{d}\Psi(\widetilde{H}_{ijt}, \beta_i | \Theta), \tag{13}$$

where Ψ is the joint distribution of individual characteristics which induce the choice of product j, and Θ is the set of parameters to be estimated.

4.3 Supply Side

The profits of firm f if given by:

$$\pi_f = \sum_{j \in \mathcal{G}_f} (p_j - mc_j) M s_j(p) - C_f \tag{14}$$

where p_j and mc_j are the price and marginal cost of product j respectively. M denotes the market size, and C_f is the fixed production cost. $s_j(p)$ is the market share of product j, which depends on the prices of all the products in the market. Under the Bertrand-Nash equilibrium, the price of product j produced by firm f must satisfy the first-order condition

$$s_j(p) + \sum_{l \in \mathcal{G}_f} (p_l - mc_l) \frac{\partial s_l(p)}{\partial p_j} = 0 \tag{15}$$

Using this set of first-order conditions, we can calculate equlibrium prices in our counterfactual experiment.

5 Estimation and Identification

We use the GMM estimator developed by BLP (1995) and the Nested Fixed Point (NFP) algorithm to estimate our model. The health effect term is constructed by model parameters and is serially correlated. To deal with this problem, we follow the estimation procedure in Narayanan, Manchanda and Chintagunta (2005). In that paper, they develop a modified BLP methodology to account for the serial correlation problem and estimate physicians' learning with respect to the efficacy of ethical drugs.

In our model, we assume the product charactersitcs are exogenously determined, but the prices are correlated with unobserved product characteristics or demand shocks. To control for this endogeneity issue, we use several sets of exogenous instrumental variables following Nevo (2000). The first set of instruments is cost shifters, such as manufacturing wage rates (Bureau of Labor Statistics, 2013), electricity prices (U.S. Energy Information Administration, 2013), sugar prices, etc. The second set of instruments is of the BLP type. Because the loacation of products in the characteristics space is assumed to be exogenously determined, we use the observed product characteristics as instruments. Furthermore, the sums of characteristics of other products produced by the same firm and the sums of characteristics of products produced by competitors are also included. The third set of instrumental variables is Hausman (1996) type instruments, prices of the same brand in other markets. The intuition behind is that the prices of the same brand in different markets are correlated due to the common production cost, but uncorrelated with market specific demand shocks. This assumption could be violated if there is a national wide demand shock, but it works well in our case.

The identification of the learning parameters depends on the variation of market shares over time. As consumers receive more and more information on the health effect of drinking water, carbonated soft drinks and other beverages, the variance of their belief becomes smaller ($\sigma^2_{H_{jt}} \to 0$). The true mean health effect H_j can be identified from the convergence of $\bar{H}_{ijt}$ to H_j. The market shares of the first period help identify the initial prior H_0. Aggregated level data limits the estimation of the initial variance. Thus, we normalize the initial variance $\sigma^2_{H_0}$ to 10.

6 Results

6.1 Demand Estimation

The estimation results are shown in Tabel 3. The main parameters of interest are the true mean health effect H_{water} and H_{CSD}. The estimates imply that the health effect of bottled water is much higher than of CSDs. Consumers obtain higher utility from consuming bottled water because it is healthier. The mean health effect of bottled water is also higher than the prior value H_0, which indicates that consumers learn the true health effects over time. And this learning process can explain the increase in bottled water consumption that we observed from data.

In terms of the linear parameters, price coefficient is negative and significant as we expected. The coefficient of sugar content is positive an significant which implies that, controlling for the health effect, consumers prefer sugar which is the main source of obesity.

6.2 A Counterfactual Experiment

Given the estimated structural parameters, we conduct a counterfactual experiment to estimate to what extent consumer learning can promote bottled water demand and reduce CSDs consumptions. More specifically, we remove all the health information from our model, and calculate new equilibrium prices and market shares. We find that consumer learning increases bottled water consumption by 7.03% and reduces regular CSDs sales by 3.25% in our sample period, which is a significant impact on beverage demand.

7 Conclusion

In this study, we use a structural approach to estimate the impact of consumer learning behavior on the rising bottled water consumption. We find that consumers learn the true health effect of bottled water and other unhealthy beverages such as CSDs over time and change their choices accordingly. Based on our findings, although consumers prefer sugar content, the main contributor to the obesity problem, policy makers can help the public reduce the consumption of sugar sweetened beverages by informing consumers about the health effect of the beverages they choose. The health information can promote healthy drinks through learning.

References

[1] Berry, Steven, James Levinsohn, and Ariel Pakes. (1995). "Automobile Prices in Market Equilibrium," *Econometrica* 63(5), 841-90.

[2] Berry, Steven, James Levinsohn, and Ariel Pakes. (1999). "Voluntary export restraints on automobiles: Evaluating a trade policy," *American Economic Review* 400-430.

[3] Beveage Marketing Corporation (2011).

"www.beveragemarketing.com/?section=pressreleses"

[4] Brown, D.J. and L.F. Schrader. "Cholesterol Information and Shell Egg Consumption" *American Journal of Agricultural Economics*, 72(1990):3285-91.

[5] Burton, M., and T. Young, (1996). "The Impact of BSE on the Demand for Beef and Other Meats in Great Britain" *Applied Economics*, 28(6), 687-693.

[6] Chang, H., and D. R. Just, (2007)."Health Information Availability and the Consumption of Eggs: Are Consumers Bayesians" *Journal of Agricultural and Resource Economics*, 32(1), 77-92.

[7] Erdem, Tulin and Michael P. Keane (1996), "Decision Making Under Uncertainty: Capturing Dynamic Brand Choice Processes in Turbulent Consumer Goods Markets," *Marketing Science*, 15(1), 1-20.

[8] Hausman,J.(1996), "Valuation of New Goods Under Perfect and Imperfect Competition," in T.Bresnahan and R. Gordon, eds., *The Economics of New Goods*, Studies in Income and Wealth Vol.58, Chicago: National Bureau of Economics Research.

[9] Kinsey, J. R., W. Harrison, D. Degeneffe, G. Ferreira, and S. Shiratori, (2009)."Index of Consumer Confidence in the Safety of the United States Food System" *American Journal of Agricultural Economics*, 91 (5): 1470-1476.

[10] McGuirk, A. P. driscoll, J. Alwang, and H. Huang. "System Misspecification Testing and Structural Change in the Demand for Meat" *J. Agr. and Resour. Econ.* 20(1995):1-21.

[11] Narayanan, Sridhar, Puneet Manchanda, Pradeep K. Chintagunta. (2005). "Temporal Differences in the Role of Marketing Communication in New Prodcut Categories" *Journal of Marketing Research* 42(3) 278-290. 1193-1205.

[12] Nevo, A. (2000). "A practitioner's guide to estimation of random-coefficients logit models of demand," *Journal of Econometrics and Management Strategy*, 9(4):513-548

[13] Popkin,B., Barclay,D. and S.Nielsen, (2005) "Water and Food Consumption Patterns of U.S.Adults from 1999 to 2001" *obesity Research* (2005)13,2146-2152.

[14] Rowley, T. (2004) “Obesity: Combating a Rural Epidemic,” *The Rural Monitor* 10(2004):4.

[15] Verbeke, W., and R. W. Ward, (2001). “ Fresh Meat Almost Ideal Demand System Incorporating Negative TV Press and Advertising Impact” *Agricultural Economics*, 25(2-3), 359-374.

[16] Yen, S.T., B.H. Lin, D.M. Smallwood and M. Andrews (2004). “Demand for Nonalcoholic Beverages: The Case of Low-Income Households” *Agribusiness* 20(2004): 309-321.

Figure 1: "Per capita beverage consumption in the U.S. "

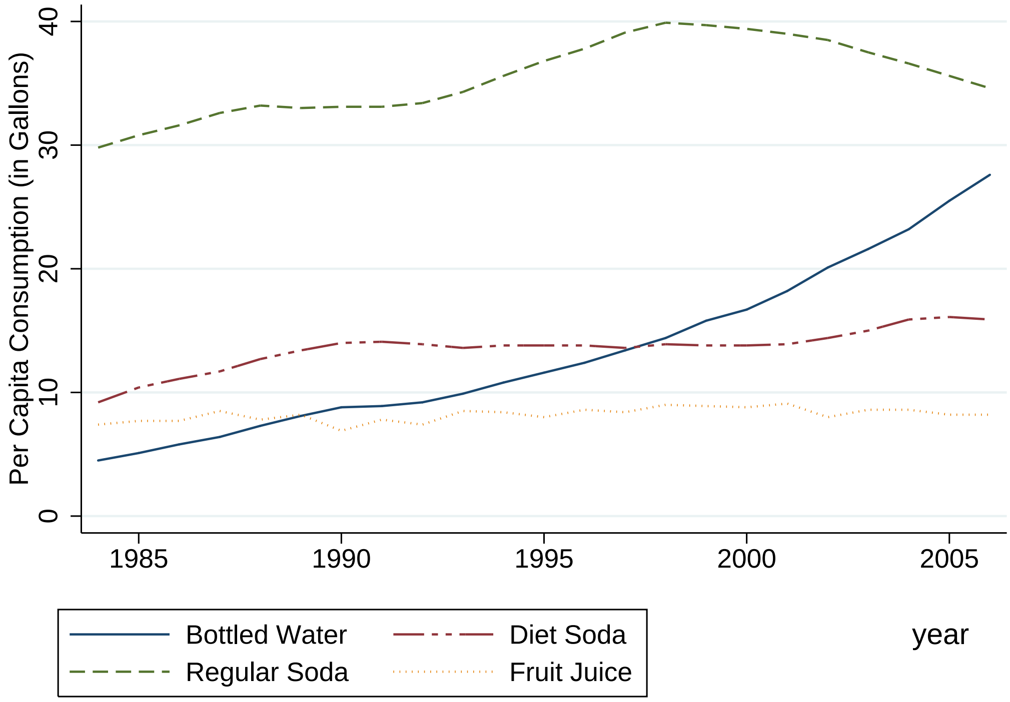

Figure 2: "Keyword: benefits of water"

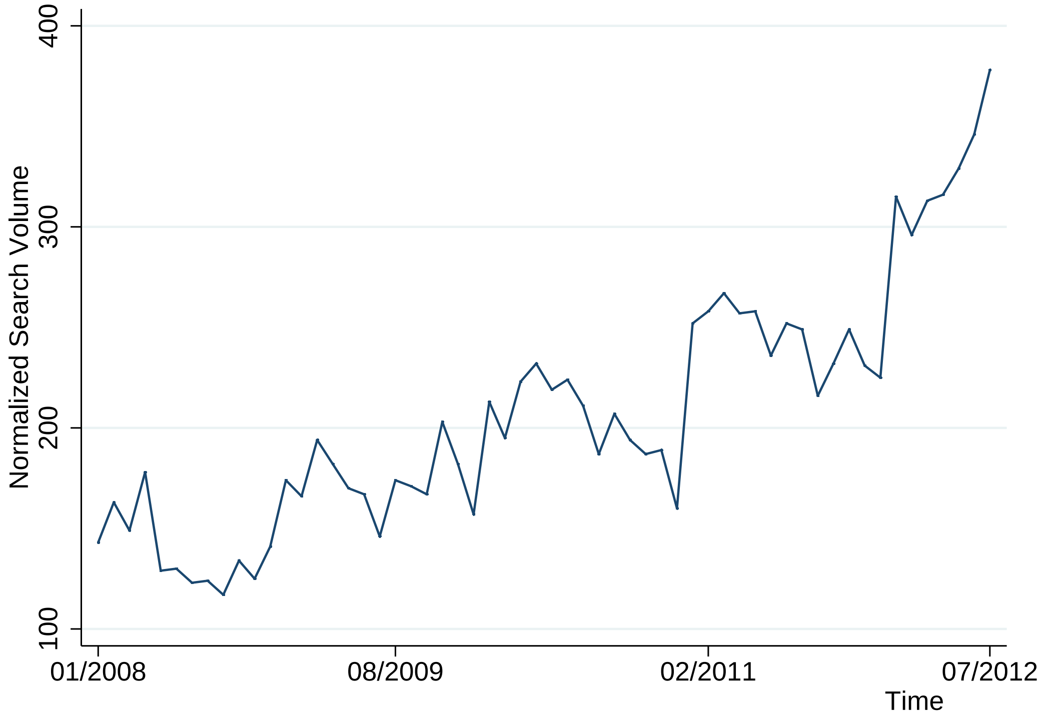

Table 1: Brands Included

Company Names	Soft Drink Brands	Bottled Water Brands
ABSOPURE WATER CO		ABSOPURE
BEV PAK INC		ADIRONDACK
COCA COLA COMPANY	COCA-COLA DT	AQUARIUS SPRING!
	COCA-COLA R	DASANI
	COCA-COLA ZERO DT	GLACEAU SMART WATER
	FANTA R	GLACEAU VITAMIN WATER ZERO
	SPRITE R	
CRYSTAL GEYSER WATER COMPANY		CRYSTAL GEYSER
DANONE GROUP		EVIAN
DR PEPPER SNAPPLE GROUP INC	DIET RITE PURE ZERO DT	
	DR PEPPER DT	
	DR PEPPER R	
	SEVEN UP DT	
	SEVEN UP R	
	SUNKIST R	
JW CHILDS ASSOCIATES		FRUIT2O
KELSO COMPANY		CRYSTAL SPRINGS
		NURSERY
		SPARKLETTS
NESTLE HOLDINGS INC		ARROWHEAD
		DEER PARK
		ICE MOUNTAIN
		NESTLE PURE LIFE
		OZARKA
		POLAND SPRING
		POLAND SPRING AQUAPOD
		ZEPHYRHILLS
NIAGARA BOTTLING LLC		NIAGARA
NIRVANA INC.		NIRVANA
PEPSICO INC	MTN DEW CODE RED R	AQUAFINA
	MTN DEW DT	AQUAFINA FLAVOR SPLASH
	MTN DEW R	PROPEL
	PEPSI DT	
	PEPSI R	
	SIERRA MIST FREE DT	
	SIERRA MIST R	
ROLL GLOBAL LLC		FIJI

Table 2: Summary statistics

	Full Sample	Sub Sample		
	All	Water	Regular CSD	Diet CSD
Sugar (g/oz)	0.98	0.00	3.50	0.00
	(1.58)	(0.00)	(0.32)	(0.00)
Caffeine (mg/oz)	1.11	0.00	2.19	2.22
	(1.70)	(0.00)	(1.86)	(1.78)
Sodium (mg/oz)	2.57	0.94	4.82	3.36
	(2.54)	(2.13)	(1.69)	(1.50)
Price (cent/oz)	2.50	2.44	2.56	2.58
	(1.31)	(1.81)	(0.47)	(0.35)
Market Share (‰)	4.64	5.08	5.06	3.13
	(9.16)	(11.35)	(7.41)	(4.08)

Table 3: Estimation Results

	Variable	Means	Standard Deviations
learning	H_0	-0.432	
		(19.121)	
	H_{water}	9.946*	
		(0.093)	
	H_{CSD}	-0.409*	
		(0.158)	
	σ_ν^2	10.53*	
		(0.029)	
Characteristics	Price (dollar/oz)	-2.480*	-0.019
		(-0.012)	(0.099)
	Sodium(mg/oz)	-0.49*	-0.532*
		(-0.009)	(0.008)
	Sugar(g/oz)	0.161*	0.424*
		(0.009)	(0.015)
	Caffeine(mg/oz)	0.218*	0.061*
		(-0.001)	(0.006)
	Constant	-29.811*	-0.031
		(0.246)	(0.147)