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Health information and consumer learning in the bottled water market

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This paper examines the impact of health information in different media outlets on bottled water consumption through consumer learning. We develop a random coefficient discrete choice model with Bayesian learning process to capture consumers' learning of health information and changes in their beverage choices over time. Consumers are assumed to have initial prior beliefs about the health effect of different beverages and to update their beliefs using health information received from different media types. Empirical results show that consumers' perceived quality of bottled water kept increasing during our sample period, and this learning process accounted for 24.44% of the industry's revenue, which is about 4.8 billion dollars per year. Comparing the effectiveness of different media outlets, we find that the sales impact of traditional media (TV and radio) is greater than online sources. Our findings highlight the contribution of health information to the bottled water industry and provide policy makers with a new direction to reduce high-calorie food consumption and improve public health.

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1. Introduction

Bottled water consumption has been growing over the last several decades in the United States, with per capita consumption increasing from 5.0 gallons in 1986 to 21.9 gallons in 2012. As a result, bottled water has become the fastest growing and most successful segment of the non-alcoholic beverages, reaching a value of $21 billion in 2012 (MarketLine, 2013a; 2013b). In contrast, other beverages have been struggling to gain or maintain market shares. For example, consumption of carbonated soft drinks (CSDs), which is the largest category in the refreshment beverage market, has been declining since 2005 (Digest, 2013). Fig. 1 presents the changes in per capita consumption of different beverages.[1]

There are a variety of reasons behind the continuing growth of bottled water. One possible explanation is consumers' awareness and learning of the health benefits of bottled water. Obesity is now commonly acknowledged as the leading public health crisis in the United States, with an estimated social cost of approximately $117 billion a year (Komesaroff and Thomas, 2007). In contrast, water consumption has been proven to be an effective aid to weight control (Popkin et al., 2005). Therefore, there has been increased interest in health, obesity and water, resulting in escalating coverage and discussion in the media and the general public. A growing number of consumers may have learned about the health benefits of the zero-calorie and conveniently bottled water over time, and then made healthier choices for themselves and their families. Since bottled water is considered a healthier alternative to CSDs, the changing trend may have important implications from the public health policy perspective.

The changing trend in beverage consumption has also reshaped the beverage industry. To maintain their profitability, CSD producers try to improve their channel efficiency by merging with bottling companies and reinvesting in vast marketing activities. More importantly, leading players in the CSD market, such as The Coca-Cola Company and PepsiCo, entered the bottled water market to capture the increasing demand. By the end of 2012, these two companies had become the third and second largest companies in the bottled water market, respectively (MarketLine, 2013a). The shifting demand had such a significant impact on the beverage industry that it is of great interest to study the driving forces behind this shift.

To examine the impact of health information and consumer learning on rising bottled water consumption, this paper formulates a structural random coefficient discrete choice model with a Bayesian learning process in the beverage market. More specifically, we assume that consumers are uncertain about the health effect of beverages and that health information affects their choices through a learning process. Consumers learn about the association between health outcomes and beverage consumption from the mass media, update their perceptions of beverage qualities, and make their beverage choices. We model this procedure by incorporating a Bayesian learning process into a random

[1] Source: (Digest, 2013).

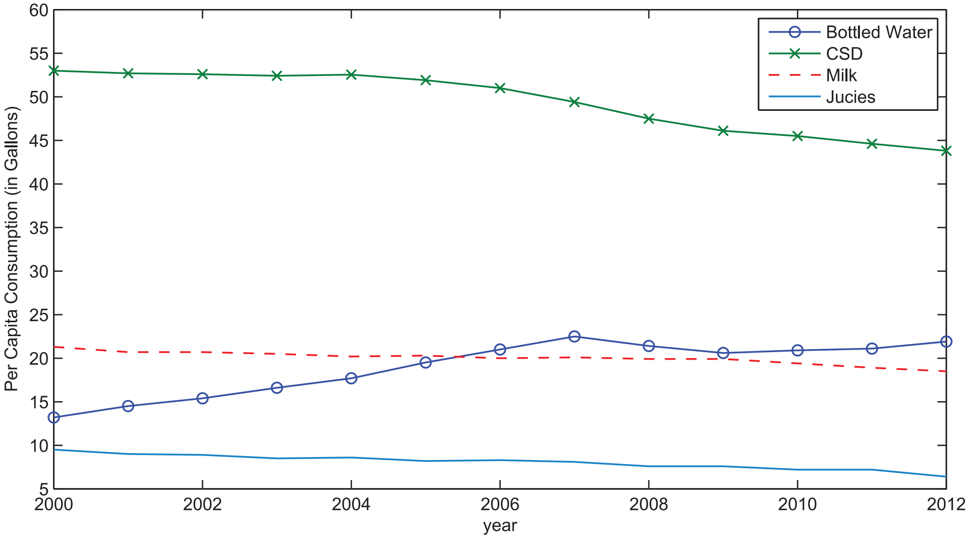

Fig. 1. Per capita beverage consumption in the U.S.

coefficient discrete choice framework (Narayanan et al., 2005). To estimate our model, we use brand level data on bottled water and CSDs from 2008 to 2012 across four Designated Market Areas (DMAs) in the United States. Combined with media information data collected from LexisNexis Academic, we empirically assess how the learning process shifts consumer preferences, estimate the value of health information, and evaluate the potential contribution of health information to public health.

Our findings confirm that consumers do learn about the health qualities of bottled water from mass media over time. Moreover, information from traditional media (TV and radio) is more informative than online sources for bottled water consumers. Given the estimates of structural parameters and the assumption of Nash–Bertrand competition in the market, we conduct a series of counterfactual simulations to estimate the value of health information to the bottled water industry and evaluate the potential contribution of mass media to public health. The main results show that 24.44% of the U.S. bottled water industry's revenue is generated by media, and the growing perceived quality of bottled water contributes about 4.8 billion dollars to the bottled water industry each year. Further, the simulation results suggest that a public health campaign that increases the overall media coverage will be effective in increasing bottled water consumption. A 10% increase in health information would increase bottled water demand by 2.12%; 20% more information would increase bottled water demand by 3.71%; and a 50% increase in information would lead to 8.62% more consumption of bottled water. Therefore, from the perspective of policy makers, it is possible to encourage consumers to switch from sugar sweetened beverages to a healthier alternative (bottled water) by informing them through mass media of the health effect of the beverages.

This paper is in line with previous studies of consumer learning that apply the Bayesian learning model in an empirical context. The seminal paper by Erdem and Keane (1996) constructs models of the behavior of consumers in an environment where there is uncertainty about brand attributes, and which consumers learn about the quality of products from advertising and their own usage experience. Crawford and Shum (2005) estimate a dynamic matching model of demand under uncertainty and focus on patients learning from their prescription experience about the effectiveness of alternative drugs. They allow drugs to be differentiated in two dimensions and endogenize patients' length of treatment by allowing their drug choices to impact their probability of recovery. Narayanan et al. (2005) develop a structural model of demand with a Bayesian learning process and model physician learning about new drugs through marketing communication over the life cycle of a new product category. Specifically, they identify an indirect effect on consumer utility through reduction of uncertainty about product quality and a direct effect on consumer utility. Zhao et al. (2011) develop a model in the wake of a product-harm crisis when consumers are assumed to be uncertain about the mean product quality level and learn about product quality through the signals contained in use experience and through product-harm. Further, consumers are uncertain about the accuracy of the messages conveying product quality information and update their perceptions of the accuracy of those messages over time. Zafar (2011) focuses on how college students form expectations about various major-specific outcomes and finds that they tend to be overconfident about their future academic performance. College students update and revise their expectations in a Bayesian manner and learning plays a role in their decisions to switch majors. The study we present here follows the empirical framework developed by Narayanan et al. (2005) and extends the literature by modeling consumers learning about categories, i.e., bottled water and CSDs, rather than individual brands.

This paper also fits into the general literature studying bottled water consumption. A few papers have studied bottled water consumption from an industrial organization perspective. For example, Bonnet and Dubois (2010) focus on vertical contracts and find that a two-part tariff with resale price maintenance is the best supply model for bottled water manufacturers and retailers in France. Other studies have examined bottled water consumption by focusing on the impact of water contamination. Abrahams et al. (2000) estimate Georgia residents' risk averse behavior regarding tap water contamination and show that risk of contamination, water quality, and demographic characteristics can affect substitution between bottled water and tap water. Loomis et al. (2009) evaluate adults' willingness to pay for bottled water in order to protect infants from drinking contaminated municipal water and find that adults are altruistic in this situation. Zivin et al. (2011) show that, from 2001 to 2005, tap water quality violations of the Safe Drinking Water Act (SDWA) increase bottled water sales significantly in Northern California and Nevada, with 22% of the increase due to microorganisms and 17% due to elements and chemicals. Different from the aforementioned studies, this paper estimates a structural demand model for bottled water within the non-alcoholic beverage market (e.g., Zheng and Kaiser, 2008; Okrent and MacEwan, 2014). With the demand estimates we can examine the substitution between healthy and unhealthy beverages and examine the impact of health information on multiple-product firms.

The rest of this paper is organized as follows. Section 2 describes the data employed. Section 3 introduces the empirical model and discusses the estimation issues. Section 4 presents the estimation and simulation results, followed by discussion and conclusion in Section 5.

2. Data

The main data employed in this research is ScanTrack data obtained from the Nielsen Company. The dataset covers supermarkets, grocery stores, and drug stores with more than $2 million annual sales in the U.S., which consists of dollar sales, volume sales, and prices for beverage products. In addition, it also provides detailed information on product characteristics (e.g. brand names, container sizes, package sizes, etc.), marketing (e.g. price and in-store displays), location and time of sales. In this analysis, we use brand level data on bottled water and CSDs in four DMAa: Atlanta, Dallas, Detroit, and Syracuse. Our sample begins in July 2008 and ends in December 2012, during which timespan we observe a noticeable growth in bottled water consumption. The frequency of observations is rolling four-week blocks, which we define as "monthly" for simplicity.

Table 1 lists all bottled water products and CSD products used in this study. Clearly, the bottled water market is relatively less concentrated: there are 25 bottled water brands owned by 13 firms. In addition, most bottled water brands belong to companies that only operate in the bottled water market. For example, Nestle Holdings focuses on the bottled water market and owns leading bottled water brands such as Nestle Pure life, Deer Park, Ozarka and Poland Spring. On the other hand, the vast majority of the CSD market is controlled by three firms: The Coca-Cola Company, PepsiCo, and the Dr. Pepper Snapple Group Inc. These firms account for 18 brands that covers 60–70% of the total CSD market. It is worth to noting that, the top two firms, The Coca-Cola Company and PepsiCo, offer their own bottled water brands. For example, the Coca-Cola-owned Dasani and PepsiCo-owned Aquafina are both leading brands in the bottled water market.

Column 1 of Table 2 provides the summary statistics of the full sample. On average, the sales-weighted average price for a beverage product is 2.56 cents per ounce, with an average market share of 7.62 ‰ in one DMA in a month. We calculate the market share of each beverage product in our sample as a share of the total potential market size in the refreshment beverage market.[2] Specifically, the potential market size is the combined per capita consumption of all types of refreshment beverages including bottled water, CSDs,

[2] The market share for product j in market m and time t is defined based on the total potential consumption of all nonalcoholic beverages including bottled water, CSDs, liquid tea, fruit juice, etc.:

$$\frac{Vol_{jmt}}{Total\ Beverage\ Volume\ Consumption_{mt}}$$

Table 1
Top beverage products included.

Firms	Bottled water products	Regular CSD products	Diet CSD products
Absopure Water Co	Absopure		
Bev Pak Inc	Adirondack		
Coca Cola Company	Aquarius Spring!	Coca-Cola R	Coca-Cola DT
	Dasani	Sprite R	Coca-Cola Zero DT
	Glaceau Smart Water	Fanta R	
	Glaceau Vitamin Water Zero		
Crystal Geyser Water Company	Crystal Geyser		
Danone Group	Evian		
Dr Pepper Snapple Group Inc		Dr Pepper R	Dr Pepper DT
		Seven Up R	Seven Up DT
		Sunkist R	Diet Rite Pure Zero DT
JW Childs Associates	Fruit2o		
Kelso Company	Crystal Springs		
	Nursery		
	Sparkletts		
Nestlé Holdings Inc	Deer Park		
	Ice Mountain		
	Nestlé Pure Life		
	Ozarka		
	Poland Spring		
	Poland Spring Aquapod		
Niagara Bottling LLC	Niagara		
Nirvana Inc.	Nirvana		
Pepsico Inc	Aquafina	Pepsi R	Pepsi DT
	Aquafina Flavor Splash	Mtn Dew R	Mtn Dew DT
	Propel	Mtn Dew Code Red R	Sierra Mist Free DT
		Sierra Mist R	
Roll Global LLC	Fiji		
Private Labels	CTL BR		

Note: "R" stands for regular drinks and "DT" stands for diet drinks.

liquid tea, and fruit juice times population in each market.[3] In terms of nutritional factors, an average beverage product contains 0.78 g of sugar, 0.88 mg caffeine,and 2.04 mg of sodium per ounce.

We further break down the sample by product categories and provide the summary statistics of the subsample in columns 2– 4. The unit price of bottled water is 2.51 cents per ounce, which is slightly cheaper than CSDs. Regular CSDs lead the market and an average CSD brand enjoy the highest market share with 8.86‰ in a DMA in a month, but are followed closely by an average bottled water brand with 7.9‰. The standard

[3] It is possible that some consumers may react to the health information by just drinking tap water. However, there is no data on per capita tap water consumption by drinking. Therefore, we could not include the substitution to drinking tap water in this analysis. Although we cannot account for tap water, we do not find any evidence that there is substantial substitution out of the bottled beverage industry over our sample period. Therefore, the substitution to tap water should not be a concern in our analysis.

Table 2
Summary statistics.

	Full sample (1)		Subsample (2) Bottled water		(3) Regular CSD		(4) Diet CSD	
	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
Price (cent/oz)	2.56	1.22	2.51	1.74	2.61	0.34	2.60	0.34
Market shares (‰)	7.62	13.0	7.90	16.2	8.76	10.91	5.60	7.10
Own brand ad (in million$)	1.00	2.50	0.30	0.02	2.01	0.08	1.10	0.05
Same firm ad (in million$)	17.17	25.64	1.98	5.09	29.16	29.60	31.50	27.75
Rival brands ad (in million$)	48.78	47.22	14.83	13.08	77.26	46.09	78.59	47.00
Sugar (g/oz)	0.78	1.48	0.00	0.00	3.5	0.34	0.00	0.00
Caffeine (mg/oz)	0.88	1.6	0.00	0.00	2.19	1.95	2.22	1.91
Sodium (mg/oz)	2.04	2.51	0.62	1.81	4.82	1.79	3.36	1.60
Media coverage								
TV and radio	29.04	14.59						
Journal and newspapers	477.06	95.22						
Online sources	79.49	46.7						

deviations of bottled water and regular CSDs are very large, suggesting a large fluctuation of demand in the beverage market. Diet CSDs capture 5.6‰ of the refreshment beverage market. In terms of nutritional factors, bottled water has no sugar, which is the main contributor to high calories and the negative health effects of CSDs. Regular CSDs, on the other hand, have 3.5 g of sugar per ounce. The sugar content for diet CSDs is also zero. While there is no caffeine in bottled water, regular and diet CSDs all have a similar caffeine content. Compared with CSDs, bottled water has a much lower sodium content.

The advertising expenditure data for each product in the U.S. beverage market is obtained from Kantar Media. Different from the sales and prices data, the advertising expenditure data is at national level instead of the DMA level. On average, a beverage product spends 1 million dollars nationally in a month. It is obvious that CSDs spend much more than bottled water products on advertising, reaching 2.01 million dollars for regular CSDs and 1.10 million dollars for diet CSDs. On the contrary, an average bottled water product only spend 0.3 million dollars nationally on advertising in a month. In fact, the CSD market is traditionally heavily advertised and advertising is a key strategy for Coca-Cola and PepsiCo's growth. In addition, many firms in the beverage industry are multi-brand firms and the advertising of one brand may also affect the demand for brands within the same firm as well as brands owned by competitors. In other words, there might be spillover effects of advertising within and across firms. It is reasonable to believe that when Coca-Cola Regular starts an advertising campaign, the spillover effect will also benefit other CSD brands within the company and will hurt competing brands like Pepsi. The average advertising expenditures by all others brands in the same firm in one beverage category (bottled water or CSD) is $17.17 million dollars. The average advertising expenditure by all rival brands is $48.79 million in a year.

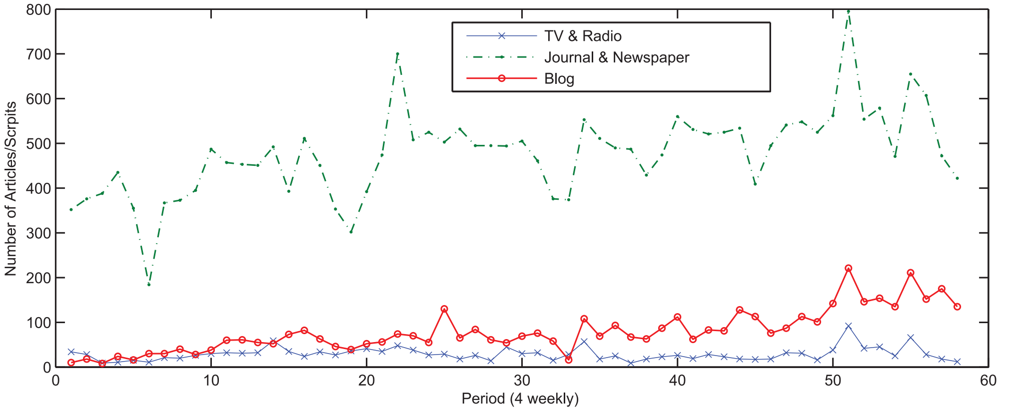

Fig. 2. Information from different sources over time.

Information provided by mass media affects consumers' perception of the health effects of different beverages. To measure the amount of health-related information received by consumers, we search the LexisNexis Academic database for the news articles and transcripts talking about health effects of bottled water. The database provides access to over 15,000 news, business, and legal sources, and we consider newspapers, magazines, TV, radio, and online sources in our study. Specifically, we use the number of the searched articles/transcripts in each month as proxies for the amount of information.[4] The summary statistics for media coverage data are also shown in Table 2. The majority of the health information on bottled water comes from newspapers and journal articles, reaching an average of 477 articles in a month, followed by online sources,[5] TV and radio. Fig. 2 shows how the media coverage changed over time. Overall, there was an increasing trend of health related information about bottled water in all media types. It is worth mentioning that our measure of the information volume may not include all the information that a consumer could gather. Consumers may also obtain and learn health-related information about beverages from other channels, such as their friends and doctors.

3. Model and estimation

3.1. Utility function

In this analysis, we use a random coefficient discrete choice model and incorporate the Bayesian learning process into the demand model following the procedure developed

[4] Given the large volume of TV scripts, newspaper articles, and online articles, we did not have the resource to analyze the text of each article over the sample period. However, we did examine the title of the information from different sources. Overall, around 70% of all health information of water is about the general health benefits of zero calories, weight-loss, staying hydrated, and how it compared to other beverages,etc. A small fraction of articles mentioned some other health benefits of improving digestion, reducing risk of heart attack, etc.

[5] On LexisNexis, the online sources or "blogs" are online web-based publications, which is equivalent to other information published via TV, newpaper, or radio. It is different from those online consumer/user generated word-of-month on social media that are mainly about personal experience.

by Narayanan et al. (2005). We assume there is a total number of J bottled water and CSD brands in the market and $j \in \{0, 1, \ldots, J\}$ denotes a beverage brand. $j = 0$ indicates an outside option in the beverage market other than bottled water and CSDs. A consumer chooses a bottled water brand or a CSD brand among competing products to maximize her utility. The conditional indirect utility that consumer i derives from purchasing beverage brand j in market m at time t is specified as follows:

$$\begin{aligned}\widetilde{U}_{ijmt} = {} & I_j \widetilde{H}_{it} + \alpha_i P_{jmt} + \beta_1 X_j + \beta_2 TV_t + \beta_3 News_t + \beta_4 Online_t \\ & + \beta_5 OwnAd_{jt} + \beta_6 FirmAd_{jt} + \beta_7 RivalAd_{jt} \\ & + \gamma_1 Dummy_{DMA} + \gamma_2 Dummy_{season} + \xi_{jmt} + \varepsilon_{ijmt},\end{aligned} \tag{1}$$

$I_j = 1$ if j is a bottled water brand and $I_j = 0$ otherwise. P_{jmt} is the unit price of product j in market m at time t. $\widetilde{H}_{it}$ is consumer i's belief about bottled water's health effect (relative to CSDs) at time t,[6] which will be explained in detail in the next section. The health information received from media will help consumers solve the uncertainty of the perceived product quality, and thus have an indirect learning effect on consumers' utility. X_j contains the observed characteristics of the beverage brand j, such as sugar, caffeine, sodium content, etc.

Advertising plays an important role in the beverage market, which may shift consumers' utility directly. Therefore, we include advertising expenditures on beverage products into the estimation and build the advertising goodwill stocks to capture the carry-over effect over time.

$$OwnAd_{jt} = nad_{jt} + \delta OwnAd_{j,t-1} \tag{2}$$

where nad_{jt} is the advertising expenditures of beverage product j at time t, and δ is the carry-over coefficient. $FirmAd_{jt}$ is the total advertising goodwill of all brands that belongs to the the same categories (bottled water or CSD) of the same firm as product j. $RivalAd_{jt}$ is the total advertising goodwill from all rival firms. The advertising goodwill of $FirmAd_{jt}$ and $RivalAd_{jt}$ as constructed in a similar way as $OwnAd_{jt}$.

Further, exposure to health information from media may also affect consumers' utility directly. Therefore we include the health information received from different types of media into the utility function directly in order to capture the direct effect. As with advertising, we construct the health information as goodwill stocks to capture the

[6] In this analysis, consumers' beliefs about the healthfulness of bottled water enters indirect utility as a constant term. Another possibility would be for consumers to have changing beliefs about the value of characteristics of beverages, like the sugar and sodium content. However, the perceived quality (or health effect) of a beverage may depend on many other factors. For example, the dissolved carbon dioxide can cause heartburn and a sour taste. The perceived health effect of different beverages is the result of many factors including sugar and sodium. That is the reason why collect everything together and put them into one term as the perceived quality of bottled water. Further, to the best of our knowledge, there were no studies trying to model a Bayesian learning process with more than one dimension except for Crawford and Shum (2005), which is not suitable for this analysis. Therefore, we believe it is reasonable to assume that consumer learn about the overall superior quality of bottled water over time.

carry-over effects:

$$TV_t = ntv_t + \delta T_{t-1} \tag{3}$$

$$News_t = nnews_t + \delta N_{t-1} \tag{4}$$

$$Online_t = nonline_t + \delta Online_{t-1} \tag{5}$$

where TV_t, $News_t$, and $Online_t$ are goodwill from three information sources and ntv_t, $nnews_t$, $nonline_t$ are the new information received from three sources at time t, respectively. δ is the carry-over coefficient.

ξ_{jmt} is the unobserved product characteristics and ε_{ijmt} is the i.i.d error term that follows a Type I extreme value distribution. To capture the heterogeneous taste of consumers, we model the distribution of consumers' taste parameter for price, α_i, as a normal distribution: $\alpha_i \sim N(\alpha, \sigma_p^2)$. α is the mean preference and σ_p is the zero-mean unobserved consumer random effects. In addition, we also include DMA dummies and seasonal dummies to control for the region and time fixed effects in this estimation.

We assume that consumers are uncertain about the true health effects of bottled water and they maximize the expected value of the utility function when making purchase decisions. The expectation about the distribution of the health effect is then given by

$$\begin{aligned} &E[\widetilde{U}_{ijmt}] \\ &\quad = E[I_j\widetilde{H}_{it}] + \alpha_i P_{jmt} + \beta_1 X_j + \beta_2 TV_t + \beta_3 News_t + \beta_4 Online_t + \beta_5 OwnAd_{jt} \\ &\qquad + \beta_6 FirmAd_{jt} + \beta_7 RivalAd_{jt} + \gamma_1 Dummy_{DMA} + \gamma_2 Dummy_{season} + \xi_{jmt} + \varepsilon_{ijmt} \\ &\quad = I_j\bar{H}_{it} + \alpha_i P_{jmt} + \beta_1 X_j + \beta_2 TV_t + \beta_3 News_t + \beta_4 Online_t + \beta_5 OwnAd_{jt} \\ &\qquad + \beta_6 FirmAd_{jt} + \beta_7 RivalAd_{jt} + \gamma_1 Dummy_{DMA} + \gamma_2 Dummy_{season} + \xi_{jmt} + \varepsilon_{ijmt} \end{aligned} \tag{6}$$

where $\bar{H}_{it}$ is the mean of the perceived health effect, which will be constructed in Section 3.2.

3.2. Learning about health effects

Consumers are assumed to have initial prior beliefs about the distribution of the health effects of bottled water. In each period, they update their beliefs using health information received from the media to form a new set of posterior belief according to Bayes' rule.[7]

[7] Another possible source of learning is consumers' own experience, which is not included in this analysis for two main reasons. First, data limitation. Our model estimation is based on aggregated, market level data. Therefore, we do not know each consumers' past consumption history to construct each consumer's learning based on their own past experience. Second, although consumers in the bottled water industry are end-users with direct experience of bottled water, there is no immediate short-term benefit. It will take a

Finally, they make purchase decisions conditional on this new belief, which then become the prior belief for the next period.

We assume that the prior belief follows a normal distribution. Let $\widetilde{H}_{i0}$ denote the consumer i's initial belief about the mean health effect of bottled water, where

$$\widetilde{H}_{i0} \sim N(H_0, \sigma_0^2). \tag{7}$$

where H_0 is the mean initial belief and σ_0 is the standard deviation.

Let H_b denote the true mean health effect of bottled water. We then assume that the information received by consumers is normally distributed around the true value because the reception of information varies among consumers. Every period, consumer i will take one draw for every signal from each media type. The nth signal received by consumer i in period t from TV and radio transcripts (T_{nit}), newspaper and magazines(N_{nit}), and online sources (B_{nit}) are given by[8]

$$T_{nit} = H_b + \nu_{nit}, \quad \nu_{nit} \sim N(0, \sigma_{TV}^2) \tag{8}$$

$$N_{nit} = H_b + \omega_{nit}, \quad \omega_{nit} \sim N(0, \sigma_{news}^2) \tag{9}$$

$$B_{nit} = H_b + \lambda_{nit}, \quad \lambda_{nit} \sim N(0, \sigma_{online}^2) \tag{10}$$

Let ntv_t, $nnews_t$, and $nonline_t$ denote the number of information signals from TV and radio transcripts, newspaper and magazines, and online sources that consumers received in period t, respectively. In this analysis, we use the information signals generated from the previous period to form consumers' learning process this period. Because information are generated continuously over a month in the real world, it is reasonable to assume that the information *generated* from the previous month will all arrive at the beginning of this month. Therefore, consumers will *receive* all information at the beginning of this period and actually learn from information *generated* from the previous month. The total information that a consumer i received at time t from TV and radio transcripts ($\bar{T}_{it}$), newspaper and magazines($\bar{N}_{it}$), and online sources ($\bar{B}_{it}$) can be expressed as:

$$\bar{T}_{it} = \sum_{n=1}^{ntv_t} \frac{T_{nit}}{ntv_t} \sim N\left(H_b, \frac{\sigma_{TV}^2}{ntv_t}\right), \tag{11}$$

$$\bar{N}_{it} = \sum_{n=1}^{nnew_t} \frac{N_{nit}}{nnew_t} \sim N\left(H_b, \frac{\sigma_{news}^2}{nnew_t}\right), \tag{12}$$

very long time for drinking water to have a significant impact on human health. Further, the health impact will also be affected by various other factors such as family history, life style, etc. Therefore, it will be very difficult for consumers to learn directly from their previous own consumption.

[8] In the Bayesian learning process, the information signal are assumed to arrive according to an exogenous process. It is possible that consumers' learning and associated purchase behavior in this period may affect the media coverage this period, which may cause a potential endogeneity problem. Therefore, our effects of the information may be overestimated.

$$\bar{B}_{it} = \sum_{n=1}^{nonline_t} \frac{B_{nit}}{nonline_t} \sim N\left(H_b, \frac{\sigma^2_{online}}{nonline_t}\right). \tag{13}$$

In each period, consumers update their prior beliefs with the information available at that time, $(\bar{T}_{it},\ \bar{N}_{it}, \bar{B}_{it})$, to form their posterior beliefs. These new posterior beliefs are also normally distributed because the normal distribution is self-conjugated. The distribution of consumers' posterior perceived healthfulness of bottled water is given by:

$$\widetilde{H}_{it} \sim N(\bar{H}_{it}, \sigma^2_t). \tag{14}$$

Specifically, the evolution of mean and variance of posterior belief are shown as follows:

$$\bar{H}_{it} = a_t \bar{H}_{i(t-1)} + b_t \bar{T}_{it} + c_t \bar{N}_{it} + d_t \bar{B}_{it} \tag{15}$$

$$\sigma^2_t = \frac{1}{\frac{1}{\sigma^2_0} + \sum_{\tau=1}^{t} \frac{ntv_\tau}{\sigma^2_{TV}} + \sum_{\tau=1}^{t} \frac{nnew_\tau}{\sigma^2_{news}} + \sum_{\tau=1}^{t} \frac{nonline_\tau}{\sigma^2_{online}}} = \frac{1}{G}, \tag{16}$$

where

$$\begin{aligned} a_t &= \left(\frac{1}{\sigma^2_{H_{(t-1)}}}\right)/G, b_t = \left(\frac{ntv_t}{\sigma^2_{TV}}\right)/G, \\ c_t &= \left(\frac{nnew_t}{\sigma^2_{news}}\right)/G, d_t = \left(\frac{nonline_t}{\sigma^2_{online}}\right)/G, \end{aligned} \tag{17}$$

In summary, the unknown parameters that need to be estimated or specified are the linear parameters α, β_1, β_2, β_3, β_4, and β_5, and nonlinear parameters (including parameters for heterogeneity, and learning) $\sigma_p, H_0, H_b, \sigma_0, \sigma_{TV}, \sigma_{news}$, and σ_{online}. Other terms (e.g. $\bar{H}_{it}, \sigma^2_t, a_t, b_t, c_t, d_t, etc$) are constructed from linear and nonlinear parameters.

3.3. Consumer choice and market share

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

$$U_{i0mt} = \varepsilon_{i0mt}. \tag{18}$$

Since the i.i.d error term ε_{ijmt} is assumed to be type I extreme value distributed, we have a closed form solution of the probability that consumer i chooses beverage brand j in market m at time t:

$$Pr_{ijmt} = \frac{exp(I_j \bar{H}_{it} + \mu_{ijmt})}{1 + \sum_{k=1}^{J} exp(I_j \bar{H}_{it} + \mu_{ijmt})}$$

where $\mu_{ijmt} = \alpha_i P_{jmt} + \beta_1 X_j + \beta_2 TV_t + \beta_3 News_t + \beta_4 Online_t + \beta_5 OwnAd_{jt} + \beta_6 FirmAd_{jt} + \beta_7 RivalAd_{jt} + \gamma_1 Dummy_{DMA} + \gamma_2 Dummy_{season} + \xi_{jmt}$.

Let $\theta = (\sigma_0, \sigma_{TV}, \sigma_{news}, \sigma_{online}, \sigma_p)$. Aggregating over consumers, the market share of product j in market m at time t is given as follows:

$$s_{jmt} = \int Pr_{ijmt} \, \mathrm{d}\Psi(\bar{H}_{it}, \alpha_i|\theta) \tag{19}$$

where Ψ is the joint distribution of the mean health effect terms and the coefficients for heterogeneity α_i given θ.

3.4. Supply side

On the supply side, suppose there are L companies that sell beverage products in market m at time t and each company holds a set of products $k(l)$. Firms are assumed to play a Nash–Bertrand pricing game. Each firm chooses a set of prices to maximize its total profits. Following Nevo (2001), the profit of firm l in market m is

$$\Pi_{lmt} = \sum_{j \in k(l)} (p_{jmt} - mc_{jmt}) M_m \times s_{jmt} \tag{20}$$

where p_{jmt} and mc_{jmt} are the price and marginal cost of beverage product j in market m at time t, respectively. s_{jmt} is the market share of beverage product j and M_m denotes total market size. Assume firms compete in prices and the existence of a pure-strategy Bertrand–Nash equilibrium. The joint profit maximization of firm l with all products leads to the following system of first-order conditions

$$s_{jmt} + \left[\sum_{h \in k(l)} (p_{hmt} - mc_{hmt}) \frac{\partial s_{hmt}}{\partial p_{jmt}} \right] = 0, \tag{21}$$

for any j belonging to set $k(l)$.

We can further express the first order condition in vector forms. Define $S_{ihtm} = -\partial s_{htm}/\partial P_{gtm}$ and

$$I_{ih} = \begin{cases} 1, & \text{if product } i \text{ and } h \text{ are both sold by the same firm,} \\ 0, & \text{otherwise.} \end{cases}$$

Let Δ be a $G_{tm}(l) \times G_{tm}(l)$ matrix with $\Delta_{ihtm} = -I_{ih} \times S_{ihtm}$. Writing the above relationship in vector notation, we have,

$$(-\Delta_{mt})(P_{mt} - MC_{mt}) + S_{mt} = 0 \tag{22}$$

where S_{mt}, P_{mt}, and MC_{mt} are $G_{tm}(l) \times 1$ vectors of market shares, prices, and marginal costs of company l in market m at time t.

3.5. Instruments

In our model, we assume the product characteristics are exogenously determined, but the prices are correlated with unobserved product characteristics or demand shocks. To control for this endogeneity issue, we use two 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) and electricity prices (U.S. Energy Information Administration). We also use lagged values of these variables, up to six periods, in our instrument matrix. The second set of instrumental variables is Hausman-type instruments (Hausman, 1996), which are prices of the same brand in other markets. The intuition behind this is that the prices of the same brand in different markets are correlated due to the common production costs, but uncorrelated with market specific demand shocks. This assumption could be violated if there is a nation-wide demand shock, but it works well in our case.

3.6. Estimation and identification

We use 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 procedure developed by Narayanan et al. (2005), which accounts for the serial correlation problem and was used to estimate physicians' learning with respect to the efficacy of prescription drugs.

The identification of the learning parameters depends on the variation of market shares over time. As consumers receive information on the health effects of bottled water continuously, the variance of their beliefs becomes smaller ($\sigma_t^2 \to 0$). The true mean health effect H_b can be identified from the convergence of perceived quality $\bar{H}_{it}$ to H_b. 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 σ_0^2 to 1. Furthermore, we set the carry-over parameter δ to 0.7, which implies a 90% decrease in the direct effect of advertising and health information in six months.[9]

4. Results

4.1. Demand parameters

The estimation results are shown in Table 3. The first panel (Panel A) of the table contains parameters describing consumer learning and the second (Panel B) consists of

[9] After performing a grid search from 0.1 to 1.0 with an increment of 0.05 for the best carryover parameters for the media variables, we concluded that carryover values around 0.5 and 1.0 yielded not only the best fit and the results were robust to changes of the carryover parameters. Therefore, we fixed the carryover parameters at 0.7, which is the same value as in Narayanan et al. (2005). Details available from the authors upon request.

Table 3
Estimation results.

	Variable	Estimate	SE
Panel A	Prior mean H_0	−0.545	0.420
	True mean H_b	474.989*	108.195
	$\ln(\sigma^2_{TV})$	13.817*	1.22
	$\ln(\sigma^2_{news})$	17.715*	1.800
	$\ln(\sigma^2_{online})$	14.607*	1.582
Panel B	Price: mean	−60.384*	1.181
	Price: standard deviation	0.638	1.247
	Sugar	0.107*	0.005
	Sodium	−0.147*	0.004
	Caffeine	0.263*	0.005
	Own advertising goodwill stock	0.095*	0.003
	Same firm advertising goodwill stock	0.002*	0.001
	Rivals' advertising goodwill stock	−0.001*	0.000
	TV and radio goodwill stock	0.283	0.161
	News paper and magazine goodwill stock	0.128	0.411
	Online sources goodwill stock	−0.076	0.133
	Constant	−4.612*	0.092
	Regional dummies	Yes	
	Seasonal dummies	Yes	

Note: * stands for $p < 0.05$. Standard errors are calculated by bootstrapping.

linear parameters that enter the utility function linearly. Most estimates are significant with expected signs. We will discuss the results in turn.

The first two parameters are the prior mean and true mean health effect of bottled water. The estimate of H_0 is not significantly different from zero, but the true health effect of bottled water, H_b in Eqs. (8)(10), is estimated to be 474.989, which is positive and significant. Since the true health effect is significantly higher than consumers' prior belief, it implies that consumers can learn about the true health effect of bottled water over time. More importantly, the estimated coefficient of σ^2_{TV}, σ^2_{news}, and σ^2_{online} are all positive and significant, implying that signals from all media types contain information about the true health effect of bottled water products (H_b), and they improve the perceived quality over time. Further, the large variances of the signals suggest that for consumers, the health information signals they received in every period are very noisy. Therefore, consumers' perceived quality of bottled water only increases slightly in each period.

Note that because we normalize the initial prior variance to one, only the relative values of variances matter. The reciprocals of variances can be viewed as the weight of information signals from different sources, which indicates their relative contribution to the learning process. By taking the exponential of the values in Table 3,[10] we can calculate the relative magnitude of variances, $\sigma^2_{TV}/\sigma^2_{online}/\sigma^2_{news} = 1/2.2/24.1$. This result can be explained as one piece of TV and radio transcripts conveying as much information as

[10] This is because we estimate the natural logarithms of variances to make sure that they are positive.

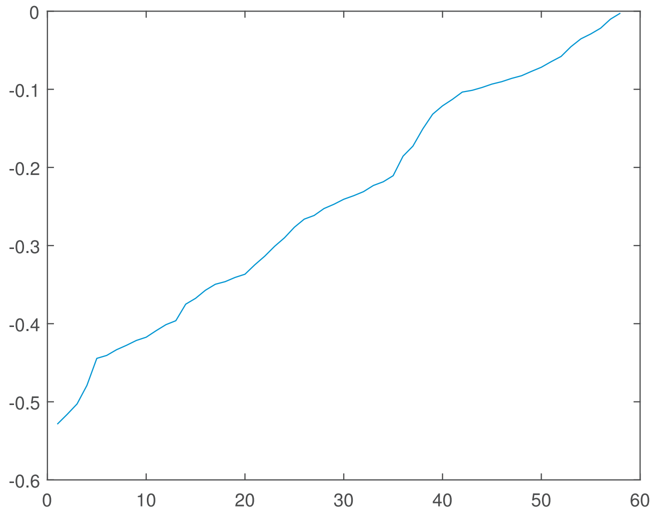

Fig. 3. Evolution of consumers' perceived quality of bottled water over time.

2.2 pieces of online sources or 24.1 articles from news from newspapers and magazine. Therefore, consumers value health information received from TV and radio the most, followed by online sources and newspapers and magazine.

Using the estimated learning parameters, we calculate the means of the posterior perceived quality of bottled water, $\bar{H}_{it}$, following Eq. (15). Fig. 3 illustrates how the perceived quality of bottled water evolves over time. Because we define the perceived quality of bottled water as a relative value compared with CSDs, the negative values of posteriors in Fig. 3 indicate that consumers still consider CSDs as a superior category. This is reasonable since the CSDs still enjoy the highest market shares in the refreshment beverage market, despite the strong growth of the bottled water segment.

What is more important in Fig. 3 is the overall trend rather than the absolute values. Over our sample period, there is an ascending trend of perceived quality $\bar{H}_{it}$, which implies the effect of health information on enhancing the perceived quality of bottled water among consumers.

The rest of the parameters in the utility function are presented in Panel B of Table 3. Price coefficient is negative and significant, as one would expect. However, the standard deviation of the price coefficient is not significant, suggesting that there is no significant heterogeneity of consumer preference in our sample period. Three nutritional factors are included as product characteristics. The coefficient for sugar and caffeine is positive and significant while that of sodium is negative and significant. This suggests that on average, consumers prefer high-sugar and high-caffeine beverages, in other words, a regular CSD product.

The advertising goodwill coefficient is positive and significant, implying that advertising has a positive impact on beverage demand. Further, the advertising goodwill of brands from the same firm also has a positive and significant impact, suggesting that there is a positive spillover effect among brands within the same firm. However, the magnitude of the impact is much smaller, compared to a brand's own advertising. Advertising goodwill from rival firms, on the other hand, has a negative impact on competing brands. Coefficients for direct effect (goodwill stocks) of health related information are not significant. This indicates that health related information from mass media affects bottled water demand by resolving consumers' uncertainty about the health consequences of consuming bottled water (which leads to the increase in perceived quality) instead of shifting consumers' utility directly.

4.2. Counterfactural simulations

Given the estimated structural parameters from the demand model, this section considers the effect of alternative levels of consumer learning and health information on beverage demand by simulating the market outcomes over the sample periods under different scenarios. Specifically, we conduct three counterfactual experiments to (1) evaluate how beverage demand and industry revenue will be affected by different levels of consumer learning, (2) examine how market outcomes could be affected by public health campaigns and (3) how market outcomes could be affected if firms react to the changing trend in beverage consumption by redistribute the advertising budget among bottled water and their CSD products.

4.2.1. Counterfacutal 1: alternative levels of consumer learning

In this section, we use the demand estimates to recalculate the new market shares for each product using the changed amount of information and recalculate the new equilibrium prices under each scenario. By comparing the new market shares, equilibrium prices, and revenue in different scenarios with the outcomes we observed in the original data, we are able to evaluate the impact of information on consumer demand and industry performance. Specifically, we simulate four different scenarios[11] to quantify the effect of consumer learning from different information sources:

1. No health related information at all.
2. No information from TV or radio.
3. No information from newspapers or magazines.
4. No information from online sources.

[11] We also did another set of simulation assuming perfect information of consumers, by plugging H_b into the utility function for all consumers. It is worth to notice that consumers' initial perceived health quality H_0 is very low and far from the true health quality H_b. Further, because the estimated variances of the signals received from different information source are very large, which means the the reception of the health information by individual consumers are very noisy. Therefore, it is a slow long-term learning process (as shown in Fig. 3). When we plug the true H_b into the utility function, the simulated market shares should be substantially different from the original market shares. The results confirm that the market share of bottled water skyrockets and the market share of CSDs drops to zero. As one can image, if every consumer's perceived health quality of water is equal to the true value, no one would want to drink the unhealthy CSDs, which would cause CSDs to lose the market completely. The details of the results are available upon request.

Table 4
Effect of consumer learning.

		Percentage change in (%)		
		Price	Market share	Revenue
No learning	Bottled water	−0.18	−24.31	−24.44
from any source	CSDs	−0.04	1.35	1.31
No newspapers	Bottled water	−0.01	−1.19	−1.19
or magazines	CSDs	0.00	0.07	0.07
No TV	Bottled water	−0.13	−17.98	−18.09
or radio	CSDs	−0.03	1.00	0.97
No online	Bottled water	−0.05	−7.10	−7.15
sources	CSDs	0.01	0.40	0.39

The results are shown in Table 4. The top panel assumes there is no learning by consumers from any sources, in which case the market shares of the bottled water segment will drop by 24.31% and, consequently, there will be a 24.44% decrease in the industry's total revenue. This suggests that health related information contributes 24.31% of bottled water demand and 24.44% of the industry's total revenue. In 2011, the total revenue of the bottled water segment was 19.9 billion dollars in the U.S., and the total revenue of CSD segment was 61.5 billion dollars in the U.S. (MarketLine, 2013a; 2013b). Given our simulation results above, the health related information generated about 4.8 billion dollars in revenue for the bottled water industry and took more than 0.83 billion dollars away from the CSD industry each year. In contrast, the CSD industry will benefit from the drop in demand for bottled water. In terms of total industry revenue, there will be an 1.31% increase for the CSD segments.

The second panel presents the simulated market outcomes assuming the absence of one of the three information sources, respectively. The demand for bottled water responds the most if there is no learning from health information in TV or radio, with a 18.09% decrease in demand. The relative contribution to revenue from three information sources is:

$$\begin{aligned}\text{TV and radio: Online Sources : Newspapers and Magazines} &= 18.09 : 7.15 : 1.19\\ &= 15.20 : 6.01 : 1.\end{aligned}$$

This suggests that revenue created by information received from TV and radio is 15.20 times more than revenue created from information from Newspapers and Magazines and revenue generated by information received from online sources is 6.01 times more than revenue created from information from Newspapers and Magazines. In other words, TV and radio provide consumers with the most informative messages, followed by online sources and Newspapers and Magazines and are the least informative. Three information sources also contribute to the reduction in consumption of CSDs.

Table 5
Health campaign.

	Percentage change in (%)			
Increase in information (%)	Bottled water price	CSD price	Bottled water market shares	CSD market shares
10	0.01	0.00	2.12	−0.19
20	0.02	0.01	3.71	−0.32
50	0.06	0.02	8.62	−0.76

4.2.2. Counterfacutal 2: impact of health campaign

Obesity is commonly acknowledged as the leading public health crisis in the United States, with an estimated social cost of approximately $117 billion a year (Komesaroff and Thomas, 2007). Previous policies have focused on decreasing the consumption of sugar-sweetened beverages, for example, by imposing taxes at the point of sale to consumers. However, the preponderant empirical evidence is that while such taxes can be generally effective in curbing consumption, they are quasi-ineffective in curbing obesity unless they are very large (Fletcher et al., 2010; Marlow and Shiers, 2010; Lopez and Fantuzzi, 2009; Zheng et al., 2013). Further, consumers are likely to switch to other sugar-sweetened beverages, such as fruit juice (Fletcher, 2011; Runge, 2011).

In this section, we simulate the impact of an alternative public policy: a nation-wide public health campaign to encourage demand for healthier foods and beverages, instead of taxing the consumption of unhealthy alternatives. Specifically, we simulate three national health campaigns on the health benefits of drinking water, which increase the amount of health related information by 10%, 20%, and 50%, respectively.

The simulation results are shown in Table 5 and revealed that more health related information can increase consumers' perception of the superior quality of bottled water products, which in turn stimulates the demand for bottled water and reduces the demand for CSDs. A 10% increase in health related information will lower the demand for CSDs by 0.19% and a 50% increase can diminish 0.76%of the demand. More importantly, 10% more health related information increases bottled water demand by 2.12%, and a 50% increase in information leads to a 8.62% increase in bottled water consumption.

As a comparison, we also simulate the market outcomes of imposing a 10% sales tax on CSDs, which is higher than the tax rate implemented in several states (e.g. Maryland, Florida, and Kentucky tax soda at a rate of 6%). The sales tax reduces CSD demand by 12.7%. However, only a fraction of consumers will switch to other sugar-sweetened beverages and the demand for bottled water is only increased by 1.67%. Comparing these two sets of polices, both the health campaign and soda tax can promote demand for healthy products (bottled water in this case) and reduce the demand for CSDs, but as we mentioned before, consumers may switch to other high calorie beverages which would weaken the effectiveness of taxes. Compared to a soda tax, providing consumers with more health related information increases the intake of healthy drinks directly and may

Table 6
Simulated percentage changes in market shares and profits for beverage companies.

Company	No consumer learning (1)		Health information increased by 10% (2)		Health information increased by 50% (3)	
	Market share (%)	Profit (%)	Market share (%)	Profit (%)	Market share (%)	Profit (%)
Coca Cola						
Bottled water	−24.30	−24.39	2.93	3.45	11.98	14.06
CSD	1.45	1.36	−0.19	−0.17	−0.76	−0.70
All products	−8.48	−8.57	−0.08	−0.09	−0.32	−0.38
Pepsi						
Bottled water	−24.23	−24.27	4.48	4.09	18.27	16.71
CSD	1.36	1.32	−0.18	−0.17	−0.74	−0.70
All products	−6.32	−6.36	−0.11	−0.12	−0.47	−0.49
Nestle						
Bottled water	−23.85	−24.20	3.68	3.51	14.81	14.31
CSD	0.00	0.00	0.00	0.00	0.00	0.00
All products	−23.85	−24.20	3.68	3.51	14.81	14.31
Dr. Pepper						
Bottled water	0.00	0.00	0.00	0.00	0.00	0.00
CSD	1.25	1.27	−0.17	−0.17	−0.69	−0.69
All products	1.25	1.27	−0.17	−0.17	−0.69	−0.69

encounter less resistance during implementation, which makes it an alternative policy instrument to encourage a healthy diet.

4.2.3. Impacts on beverage companies

As mentioned earlier, the changing trend in beverage consumption has also reshaped the beverage industry. To maintain their profitability, stay competitive, and capture the increasing demand, leading CSD producers, Coca-Cola and Pepsi, have entered the bottled water market and own multiple top bottled water brands. In this section, using simulation results from the previous section, we calculate the impact on market shares and profits for leading companies in both bottled water and CSD market under each scenario. The top three companies in the bottled water market are Nestle, Pepsi, and Coca-Cola, while the top three companies in the CSD market are Coca-Cola, Pepsi, and Dr. Pepper.

Table 6 provides the simulated percentage changes in market shares and profits for each company in each segment. Column 1 presents the impact when there is no consumer learning about health information at all (counterfactural 1). As a result, the bottled water sections of Coca-Cola, Pepsi and Nestle all experience a drop in market share and profits, ranging from −24.23% to −23.85%. Since no consumer learning about the health benefit of bottled water would constitute an industry-wide shock, common to all companies and brands, the magnitudes of the impact are similar across all firms. At the same time, when there is no consumer learning, some consumers may switch to CSD products, resulting an increase in CSD consumption. For example, Coca-Cola and Pepsi's profits in the CSD segment will be increased by 1.36% and 1.32%, respectively. Hence, although losing in the bottled water market when there is consumer learning, Coca-Cola and Pepsi will be compensated, at least partially, from the profit increases in the CSD market. The overall profit will only be decreased by 8.57% for Coca-Cola, and 6.36% for Pepsi. Nestle, however, will suffer a 24.2% decrease in profits since there are no CSD products in that company's product portfolio. Dr. Pepper's profit, on the other hand, will be increased by 1.27%, without bottled water products.

Columns 2 and 3 present the simulated changes in each company when there is a nation-wide health campaign such that health related information on media will be increased by 10% or 50% (counterfactural 2). When there is a 10% increase in health information, the bottled water sections for the three leading companies, Coca-Cola, Pepsi, and Nestle, will all benefit and the profits will be increased by around 3.45%, 4.09% and 3.51%, respectively. On the other hand, as more consumers choose bottled water, profits of the CSD segment will drop 0.17% for both Coca-Cola and Pepsi. Therefore, the net profit of Coca-Cola in both segments will be dropped by 0.09%. Similarly, the net profit change for Pepsi is around 0.12%. However, since there is no bottled water product for Dr. Pepper, its total profits will be decreased by 0.17%, based on the CSD segment alone. The simulation changes are also consistent when assuming a 50% increase in health information in media. For Coca-Cola and Pepsi, although the health campaign will drive consumers away from the CSD market, increased profits in the bottled water market will partially offset the losses in CSD, resulting a much smaller overall decrease in profits for Coca-Cola and Pepsi.

4.2.4. Counterfacutal 3: redistribution of advertising budgets

The beverage industry is heavily advertised and advertising is a key strategy for Coca-Cola and Pepsi. Therefore, facing the changing trend in beverage consumption, Coca-Cola and Pepsi might have the incentive to redistribute their advertising budgets among bottled water and their CSD products to stay competitive. In this section, given the substantial difference of advertising expenditures between bottled water and CSDs, we consider one scenario when Coca-Coca and Pepsi decide to cut the advertising expenditure of all their CSD products by a certain percentage and spend the budget on their bottled water products evenly. Note that the current simulation assumes a static supply side. The full supply side analysis of the optimal advertising decision, although very interesting, is beyond the scope of the present study. Modeling firm responses of prices, product offerings and especially advertising expenditures over time would require a structural dynamic game because of the long lasting effects of advertising. Specifically, we simulate the following three scenarios:

1. Coca-Cola and Pepsi redistribute 5% of CSD advertising budget to bottled water.
2. Coca-Cola and Pepsi redistribute 10% of CSD advertising budget to bottled water.
3. Coca-Cola and Pepsi redistribute 20% of CSD advertising budget to bottled water.

Table 7
Simulated percentage changes in market shares and profits for beverage companies.

Company	Redistribute 5% advertising budgets (1)		Redistribute 10% advertising budgets (2)		Redistribute 20% advertising budgets (3)	
	Market share (%)	Profit (%)	Market share (%)	Profit (%)	Market share (%)	Profit (%)
Coca Cola						
Bottled water	16.79	16.99	36.01	36.57	84.49	85.71
CSD	−2.23	−2.28	−4.51	−4.56	−9.37	−9.24
All products	−0.48	−0.65	−1.01	−1.38	−2.28	−2.90
Pepsi						
Bottled water	7.91	6.64	16.08	13.81	35.57	29.86
CSD	0.07	0.04	0.11	0.04	−0.10	−0.16
All products	0.23	0.24	0.41	0.44	0.65	0.70
Nestle						
Bottled water	−2.54	−2.47	−5.08	−4.96	−10.09	−9.81
CSD	0.00	0.00	0.00	0.00	0.00	0.00
All products	−2.54	−2.47	−5.08	−4.96	−10.09	−9.81
Dr. Pepper						
Bottled water	0.00	0.00	0.00	0.00	0.00	0.00
CSD	0.98	1.02	1.91	1.99	3.63	3.73
All products	0.98	1.02	1.91	1.99	3.63	3.73

The results on all four firms are presented Table 7. Because Nestle and Dr.Peper only own brands in one segment, they do not change their advertising expenditures. For Coca-Cola, as expected, its profits in the bottled water sector are increased by 16.99% and profits in the CSD sector dropped by 2.88% when 5% of CSD advertising budget are spent on bottled water. However, the net profit change for Coca-Cola is negative, with a 0.65% decrease. On the contrary, Pepsi gains 6.64% and 0.04% increase in the bottled water and CSD market, separately. And its net profits experience a 0.24% increase overall.

The main reason behind this difference between two firms could be the difference in adverting expenditures for the two firms. Coca-Cola, as the leader in the CSD market, outspends its rival greatly. Coca-Cola's average advertising spending is $2.92 million for CSD and $0.75 million for bottled water in one DMA in a month while for Pepsi, it is only $1.02 million on CSD and $0.05 million on bottled water. Therefore, by all reducing 5% of CSD advertising expenditures, Coca-Cola faces a larger drop in dollar amount which causes it to lose the market share in CSD. On the other hand, although the trend in bottled water consumption has been on the rise, CSD still leads the market with almost doubled market shares. As a result, for Coca-Cola, the profits increase in the bottled water sector generated by more advertising is not higher enough to compensate its loss in the CSD sector due to advertising reduction. For Pepsi, it still gain on the CSD market because the cut of its largest competitor's advertising expenditures.

The pattern persists when the advertising budget redistribution are increased to 10% and 20%. Coca-Cola will lose more overall as cutting more CSD advertising although the profits in bottled water will increase largely. Note that Pepsi's profit in CSD will start to decrease as it redistribute 20% of CSD advertising spending to bottled water. Further, Nestle's profits will drop significantly as Coca-Cola and Pepsi increase their advertising spending on bottled water. However, Dr. Pepper will be better off when its competitors all cut their advertising expenditures in the CSD market. To some extent, this simulation results is consistent with the fact that the CSD industry relies on advertising heavily and explains why Coca-Cola and Pepsi choose to spend much more on CSD but less on bottled water at this moment.

5. Conclusion

In this study, we use a structural approach to estimate the impact of health related information from different media outlets on bottled water demand. We find that although information has no direct impact on consumer utility, it can help consumers learn about the true health effects of bottled water over time and change their choices accordingly. The contribution of the health information to bottled water companies is about 4.8 billion dollars per year, accounting for more than 24% of the industry revenue. We also show that increasing the provision of health related information can further reduce unhealthy beverage (CSDs) demand and increase healthy beverage consumption (bottled water) significantly.

Our findings have implications to both managers and policy makers. For managers, given the influence of health related information on consumer preferences, bottled water producers can actively reveal the health effects of their products. When doing this, firms need to select communication channels carefully. Traditional media like TV and radio seem to be more informative to consumers, followed by online sources. CSD companies, besides fighting against the declining trend in their market, can move to the bottled water category to capture the rising demand. From the policy makers' perspective, our results suggest that a public health campaign could be effective in encouraging the consumption of healthier foods and beverages, compared with other policy instruments such as taxation.

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